Association for Institutional Research

PROFESSIONAL FILES | SPRING 2015 VOLUME

Supporting quality data and decisions for higher education.

Letter from the Editor

Association for Institutional Research

This volume of Professional Files brings us two articles on very different topics, but with a common theme—relationships.

Wang introduces Social Network Analysis, a data visualization technique that focuses on the relationships among cases, instead of just their attributes. Her three examples applying this technique to common IR study questions will make you want to start building your own SNA models right away!

Carpenter-Hubin, Sullivan, and Herbers share their experience building relationships with faculty through a collaborative study of faculty workload and resources. Their insights into how to work as peers respectful of each other's expertise can serve as a model for our own research partnerships.

Consider this a reminder to nurture your own relationships with IR colleagues by sharing your work in AIR Professional Files!

Sincerely,

Sharron L Ronco

Sharron Ronco

IN THIS ISSUE...

EDITORS

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ARTICLE 136

Association for Institutional Research

APPLICATIONS OF SOCIAL NETWORK ANALYSIS IN INSTITUTIONAL RESEARCH

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Abstract
Social network analysis (SNA), with its distinct perspective on studying relations and its exceptional capability to visualize data, should be embraced by institutional researchers as a promising new research methodology complementary to inferential and exploratory statistics. This article introduces SNA through discussion of three analytical studies on topics highly relevant to institutional research (IR): (1) double-majors, (2) gatekeeping courses, and (3) STEM pipeline leaking. The unique approach of SNA in exploring, analyzing, and presenting data has great potential for advancing IR's analytical capacity.

INTRODUCTION

Institutional research (IR) professionals frequently adopt new analytical tools and research methodologies. This has allowed more sophisticated studies to be carried out that better inform institutions' policy making, which leads in the long term to students being better served. Traditional descriptive and inferential statistics, from simple frequencies and cross-tabulations, to the whole family of regressions, to more-advanced techniques such as survival analysis and structural equation modeling, have sufficiently fulfilled a large part of IR's analytical functionality. At the same time, the large amount of data found in IR and the nature of IR research that emphasizes identification of patterns, predictions, and possible interventions, coupled with high-capacity software such as SAS, have made exploratory statistics a new frontier in IR. The recent interest in data mining and predictive modeling exemplifies this shift.

However, a missing piece of IR analytics is the study of relations. Traditional statistical methods assume the observation independence—that is, they assume that observations of a study are not related to one another, but rather can be independently examined by various internal and external attributes (Chen & Zhu, 2001). The observations in higher education settings, however, often are not independent. The activities of higher education and the people involved are relational and interactive in nature. Examples of these activities include co-authorship of scholarly publications, faculty collaboration on research projects, peer influence among students with specific ethnic or social backgrounds, mentorship between faculty members and students, formation of learning communities among students with shared academic interests, and so forth. Relations also extend beyond people: for example, majors within a discipline are interrelated by overlapping course offerings, colleges and universities are interrelated by students transferring in and out, and states form a network through out-of-state student enrollment.

Such networks of relations are extensive in higher education, but few studies have addressed their dynamics and implications, partly because of the methodological limitations of inferential and exploratory statistics. As Wasserman and Faust (1994) in their classic book of social network analysis (SNA) stated, "The focus on relations, and the patterns of relations, requires a set of methods and analytic concepts that are distinct from the methods of traditional statistics and data analysis" (p. 3). The inadequate understanding of relations and interactions among the various entities in higher education calls for the addition of network analysis into IR's analytical paradigm.

At the intersection of inferential statistics, exploratory statistics, and network analysis is data visualization—or the representation of data through graphical means. However, "data visualization . . . involves more than just representing data in a graphical form (instead of using a table). The information behind the data should also be revealed in a good display; the graphic should aid the readers or viewers in seeing the structure in the data" (Chen, Härdle, & Unwin, 2008, p. 6). As the well-known statistician and pioneer in data visualization Edward Tufte stated, "At their best, graphics are instruments for reasoning about quantitative information. . . . Of all methods for analyzing and communicating statistical information, well-designed data graphics are usually the simplest and at the same time the most powerful" (Tufte, 2001, p. 13).

Founded on graph theory, network analysis is exceptionally well developed in generating meaningful and intriguing visual representations of data. While charts and graphs are integral components of inferential and exploratory statistics, graphics is at the heart of network analysis. It is the way that an underlying network structure can be uncovered, while at the same time providing the vocabulary through which network properties can be described. At a time when effective communication of findings to institutions' administrators and other constituents is more important than ever to further data-driven and research-based policy making, network analysis, with its expertise in data visualization, can be especially beneficial to IR.

This article introduces SNA to the IR community. As a well-established method that has been widely used in social sciences, SNA can contribute a great deal to IR with its unique perspective on relations and its power in visual presentation. The following will (1) introduce basic concepts in SNA, (2) present three studies that used SNA, and (3) discuss issues key to successfully applying SNA in IR.

SOCIAL NETWORK ANALYSIS AND ITS BASIC CONCEPTS

SNA is inherently an interdisciplinary endeavor that uses social psychology, sociology, statistics, and graph theory. Beginning in the 1970s, the empirical study of various networks has played an increasingly important role in the social sciences. Among many of its applications, SNA has been used to understand the diffusion of innovations, the communication of news, the spread of diseases, the culture and structure of social organizations and business corporations, the formation of political views and affiliations, and so forth (Carrington, Scott, & Wasserman, 2005). More recently SNA has gained significant use in studying online communities and social media such as Facebook and Twitter.

The complicated mathematical background of SNA is beyond the scope of this article. However, it would be helpful to explain in simple terms several basic yet essential concepts used in the examples of analytical works described in this paper: vertice or node, edge, degree, directed and undirected graph, weight, modularity, and centrality.

Borrowed from graph theory, the interconnected objects in SNA are represented by mathematical abstractions called vertices (more commonly called nodes), while the links that connect some pairs of nodes are called edges. The number of edges incident upon a node is defined as degree. Typically, a graph is depicted in diagrammatic form as a set of dots for the nodes, joined by lines or curves for the edges. When applied to a study, nodes represent the observations of a study, and edges represent the relations between the observations of a study. If the relations are initiated from certain observations to others, the edges would be represented with arrows from the initiators to the receivers, and the graph would be directed. Conversely, if the relations between two observations are mutual, the edge would be represented with a line segment connecting the two, and the graph would be undirected. A graph is weighted if a value or a weight is assigned to each edge. Depending on the problem at hand, such weights might represent a diverse set of attributes of the relationship (Hanneman & Riddle, 2005).

For demonstration, Figure 1 is a weighted undirected graph representing a hypothetical network of faculty collaboration. Nodes 1–10 are faculty members. Edges exist between those who collaborated on grant proposals, and weights on the edges denote the number of grant proposals that the two faculty members submitted together. As seen

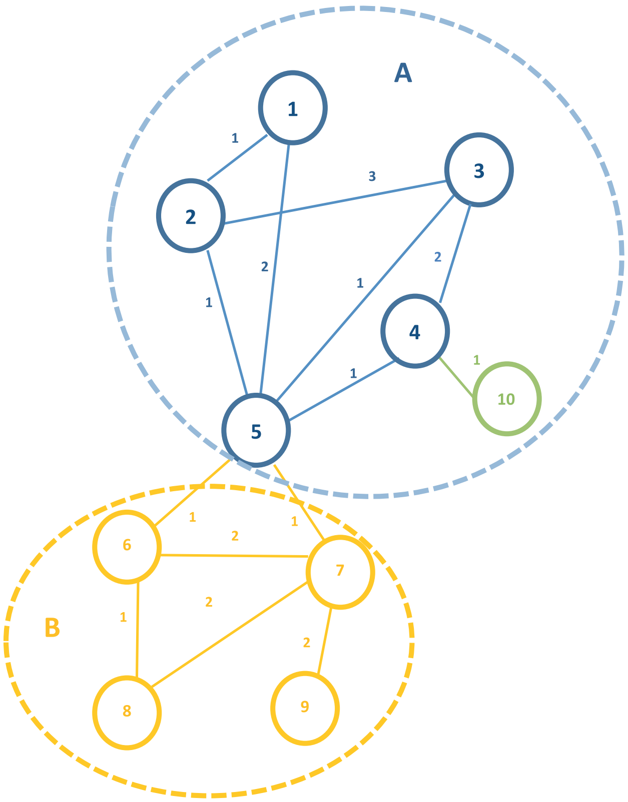

Figure 1. Demonstration of Basic Concepts in Social Network Analysis

in the graph, Faculty 2 worked with Faculty 1 once, with Faculty 5 once, and with Faculty 3 three times on grant proposals; the node representing Faculty 2, therefore, has a degree of three and a weighted degree of five.

Modularity is one important measure of the network structure. It divides a network into modules, also called groups, clusters, or communities. Networks possessing community structures function differently from average networks, so identification of such community structures can have substantial importance in understanding the dynamics and properties of the network. The mathematical idea of the modularity measure is to compute the difference between the number of edges falling within groups and the expected number of edges in an equivalent network where edges are placed at random (Newman & Girvan, 2004). Large differences would indicate nodes being densely interconnected while being only sparsely connected with the rest of the network—in other words, forming modules. Network analysis software can generate this measure and partition the network by its underlying community structures.

Centrality is another important measure, examining the relative importance of a node within a graph. There are three main types of centrality: degree, closeness, and betweenness. Degree centrality is defined as the number of edges that a node has. The nodes having higher degrees are related to other nodes, and therefore are at positions in the network that are more central. Closeness centrality emphasizes the distance of a node to all other nodes in the network. Betweenness centrality focuses on the position of a node between pairs of nodes. The higher betweenness of a node means more nodes depend on it to make connections with other nodes. Centrality can be evaluated with a set of statistics, such as Freeman Degree Centrality, Geodesic Path Distances, Eigenvector Centrality, Hierarchical Reduction, and so forth (Hanneman & Riddle, 2005). This article does not attempt to elaborate on details of these statistics; the readers are encouraged to obtain more information (e.g., Carrington et al., 2005; Chen et al., 2008; Tufte, 1990, 2001; Wasserman & Faust, 1994). The output of the above-mentioned statistics for the hypothetical network in Figure 1 is provided in Table 1 (next page).

For SNA, however, the statistics are often not the end product. Unlike inferential and exploratory statistics, the graphs in SNA are at the core of explaining and understanding findings, as the relational statistics are incorporated into graphs through the visualization process. Figure 1 shows two modules; Module A, consisting of faculty members 1 through5 and faculty member 10, and Module B, consisting of faculty members 6 through9. Members of each module worked more frequently within rather than across the modules.

Table 1. Demonstration of Basic Relational Statistics Output in Social Network Analysis

Id	Label	Modularity Class	Degree	Weighted Degree	Closeness Centrality	Betweenness Centrality	Eigenvector Centrality
1	Faculty 1	0	2	3	0.47	0.00	0.44
2	Faculty 2	0	3	5	0.50	0.01	0.57
3	Faculty 3	0	3	6	0.53	0.03	0.59
4	Faculty 4	0	3	4	0.53	0.22	0.49
5	Faculty 5	0	6	7	0.75	0.65	1.00
6	Faculty 6	1	4	6	0.60	0.18	0.71
7	Faculty 7	1	4	7	0.60	0.18	0.71
8	Faculty 8	1	2	3	0.41	0.00	0.40
9	Faculty 9	1	2	4	0.41	0.00	0.40
10	Faculty 10	0	1	1	0.36	0.00	0.14

Faculty 5 worked mainly with faculty 1 through4, but also worked once with faculty6 and once with faculty 7, thus bridging the two modules. A closer look at the departmental affiliation shows that faculty in Module A are from the biology department, and faculty in Module B are from the psychology department. Faculty5, a professor in biology, has research interests in neuroscience and has actively collaborated with professors in psychology. Faculty 10 is a statistician from the mathematics department who built a collegial relationship with Faculty 4 and who was once asked to work with him on a grant.

It can also be observed that Faculty 5 is at the center of the network in all three centrality measurements. Faculty 5 is identified as an active researcher in the two fields of biology and psychology by the high degree centrality (shown in Table 1 as Degree of 6 and Weighted Degree of 7), as a good collaborator with all other researchers by the high closeness centrality (shown in Table 1 as 0.75), and as the key person for promoting interdisciplinarity between the two fields by the high betweenness centrality (shown in Table 1 as 0.65).

APPLICATION OF SOCIAL NETWORK ANALYSIS IN THREE STUDIES

This section will describe the application of SNA through three examples of small-scale analytical work: (1) a study of double-majors that used the modularity measure of SNA to reveal the connectivity among majors that can inform student advising; (2) a study of gatekeeping courses that used the measure of centrality to identify major-specific and general-education courses that students failed before dropping out of the institution; and (3) a study of STEM (science, technology, engineering, and mathematics) pipeline leaking that examined students who started in STEM majors but subsequently graduated in non-STEM majors.

The three studies were conducted using the open source software Gephi (http://gephi.org). As a tool specifically developed for network analysis, Gephi has at its core a set of algorithms, called layouts, that detect and generate graphical representations of network structures. The layout ForceAtlas, for example, probably the most used force-directed layout, simulates a physical system in which nodes repulse each other like magnets, while edges attract their nodes like springs. These forces create a movement that eventually converges to a balanced state of spatialization of the nodes and edges, revealing the structure and features of the network. Layouts have their specialties that suit networks of different sizes and emphasize different features. Layouts such as ForceAtlas2 and OpenOrd work with big networks, Circular and Radial Axis emphasize ranking, and GeoLayout uses latitude/longitude coordinates to visualize geographical networks.

The software also provides calculations of relational statistics unique to network analysis. Measures for modularity and centrality, among other statistics, can be generated with relative ease. The statistics can then be used in visualization; for example, the computed modularity allows partitioning of nodes into groups and reveals the community structure of the network. The statistics can also be saved into the data set and used in other statistical analysis; for example, the eigenvalue for centrality of each observation can be a new predictive variable in a regression model.

Graphs generated through Gephi are the main tool used to present findings of the three studies. Main features are shown, while detailed institution-specific figures that could have been shown as labels accompanying the nodes and edges are removed from the graphs.

Study 1: Double-Majors

Many college students concurrently pursue studies in two or more majors. Faculty and student advisors may anecdotally know some of the popular combinations of majors in their discipline; IR analysts, however, would want to approach the phenomenon of double-major with empirical evidence.

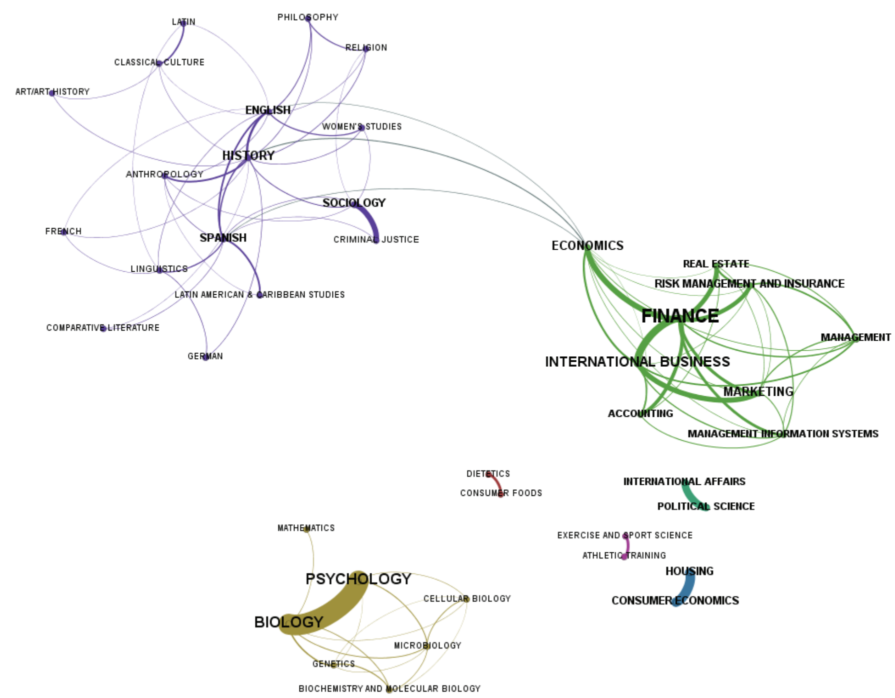

Figure 2. Double-Major Combinations of Bachelor's Degree Recipients

Five years (2009–13) of undergraduate degree data were compiled to ensure adequate sample size and to minimize fluctuations over the years. The data file contained majors, combinations of double-majors, and the number of students awarded degrees in each double-major. After applying the layout algorithm of ForceAtlas, the partitioning based on the statistics of modularity, and the filtering that eliminated majors with fewer than five students graduating with double-majors every year over the study period, a network structure emerged with more than 1,500 baccalaureate graduates in two of the approximately 40 or (Figure 2).

Majors clustered into groups based on their connections with one another after the modularity measure was employed. Three areas of study appeared prominently in the graph where double-majors concentrated—economics/business, arts/humanities, and biological sciences/psychology. Four free-standing yet strongly tied pairs of majors were also identified—international affairs/political science, housing/consumer economics, exercise and sport science/athletic training, and consumer foods/dietetics. Clustering of majors into groups provides an empirical verification that double-majors occur most often within disciplines where connectivity between course offerings, degree requirements, and administrative procedures facilitates the pursuit of double-majors. The font size of the major titles is proportionate to the weighted degree of the major—that is, the number of students in this major who also graduated with a degree in another major. It can be seen that finance, psychology, biology, international business, and economics had the most students graduating with double-majors. The thickness of the edges is proportionate to the number of students taking on the corresponding pair of majors. It is then observed that over the five-year period psychology/biology, housing/consumer economics, international affairs/political science, finance/international business, and finance/economics were the top five most popular double-major combinations.

As Edward Tufte (2001) stated, "Modern data graphics can do much more than simply substitute for small statistical tables" (p. 9). The visual presentation in Figure 2 of the double-major data not only conveys information in a more coherent and succinct fashion than a tabular presentation, but also reveals the data at multiple levels not conveniently available in table form. It provides a broad overview of the areas of study within which double-majors tend to form, as well as the details of specific majors and major combinations. As groupings of majors surface through the modularity measure of SNA, more insights emerge. . These patterns of double-majors that graduates have successfully followed can serve as evidence for student advisors in their discussions with students contemplating taking on another major of study. University administrators might want to strengthen existing partnerships or explore new linkages between majors to enrich students' educational experiences and promote their future employability.

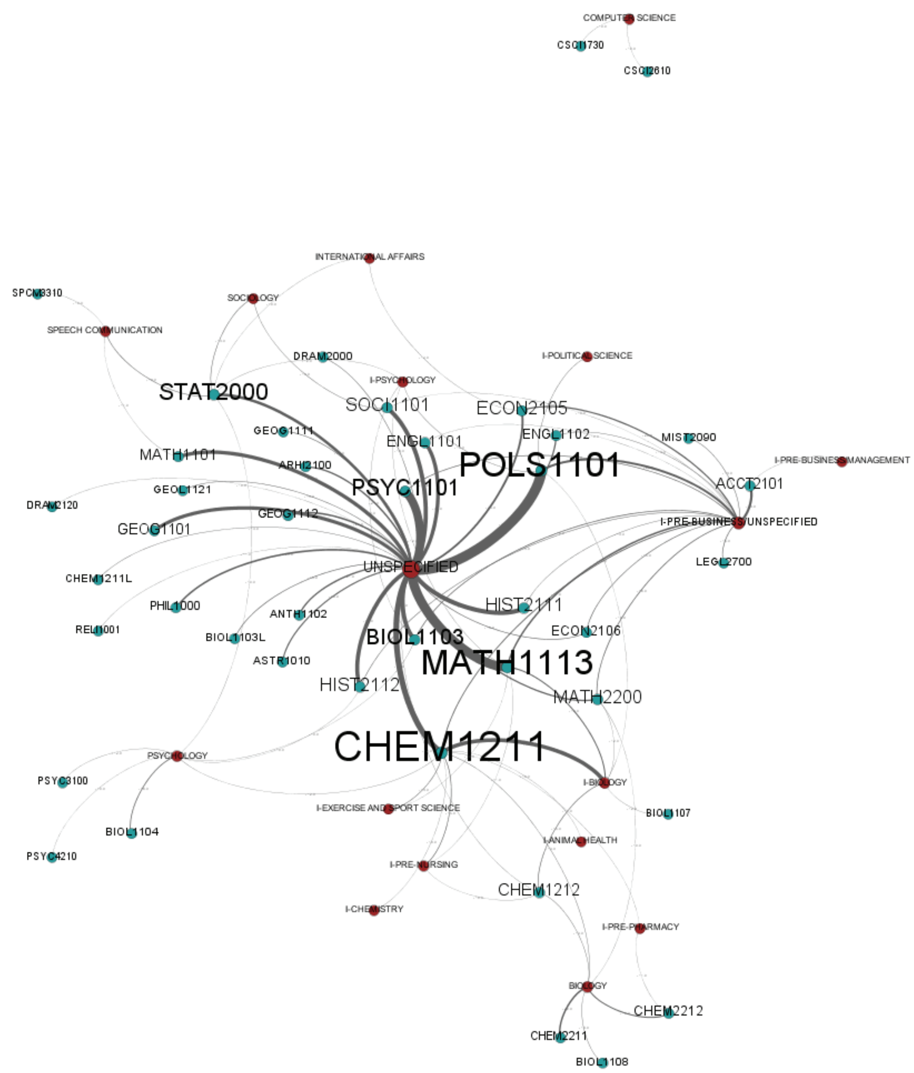

Figure 3. Failing Courses and Last Major of Undergraduate Dropouts

Study 2: Gatekeeping Courses

Entry-level gatekeeping courses have been known to pose challenges to students and to potentially lead to attrition, particularly in STEM majors. It is very important for institutions focused on retaining and engaging students to help those students succeed in courses that most frequently serve as gatekeepers. Identification of these courses is inevitably the first step.

This study tracked students from four first-time, full-time freshmen cohorts (Fall 2004–Fall 2007) to identify dropouts—those who had neither graduated nor remained enrolled six years after their initial matriculation. For those dropouts who had failing grades on record, the failed courses and the majors that they last enrolled in before leaving the institution were compiled. Over 1,500 students from 17 majors with 42 potential gatekeeping courses were included in the study.

Figure 3 is the visual representation of relations between failed courses, indicated by green nodes, and last majors, indicated by red nodes. Plotting was based on the degree centrality of the majors in this course-major network. The star network at the center of the graph made it clear that most of the dropouts left the institution with an unspecified major—in other words, they left early in their college life before declaring a major—and the many courses surrounding the unspecified major were the failed courses that could be potential hurdles to student retention. Among them, five introductory courses—Precalculus (MATH1113), American Government (POLS1101), Elementary Psychology (PSYC1101), Freshman Chemistry I (CHEM1211), and Basic Concepts in Biology (BIOL1103)—have prominent edges in the graph. The thickness of the edges between these courses and the unspecified major is proportionate to the number of students with an unspecified major who failed these courses. Furthermore, these five courses were actually the most challenging for students from all majors, as indicated by the size of their title in the figure. The size is proportionate to the total number of students who failed these courses regardless of their major.

The university also lost students in the other red-node majors—computer science, prebusiness, psychology, biology, and so forth. These majors are located on the periphery of the graph because of their relatively low centrality in this course-major network. Failing of certain major-specific courses was potentially related to dropping out of these majors. For example, two foundation courses in computer science, Systems Programming [CSCI1730] and Discrete Mathematics for Computer Science [CSCI2610], were probably weeding out students. An introductory accounting course, Principles of Accounting I [ACCT2101] and an introductory economics course, Principles of Macroeconomics [ECON2105], were stumbling blocks for some students in prebusiness. The introductory statistics course [STAT2000] might have been a source of struggle for some students with sociology, speech communication, international affairs, and psychology majors.

One of the principles that Tufte (1990) suggested for the good practice of statistical graphics is "enhancing the dimensionality and density of portrayals of information" (p. 9). Figure 3 combined three dimensions of information—the gatekeeping courses, the majors that lost students, and the relationship between majors and courses—in one graph, while the same information in tabular form would have been cumbersome and lacked clarity. Instead of providing an isolated view of students and courses confined to a specific major, Figure 3 allows examination of more comprehensive course-taking patterns across majors. More importantly, the graph vividly points to possible directions for further investigation and action. University administrators might want to evaluate teaching and learning in the five introductory courses revealed as gatekeepers in the graph. Perhaps factors like a large-lecture form of pedagogy, one-way passive learning, or an emphasis on memorization over critical thinking, might have contributed to the students' failings. Strategies could then be developed to engage both the faculty and the students to change these gatekeepers into gateways of student success. The department head of biology might learn from the graph that for students intending to major in biology, Freshman Chemistry I (CHEM1211) and II (CHEM1212) together with Principles of Biology I (BIOL1107) were the most challenging courses, and that for students who succeeded in these courses and officially enrolled in biology as a major, the next set of courses in the sequence—Modern Organic Chemistry I (CHEM2211) and II (CHEM2212), and Principles of Biology II (BIOL1108)—were road blocks. A long-term plan focusing on building a solid foundation for further study in this major may be needed. Curriculum and pedagogy designed with intentional sequencing may help ensure adequate preparation and smooth transition of students for each section of the course sequence.

Study 3: STEM Pipeline Leaking

Government, educators, and industry leaders have long been concerned about STEM pipeline leaking, where students depart from academic and career paths in science, technology, engineering, and mathmatics. According to the BusinessHigher Education Forum (2010), only 4 percent of the 4 million ninth-graders in the United States in 2001 would be STEM college graduates by 2011. This study attempted to revealan aspect of the leakage along the STEM pipelineby identifying undergraduate students in STEM majors who changed their academic pursuit to non-STEM majors.

Students from five first-time full-time freshmen cohorts (Fall 2003–Fall 2007) were tracked through fiscal year 2013 for bachelor's degree attainment. Those who first declared a major in STEM (based on the National Science Foundation definition) and later graduated in non-STEM majors, and whose major GPA was 3.0 or above when leaving STEM, constituted the group for this study.

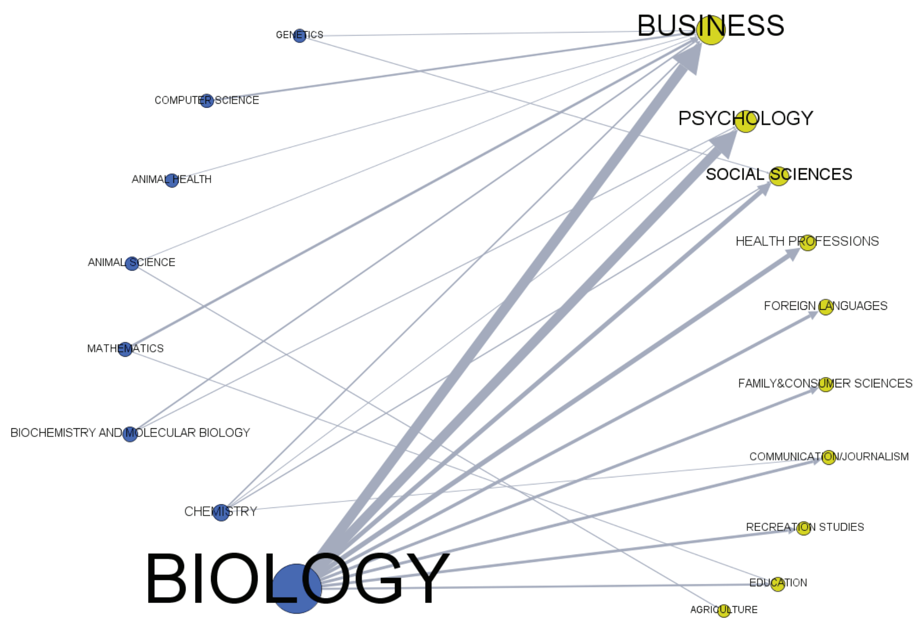

Figure 4. STEM Major Students Graduating in Non-STEM Majors

A directed graph using the Circular Layout was built to show the migration between majors. For focus and clarity, only STEM majors with ten or more students in the five freshmen cohorts who later graduated in non-STEM majors were retained. The results in Figure 4 represent about 800 students in eight starting STEM majors who graduated in ten non-STEM fields. The blue nodes on the left side represent starting STEM majors, sorted and sized by the number of students leaving for any non-STEM major. The yellow nodes on the right side represent ending non-STEM majors classified into disciplines by the first two digits of the major CIP code, sorted and sized by the number of students transferring in from all STEM majors. The thickness of the edge between two nodes is proportionate to the number of students changing majors.

Figure 4 is mainly descriptive. By mapping the migration of students, the status of retention and persistence in STEM majors at the institution is illuminated. The graph does not intend to address the many facets of the issue, but rather to show the non-STEM destinations for STEM majors who were in solid academic standing in their STEM major. These students might intend to pursue postgraduate professional programs, or plan for careers other than basic research, or simply want to explore studies beyond STEM. Instead of a divisive view of STEM versus non-STEM, the linkages in the graph present an opportunity for cooperation between the two fields.

A major-minor partnership can be one way to bridge the two fields. Possibilities exist for interdisciplinary collaboration between computer science and management information systems in business; mathematics and econometrics or finance in business; biology and dietetics study or nutrition science in family and consumer sciences; and so on.. Certificate programs can be another option—for example, a certificate program in science journalism could be an option for students in biology or chemistry who are also interested in journalism; a program in math education could be an option for mathematics students who have an interest in education; or a program in health promotion could be a good fit for biology students aspiring to a career in health professions. If the demanding workload of a STEM major prohibits formal pursuit of another area of study, an area of emphasis that blends in courses from a relevant non-STEM major may meet students' needs. Other possibilities may include joint projects or the incorporation of governmental, societal, or cultural implications of science and technology into the teaching of STEM.

Figure 4 illustrates many opportunities to bridge the gap between STEM and non-STEM, and suggests the need for an orchestrated effort from departments on both sides to foster a campus-wide culture change geared to encourage students to stay in STEM without missing opportunities present in non-STEM fields.

DISCUSSIONS

In addition to the Gephi software that was used to conduct the above three studies, other open source software for network analysis include UCINET, Pajek, and R. All offer functions such as importing and filtering data, visualizing and spatializing network structures, generating relational statistics, and manipulating and exporting graphic presentations (Bastian, Heymann, & Jacomy, 2009). Their flexible interfaces and interactive ways of analyzing data make them accessible to IR analysts of different levels.

There are two issues critical to the successful application of SNA in IR. First is an open mind that sees relations and tries the network approach in conducting research on topics old and new. Network analysis, especially, allows new leverage for answering traditional research questions in IR. Relational statistics generated in SNA can provide alternative explanations to traditional theories, or can explain additional variance when they are being entered into established models. Studies that provide good examples of SNA include work investigating social network and college students' sense of community (Dawson, 2008); student networking in an online learning environment (Dawson, 2010); peer influence on student persistence and retention (Eckles & Stradley, 2012; Thomas, 2000); the extent to which size and density of a student's social network predict academic achievement (Fletcher & Tienda, 2009; Skahill, 2003); and the effect of roommate and friend network on racial attitude and cultural competency (Levin, van Laar, & Sidanius, 2003; van Laar, Levin, Sinclair, & Sidanius, 2005); faculty co-authorship and co-citation (Girvan & Newman, 2002; Mählck & Persson, 2000; Otte & Rousseau, 2002; Perianes-Rodríguez, Olmeda-Gómez, & Moya-Anegón, 2010). However, few studies have been done on the formation of network, or on the university social network as a whole in which the student network, the faculty network, and the staff network interact. More robust and varied studies on SNA are needed to enrich the literature in higher education in general and in IR in particular.

The second issue is how to visually present the data with proper functionality and aesthetic form. Excellence in data visualization lies in the delivery of patterns and their implications uncovered from a data set in an intuitive, informative, and productive way, to improve understanding and encourage audience engagement (Friedman, 2008). The various network analysis software products provide highly configurable layout algorithms for generating graphs, and tools for modifying the display parameters of the graphs. They are readily available to the analyst, but only the right use of them can achieve balance between information accuracy and visual attractiveness, and can ultimately facilitate understanding of the data. The graph should lead the viewer to think about the substance and to see the differences, rather than be distracted by the graphic design. Most often, multiple aspects of the data set can be presented in one graph; a clear focus serving a clear explanatory purpose is thus important for the graph to be meaningful. Sometimes details are sacrificed to render the graph with clarity; tabular and verbal descriptions of the data set then must be closely integrated with the graph for full reporting of the findings. And above all, "an ill-specified model or a puny data set cannot be rescued by a visually appealing graph" (Tufte, 2001, p. 13).

SNA is not meant to replace inferential and exploratory statistics, but rather is a complement that greatly enriches traditional model- building by allowing the study of unique research questions concerning a network type of relationships. IR has been a relative latecomer to network analysis. However, as more relational data (e.g., institutional records, email corpora, online learning management systems, and social media Web sites) are collected and become more easily accessible, IR researchers will have more opportunities to apply SNA and thus to appreciate the unique insights this method offers. SNA should emerge as an important tool as IR increasingly assumes the role of a local and national key player in educational statistics, analytics, and policy making.

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ARTICLE 137

TWO HEADS ARE BETTER THAN ONE:
A Collaboration between Institutional Research and Faculty for a More Meaningful Analysis of the STEM Faculty Experience

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Abstract
Institutional researchers come to their field from a variety of educational and work experiences. Regardless of their expertise, however, it is difficult—if not impossible—for a single researcher, or even a large team of researchers, to know and understand all the nuanced differences among the many disciplines found in a comprehensive university. This paper discusses the collaboration between institutional researchers and faculty to evaluate the faculty experience in science and engineering. Rather than discussing the outcome of that evaluation, this paper focuses on the value of the collaborative process.

INTRODUCTION

The Ohio State University's project Comprehensive Equity at Ohio State (Project CEOS), which was funded by a grant from the National Science Foundation, focuses on retention of women faculty in the STEM disciplines (science, technology, engineering, and mathematics). Project CEOS has worked intensively with administrators and faculty in three STEM colleges (Engineering, Veterinary Medicine, and the Division of Natural and Mathematical Sciences within Arts and Sciences). Project CEOS researchers wished to study and evaluate resource allocation and working environments for men and women faculty in these units to understand whether Ohio State has problems similar to those identified in the landmark Massachusetts Institute of Technology (MIT) study, "A Study on the Status of Women Faculty in Science at MIT" (Chisholm et al., 1999), described below.

At the request of Project CEOS, the Office of Academic Affairs appointed a committee to study resource allocation and working environments. The committee was charged to identify important resource parameters of the work environment for faculty, and then to measure those parameters appropriately in order to ascertain whether gender was an explanatory variable.

The committee included four women and five men holding the following staff and faculty positions:

- Assistant vice president, Institutional Research and Planning
- Associate director, Institutional Research and Planning
- Director, Human Resources Organizational Metrics and Data Analytics
- Professor, Evolution, Ecology, and Organismal Biology; principal investigator, Project CEOS
- Chair, Faculty Compensation and Benefits Committee; professor, Comparative Studies
- Professor, Veterinary Biosciences
- Associate provost and director, The Women's Place; professor, City and Regional Planning
- Professor, Statistics
- Professor, Electrical and Computer Engineering

The results of the committee's work have been published in a special report (Herbers & Desai, 2012). The actual findings are of interest, but here we focus on the value of the collaborative process, with particular emphasis on the insights brought to bear by the faculty who work in the relevant environments and how those insights shaped the analysis. Our experiences show how understanding patterns in data concerning faculty work is best achieved through collaboration between institutional researchers and faculty from multiple disciplines in the discussions and analysis. Furthermore, such efforts provide faculty with opportunities to learn about disciplines outside their own.

COMMITTEE BACKGROUND

"Institutional researchers should seek opportunities to collaborate with faculty. They can provide a valuable service to faculty and enhance the scholarly value and intellectual rewards of their own work" (Delaney 2009, p. 35).

Colleges and universities rely on research professionals for the collection, reporting, and analysis of institutional data to support decision-making and to provide for accountability. These institutional researchers work with data sets that address a wide range of topics, including budgets, personnel, students, and square footage of lab space to develop an overall portrait of how the institution works. Given the range of research topics, it is not surprising that the educational background of institutional researchers is anything but standard. Nationally, 30 percent of all institutional researchers hold their highest degree in the social sciences, with another 60 percent distributed fairly evenly across education, STEM fields, and business. The remaining 10 percent are found in humanities and other disciplines (Volkwein, Liu, & Woodell, 2012). The committee had access through its two Institutional Research and Planning (IRP) members to the expertise of the full IRP group at Ohio State; members of that group hold advanced degrees in public affairs, business administration, psychology, library sciences, and higher education and student affairs. This combination of education yields a team that is trained in quantitative and qualitative research, program evaluation, bibliometrics, semantic analysis, and project management. With an average tenure at Ohio State of more than ten years, the institutional research (IR) staff also has valuable historical knowledge of the university.

The faculty expertise on this committee was highly quantitative. Because they come from science and engineering backgrounds, the faculty members were able to think carefully about confounding variables, outliers, methods for pooling data, and specifics of statistical analysis. Their understanding of how their work is represented by institutional data and how that representation can be skewed by faculty whose work lies outside his or her disciplinary norms was tremendously important to this study. This evaluation required us not only to analyze existing data, but also to delve into local department culture to understand those data.

IRP staff have worked closely with Ohio State faculty over the years, most commonly providing, as suggested by Delaney, "a valuable service"—data and analysis to support faculty scholarship or for faculty bodies to consider as part of faculty governance and decision-making. This project, however, had a distinctly different collaborative approach. Committee members recognized from the beginning that both staff and faculty had important contributions to make, with staff responsible for providing quality data and analyses, and faculty responsible for ensuring that the data were gathered and the analyses were performed with the appropriate background understanding and context. The committee learned early in its deliberations, however, that faculty were not always knowledgeable about research and teaching norms in STEM disciplines other than their own. The process of establishing context for the data thus became one of discovery by the whole committee, rather than instruction from faculty to staff. The IRP staff and faculty were peers on this project, each contributing her or his own methodological and content expertise for the good of the committee as a whole.

THE EVALUATION

As the first effort to evaluate STEM faculty resource allocation and work environment by gender for our institution, this project required careful deliberation before plunging into data analysis. The committee members were highly aware of the potential impact of a study that included gender as a variable. It therefore became imperative that we develop methodologies that would stand up to intense scrutiny.

The committee met every other week over a three-month period and interacted frequently via email, spending the first several weeks discussing its charge and what kinds of data would be most important. The first decision was to concentrate on resource allocation to tenure-track faculty, because this group demands the greatest share of faculty resources, and because the institution makes long-term commitments to its tenured faculty. Our discussions at this stage centered on the kinds of resources important for faculty as well as the kinds of data that were available. Faculty members on the committee brought up a suite of issues for which centralized data simply do not exist (e.g., advising loads, library resources, and opportunities for collaboration). The interplay between staff and faculty at this stage was crucial: as faculty members brought up resources they considered crucial to their professional success (library subscriptions to certain journals, availability of certain equipment, access to graduate student assistants), IR staff found themselves challenged to identify appropriate measures from their databases. Ultimately, the committee settled on four parameters of most interest for resource allocation: salary, start-up accounts, square footage of lab space, and teaching loads. Not all identified data were available through central institutional repositories, but faculty members of the committee were able to identify additional data sources. This supplemental information included data on start-up accounts offered to incoming faculty and data on teaching loads for the health sciences disciplines, whose teaching assignments are not accurately captured in the institutional data maintained by the Office of Enrollment Services. These additional data were available from college deans' offices. Next we describe the discussions that led to the final analysis reported in Herbers and Desai (2012).

Literature Review

Faculty and staff on the committee reviewed previous scholarship related to gender disparities in faculty salaries, teaching, and service assignments and research productivity. Most such studies base their work on survey data, and often use the National Survey of Postsecondary Faculty as a source. Recently, the National Research Council released *Gender Differences at Critical Transitions in the Careers of Science, Engineering and Mathematics Faculty,* which looked not only at salary and workload issues, but also at the allocation of laboratory space and start-up packages (National Research Council, 2010). Data for this study were collected through a survey of tenured or tenure-track faculty and department administrators from the 89 universities then categorized as Carnegie Research I.

Perhaps the most well-known study of gender disparities in science disciplines at a single institution is the MIT study "A Study on the Status of Women Faculty in Science at MIT" (Chisholm et al., 1999). A faculty committee collected data from the Office of the Dean of Science and from institutional researchers in the MIT Planning Office. In addition, that faculty committee conducted interviews with women faculty and department heads. This study found that female faculty received lower pay and fewer resources than their male colleagues, despite equal professional accomplishments.

It became apparent to the Ohio State University committee that many of the variables used in these earlier studies were already collected in our institutional data sets, with additional data collected by individual colleges. Thus, the committee decided not to include a faculty survey in the research and analysis design.

Faculty Salaries

IRP provided faculty salary data, normed to a nine-month appointment. In our initial review of those data, we discussed determinants of faculty salaries that complicate the kind of granular analysis we intended (e.g., rank, time in rank, discipline, scholarly record). Because we were most interested in determining whether a gender gap existed for salary, the committee needed to employ techniques that would eliminate potentially confounding factors. The discussion on these factors was robust and lively. Committee members readily agreed that salaries for assistant professors are relatively uncomplicated, reflecting starting salaries at market and a short timespan within that rank. Thus evaluating salaries for assistant professors required that we control for market conditions but relatively little else.

By contrast, salaries for tenured senior faculty reflect a multitude of factors: (1) salary compression, which results when raise pools do not keep pace with market increases in starting salaries; (2) time in rank, which should reflect the number of raise cycles leading to higher salaries for those promoted years ago; (3) the system of merit raises employed by the institution, which produces variation within a cohort that reflects differential productivity; (4) other market forces (e.g., external offers, hires from other universities, previous administrative experience, demand for a particular focus within a discipline), which lend further nuance to data interpretation. In order to focus on the variable of greatest interest, gender, we had to control for other factors that affect faculty salaries.

The committee started by eliminating outliers (e.g., administrators including deans, associate deans, and chairs) as well as individuals holding endowed professorships and those with recent prior administrative experience (e.g., former deans). Even though the salary data were deidentified by IR staff, the faculty representatives were able to infer identities of many individuals involved; the discussions that devolved allowed us to make valid decisions on potential outliers. In particular, the faculty representatives were able to note individuals who had been hired or named as University Distinguished Professors or Eminent Scholars. To a considerable extent, this identification of especially stellar faculty as outliers reduced the effect of other market forces.

The initial data analysis was granular, but it quickly became apparent that some pooling would be needed because of the paucity of women in some departments or ranks. The committee therefore spent considerable time discussing how to aggregate faculty into groups for statistical analysis. Time in rank for associate professors can reflect norms about how long individuals serve in that rank. Conversations among the faculty representatives revealed that the expectation for the length of time for promotion to professor in some units is within five years, whereas the norm in other units is within seven or eight years. Committee members agreed that faculty members who had been associate professors for 11 years or longer were likely to be less productive than those who had been promoted within that time frame. Thus, pooling among associate professors should reflect variation in the norms for promotion to professor as well as the shared perception of lower productivity for long time at that rank.

Similarly, faculty revealed during the group discussions that some departments routinely hire at the professor rank, while others do so rarely. While this is information that can be discovered and confirmed from the data, this hiring practice was not known to the IRP or the Human Resources staff. Furthermore, this information would not have been established without the faculty input. The institutional data showed time in rank only at Ohio State, and thus were only interpretable for those who had spent most of their career at our institution. One of the more difficult topics for salary analysis was how to pool groups of professors. After considerable discussion, the committee settled on the following seven categories of professors:

1. Assistant professors
2. Associate professors in rank 0–5 years
3. Associate professors in rank 6–11 years
4. Associate professors in rank 12+ years
5. Professors in rank 0–5 years
6. Professors in rank 6–11 years
7. Professors in rank 12+ years

The committee also spent considerable time discussing market forces across disciplines. Entry-level salaries, a reasonable indicator of market conditions, varied substantially across the departments the committee studied. The IR staff were able to provide an initial examination of those markets, and the committee then grouped departments that shared similar market forces, with the stipulation that departments would be pooled only within a college. For example, salaries for electrical engineers and computer scientists were comparable, as were salaries for geologists and ecologists.

After these discussions, the committee agreed that we had a reasonably valid data set to examine and recommended evaluation of the data using multiple regression, with gender as both a main effect and an interaction term with rank, time in rank, and department group. Scholarly record was not included in the analysis, in part because the variance by rank and by disciplines meant that classifying faculty according to their level of productivity was problematic.

Start-up Costs

In the STEM disciplines newly hired faculty are offered funds to support purchase of equipment, hire laboratory personnel, and travel. These start-up accounts are negotiated as part of the original offer, and they can be substantial: for hires at the professor level in the experimental sciences, start-up accounts exceeding $1 million are common. There is substantial variation across disciplines with regard to normed start-up figures, and even within departments there can be wide variation that depends on the research area of faculty being hired.

Discussion revealed how difficult it can be to interpret those data. First, no standard definition exists for what is included in start-up costs. In addition to the start-up account, commitments to new faculty can include laboratory/office renovations, major equipment purchases, summer salary support, graduate assistant support, and time released from teaching; all of these additional measures help to attract the best faculty and should not be discounted. Even so, the committee was forced to restrict its attention to the start-up account in the narrowest sense.

The IRP staff collected start-up data from college offices and provided it in summary form to the committee. This was the first time the IRP staff had collected start-up data, and they were guided entirely in their collection and analysis by the committee faculty. Faculty representatives were able to highlight complications in the data, and to suggest ways to move toward a statistical analysis. First, the rank of hire mattered: senior hires demand and receive larger start-ups than do entry-level faculty. After discussion, the committee decided to examine only start-up data for new hires as assistant professors, which represented reasonable sample sizes for both men and women.

Even so, pooling of data across departments became important again. Our discussion showed that the categorizations of faculty by rank and years in rank were not necessarily useful for analyzing start-up accounts. Faculty expertise about market forces that determine start-up accounts was critical to identify clusters of departments that were similar, but not identical, to those developed for faculty salaries. As an example, Chemical and Biomolecular; Materials Science; and Mechanical and Aerospace were clustered based on faculty advice, whereas Biomedical Engineering was kept separate. This was not a decision that staff could have made based on data available to them.

A final additional complication derived from subdisciplinary differences within a unit; for example, theoretical scientists and empirical scientists require very different infrastructure yet reside within the same department. While acknowledging the issue, faculty recommended that the committee ignore it.

Therefore, the final analysis of start-up data focused on assistant professor hires and became a simple 2-way ANOVA with gender and disciplinary cluster as independent variables.

Lab Space

Lab space is highly prized by experimentalists. Rooms for specialized equipment; bench space for students, postdoctoral researchers, and technicians; as well as ancillary spaces (e.g., conference rooms, common equipment rooms, and office space) contribute to faculty research productivity. The quality of the lab space matters, with clean modern lab space in a well-maintained building serving as an important recruitment tool.

Our institution uses square footage of lab space as the primary datum, without information on quality; from the outset, then, the committee had to ignore issues such as age of the building, years since renovation, reliability of infrastructure, and other measures of space quality. Furthermore, centrally collected data on lab space assignments by gender were available only for faculty with externally funded research; new hires as well as more senior faculty without funding were not included in that database, and centralized data did not allow us to examine usage of shared space, equipment space, and office space. One of our colleges had conducted its own space inventory that was comprehensive, but for the other colleges the committee had incomplete data focusing solely on square footage of research laboratory space.

The committee discussed issues concerning lab space assignment, for which decisions are local and idiosyncratic. A scientist with 2 graduate students and 1 postdoctoral researcher requires fewer benches than a colleague with 15 graduate students and 6 postdoctoral researchers. Those who travel to do their research (e.g., tropical ecologists, field geologists, high-energy physicists, astronomers) command less space than those who gather data primarily in Ohio State labs. Thus the amount of space assigned to a faculty member reflects a myriad of variables invisible to IR staff.

Despite those complications, the committee did have some a priori expectations. Overall, junior faculty require less space than senior colleagues, leading us to include rank as a covariate. Similarly, the amount of external funding can drive space needs. Finally, the ethos of space assignments is relatively constant within a department. The committee ultimately agreed that the data could be analyzed via a regression model with rank, gender, total external funding, and department as independent variables, but were aware of numerous unmeasured factors that could explain additional variance.

Teaching Assignments

Teaching includes a variety of different modalities, and each institution—and, at Ohio State, each college within each institution—sets its own definition of how teaching is measured. In the sciences, teaching includes classroom lecturing, overseeing graduate research assistants who offer laboratories and recitations, proctoring and grading, leading seminars and colloquia, supervising graduate and undergraduate research students, and supervising students in clinics. Disciplines vary in the distribution of courses offered (some have heavy service course responsibilities while others primarily teach their own majors), norms for team-teaching, class size, numbers of graduate students, and so on.

The committee examined centrally collected data that sparked illuminating discussions that revealed widely divergent department mores. First, the committee learned that units vary substantially in how they report instructors of record; for example, a single course may be taught by four or five faculty, with only one recorded in the registrar's database. Indeed, one of our college representatives stressed that those central data failed entirely to capture the relevant effort information; for that unit the committee used college-supplied teaching data.

Faculty discussions of practices in their own departments enlightened committee members, faculty, and staff alike as to how differently units handled academic-year release time. Faculty who secure external funding can use those dollars to support a portion of their salary, which in turn releases them from teaching. In some units, garnering such release time is the expectation whereas in others it is disallowed. Not surprisingly, faculty in those units for which release time is an expectation teach less than those in which it is not permitted.

Third, considerable variation in teaching load derives from enrollments in courses collectively binned as independent studies courses; these include readings, seminars, research supervision, and other kinds of tutorial efforts. Most units hold expectations for faculty to engage in such activities, but they are rarely codified. Rather, faculty have broad discretion accepting students to their research groups, offering seminar courses, and supervising undergraduate internships. Furthermore, many faculty members supervise students who are not enrolled for credit. These kinds of teaching efforts typically are not assigned as part of a workload discussion, but rather are undertaken on the basis of individual faculty initiative. Even so, units can use data on independent studies teaching to make assignments for didactic teaching, such as providing a course release for a faculty member supervising independent studies for 12 graduate students.

Fourth, didactic courses themselves vary tremendously in terms of the kinds of effort required of faculty. Large introductory courses require extensive administrative overhead (managing the course Web site, answering endless emails, overseeing teaching assistants), whereas smaller upper-division and graduate courses require a different kind of preparation. Committee discussions on this topic again uncovered variable cultures across disciplines in terms of the mix of such courses offered, as well as the kinds of students who enroll. Some units offer numerous courses to benefit students outside their discipline (general education or other service courses), while others serve primarily their own majors. After discussion of these complications, we settled on three categories of didactic instruction (introductory, advanced undergraduate, and graduate/professional).

The committee wrestled with several measures of teaching effort, including the number of courses taught, the number of credits hours taught, the number of contact hours associated with a course, and the number of students taught per term. Of those four, the committee settled on the first two as the best metrics for comparing teaching loads among faculty.

Ultimately, we settled on regression analysis of number of courses and number of credit hours as a function of gender, faculty rank, discipline, and course level.

CONCLUSIONS

Gender did not explain variation in our analyses, which is heartening (Herbers & Desai 2012). Most importantly, that central result is credible because of the committee discussions that acknowledged nuance, and decisions that allowed for comparisons that minimize confounding variables. Analysis of faculty workload and access to resources are fraught with difficulties (Dennison 2011), and can best be accomplished when IR officers collaborate with those whose work they are studying: in other words, the faculty.

Our process took over a year to complete, including iterations of analyses and refinement of the baseline data. Committee members, each steeped in one discipline, continually learned from each other about how variable department cultures can be within one institution. Furthermore, we all learned about the power and limitations of centrally collected data as we strove to develop protocols for meaningful data analysis. Our experiences showed that involving faculty for analysis of data about their work is crucial to producing reliable and credible results.

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