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R&D ecology: using 2-mode network analysis to explore complexity in R&D environments

Jonathon E. Mote*

Department of Sociology, Center for Innovation, University of Maryland, College Park, MD, USA

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Abstract

It has been demonstrated that a complex division of labor provides for the diversity of knowledge that is critical for organizational innovation and productivity [Hage, J., 1999. Organizational innovation and organizational change. Annual Review of Sociology 25, 597–622]. This article examines the impact of complexity in an R&D setting and adopts the approach that collaborative research involves a range of specialties and skills, which can be viewed separately from the individuals involved in the collaboration process. To explore this hypothesis, the use of 2-mode network analysis allows for an examination of the interrelationships of these competencies within a cluster of R&D projects in a large multi-disciplinary national laboratory. These networks of competencies are shown to have structural characteristics, which impact on the productivity of research projects. It is argued that the interrelationship of network structure and complexity should be given consideration in the management of R&D projects.

JEL classification: O32

Keywords: Social networks; R&D management; Innovation; Complexity

1. Introduction

In recent decades, research and development (R&D) has become an increasingly specialized and complex endeavor (Boesman, 1997; Kodama, 1992; Miller and Morris, 1999). One component of this growing complexity has been the growing use of projects and

* Tel.: +1 301 405 9746; fax: +1 301 314 6892.
E-mail address: jmote@socy.umd.edu.

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teams to pursue R&D (Shenhar, 2001; Thamhain, 2003), including the use of virtual teams (Gassmann and von Zedtwitz, 2003) and the adoption of a matrix structure (Katz and Allen, 1985). While the management of R&D, in general, presents numerous management challenges (McDermott and Colarelli O'Connor, 2002; Sherma, 1999; Van De Ven, 1986), very little attention has been given to managing the diversity and complexity of R&D projects and teams (Jordan et al., 2004; Shenhar, 2001; Thamhain, 2003; Balachandra and Friar, 1997). Although it is has been demonstrated that a more complex division of labor has a positive impact on organizational outcomes, such as organizational innovation (Hage, 1999), the impact of such diversity on research productivity is still a matter of debate (Reagans and Zuckerman, 2001).[1]

Despite the gap in the literature about managing the diversity of R&D projects, there is a large and rich related literature on intra-organizational dynamics in R&D, including important contributions from the literature on social networks. In particular, the latter studies have examined a number of roles that networks play in R&D, including communication networks (Allen, 1970), knowledge flows (Almeida and Kogut, 1999), diversity (Reagans and Zuckerman, 2001), idea innovation chains (Hage and Hollingsworth, 2000, and interorganizational networks (Powell et al., 1996). Yet, there is very little in the literature that examines how projects, as distinct units of research, interact within an organization, as in Grabher's notion of a "project ecology" (Grabher, 2002) or Tuomi's "ecological framework" (Tuomi, 2002). In contrast to the field of organizational (population) ecology, which utilizes demographic concepts (Baum, 1996), a more ecological approach might seek to "explore interdependencies between projects and the firms as well as the personal relations, localities, and corporate networks on and around which projects are built" (Grabher, 2002, p. 246). With this in mind, it is argued in this paper that the interactions between projects and other organizational units represents another level of social structure that needs to be taken into account in the management of R&D.

To explore these interrelated issues—project diversity and project ecology—this paper examines the interactions between two organizational categories in an R&D organization, research projects and research departments. Specifically, this paper utilizes data from a sample of 20 project teams drawn from a large, multi-disciplinary national laboratory. The laboratory's research departments encompass a diverse range of scientific and applied disciplines, including biology, physics, engineering, and computational sciences. Because the members of the research projects are drawn from the laboratory's various research departments, it is possible to explore the impact of the complexity of labor by analyzing the interrelations between project teams and research departments.

The method that is employed to explore the question of how R&D projects "interact" is 2-mode network analysis. Specifically, we will look at the network structure of the sample by examining the co-membership of researchers in projects and research centers. While typical network analysis examines the interrelations between the same set of persons or entities (1-mode analysis), 2-mode analysis looks at the relations between two equally

[1] It is important to note, however, that diversity in this context does not refer to the demographic categories of team members as in Reagans and Zuckerman (2001), but rather to the variety of R&D projects and the range of scientific disciplines represented within R&D teams and projects.

interesting sets of persons or entities (Borgatti and Everett, 1997). For instance, a 2-mode analysis can look at affiliation networks, which consist of sets of relations between individuals and events, such as women and social events (Borgatti and Everett, 1997), or co-membership of individuals in organizations, such as the analysis of overlaps in the corporate board memberships (Galaskiewicz, 1985). In the latter example, 2-mode analysis offers the ability to look at the network of relations between different groups based on the membership of individuals in two or more groups.

In short, the use of 2-mode network analysis allows for a novel examination of the impact of complexity on productivity by mapping scientific competencies (departments) to scientific applications (projects). More specifically, we will be looking at interrelationships between R&D projects and research departments whose boundaries are demarcated, more or less, by scientific disciplines. To a certain extent, this excludes the individual altogether and focuses on research projects as nodes and further, as bundles of skills and attributes related to different scientific areas of interest. While differences in competencies can correspond directly to disciplines and subject matter (biology versus physics, for example), these differences might also arise due to different areas of research or research methodology (experimentation versus simulation, for example). In this manner, the use of 2-mode analysis offers a different perspective on network relationships between research projects and research departments.

After a brief overview of the relevant literature to frame our question, we discuss in greater detail the data and methods utilized and present our analysis and finding. In order to gauge the efficacy of this type of analysis, we then analyze our findings with respect to the productivity of research projects, focusing on two primary variables, project centrality and research productivity. The study concludes with a discussion of the results and implications for further research on scientific productivity and R&D management.

2. Organizational innovation and complexity

Despite the increasing amount of complexity in the R&D process, the impact of complexity on R&D is still relatively understudied (Kim and Wilemon, 2003). Indeed, one aspect of complexity that has recent scant attention is the role of the diversity (complexity) of R&D project teams, either demographic or scientific (disciplinary) diversity. Of particular concern in this paper is the role of scientific complexity, defined here as the number of disciplines or departments involved in a project (Larson and Gobeli, 1989). This notion of scientific complexity is important, because it relates to the division of labor in R&D and scientific research. Before we turn to a discussion of complexity in R&D, we first briefly review the role of complexity in the literature.

In general, it has been recognized as far back as Adam Smith (Smith, 1976 [1776]) that a more complex division of labor has a positive impact on productivity. Later, Weber argued that a highly specialized and complex division of labor, coupled with the bureaucratic form of organization, allowed for greater productivity and efficiency (Weber, 1978). As Durkheim similarly observed, an ever increasing complex division of labor was a natural outcome of the development of modern society, although he recognized that ‘‘pathological’’ forms of the division of labor could have unintended, even negative, results (Durkheim, 1965). More recently, Chandler (1977) detailed how a complex division of labor supports the application of technology and increasing productivity.

In the organizational literature, the role of a complex division of labor has been identified as a critical factor in facilitating organizational innovation. In a recent comprehensive review of the organizational innovation literature, Hage (1999) identified three primary determinants of organizational innovation that have arisen in previous studies: a complex division of labor, an organic structure, and the adoption of a high-risk strategy. Of these three determinants, Hage argues that a complex division of labor is most important because it encompasses the organizational learning, problem-solving, and creativity capacities of an organization. While most studies of organizational innovation have tended to address the connection between organizational structure and management practices particularly, as this connection relates to facilitating or inhibiting the adoption of innovations, such as new technology or organizational practices (Zammuto and O'Connor, 1992; Damanpour, 1991), the study of organizational innovation also encompasses aspects of scientific productivity, that is, the generation of new products and ideas (Stuart, 1999; Larson and Gobeli, 1989).

Within the R&D literature, a number of recent studies have explored the connection among complexity of labor, organizational innovation and productivity in R&D. Perhaps most well known is Cohen and Levinthal's (1990) concept of absorptive capacity, which captures a firm's ability to evaluate and utilize outside knowledge. Analyzing investments by firms in R&D; Cohen and Levinthal demonstrated that overlapping diversity of expertise among internal units could create cross-functional interfaces that enhance a firm's absorptive capacity. In their work on idea innovation chains, Hage and Hollingsworth (2000) undertake a broad overview of the literature and identify how the diversity of competencies or knowledge in the R&D process is a key indicator of innovation. In addition, Zammuto and O'Connor (1992) in a review of the literature on the adoption of advanced manufacturing technologies (AMT) highlighted that previous studies demonstrated that at higher levels of automation, complexity had a multiplier effect on the adoption of AMTs. Finally, Larson and Gobeli (1989), in a study of 546 development projects, found that more complex projects as represented by the number of different disciplines or department involved in a project, had a higher degree of success. These studies do not represent an exhaustive discussion of the literature, but rather are indicative of a general consensus surrounding the positive impact of complexity on productivity in R&D settings.

But the connection between complexity and productivity, including scientific productivity, is not a straightforward one. In Alter and Hage (1993), the relationship between task complexity and productivity was examined in an inter-organizational study of social service agencies. While the focus was on non-profit organizations, not on R&D organizations, Alter and Hage demonstrated that task complexity was directly related to increased productivity, but that the types of networks that emerge in inter-organizational collaboration to help coordinate task complexities play a key role in determining success. In a review of the literature on complexity in R&D, Kim and Wilemon (2003) constructed a detailed typology of organizational complexities, including a complex division of labor and highlight the tradeoffs associated with complexity. In particular, Kim and Wilemon discuss the complexity *between* functional groups, as in a complex R&D project, and the challenges associated with the coordination and management of such intra-organizational complexities.

As the studies by Alter and Hage, and Kim and Wilemon suggest, intra-organizational networks can play an important role in facilitating or mitigating the impact of complexity. In the next section, we discuss in greater detail the interrelationship between complexity and networks in R&D and the impact on innovation and productivity.

3. Complexity, networks, and research productivity

While the role of social networks in scientific research and R&D is recognized, it has often been overlooked in favor of the formal structure of the research organization (Senter, 1987). Nonetheless, a number of seminal efforts in 1960s and 1970s have served to illuminate the role of social networks in science, such as Price's (1965) study of citation networks, Zuckerman's (1967) examination of collaboration among Nobel laureates, Crane's (1969) exploration of the invisible college hypothesis, and Allen's (1977) examination of communication networks and knowledge flows. Since the early 1980s, however, there has been a tremendous increase in work on social networks in research (Rogers et al., 2001). These recent studies on social networks in science and R&D have encompassed a range of analyses, including studies of knowledge and learning networks (Liebeskind et al., 1996; Bozeman and Corley, 2004), inter-organizational networking of research organizations (Powell et al., 1996), and intra-organizational networks (Smith-Doerr et al., 2004; Ahuja et al., 2003).

Within this growing social network literature, a number of studies have looked at the interplay of complexity, networks and research productivity. One of the earliest studies was Allen's (1970) study of the communication networks of individual researchers in different organizations. Allen found that ''high'' performers not only had more intense communication networks, but also maintained a more diverse range of contacts, including those outside the researcher's respective field. Further, in a larger study, Allen (1977) confirmed that intensity and diversity of communication networks were directly related to increased R&D performance. In general, the role of these ''gatekeepers'' is an important one, as they are the individuals who frequently obtain information external to the group and then share it within the project team (Allen, 1970, 1977; Katz and Tushman, 1981). These results are consistent with those found in more recent studies. For instance, researchers with more ''cosmopolitan'' collaboration networks have been demonstrated to be more productive in terms of publications (Bozeman and Lee, 2003) and receiving research grants (Bozeman and Corley, 2004).

Despite the growing number of studies that have examined the role of networks in R&D, many of them continue to discuss networks in general terms and have not utilized the tools of network analysis that have been refined and honed in recent decades.[2] In this regard, two recent studies point illustrate the utility of these tools in understanding the relationship

[2] Interestingly, this echoes a comment by Brieger (1976) that ''despite the increased attention accorded to the empirical study of social networks among scientists, there has been remarkably little concern for the possibility of using network phenomenology itself as a guide.''

between complexity, networks, and productivity. Ahuja, Galletta, and Carley's (2003) study on the Soar group, a virtual R&D project, found that a project members' central location in the project network was the dominant predictor of individual performance. Although the study did not directly address the issue of complexity, the study did differentiate individuals on the basis of functional roles (users and developers) and status (faculty, senior researchers, and students). The study found that centrality was a stronger predictor of performance than individual characteristics. Reagans and Zuckerman (2001) explored the question of whether demographic diversity contributed to R&D productivity. The study found that diversity itself was not linked to productivity, but rather that two components of project teams, network density and network heterogeneity, were linked. As they argue, these network processes worked to enhance a team's coordination and learning capabilities.

In summary, the social network literature suggests that networks play a key role in the link between complexity and productivity. As one would expect intuitively, network density and network location help to account for a team or individual's productivity, as found in Ahuja et al. (2003) and Reagans and Zuckerman (2001). However, it is not clear how network mechanisms might affect productivity when the question about complexity of labor is reframed in terms of the diversity of scientific competencies, an important issue when R&D teams increase in complexity. It is this question we now turn to investigate.

4. Data

The primary data used in this study come from a sample of scientific researchers in 20 research projects at a large national laboratory. The laboratory currently employs over 8000 researchers in over two dozen disciplinary centers and has a multi-billion dollar budget. As noted in the introduction, these large laboratories are interesting settings to explore questions about R&D, but have been largely overlooked in the literature. Further, this laboratory supports a great deal of basic research, and very few studies have taken a network perspective on basic research activities.

The selection of the 20 projects was conducted as part of a larger study focused on developing case studies on performance measurement and scientific progress. The 20 projects used in the case studies and this research were selected from a pool of 400 R&D projects based on the following criteria:

1. at least US$ 300,000 in annual funding;
2. in the second year of funding (as of 2003);
3. representation of all investments areas at the laboratory.

All of these projects are 3 years in length (with very limited potential for renewal), and annual funding ranges from US$ 30,000 to over US$ 1 million. The overwhelming majority of projects received between US$ 250,000 and 350,000 in annual funding. Out of the 400 possible projects, 54 met the first two criteria. Because not all of the laboratory's investment areas had projects that met the first two criteria, it was not possible to have complete representation of all investment areas. Nonetheless, the 20 projects that were selected represent an adequate, although not complete, cross-section of the laboratory's research projects. While 16 of the selected projects averaged roughly US$ 300,000 in annual funding, four of the selected projects represent much larger (over US$ 1 million annual funding) and longer-term (4–5 years) efforts. These projects were included as they represent a significant effort by the laboratory to pursue new areas of research. The resulting sample consists of 216 researchers in 20 R&D projects, representing 20 different internal research departments.

In this analysis, the research departments are assumed to represent different research competencies, and the number of departments represented in a given project is determined to be the complexity of labor in that particular project. While this assumption does have precedent, such as Allen's (1977) distinction between scientists and engineers and Larson and Gobeli's (1989) use of functional departments, it does require a caveat. The lab's departments are not strictly organized along functional divisions, such as college departments, but rather by areas of focus (i.e., combustion, transportation, energy components, etc.). Hence, it is possible that a range of functional specialties could be represented within each department. Nonetheless, it is assumed that researchers from each of the departments lend something different—a competency, a skill, a cognitive map, etc.—than researchers from other departments. Indeed, this paper suggests that conceptualizing research departments in this manner offers a good example of the kind of tacit knowledge that Von Hippel (1994) argues is limited and far from routine. Table 1 illustrates the types of diversity that exists within a handful of projects.

In addition to representing only a small fraction of the laboratory's overall research portfolio, it is important to note that these projects also represent only a small portion of each researcher's project portfolio. Based on responses from a 2003 survey of the laboratory, the average researcher's project portfolio is about five projects. Along with the data on the center affiliation of project personnel, this analysis also utilizes data on each project's productivity. Unlike most studies of R&D productivity that focus on individual performance, this study follows other recent studies in looking at network effects on the project or team performance (Smith-Doerr et al., 2004; Reagans and Zuckerman, 2003). In this analysis, productivity is

Table 1
Disciplinary diversity within selected projects

Project 1	Project 10	Project 15	Project 18
Combustion and Physical Sciences	Energy and Transportation Security	Combustion and Physical Sciences	Defense Programs
Exploratory Systems and Development	Microsystems S&T and Components	Energy Components and Metrology	Energy Components and Metrology
Information and Computation Sciences	Materials and Process Sciences	Information and Computation Sciences	Executive Support
Materials and Engineering Sciences	Nuclear Weapons S&T	Physical and Chemical Sciences	Infrastructure and Information Systems
Materials and Process Sciences			
Microsystems S&T and Components			
Physical and Chemical Sciences			

defined as patents, papers, and hypotheses proven, and the data are self-reported by each project on an annual basis. In many ways, this way of measuring productivity is incomplete (Jordan and Malone, 2002; Kerssens-van Drongelen and Bilderbeek, 1999), but this issue is beyond the scope of this paper (see Mote et al., 2004 for a more complete discussion). Rather, it is assumed that the performance data used in this analysis are only a rough approximation of a project's productivity, and by no means takes into account all aspects of productivity, such as advancements in scientific knowledge or learning.

The description of the data sources immediately suggests some qualifications that must accompany any conclusions drawn from this investigation. First, as discussed above, the sample is not a random selection, but does offer an adequate cross-section of the laboratory's project portfolio. Because larger projects are expected to be more productive, it is likely that some selection bias exists in this direction, and we attempt to at least partially control for this using regression analysis. Second, because the projects were selected as part of a group of case studies, this research has some of the limitations of a case study. It cannot be claimed that these results on network structure will hold for the rest of the research laboratory, nor even for other projects funded through this particular lab program. Finally, the performance data utilized in this analysis are limited in scope because data represents only a single year in the life of the project. Since these measures—patents and publications—tend to be lagging indicators of a project's success, and these projects are of typically 3 years in length, it may not give an accurate representation of project's lifetime productivity. However, the techniques for investigating complexity using new methods are demonstrated, and it is argued that the results could be validated with additional studies utilizing more complete data of a laboratory's structure and performance.

5. Analysis of the data

The primary theoretical issue in this analysis is the interrelationship between complexity of labor and intra-organizational networks on research productivity. Following our discussion of the literature, we are interested in determining to what extent intra-organizational networks facilitate or mitigate the impact of the complexity of labor on productivity.

5.1. Descriptive analysis

Network researchers typically assume that networks have effects, but it could just be the case that simply having a more diverse group of project personnel, combining applied and basic researchers for instance, could be the determining factor, absent any network affects. Hence, we need a point of comparison for the network analysis. A preliminary approach might be to use descriptive data, simply reducing the notion of complexity to the sheer number of different laboratory units (centers) involved in a research project. As Table 2 illustrates, it is possible to look at the number of project personnel by center and arrive at a standardized figure of complexity for each project. The latter is essentially the number of centers divided by the total personnel for each project, with a figure of 1 representing the most diverse pool of labor possible, i.e., each researcher comes from a different center.

Table 2
Number of personnel by project

Project	Total personnel in project	Number of departments in project	Average personnel by department	Standardized project complexity
1	13	7	1.86	0.54
2	5	2	2.50	0.40
3	37	7	5.29	0.19
4	28	6	4.67	0.21
5	10	3	3.33	0.30
6	6	3	2.00	0.50
7	6	2	3.00	0.33
8	7	1	7.00	0.14
9	10	3	3.33	0.30
10	8	4	2.00	0.50
11	6	2	3.00	0.33
12	7	1	7.00	0.14
13	6	3	2.00	0.50
14	6	2	3.00	0.33
15	5	4	1.25	0.80
16	10	2	5.00	0.20
17	21	6	3.50	0.29
18	7	4	1.75	0.57
19	5	2	2.50	0.40
20	13	6	2.17	0.46
Total	216	20	10.80	0.09

Looking at the descriptive data, it is clear that there is wide variation among the projects in the number of personnel and departments. In general, the projects with more personnel tend to have more departments represented in the project composition. The standardized project complexity reduces this variation relating number of personnel to the number of departments in a project. In Table 3, those projects, which have a standardized project complexity greater than .50, are highlighted in yellow. As we see, the projects with the highest standardized project complexity are 15, 18, 1, 6, 10, and 13. While the descriptive data give us a rough sense of the most "complex" projects, it does not take into account how projects might be "connected" to one another through shared departments, which could highlight which departments or "competencies" are most important or if there are particular structural configurations of competencies which yield greater productivity.

5.2. Social network analysis

5.2.1. Arranging the data

The primary network data of interest data is the project and department affiliations of the researchers. These affiliations are then arranged as a 2-mode project-by-center matrix. The matrix (**X**) is arranged where $x_{ij} > 0$ if project i has a researcher from center j and $x_{ij} = 0$

Table 3
Research projects by center affiliation data

	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t
1	4	0	1	1	0	0	0	0	0	0	0	0	0	4	1	1	1	0	0	0
2	0	0	1	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	22	0	7	2	0	0	0	0	0	0	1	0	0	0	0	1	3	0	1	0
4	3	0	2	0	0	0	0	0	0	0	0	0	0	10	4	2	7	0	0	0
5	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	4	0
6	1	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
7	0	0	5	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
9	0	0	0	0	0	0	0	0	0	7	0	0	1	0	0	0	2	0	0	0
10	0	1	5	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
11	0	0	0	5	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0
13	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	3	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	2	0	0	0
15	1	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	1	0	0	0
16	0	0	9	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	8	3	0	0	1	0	0	0	5	0	0	2	0	2	0	0	0	0
18	0	0	0	0	0	0	0	1	0	0	0	2	0	0	0	0	0	1	0	3
19	0	0	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	1	1	0	0	6	0	0	2	0	0	0	0	1	0	0	2

otherwise. The resulting matrix is displayed in Table 3, with projects represented by numbers and centers by letters.

The methods utilized to analyze the network data will be those developed by Borgatti and Everett (1997). Because most network analysis is geared towards 1-mode matrices, the study of 2-mode introduces a number of challenges, in particular, the graphical representation of correspondence analysis between the two sets of persons or entities. As Borgatti and Everett point out, ''the distances in (2-mode) correspondence analysis are not Euclidian, yet human users of the technique find it very difficult to comprehend the maps in any other way'' (1997, p. 247). Their primary solution is to treat the data as a bi-partite graph and compute geodesic distances to be used in ordinary multidimensional scaling and other network measures. All social network measures and figures were derived using the software program Ucinet 6.0 (Borgatti et al., 1999).

5.2.2. Multi-dimensional scaling

Following Borgatti and Everett (1997), we first derive a graphical representation of the data, treating the data matrix as a bi-partite graph, computing geodesic distances and submitting this matrix to multi-dimensional scaling. However, it is important to point out that this approach relies solely on the pattern of connections, rather than the spatial position of the nodes or the length of lines. Using Ucinet, this procedure yields the following diagram.

Fig. 1 represents a multi-dimensional scaling of the network of connections between projects and departments. As such, the figure allows for visual identification of the structure of social relations among the projects and departments, as well as the key players within this intra-organizational network field. In the graph, projects are represented with

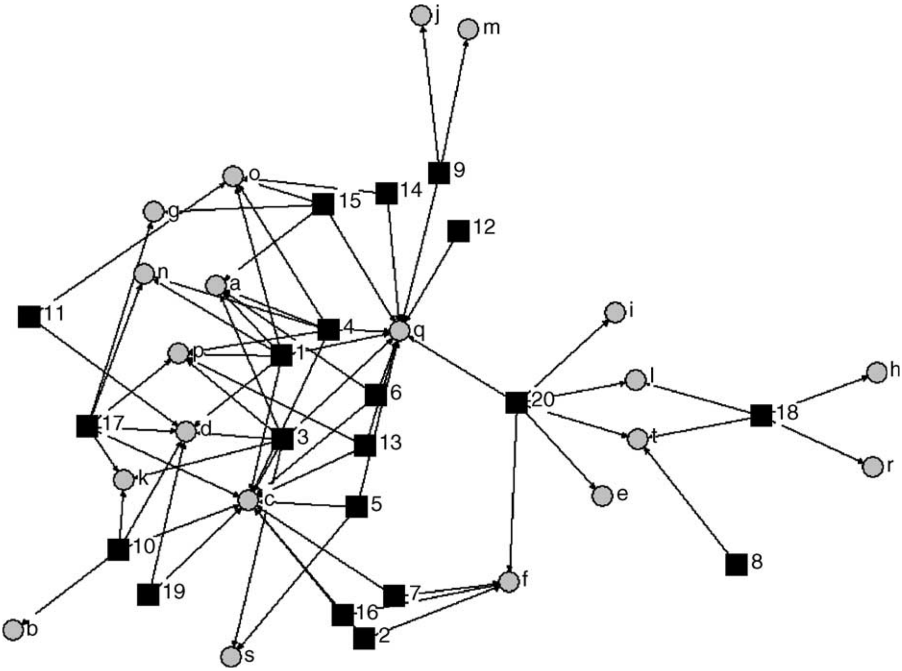

Fig. 1. The network of projects and centers.

square nodes and centers with round nodes. It is possible to locate two distinct clusters of projects and departments on the left and right side of the diagram. As one would expect, the larger projects with personnel from a greater number of departments, such as projects 3, 4, and 17, are more centrally located in the larger cluster on the left. In contrast, a handful of projects, such as projects 9, 18, and 20, appear to act as intra-organizational intermediaries, bridging the larger cluster of projects and departments with the smaller cluster.

5.2.3. Measures of centrality

Because we are most interested in exploring the connections of projects to departments and identifying those projects most centrally located within the departmental structure, we will focus on selected measures of centrality: degree centrality, betweenness, closeness, and eigenvector centrality. In general, centrality measures are focused on the number and distance of ties a network actor has with other members of the network (Scott, 1991). In a sense, the use of centrality measures gives us some indication of the potential flow of knowledge and communication between projects and departments.[3] As Freeman (1979, p. 22) discusses, however, the first three measures of centrality—degree, betweenness, and closeness—implies "three competing 'theories' of how centrality might affect group

[3] Network centralization (or global centrality) is a related measure that assesses the degree to which an entire network is focused around a few central nodes (Scott, 1991). As this analysis looks at only a partial representation of the entire organizational network field, centralization has been omitted.

processes—centrality as control, centrality as independence or centrality as activity.'' The fourth measure of centrality—eigenvector centrality—can be considered an extension of degree centrality, reflecting that centrality is not simply a matter of one's own network ties, but also the network ties of those to which you are connected (Bonacich, 1987). As we discuss in greater detail below, the measures of centrality then offer four different ways of identifying how network structure might affect complexity and productivity. While measures of centrality are complicated in 2-mode analysis, as Borgatti and Everett (1997) demonstrate, representing the 2-mode data as a bipartite graph allows for the utilization of standard measures of centrality.

Most simply, degree centrality is the number of nodes to which an actor is adjacent, and it offers an idea about the potential communication activity of an actor, that is, the higher measure the greater potential for activity within the flow of communication (Freeman, 1979). As Borgatti and Everett (1997) point out, 2-mode analysis offers a straightforward interpretation in the 2-mode case. In contrast, closeness indicates the potential independence of an actor from the flow of communication. As Scott indicates, the simplest notion of closeness is calculated from the sum of the geodesic distance to *all other points* in the graph, and a node is ''close'' if it lies at short distance from many other points (Scott, 1991). In this manner, an actor is centrally located but is not dependent on others as ''intermediaries'' or 'relayers' of information (Freeman (1979), p. 224). Betweenness is defined as the extent to which a node is ''between'' two other modes (Scott, 1991), and it captures the capacity for an actor to play the role of intermediary in the network, connecting two actors that are not otherwise connected. The measure is complicated in the 2-mode case because the use of a bipartite graph means that paths can originate and terminate at a node from either vertex set (Borgatti and Everett (1997), p. 256). In other words, the betweenness of a project or department is a function of paths from project to project, from projects to departments, and from departments to departments. Nonetheless, betweenness can be considered a measure of the extent that an actor can control the flow of information. Finally, eigenvector centrality is a variant of degree centrality and ''is proportional to the sum of centrality of the nodes, it is adjacent to (Borgatti and Everett (1997), p. 257).'' In general, eigenvector centrality captures not only how many actors you ''know,'' but how many actors they ''know'' as well. In this manner, an actor that is connected to many actors (high degree centrality), who are themselves well connected (also with high degree centrality) has a high level of eigenvector centrality. Conversely, an actor who is connected only to actors who are less connected (isolates or near isolate) does not have a high level of eigenvector centrality, even if they have a high measure of degree centrality. In a sense, eigenvector centrality offers a measure of the diversity of a node's network.

In Table 4, the raw and normalized measures of centrality are listed for each project and Table 5 tabulates the top five projects for each measure.[4] In both tables, the measures of centrality have been associated with their potential network impacts, activity,

[4] Although Borgatti and Everett (1997) suggest an additional normalization step for 2-mode data, we are indebted to an anonymous reviewer who pointed out that normalization is needed for comparing across modes, but not comparing within a single mode. As the analysis is primarily concerned with only comparing projects, we have not undertaken the 2-mode normalization.

Table 4
Centrality measures for projects

Projects/ centers	Number of personnel	Number of centers	Degree (activity)	Ndeg	Closeness (independence)	Betweenness (control)	NBet	Eigenvector (diversity)	NEig
1	13	7	13.00	33.33	42.39	76.947	10.384	.317	44.798
2	5	2	5.00	12.82	33.62	9.283	1.253	.083	11.743
3	37	7	37.00	94.87	42.39	94.299	12.726	.296	41.810
4	28	6	28.00	71.80	41.49	52.281	7.055	.278	39.288
5	10	3	10.00	25.64	38.24	23.610	3.186	.150	21.173
6	6	3	6.00	15.39	38.24	15.465	2.087	.176	24.864
7	6	2	6.00	15.39	33.62	9.283	1.253	.083	11.743
8	7	1	7.00	17.95	23.78	0	0	.003	.466
9	10	3	10.00	25.64	33.62	75.00	10.121	.068	9.553
10	8	4	8.00	20.51	30.47	43.901	5.925	.137	19.419
11	6	2	10.00	25.64	27.47	2.476	.334	.070	9.861
12	7	1	6.00	15.39	32.50	0	0	.063	8.903
13	6	3	7.00	17.95	38.24	16.275	2.196	.178	25.207
14	6	2	6.00	15.39	33.62	6.776	.914	.094	13.255
15	5	4	5.00	12.82	35.46	32.916	4.442	.147	20.835
16	10	2	10.00	25.64	33.62	9.283	1.253	.083	11.743
17	21	6	21.00	53.85	31.97	33.749	4.554	.216	30.578
18	7	4	7.00	17.95	24.68	76.00	10.256	.007	.984
19	5	2	5.00	12.82	29.55	2.240	.302	.111	15.638
20	13	6	13.00	33.33	40.63	275.217	37.141	.087	12.268

independence, control, and diversity. Looking at both tables, the five projects with the highest degree centrality are also the largest projects with the greatest number of departments represented in their project composition (3, 4, 17, 1, and 20). Of course, this makes intuitive sense because degree centrality simply measures the total number of connections. Because the rankings of the normalization of degree centrality remain the same, we can conclude that the rankings of degree centrality are, indeed, a factor of the size of the projects. The measures of betweenness roughly match those of degree centrality, however, the rank order has changed significantly. Indeed, the high ranking of project 20 confirms the intermediary role between the two main clusters of projects and departments suggested in Fig. 1. In contrast, the measures of closeness highlight a very different set and ranking of projects (18, 11, 19, 10, and 17). With closeness, a lower score indicates a project with a higher closeness ranking. Referring back to Fig. 1, all five of these projects were located on the periphery of the network diagram, indicating that these projects did not

Table 5
Centrality rankings of projects

Ranking	Degree (activity)	Closeness (independence)	Betweenness (control)	Eigenvector (diversity)
1	3	18	20	1
2	4	11	3	3
3	17	19	1	4
4	1	10	4	17
5	20	17	10	6

rely on a large number of connections but still remained in central positions for receiving information. The three projects that were the most "close" to all other points on the graph (as identified by lower closeness scores) were 18, 11, and 19. Looking at measures of betweenness, we see that projects 20, 3, and 1 have the highest measures, while projects 1, 3, and 4 have the highest eigenvector centrality measures.

Across the measures of centrality, projects 1, 3, 4, and 17 stand out as the most central projects. In our simple descriptive approach to the data, only project 1 ranked high. Further, the highest ranked project in the descriptive data, project 15, is typically ranked in the middle of the pack on the centrality measures. As expected, projects with the largest number of personnel are the highest ranked, although the closeness measure seems to be more appropriate for smaller projects (18, 11, 19, and 10).

6. Analysis of performance data

6.1. Performance data

Turning to projects' performance data, we can begin to assess the efficacy of network analysis in determining the impact of complexity on productivity. The productivity reported by the projects in 2002 is listed in Table 6. Because we are only looking at 1 year of productivity in the 3-year life of a project, this may explain why some projects have no reported performance figures in the table. The projects may, in fact, have reported performance figures in the previous and/or concluding year of the project. Of the 13

Table 6
Project performance data

Project	Refereed publications	Other reports and publications	Total publications	Patent disclosures	Patent applications	Patents granted	Total patent actions
1	21		21	14	8	4	26
2		3	3	3			3
3	22	3	25	2	1		3
4	5		5	1			1
5				2			2
6							
7							
8		1	1				
9	3	2	5				
10	2	2	4				
11		4	4	1			1
12							
13		2	2				
14							
15				1			
16							
17		6	6	1			1
18		3	3	13			
19							
20							

Table 7
Correlation matrix for project variables

	Mean	S.D.	Personnel	Centers	Standardized complexity	Degree centrality	Closeness centrality	Betweenness centrality	Eigenvector centrality
People	10.80	8.48							
Centers	3.50	1.93	0.745**						
Standardized complexity	0.37	0.17	−0.386	0.229					
Degree centrality	11.00	8.40	0.994**	0.739**	−0.382				
Closeness centrality	34.28	5.47	0.524*	0.623**	0.087	0.504*			
Betweenness centrality	42.75	62.27	0.348	0.636**	0.197	0.337	0.417		
Eigenvector centrality	0.13	0.09	0.689**	0.768**	0.080	0.685**	0.778**	0.132	
Research productivity	5.80	11.50	0.491*	0.649**	0.052	0.494*	0.463*	0.203	0.690**

* <0.05.
** <0.001.

projects that reported performance data, the network analysis of complexity identified seven. The projects identified as ‘‘complex’’ by the simple descriptive approach (1, 6, 10, 13, 15, and 19) only identified four with reported productivity, and further, those identified by this approach were not the most productive projects.

6.2. Correlation matrix

To better determine the impact of complexity and the measures of centrality on productivity, a bivariate correlation matrix was constructed. In Table 7, we see that the number of centers and all of the measures of centrality, except betweenness, were significantly correlated with productivity. As expected, the number of personnel and centers were highly correlated with productivity, but the number of centers showed a stronger relationship. Among measures of centrality, eigenvector centrality had the strongest relationship with productivity, and indeed, the coefficient was even larger than that for the number of centers. Interestingly, betweenness did not show a significant relationship with productivity, suggesting that the intermediary role does not lend itself to increased productivity.

6.3. Regression results

As the analysis has demonstrated so far, there is a relationship between the number of centers, selected measures of centrality, and productivity. In order to better isolate the impact of centers and centrality on productivity, at least on a superficial basis, a regression analysis was conducted using productivity as the dependent variable. We estimated six simple models using various complexity measures. In Model 1, we only included the

Table 8
Linear regression of scientific productivity (papers and patents) on measures of complexity

	Model					
	1	2	3	4	5	6
Personnel	.015	−0.427	−0.606	−.090	0.002	−0.116
Centers	.638**	1.049*	.641**	.952**	.588*	0.353
Standardized complexity	–	−0.353	–	–	–	–
Degree centrality	–	–	0.623	–	–	–
Betweenness	–	–	–	−.371	–	–
Closeness	–	–	–	–	0.096	–
Eigenvector centrality	–	–	–	–	–	.498*
R^2	0.422	0.453	0.427	0.499	0.427	0.516

$N = 20$.
* <.1.
** <.05.

number of personnel and centers. In successive models, these variables were retained as control variables and each measure of centrality, as well as standardized complexity, was included separately. The results of the regression are displayed in Table 8.

The results of the regression analysis indicate that R&D productivity is significantly affected by the number of centers, but the impact of measures of centrality is mixed. More specifically, the regression coefficients for the number of centers are both positive and significant across most of the models. In Model 6, however, the regression coefficient for the number of centers is substantially reduced and no longer significant. Rather, the regression coefficient for eigenvector centrality is both larger and significant, although only at $p < .1$. Further, the R-square for the model is higher than that for Model 1. Also of interest is the result on the regression on betweenness with a negative regression coefficient. Similar to the correlation analysis, the regression suggests that the role of intermediary does not lend itself to increased productivity.

7. Concluding discussion

Although marked by some shortcomings, the results of the study are suggestive that the complexity of labor is indeed an important factor that contributes to research productivity. Further, the analysis suggests that network analysis can be a useful tool in determining the relationship between complexity and productivity. The most interesting findings were those from the regression analysis on the impact of eigenvector centrality and betweenness on productivity. Indeed, the results of these two measures indicate that a strategy of connecting projects to departments that are, in turn, well-connected to other projects has a clear advantage over a strategy of having projects acts as bridges between distinct clusters of departments. When one takes into account the changes that have occurred in R&D organizations in recent decades, these findings make intuitive sense. In the past, R&D, particularly basic research, was largely pursued separately by functional departments. In this manner, functional departments constituted separate and unconnected communities of interest. However, the organization of R&D along strictly along functional lines has declined, and the move to more project-oriented R&D has achieved a significant amount of cross-functional integration. As functional lines have eroded, more R&D workers interact and share a common language (Dougherty, 1992).

Within this milieu of greater cross-functional integration, the role of intermediary (as measured by betweenness) becomes less important as a strategy for increasing R&D productivity. Interestingly, Ahuja (2000) similarly found that an increase in structural holes has a negative impact on the innovation output of the intermediary firm in an inter-organizational network. Rather, the capacity for innovation and productivity is increased not just by connecting to more functional areas, but connecting to other functional areas that are, in turn, also connected to a large number of functional areas (a project's eigenvector centrality). For example, this suggests that connecting to other central projects might have a multiplier effect on absorptive capacity by increasing the capacity for acquiring new knowledge and developing innovations. In short, a project's productivity is a function of the productivity of the other projects to which it is connected.

What has been left out of the study is a greater analysis and discussion of the role of departments, that is, the research competencies. Clearly, a more comprehensive understanding of the dynamics of the complexity of labor must take into account the interrelationships of these competencies, particularly with regard to the functional roles played by project members (as in Ahuja et al., 2003). In this manner, it is important to determine not only what the project members *know*, but also what they *do* within the context of the project. But such a discussion raises a number of questions that cannot be answered with the data at hand.

In summary, it is clear that complexity defined simply as greater heterogeneity is too simple. Rather, the analysis suggests that one needs to take into account the network structure of the projects and departments, the constellation of people and competencies, as a complement to other network and group processes in an R&D setting (as discussed in Brown and Eisenhardt, 1995 and Reagans and Zuckerman, 2000). As Kim and Wilemon (2003) argue, the increase in complexity in new product development, and by extension, R&D in general, present challenges to management that cannot be overlooked. The results of this study are promising and highlight not only another level of structure within the framework of complexity, but also the utility of network analysis in understanding and measuring this element of complexity.

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