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Careers and clusters: analyzing the career network dynamic of biotechnology clusters

Steven Casper[a,*], Fiona Murray[b]

[a]*Keck Graduate Institute, 535 Watson Drive, Claremont, CA 91711, USA*
[b]*MIT Sloan School of Management, Massachusetts Institute of Technology, 50 Memorial Drive E52-551, Cambridge, MA 02142, USA*

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Abstract

Access to a pool of talented employees is an important element of entrepreneurial firms' ability to build innovative capabilities. Through an empirical examination of two European biotechnology clusters – Cambridge, UK, and Munich, Germany – we investigate the degree to which macro-labor market institutions shape the micro-dynamics of career affiliation networks between scientific employees. Using bibliometric methods to trace careers and a series of social network analysis methods, we examine similarities and differences in career network dynamics across the two clusters. In particular, we investigate whether patterns of long-term employment within most German large firms, as opposed to more short-term employment in the United Kingdom, affects network structure, network performance and network composition in the two clusters. We show that contrary to the expectations of comparative institutional theory, network structures are grossly similar across the two clusters and, moreover, the performance of these networks as measured by "small-world" methods are similar; career affiliation networks in the two regions are formed through social interactions that appear largely unrelated to macro-institutional factors. Where the macro-institutional forces are effective is as a gatekeeper to network composition: the Cambridge network contains a roughly equal mix of scientists with recent industry and scientific experience, whereas the Munich network is populated almost entirely by academic scientists with no prior industrial experience.

Keywords: Careers; Biotechnology clusters; Application networks; European labor markets; Comparative institutional forces

* Corresponding author.
E-mail addresses: steven_casper@kgi.edu (S. Casper), fmurray@mit.edu (F. Murray).

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1. Introduction

Talented managers and scientists provide high-technology firms with the human and social capital that forms the basis of their innovative capabilities and performance (Becker, 1962; Higgins and Gulati, 2003). There is increasing recognition that firms' access to such human capital is mediated by labor markets and the institutions in which they are embedded. In particular, recent scholarship has suggested that the structure of labor markets has important performance implications for high-tech entrepreneurial clusters (Almeida and Kogut, 1999; Audretsch and Feldman, 1996). As such, the structure and dynamics of labor markets for scientific talent are now of great interest to scholars and policymakers. While the qualitative and quantitative evidence from studies in a diverse cross-section of industries spanning semiconductors and textiles highlights the implications of labor market variations in industry outcomes, we have a very limited window on the mechanisms at work in these markets. In particular, there is currently no systematic analysis that examines the precise micro-level career dynamics through which macro-level institutions shape labor markets. Thus our ability to explain and predict labor market differences at the cluster level is limited.

This paper uses empirical data from high-technology (specifically biotechnology) clusters to examine whether and how differences in macro-level labor institutions are reflected in the micro-level career dynamics of scientists in high-technology clusters. In particular, we ask two questions: How do the career dynamics vary across the two biotech clusters? And, to what extent does such variation fit with the predictions that can be drawn from institutional theory?

We address these questions by observing the career affiliation networks that arise for scientific employees in a sample of biotechnology firms from two clusters in distinctive institutional settings. Our approach is to use a range of social network methods to move beyond firm-level approaches to analyze differences and similarities in cluster-wide networks in terms of their structure and composition. We define these networks as the past career affiliations for employees in biotechnology firms in each cluster. Our novel use of affiliation networks provides an important perspective linking the macro-dynamics of labor institutions to the micro-career dynamics. While these networks instantiate the micro-career dynamics of individual employees, at the cluster level they characterize the social networks formed through previous employment and structured through labor market institutions. More than simply analyzing career paths, these networks provide insights into the social structures that characterize the ties among employees in a cluster's labor market and therefore the nature of human *and* social capital available to firms in the cluster.

We observe and characterize these career affiliation networks for two biotech clusters – Cambridge, UK, and Munich, Germany. These two countries represent canonical exemplars of alternative labor market institutions – Germany as a coordinated market economy with traditionally rigid labor market institutions and long-term employment at most large companies, and the UK as a liberal market economy with more deregulated labor markets and employment systems that broadly embrace ''hire and fire'' (Casper and Murray, 2003). The clusters are also representative of biotech clusters in Europe and exhibit considerable similarity in the scientific expertise, strategies and available finance while they are embedded in quite distinctive labor institutions. We would therefore expect the career networks to show considerable variation between the two clusters. Specifically we propose that the networks will vary in their density, efficiency, centrality and composition.

Our empirical evidence suggests that network structures are grossly similar with career affiliation networks being both robust and efficient and formed through social interactions that appear largely unrelated to macro-institutional factors. Where macro-institutions seem to be effective are as gatekeepers to network composition, segregating how particular communities of experts – particularly scientific versus technical experts – enter into particular regional clusters. This distinction between scientific experts – those whose most recent past affiliation is with the scientific/academic community and technical experts – individuals entering biotechnology firms from either previous biotech or pharmaceutical industry experience is an important one (Murray, 2002). By building career affiliation networks for both clusters, we provide empirical evidence for the differences in micro-career dynamics across the clusters. This approach also allows us to explore the degree to which macro-institutional differences can be empirically identified in the micro-career dynamics of high-tech firms – dynamics that have been shown to have important performance implications. In doing so, we gain deeper insights into the structure and dynamics of labor markets in biotechnology clusters, the processes which link different communities, organizations and individuals in the pursuit of novel scientific opportunities and the role that labor market institutions play in shaping careers, career networks and the access of entrepreneurial firms to talented labor.

The rest of the paper is organized as follows. Section 2 reviews the theoretical foundations of the micro-career dynamics perspective and the predictions from institutional theory as to how differences among labor market institutions will be reflected in different career dynamics. We then present our chosen empirical setting and the cluster and firm sampling strategy; define our data gathering methods and highlight our definition of career affiliation networks. We present our analytical methodology and results, and finally we end with a discussion of the implications of our findings for network analysis, comparative institutional theory and theories of high-tech clusters, policymakers and entrepreneurs.

2. Theoretical perspectives

2.1. Micro-career dynamics

The micro-career perspective on high-tech entrepreneurial firms has focused on the role of employees in providing key assets to firms. The most salient, and measurable, dimension of an employee's contribution to the firm is their career. And in a recent stream of scholarship based on data from high-technology firms in the fields of biotechnology, semiconductors and software, the combined careers of the management team have been shown to have an important impact on firm performance (Higgins and Gulati, 2003; Burton et al., 2003; Saxenian, 1994). At the cluster level, there is empirical evidence that career dynamics and, in particular, career mobility play an important role in innovative performance (Almeida and Kogut, 1999). Overall, the literature linking career dynamics to firm and cluster performance highlights three key elements of career networks: connectivity and robustness, efficiency, and diversity.

When individuals hired by firms have a significant degree of mobility between firms, then the network of their past affiliations becomes extensive and ultimately at a cluster-level, highly inter-connected. This insight is exemplified by the work of Saxenian (1994) whose thick description of the success of Silicon Valley focused on the mobility of technical employees from one firm to the next after relatively short periods of tenure. Mobility was defined as the central mechanism fueling rapid innovation, with employees taking ideas gained in one career experience and applying them to the next. Not only did mobility provide human capital in the form of new ideas, but also social capital through the ability to access many others in the network through past shared affiliation. In a quantitative examination of this hypothesis, Almeida and Kogut (1999) show that rates of patenting are higher for the semiconductor firms in the Silicon Valley region compared to other regions and that the extent of mobility of patent inventors from one firm to another within and into the region was a key determinant. The "small-world" literature also highlights the importance of network structure, specifically in their discussions of robustness. Robustness is measured by an estimate of the "cliqueness" of people within the network with cliques creating durability. It is driven by the insight that people have a tendency to form local cliques with people with whom they share similar characteristics. For example, if Bob, Shelly, and Ted are all bioinformatics experts and if Bob knows Shelly and Shelly knows Ted, then it is highly likely that Bob also knows Ted. When the clustering of people into cliques is high the robustness of a network increases, as within a clique where everyone knows everybody it is unlikely that a given person will serve as a lynchpin in the network, potentially destroying connectivity within the network by leaving. This stream of literature suggests that an important aspect of innovative clusters is a densely connected and robust network of employees who share many overlapping past career affiliations to a large number of different past employees.

A second characteristic of career affiliation networks that is central to the functioning of the cluster is efficiency. Efficient networks are those in which firms can access a large number of different nodes – sources of knowledge, status, etc. through a relatively small number of connections. Small-world theorists measure efficiency by the number of nodes a member of a network would, on average, have to "go through" to reach another member of the network – usually referred to as the path length. The shorter the average path length, relative to the overall size of the network, the more efficient is a network. In clusters characterized by efficient networks, we might assume that firms will have access to a large number of unique nodes in an efficient and effective manner. This intuition is certainly born out by the importance of career experience in big pharmaceutical firms for the performance of biotechnology companies. Taken together with the evidence from Silicon Valley firms on the importance of founding team experience, this suggests that efficient access to a range of resources is critical. And, more than the aggregation of individual careers, the career affiliation network perspective provides us with insights into the efficiency of the network for the entire cluster.

While efficiency highlights the importance of reaching a large number of nodes, network diversity suggests that it is critical that those nodes are diverse in nature. For example, in research on a sample of Silicon Valley firms, Burton et al. (2003) show that past affiliation to (and therefore nodes of) large established and high-status firms has an important effect on the performance of entrepreneurial firms. In the biotechnology sector, firms benefit from several key assets established through the diversity of the career experience of different employees: the career experience of the management team, particularly in horizontal or downstream firms (other biotechnology firms or large pharmaceutical firms) impacts firm IPO performance (Higgins and Gulati, 2003). Likewise for scientists, the past career experience of scientist-entrepreneurs provide critical social capital when they leverage networks of former students and colleagues established throughout the course of their academic career for the benefit of the firm (Murray, 2004); and star scientists contribute essential tacit knowledge generated through their career experience (Zucker et al., 1998, 2001). Thus the ability of firms in a cluster to access employees with past affiliations to a diversity of organizations becomes another critical element of a successful labor market. At least in biotechnology this diversity might be expected to translate into a mix of academic, pharmaceutical and established biotech network nodes.

While studies of micro-career dynamics generally highlight effects at the firm level, some empirical evidence suggests that regional differences in micro-career dynamics also arise between high-tech clusters. To the extent that comparative research exists, the traditional explanation for inter-cluster differences is a cultural one – Saxenian (1994) identifies local culture as the source of mobility differences between Silicon Valley and the Boston/Route 128 semiconductor clusters. One problem with cultural explanations is the inability to explain the mechanisms of change. For example, while the circa 1980s culture of Boston's Route 128 semiconductor firms was risk-adverse and conservative (limiting inter-firm mobility through long-term employment practices and limited new start-up ventures), the same region now boasts a leading biotechnology cluster full of small risk-acceptant firms and flexible local labor markets (Cortright and Mayer, 2003).

2.2. *Macro-institutional influences on micro-dynamics*

In contrast, the macro-institutional literature provides some insight into cluster variation in labor markets (at least from a cross-national perspective). Specifically, we propose that an alternative view on inter-cluster differences – one that privileges institutional variation as the driver of career affiliation networks and variation across labor markets – could provide important novel and predictive insights. This view is based on the significant comparative institutional literature examining the macro-foundations of how innovation and innovative labor markets are organized differently across capitalist economies.

This literature examines how national institutions governing labor, financial and product markets support or constrain firms as they engage in certain types of innovative activities (Zysman, 1975; Nelson, 1991; Mowery and Nelson, 1999; Hall and Soskice, 2001). The varieties of capitalism literature have identified at least two distinctive "types" of economies characterized by differences in their organization of market institutions: organized stakeholder economies and liberal market economies. Within this framework Germany, and most other Northern European economies, is typically categorized as an organized economy, with the other end of the spectrum being "liberal market" economies represented by the United Kingdom and the United States. One of the key assertions made in the institutional literature is that within organized economies most skilled employees develop long-term careers *within* companies resulting in relatively inflexible labor markets, facilitated by the organization of Germany's companies into a "social" system shaped by company laws and industrial relations that give statutory bargaining rights to employees and other non-financial stakeholders. On the other hand, in more deregulated liberal market economies a more fragmented industrial relations system and shareholder-dominated corporate governance are conducive to much more flexible labor markets as firms can routinely "hire and fire".

Within this framework, the performance of high-technology firms has been explained in terms of specific national institutions that impact the viability of particular organizational arrangements within firms. For example, Hall and Soskice (2001) discuss how firms within the German-coordinated market environment tend to specialize and excel in incrementally innovative strategies, whereas firms within the American liberal market environment tend to specialize and excel in radically innovative strategies. However, one significant limitation with such comparative institutional studies is that while they have resulted in detailed typologies of different national business systems and in respect to the labor market institutions (see, e.g. Streeck, 1992; Hollingsworth, 1997; Whitley, 1999), little attention is given to the mechanisms through which such national institutions might lead to distinctive employment processes and regional labor markets, the exception being the work on the Italian textile districts (Locke and Richard, 1995) and European biotechnology (Casper and Murray, 2003). The central critique of the institutional macro-labor market approach is therefore the limited connection made between macro-institutions and the micro-dynamics of individual careers through which these institutional differences are enacted.

In building this connection, we propose a number of mechanisms through which macro-labor institutions might be expected to influence career networks and we find several aspects of cluster dynamics that are under-determined by labor market institutions. From the literature on labor institutions, the key practices that we might expect to have a bearing on careers in high technology, specifically biotechnology are the typical length of employment and the expectations of mobility between jobs and between sectors. We propose that institutional factors would shape the three attributes of career affiliation networks outlined above with this expectation formed in part on the basis of the large literature demonstrating that institutional factors impact the organization and human resource structures of firms (Aoki, 1992; Streeck, 1992; Kogut, 1993; Zysman, 1975).

2.2.1. Network structure

Based on institutional theory, we would expect that the structure of career affiliation networks across the German and UK clusters would differ. Within Germany, long-term employment at established firms and fairly rigid labor market structures suggest that scientists move from job to job infrequently. This should lead to numerous long-term ties across an organization, but fewer inter-organizational ties, i.e. if a scientist changes jobs infrequently, then inter-organizational ties generated through employment at different organizations should not develop. Therefore, the Munich network should be *sparser* than the Cambridge network: fewer inter-organizational career affiliation ties should exist for Munich scientists compared to Cambridge scientists. If job mobility is lower in Munich than in Cambridge, then scientists should develop, on average, fewer ties over their career as they have worked in fewer organizations. Moreover, the Munich network should be more *fragmented* than the Cambridge network. This expectation again follows from differences in career structures and inter-firm mobility. If scientists within German firms move infrequently (or, when moving, to a relatively close-knit group of firms, such as corporate spin-offs), then there should be fewer ties linking groups of scientists within the Munich network compared to the Cambridge network. On the other hand, if mobility is higher within liberal market economies such as the United Kingdom, scientists within the Cambridge cluster should more easily develop inter-organizational career affiliation ties and this will therefore translate into a denser and a more robust network.

2.2.2. Network efficiency and robustness

From the institutional perspective, network efficiency is likely to derive in part from mobility among employers, although the precise institutional dynamics that are likely to drive efficiency are unclear. On the one hand, we might expect that the German system with long-term employment will have quite concentrated nodes – with individuals' past careers passing through only a few nodal firms, long-term employment and labor market rigidities do not predict the heterogeneity of those firms and therefore whether short path lengths might be expected in Germany relative to the UK. We therefore expect the Cambridge network to outperform the Munich network on both its relative efficiency in transmitting information across the network and its robustness or durability characteristics. If the Munich network is more fragmented and has a sparser tie structure, then it is likely that information will flow less efficiently through the network. Due to the expectation of higher fragmentation, we expect the Munich network to also be less robust, meaning that its efficiency is likely to deteriorate more quickly than that in the Cambridge network when members decide to exit.

2.2.3. Network diversity

In contrast, the institutional perspective does suggest that in national systems such as the UK characterized by mobility we might expect more diversity as employees have more opportunities to work with different types of institutions. We would anticipate that the *diversity* of the Cambridge network should be higher than that in the Munich career affiliation network. Scientists take jobs in biotechnology firms from two general sources: previous industry jobs or from academia. As the biotechnology clusters we are studying are relatively new, we expect relatively few people to come from biotechnology firms (though they may move into the region from biotechnology companies in other countries or regions). Most people will move to their current job from large pharmaceutical companies or from academic positions. We have no expectations about the structure of academic career markets. However, as discussed below both regions are home to prestigious centers of academic biomedical research. University labs and institutes should therefore be a source of employees to firms in both regions. However, as we expect mobility into and out of large pharmaceutical companies to be higher in UK firms than in German firms, the composition of scientists should include both academic and industry scientists in Cambridge, but primarily academic scientists in Munich; the diversity of the Munich career affiliation network should be lower. However, the national institutions literature provides little guidance as to the nature of mobility and employment paths out of academia or on the question of whether firms hire from outside national or regional labor markets as a means of establishing diversity.

3. Empirical setting and sample

3.1. European comparison – UK and Germany

Our research design is focused on biotechnology clusters in the UK and Germany. As noted above, these two countries serve as canonical examples in the ‘‘varieties of capitalism’’ literature (Hall and Soskice, 2001). In addition to being clear examples of countries with different labor market and company employment institutions, the UK and Germany house two of the most important European biotechnology clusters, located Munich and Cambridge. Our research design is thus well suited to examine to what extent and along what dimensions national differences in macro-labor market organization impact local labor market networks and micro-career networks. While the UK and Germany illustrate important macro-labor market differences, they are similar along a number of significant dimensions allowing us to control for several alternative explanations for career network differences we find. Specifically, we need to control for other sources of labor market variation including the potential supply of trained scientists, academic researchers and pharmaceutical employees. With respect to scientific training and research, these two countries are the leaders in funding public biomedical research (Wellcome Trust, 1998) and thus can be expected to generate relatively similar amounts and types of biomedical science that can be commercialized into a biotechnology sector which will therefore generate similar demand for talented technical/scientific experts. Furthermore, both countries have a strong commitment to Ph.D. education and therefore generate a supply of highly trained basic scientists. Furthermore, the two countries have large pharmaceutical industries, both of which predate the establishment of biotechnology in the 1970s, that serve as potential reservoirs from which senior scientists (and scientific managers) can potentially be recruited.

3.2. Biotechnology clusters – Cambridge and Munich

Within Germany and the UK, we have chosen the biotechnology-intensive clusters of Munich and Cambridge respectively. Munich and its environs is one of several German biotech clusters but has emerged as Germany’s largest life-science research complex (Casper and Murray, 2003). Research in the area is dominated by several large life-science departments and teaching hospitals belonging to the University of Munich. This includes the Munich Genezentrum, an autonomous department of the University launched in the 1980s to conduct interdisciplinary genetics research. The city is also home to the Max Planck Institute (MPI) for Biochemistry, employing over 800 scientists and technicians. MPI has become a leading center for research in the area of cell signaling, an area of biochemistry with particularly strong commercialization potential. The region also houses the GSF Institute for Environment and Health Research, a core coordinator of German contributions to the International Human Genome Project, which also houses the Munich Information Center for Protein Sequences.

The Cambridge cluster, together with the biotech cluster around Oxford and in London forms the core of the UK biotech industry. Cambridge has a range of important scientific institutions centered on the University including a number of top rated departments within the life sciences arena that receive substantial in public funding for science.[1] The University has also played a strong historical role for the development of the intellectual foundations of the biotechnology industry as the locale for Watson and Cricks' ground breaking work on the structure of DNA some fifty years ago. Cambridge is also home to affiliated life-sciences research institutes: the Medical Research Council (MRC) Laboratory for Molecular Biology – another important contributor to the early foundations of molecular biology, research on protein crystallography and DNA sequencing techniques – the MRC Center for Protein Engineering and the Sanger Centre. Together with the European Bioinformatics Institute (EBI) the Sanger Centre forms a large, specialized, and world-class scientific research organization. Sanger is one of the world's largest gene-sequencing centers responsible for decoding over one-third of the genome as part of the public Human Genome Project. Its director during the genome project was Dr. John Sulston, recently awarded a Nobel Prize for his contributions to gene sequencing. Similarly, the EBI is located in close proximity to Sanger and is a leader in developing the software used to manage the huge volume of genetic code created by new genomics technologies.

3.3. Cluster data

For each cluster, we collected data on biotechnology firms formed between 1995 and 2003.[2] A preliminary list of firms was gathered from regional industry association web sites and then supplemented by personal interviews and snowball sampling. For each firm, we then conducted bibliometric searches on the Web of Science, looking for publications that included the firm in the institutional affiliation field (which can be interpreted as having at least one of the publication authors affiliated to the firm). We then included only firms with at least one scientific publication from which we could identify scientist employees and a web site for which we could identify senior scientists within the firm.

This methodology is biased towards scientifically intensive companies (those that are pro-publication, Henderson and Cockburn, 1994) but this methodology is likely to include rather than exclude firms with a high innovative capacity and with a greater dependence on career dynamics (based on evidence from studies that link innovative capacity to the

[1] This rating system is applied to all British Universities that receive public funding for research and education. It is a department by department ranking of the quality of research and teaching which is used to determine subsequent allocations of funding. The highest rating is a five star. In the life sciences, relevant departments include chemistry, biochemistry, biology, etc.

[2] For the German cases, this methodology includes most biotechnology firms due to the recent development of the clusters. The Cambridge database is truncated, missing a few older biotechnology companies (most notably Cambridge Antibody Technologies, a relatively large biotechnology firm founded in 1993). Excluding firms could influence the social network statistics produced. If there were differences in the human resource structures of the older firms opposed to the newer firms this could impact attributes (or the composition) of nodes within our network. Likewise, excluding scientists with important positions in the social networks we are examining might impact structural characteristics of the network. While our end results lead us to believe these problems have not occurred, this bias may well exist, but only for the comparison case of Cambridge.

Table 1
Descriptive statistics for Cambridge and Munich clusters

	Cambridge	Munich
Total firms	29	28
Firms with at least one publication	10	9
Average number of publications per firm (range)	5.0	6.1
Total scientists identified for cluster	71	82
Average number of scientists per firm (range)	7.9	9.1

embeddedness of firms within areas of high inter-firm mobility (Almeida and Kogut, 1999). As Table 1 illustrates, these methods allowed us to identified nine firms located in Cambridge and 10 firms in Munich, about one-third of new biotechnology ventures in each cluster.

Finally, we collected descriptive statistics for all companies (age, overall employment within the firm and whether the company was performing drug discovery research). Eight of the Munich firms and six of the Cambridge firms were working in the general area of drug discovery (in contrast to firms developing discovery tools, diagnostics, etc.). For these firms, we collected information on the progress of their drug candidates in clinical trials. This metric is commonly used as a performance indicator in studies of the pharmaceutical industry. We will use this data later in the paper to suggest that substantial differences in performance might be caused by social network variables.

4. Methods

4.1. Career affiliation networks

Careers are an important mechanism through which micro-career dynamics such as mobility, accumulated social capital and human capital are established (Baker, 2000; Uzzi, 2003; Burton et al., 2003). For scientists and other technically trained individuals, careers encompass not only employment within traditional business organizations, but also scientific training and faculty positions. These activities together with the informal, collegial nature of the invisible college contribute to the capital that scientists may bring to firms (Murray, 2004). Following the literature on inter-firm mobility, we define career affiliation networks as the social networks formed through previous employment or training. While these networks instantiate the micro-career dynamics of individual employees, it is at this cluster-level of analysis that we would expect to see macro-institutional effects in action. This approach allows us to develop comparable career affiliation networks for the two clusters and then probe the similarities and differences in the two networks relating these features to the distinctive macro-institutional context.

4.2. Bibliometric approaches

Our methodology is to develop a career history for all those employees within the biotechnology clusters under investigation that were identified as having published as employees of the firm. We then use career histories to build career affiliation networks of shared past affiliations. The employees were identified using bibliometric methods, supplemented in some cases by Internet searches, to identify scientists working for companies and compile information on their career histories. Scientists were identified in most cases by author affiliations on scientific publications located within the ISI Web of Science database; if a co-author to a publication listed the firm as his or her affiliation, we assumed this person was employed by the company. Most firms also maintained web sites listing the names of senior scientists occupying management positions within the firm. We also included these individuals within our database. We identified 71 scientists located in Cambridge firms and 89 in Munich. Career histories were constructed using bibliometric methods. Again using the ISI Web of Science we developed publication histories for all scientists beginning with 1981, the year the ISI Web of Science began tracking publications. For senior scientists, we supplemented bibliometric data with career histories listed on company web sites when possible. We also employed Google searches on all authors, yielding in some cases supplemental career information and in rare cases, complete resumes.

The advantage of using bibliometric methods for career searches is that it yields similar information about all employees within the database. Moreover, the method is particularly promising for studies of the biotechnology industry due to its high scientific intensity and dependence upon basic research – yielding a large number of publications. We chose not to develop more systematic data for individual companies through direct contacts in order to preserve a consistent selection strategy that would yield similar information (and similar biases) about scientists working in each firm.

This methodology produces reasonable data on the careers of most scientists, but does generate some missing data, notably jobs in which a scientist did not publish. For example, a person might have been employed at a firm that had a ‘‘no publication’’ policy, and then moved to a subsequent firm that encouraged publication. We do not believe this is a significant problem for two reasons: (i) a majority of the non-senior scientists within our data set moved to their current company job directly from academia (where publication is virtually a given) and (ii) there are relatively few gaps in publication histories leading us to believe that for most scientists publication provides a consistent trace of employment. For the senior scientists, we were able to capture and confirm complete career history from profiles on web sites. However, it is possible that we missed some previous industry jobs for more junior scientists.

There are two drawbacks of using bibliometric methods, however, both of which create missing data. First, the ISI Web of Science only identifies authors by last name and initials, often conflating multiple authors into single publication records. Second, except for a paper’s first author, names and affiliations are not linked in ISI Web of Science. This means that, using ISI Web of Science records alone, we could often not be sure of an author’s precise affiliation, particularly in previous jobs. Many extraneous co-authors also had to be eliminated through cross-checking scientific fields. This was facilitated by the fact that one of the project members (Murray) has graduate science training; we also employed a geneticist as a research assistant to help minimize this problem. In cases where two or more authors worked in broadly similar fields, or when we needed to verify that changes in affiliation actually represent new jobs, we used supplemental bibliometric searches.

This was usually done using Pubmed, another biomedical bibliometric search engine that contains links to complete articles or abstracts that include complete author/affiliation information. This strategy works for most publications published since the early 1990s. However, for some earlier publications and for obscure journals lacking on-line publication we were unable to verify author information. In cases where we had no prior jobs for a scientist this person was removed from our database. In other cases of partial data we kept the scientist in the database but only include jobs that could be verified.

4.3. Network analysis

We used career histories to create two-mode networks that establish ties between scientists on the basis of common prior employment affiliations. It is important to note that in this analysis we do not include the timing of affiliations and therefore ties are made on the basis of affiliations without the additional check that two individuals were employed at the same affiliation during a shared period of time. While simultaneity would be a stronger indicator that these two scientists share an actual tie, we are satisfied that our data do represent not only shared affiliations but also a social connection for several reasons: First, the vast majority of jobs in our dataset occurred during the 1990s, increasingly the likelihood of a direct tie or that individuals in our dataset share common acquaintances within prior affiliations which could be used to pass information between individuals. Second, affiliations in our data set include a few large pharmaceutical firms, many smaller biotechnology companies, and a great deal of academic affiliations for which simultaneity may be less important than membership of a university or department at some point in time.

Finally, we were able to code most affiliations at a fine grain of organizational detail, further maximizing the likelihood that social connections exist. While we could only code companies at the firm level (e.g. ''British Biotech''), we had a choice of how to code academic affiliations. Coding only the university (i.e. ''University of Munich'') would inflate the number of common ties within our data set. We decided to code all academic affiliations at the department or institute level (e.g. ''University of Munich, Dept. of Biochemistry'' or ''Max Planck Institute for Biochemistry, Munich). Doing so should help ensure that two scientists, when they do share a prior affiliation tie, have a reasonably high chance of actually knowing one another directly or through common acquaintances.

5. Results

Our results are presented in three parts along the lines of our theoretical expectations. We first compare various aspects of network structure, including their relative sparseness, fragmentation, and density. Second, we compare the efficiency and robustness of the two networks employing ''small-world'' techniques. Finally, we examine the diversity of the two networks in terms of the composition of the past employers and the connections among them. We develop our results using a well-known social network analysis software program, UCINET. We also present network visualization figures for which we used the Netdraw program.

5.1. Network structure

Comparative institutional analysis leads us to expect differences in the basic structure of the Cambridge and Munich career affiliation networks: specifically that the Munich network should be more fragmented and sparser than the Cambridge network. Fragmentation can be measured through examining the size and distribution of networks components (i.e. clusters of scientists connected through career affiliation ties). If Cambridge is more connected then we should observe one large, well-connected component as a result of extensive mobility. The Munich network should be more fragmented – a number of smaller components should exist. Sparseness can be measured through analyzing the density and distribution of ties linking scientists within the network. We now discuss both measures.

Figs. 1 and 2 present network visualizations of the complete networks for Cambridge and Munich. These figures highlight the remarkable similarity in the general structure of the two networks. Table 2 presents descriptive statistics on the distribution of components and their size within each network and a *t*-test comparing the distribution of components between Munich and Cambridge. A high degree of connectivity exists within each network, as measured by the percentage of people connected into the largest cluster, commonly known as the main component. Almost three-quarters of the Cambridge scientists are connected to one another through the main component, and roughly two-thirds of the Munich scientists are in the main component. While there are no hard and fast

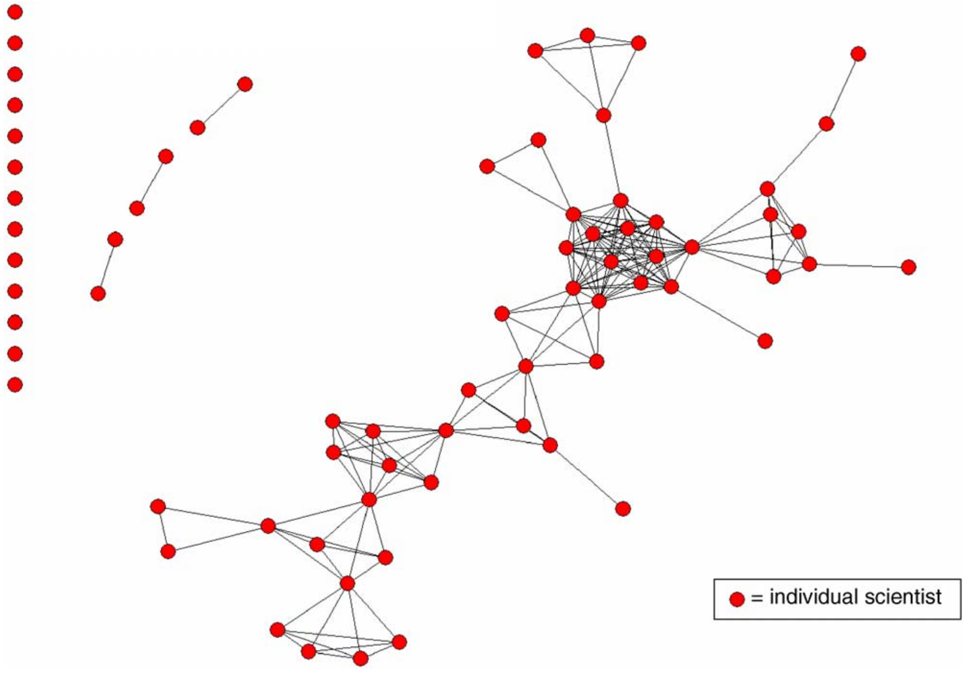

Fig. 1. Cambridge career affiliation network.

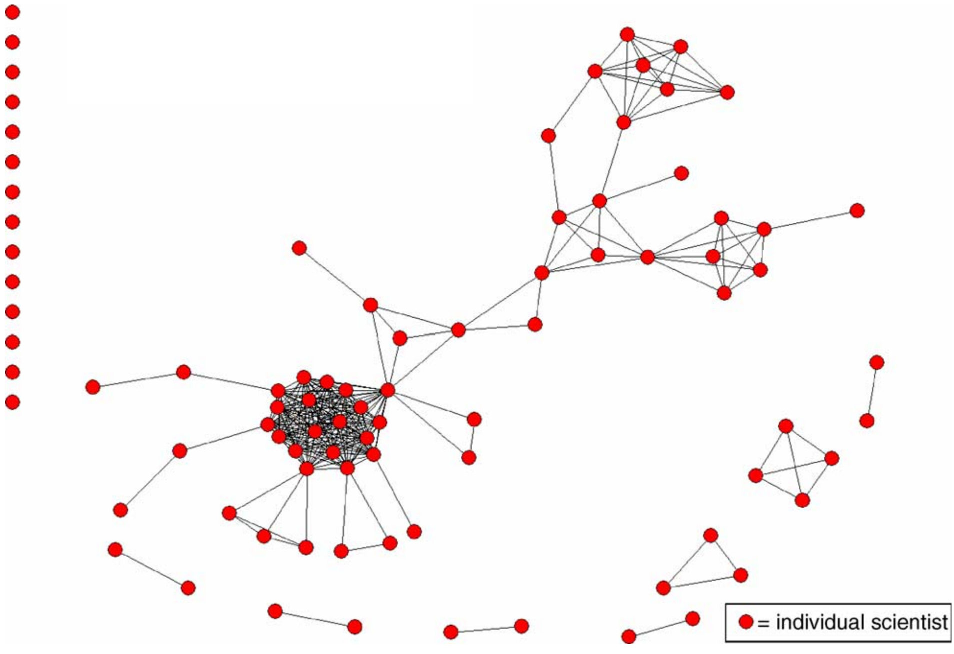

Fig. 2. Munich career affiliation network.

rules as to the size or percent of a network that must be in the core component to make a network useful for analysis, some other recent research on inter-organizational networks within biotechnology found about half of network members to be in the core component (Owen Smith and Powell, 2004). This level of connectivity suggests that firms in the cluster are related through the past affiliations of their employees and as such the potential arises for them to share social ties in addition to human capital. There are virtually no differences in the component structure across the two networks: the *t*-test result comparing the distribution of components is 0.98. Thus, our expectation that macro-level labor market institutions would impair the development of a cohesive career affiliation network in Munich is incorrect (see Tables 3 and 4).

Turning next to the organization of ties within the network, we again find similar results across the Cambridge and Munich networks. The two networks have virtually the same density, or number of actual ties in proportion to possible ties within the network. Both networks are sparse with only about 6.8% of possible ties actually formed. The distribution of ties across individual nodes (or scientists) is also similar, with the mean number of ties

Table 2
Distribution of components (t-test = 0.98)

	Total number	Number of isolates	Largest (% of total)	Mean	S.D.
Cambridge	17	13	52 (73%)	1	12.3
Munich	21	13	56 (64%)	1	11.9

Table 3
Descriptive statistics: ties (*t*-test = 0.25)

	Density of ties within network	Distribution of ties across nodes			
		Least	Most	Mean	S.D.
Cambridge	0.0681	0	17	4	4.7
Munich	0.0679	0	21	3	7.1

Density = existing ties/possible ties; *t*-test is for the distribution of ties within the network.

hovering between 3 and 4 across the two networks. The variance in number of ties per node does differ somewhat across the two networks; the variation in this distribution is higher in Munich than that in Cambridge. While both networks have a core of scientists sharing dense career affiliation ties (see Figs. 1 and 2), this core is more centralized in the Munich network. To verify this result, we computed data on degree centrality for both networks. The results on the distribution of centrality across nodes is virtually identical to the results for tie distribution; the centrality data also shows, however, that the overall level of centralization is similar and relatively low, at about 20%, for both networks. Nonetheless, to the extent that a large number of ties are an indicator of social capital, then this capital is more concentrated in Munich than Cambridge. Empirically, however, the result may be driven by a large number of scientist affiliations to the Max Planck Institute for Biochemistry which serves as the institutional origins of three of the Munich companies. In Cambridge, no university department or institute founded more than one company, leading to a less concentrated network.

So far the Munich and Cambridge career affiliation networks are far more similar than we expected on the basis of the macro-institutional perspective. At least by these measures, labor market institutions appear not to have shaped the structure of these career affiliation networks. However, given the general sparseness of ties within each network, the existence of large, cohesive main components within each network suggests that career affiliation ties plausibly represent useful social ties that are resources for individual scientists, and, at the cluster level, could improve cluster performance as suggested by prior research on mobility.

5.2. Network performance: "small-world" analysis

In order to examine the performance of the two networks we use a methodology developed by Watts (1999) to measure the "small-world" characteristics of networks. Doing so involves measuring the efficiency and robustness of the actual network and comparing these measures to those in a random comparison network with the same number

Table 4
Degree centrality and network centralization (*t*-test = 0.25)

	Mean node centrality	S.D.	Network centralization
Cambridge	4	4.6	21.3%
Munich	3	7.0	19.8%

Table 5
Small-world statistics

	Actual network		Random comparison network of same size and density	
	Path length	Cluster coefficient	Path length	Cluster coefficient
Cambridge	3.701	0.855	2.312	0.126
Munich	3.578	0.835	2.085	0.148

of people (nodes) and the same density of ties between nodes. As discussed earlier, efficiency is defined as the average number of nodes a member of the network must ''go through'' to reach another member, called the path length. Robustness describes the relative ability of a network to sustain connectedness when nodes are removed from the network. Robustness is high when most members are organized into cliques or ''small-world'' in which everyone knows everyone. This is measured by the clustering coefficient. The clustering coefficient is a mathematical measure of such cliqueness based on the local triangulation of ties across individual nodes within the network; it produces a measure between 0 and 1 with 1 indicating high clustering.[3]

In small-world networks, efficiency and robustness are connected concepts because efficiency is maintained through a smaller number of ties connecting members of different cliques. These ties are central to the performance of the network, as they allow people to efficiently access information (or resources) across different cohorts of individuals within the network. Based on mathematical models and surveys of a large number of actual networks, Watts (1999) argues that randomly generated networks are typically very efficient (i.e. have low path lengths) but are prone to disruption when nodes are randomly removed (i.e. they have low clustering coefficients). In contrast, small-world networks should also have high network efficiency but be more robust to the loss of nodes due to the existence of cliques (i.e. high clustering coefficients). Therefore, a network has small-world properties when, compared to a simulated random network of the same size and density, both networks have similar path lengths but the real network has a higher cluster coefficient.

Table 5 displays the results of our small-world analysis for the Cambridge and Munich networks. These results again show that the Cambridge and Munich networks display remarkably similar small-world network structures. Cluster coefficients are very high for both networks (averaging about 0.8 compared to 0.1 for the random networks) indicating that small-world ''cliques'' predominate across these networks and demonstrating that they are very robust. The path length results are also similar across the two networks, with very little difference between the Cambridge and Munich cases.

Of particular interest, however, is the fact that in both cases the real network path length is somewhat higher than those of the random networks (e.g. on average 3.5–2.5). While comparable to other social networks that have been labeled ''small-world'' (see, e.g. Kogut

[3] (Newman and Park, 2003) has argued that within many affiliation networks coefficient correlations are biased upwards as groups of individuals are selected into the network on the basis of a current joint affiliation, such as working for the same company. By only including prior job affiliations our data avoids this problem.

and Walker, 2001), we were surprised by this result; it suggests that career affiliation networks could be more efficient. One possible explanation for higher than expected path lengths is missing data, as discussed earlier. If missing jobs lead to missing ties, this could artificially decrease our estimate of overall efficiency. However, because our results are similar across Cambridge and Munich we do not believe missing data is driving this result. More likely, the result is driven by relatively high variation in average path lengths across individual scientists. Referring back to Figs. 1 and 2 we can see that a substantial number of scientists are weakly connected to the network through relatively long peripheral ''spokes'' connected to the main hub. If these spokes were more tightly connected to the core network hubs, then network efficiency would be increased. However, most scientists located in periphery positions in the network are junior scientists many of whom did their academic training in a geographical location outside the core cluster. Their peripheral position probably indicates their generally low status within the network and their recent entry into the network. This hub and spoke characteristic probably accounts for the higher than expected path lengths and may be related to the hierarchical nature of the scientific communities.

The existence of small-world characteristics, particularly within very sparse networks such as these, suggests that neither network is random in formation – social processes impact their structure. However, as with our data on the structure of the networks, it appears that institutional differences in labor market organization and general employment practices by firms across the UK and German business systems do not appear to impact the structural characteristics of these networks.

5.3. The diversity of networks

While macro-institutional variation exists between the German and UK labor markets, contrary to current theory this variation does not appear to impact the structure of networks (or at least do so in similar ways between clusters). It may nevertheless impact career affiliation networks along another salient dimension – network composition. Specifically, institutions could impact network entry. Most successful biotechnology firms draw upon heterogeneous communities of experts (Higgins and Gulati, 2003). This includes academic scientists with experience in the company's founding technology, scientists and engineers with corporate experience in more downstream commercialization processes, and a range of non-technical managers and financial experts. Based on research on high-technology firms, we might expect that regional clusters prosper not only when there is mobility but also dense labor market pools of various experts whose careers develop as firms prosper and, at times, die. The ability of particular clusters to support the careers of heterogeneous communities of experts should be strongly linked to the success of firms in each region and, over time, overall cluster performance.

In examining heterogeneity in network composition, our data allow us to explore the degree to which firms in each cluster draw expertise from two distinctive communities, that we will label the scientific and the technical communities (following the distinction made by Murray, 2002). These communities are distinctive because they bring the firm different knowledge and different social ties and yet both have been shown to be important for the commercialization of biotechnology (Casper and Kettler, 2001; Murray, 2004;

Owen-Smith and Powell, 2004; Powell et al., 1996, 2002). The scientific community comprises the network of scientists whose most recent job was in academia. The primary skill sets they bring to the company are those formed in academic labs, their personal network of ties will be their local laboratory connections – former students and advisors and their invisible colleague of colleagues in basic research positions (Murray, 2004; Crane, 1972; Bozeman et al., 2001). Zucker et al. (1998) have carefully documented the importance of academic links, and particularly those to ''star scientists'' to the performance of biotechnology firms.

A second group of scientists, which we label the technical community, have moved to their current job from a previous job in industry. These individuals will have a combination of academic and industry skill sets, and, in contrast to members of the scientific community, will presumably have developed social ties with other industrial scientists (Saxenian, 1994; Flemming et al., 2004). Obtaining scientists with industry experience (tapping into the technical community) is generally important for all science-based firms because these scientists are more likely to have experience in developing commercial applications for promising academic technologies. Within the biotechnology industry, however, obtaining such a cadre of commercially experienced scientists is particularly important due to the complexity and regulation of drug development processes. This applied knowledge is virtually impossible to develop within a pure academic research setting; it is knowledge learned through experience in moving drug candidates from preclinical experiments into multiyear drug development pipelines. This expertise has been developed primarily in large pharmaceutical companies. Over time, it has spread to a few smaller biotechnology companies as scientists leave ''large pharma'' jobs to work in the biotechnology industry and the industry matures to the point that successful products have actually moved through the value chain into the market.

Our career history data allows us to readily examine whether each scientist came (most recently) from the scientific or technical community. Table 4 examines the nature of the most recent employment for all scientists. It documents important differences in the composition of the networks. We demonstrate that Munich lacks a heterogeneous community of scientists working within its firms. Instead the vast majority (84%) of Munich cluster scientists come straight from academia while only about half (54%) of Cambridge scientists have their immediate past affiliation to the scientific community. We also find that about one-third (34%) of the Munich academic scientists moved to the firm directly from that firm's academic founder lab. In subsequent analysis, not shown here, we examined the extent to which Munich scientists have worked within the founding lab of their company at some prior point in their career. Numerous additional founder lab linkages were found through this analysis, leading us to conclude that close to half of all Munich-based biotechnology-employed scientists we located had worked for their firm's founding lab at some point in their academic career. This research also extended the findings from Munich to three other prominent German clusters, with similar results. Out of 299 total scientists across Germany only 32, or 11%, worked in industry at their prior job; thirty five percent were previously employed in their firm's founder lab (see again Casper et al., 2004). These findings suggest a dramatically stronger linkage between academic labs and companies than appears to exist in the UK. They also reinforce the finding of research in the US that one contribution of founding scientist-entrepreneurs is social ties to their

Table 6
Most recent past employment affiliations of scientists

	Munich	Cambridge
Founder lab	28 (34%)	15 (21%)
Other academic lab	41 (50%)	23 (32%)
Total scientific community	69 (84%)	38 (54%)
Biotech	8 (10%)	10 (14%)
Large pharma	5 (6%)	23 (32%)
Total technical community	13 (16%)	33 (46%)
Total	82 (100%)	71 (100%)

Source: Career histories developed by authors using ISI Web of Science author affiliations.

laboratory which may lead to mobility of key laboratory members to the firm (Murray, 2004). Indeed, founder lab linkages are the primary source of scientific talent for most German biotechnology companies (see Table 6).

To complement these findings on network diversity, we also present evidence on the composition of the key institutional nodes within the network in terms of their centrality. For this measure, we use betweenness centrality, a common measure of the importance of each node in terms of their connecting other nodes to each other within the network (see Owen Smith and Powell, 2004). Table 7 lists by rank order the top ten nodes in each network. The Cambridge results again confirm the high involvement of both the technical and scientific communities to the regional cluster. Several prominent Cambridge University departments are included in our list, most of which are also founding labs of companies. And as expected, large pharmaceutical firms hold prominent positions within the network, including holding three of the top four positions.

Table 7
Central nodes in the Cambridge and Munich networks, measured by betweenness centrality

	Cambridge	Munich
1	Glaxo/Welcomme	German Cancer Research Institute, Heidelberg
2	Pfizer	Morphosys
3	University of Cambridge Cancer Research Center	Max Planck Institute for Biochemistry, Munich
4	SmithKline Beecham	Max Planck Institute for Immunology, Freiburg
5	MRC Institute for Molecular Biology, Cambridge	University of Frankfurt, Department of Internal Medicine
6	Roune-Poulenc	GSF Nuremburg
7	University of Cambridge, Department of Pathology	Boehringer Ingelheim
8	University of Cambridge, Department of Chemistry	Dana Farber Cancer Institute (Harvard Med Sch)
9	University of Cambridge, Department of Physiology	ETH Zurich
10	University of Oxford, Institute for Molecular Medicine	Max Planck Institute for Plant Genetics, Cologne

The Munich results again document the dominance of the scientific community within its network; only two business affiliations hold prominent positions within this network. One of these firms, Morphosys, was among the first spin-outs of the region's most important scientific institutes, the Max Planck Institute for Biochemistry. Morphosys' prominent position is partly derived from several of its executives and scientists leaving to start another local company, Xerion. We were surprised however to learn that only three of the top ten affiliations, in terms of betweenness centrality, are located in the immediate Munich area. Many central organizations within the Munich network are located elsewhere in Germany (particularly the Heidelberg area) and abroad. The Munich region appears to be strong in drawing on scientific talent. Broader research on the geographic origin of scientists, scientific advisory board members, and academic collaborators also documents the widespread geographic dispersion of social networks surrounding Munich biotech firms (Casper and Murray, 2004). The ability to attract externally located employees, advisors, and collaborators into the network may speak to the strength or promise of resources in the Munich area. However, this could also help account for the more concentrated distribution of ties within the Munich network, creating a central core of local scientists with ties to one another and a periphery of scientists that have recently moved to the area and thus have fewer ties to other local scientists.

Our findings on diversity strongly support our expectations from institutional theory. A key finding of the ''varieties of capitalism'' literature is that, in contrast with the UK, German large companies have developed long-term employment patterns and, moreover, tend to privilege senior engineers and scientists when recruiting top management. The apparent unwillingness of German senior pharmaceutical scientists to move to small start-up biotechnology firms is consistent with institutional predictions. Thus while institutional factors do not appear to influence the structure of career affiliation networks, they have strongly influenced their composition.

Evidence that a relatively large number of senior scientists working within Cambridge companies have moved from jobs in large pharmaceutical companies also strongly supports institutional theory. Moreover, these ties are important for the formation of young clusters in which inter-firm mobility between local biotechnology firms is necessarily low; large pharmaceutical companies (or potentially medical device firms) are likely to be the only source of industry-specific expertise from the technical community. German biotechnology firms appear unable to systematically recruit senior scientists from the several large pharmaceutical companies active in the country. While we have not addressed the performance of companies within clusters, our analysis strongly implies that the lack of industry expertise within Munich firms should result in weak performance (see Casper et al., 2004 for such evidence).

6. Discussion and conclusion

This paper examines the degree to which the macro-institutional setting created by labor markets shapes the micro-dynamics of how careers are enacted. Our results have implications for network analysis, institutional theory, theories of cluster formation, and firm performance in biotechnology.

Through their careers, scientists (like other individuals) weave a fabric of past affiliations which bring them important skills and knowledge but also critical social connections to past colleagues, students, and advisors. By developing a systematic method of gathering career information for scientist employees on the basis of bibliometric analysis, we have operationalized the concept of cluster-wide career affiliation networks – a concept that is central to our understanding of how firms in high technology clusters benefit from being part of a cluster rather than isolated in a more atomistic setting. Having built these career affiliation networks we have examined the structure, performance, and diversity of these networks in two different institutional settings. This provides us with deeper insights into the mechanisms through which institutions impact careers, career affiliation networks and firms.

The application of these techniques allows us to explore the possible connection between institutional environment and social networks. As with many other studies of social networks (Kogut and Walker, 2001; Uzzi, 2003; Watts, 1999), we find that broadly similar and coherent networks have formed in both the Cambridge and Munich networks, and that these networks have similar performance characteristics in terms of efficiency and robustness – as measured by ''small-world'' theory. These results suggest that the expectations of institutional theory are incorrect for these cases. However, while the structural results suggest similarity our findings on diversity suggest variation. The novel analytical lense that we have developed on small-world by further parsing out affiliations into two distinctive communities – scientific and technical – provides us with further insight into the structural properties of the network beyond simple employee count statistics. We find that while the overall network structure is quite stable across the two clusters, once the scientific/technical distinction is made, the clusters show important differences, namely in the vibrancy of the Cambridge technical community and the absence of such a community in Munich.

Notably our results suggest that the German network is structured around past career affiliations within the scientific/academic community with very limited mobility into biotech firms from the large pharmaceutical firms in the region. Thus, while we were correct in suggesting that our findings on network structure and performance contradict the expectations of institutional theory, another interpretation of the evidence is that patterns of job mobility within German are in fact strongly dominated by long-term careers to the extent that virtually no network of scientists with industry experience exists within Munich.

A further perspective on the similarity in network structure on the one hand and variation in network composition on the other is that in spite of the differences in network composition, robust career affiliation networks can be generated from a variety of sources. While the diverse Cambridge career affiliation network emerges from a mix of academic and industry institutions and establishes an efficient and connected network as might be expected, job mobility within the German academic system produces a similarly cohesive network structure. We find that while the overall structure of networks are shaped by social processes in that they display small-world characteristics, these social processes are not clearly influenced by institutional factors and therefore the two networks look very similar. This implies that social factors outside the purview of standard research on comparative business systems must account for the social structuring of these networks. This suggests some important underlying dynamics in the ways in which scientific careers are enacted, at least among those scientists whose expressed preference is to engage in building a biotech cluster through employment in early stage entrepreneurial biotech firms. For instance, the social relationships found within our networks could be structured through prior professional affiliations within biomedical research communities, as highlighted by literature on ''epistemic cultures'' within science (Knorr Cetina, 1999).

While structural characteristics are important, the nature of the social capital within the Munich and Cambridge clusters does vary: Munich biotech firms have limited access to the commercial development expertise in big pharma nor do they have an obvious referral network pharmaceutical firms who may be important alliance partners and bring valuable reputational capital (Stuart et al., 1999). In Cambridge, large pharmaceutical firms such as SmithKlein Beecham and Glaxo have seeded the biotech cluster, perhaps in part driven by the changes wrought by merger and acquisition activity. Lacking profound changes in the German system of employment within large pharmaceutical firms, the Munich cluster will lack these critical network resources. This will only change if local biotechnology firms adopt patterns of inter-firm mobility that are characteristic of the broader international biotechnology industry.

The lack of overall network variation together with the variation exposed by the scientific/technical community distinction has important implications for institutional theories of labor markets. When disaggregated into scientific and technical communities it becomes clear that career affiliation networks are importantly structured by institutional factors. Through structuring the employment practices of existing firms (and particularly in our case large pharmaceutical companies), institutions serve as gatekeepers, regulating entry into the network of industry scientists available to local biotechnology firms. The fact that the resultant overall networks are similar ''small-world'' is evidence of the robust nature of small-world structures. Nevertheless, the sub-structures that make up these worlds are distinctive and institutionally driven.

Our more detailed findings on the scientific community have further implications for institutional theory. We find that the affiliation network for the scientific community has a different fine grained structure between Munich and Cambridge: Munich relies more strongly on founder lab connections. This resonates with the university ties literature – but rather than simply a manifestation of tech transfer etc. it suggests the importance of institutional factors as they shape scientific institutions and scientific careers (Whitley, 2003; Gittelman, 2001). Thus while we began the project with a primary interest in economic (labor market) institutions our findings make it apparent that the organization of scientific research institutions may also play an important role in structuring the social networks of entrepreneurial clusters. Thus, we can both highlight and start to disaggregate two distinctive institutional effects that are likely to be of critical importance for science-based firms.

Finally our results have potential performance implications for firms in the Cambridge and Munich clusters. On the basis of the growing literature showing that diverse and experienced management teams lead to stronger firm performance in the US (Higgins and Gulati, 2003; Shane and Stuart, 2002; Burton et al., 2003; Owen-Smith and Powell, 2004), we speculate that the differences in network composition and sub-structure discussed here will influence the innovative intensity of firms in Cambridge and Munich. It remains for future research to make a thorough test of the degree to which career affiliation networks shape firm and cluster performance.

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