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ABSTRACT

The external acquisition of technological knowledge is a central theme in research on technology management. In this paper it is argued that technological communities may provide a useful unit of analysis to study information and knowledge exchange among scientists and engineers working on a particular research agenda. Based on a worldwide survey of more than 2,000 individuals engaged in the research and development of neural network technology, the dynamics within that particular community are explored. The primary focus is to compare the characteristics of academic and industrial researchers, with special attention given to the timing of their entry into the field.

1. Introduction

Understanding the external acquisition of technological knowledge has become an important theme for many students of the management of technology and R&D. A number of recent trends in R&D warrant this attention; namely, the increasing scale, intensity and specialization of research; the internationalization of R&D; the growing number of inter-organizational research links and ventures; and the potential impact of computer communication networks and information technology on the conduct of research activities (Williams and Gibson, 1990). As a consequence, the location of research is becoming increasingly "fluid," both in an operational and organizational sense, as research contacts and administrative boundaries expand from localized research systems to national and international networks (Howells, 1990). Generic technological knowledge is becoming easily accessible to nations and to companies that make the needed investments in science and engineering capabilities. Well-trained engineers and scientists will know roughly the same things and will communicate with each other regardless of where they are located (Baumol, 1990; Nelson, 1990a).

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An industrial R&D laboratory faces a dual challenge. On the one hand, it looks internally, trying to build its own competitive advantage based on proprietary technological knowledge. This is the well-entrenched notion of the "local" character of technology development (Allen, 1977). On the other hand, the industrial laboratory looks toward the external world to monitor developments that might yield opportunities or threats to the firm. Monitoring the external technological environment requires an active role on behalf of the firm. The participation of researchers in national and international networks, their mobility and their information exchange behavior are key ingredients in this outward perspective (Pavitt, 1991; Rothwell and Dodgson, 1991).

In the wake of these findings, it has also become increasingly apparent that most firms find it difficult to block information from flowing to their competitors:

> What may be more surprising, it appears that in many cases firms do not try to block information flow, and in others actively support it by encouraging employees to publish, to talk at technical society meetings, etc. (Nelson, 1990b).

The question is: Why would firms behave in such a manner? Contrary to the notion that a firm can strengthen its competitive advantage by carefully protecting its technological knowledge from its environment, Nelson claims, "There are industry-wide efficiency gains to be had by sharing technology. Everyone would be better off if everyone shared"(Nelson, 1990b). But it is not because sharing increases industry gains that individual firms are inclined to share. Rather, it is much more likely that firms share competitively relevant technical information as a form of quid-pro-quo (von Hippel, 1988). Nonetheless, fostering technical information flows may offer a number of additional advantages to the firm even without requiring reciprocity.

Indeed, if one wants to stake claims to newly developed knowledge, one has to release information. This is the intent of the patent system. At the same time, this disclosure enables the firm to attract customers, to enhance its image as a technological leader, to compete for competent scientists and engineers, to inform suppliers about its technological capabilities, and to attract the interest of investors. Moreover, although the release of information through a publication or presentation is often viewed as an act of full disclosure of knowledge (so that the work can be easily replicated by other researchers), this is rarely the case. Even with purely scientific work, seldom does an article disclose everything one needs to know in order to repeat the experiment (Collins, 1982). In some cases the information is simply too complex or requires too much detail in order for it to be fully detailed in a journal article or presentation. However, in other cases, the lack of complete disclosure occurs because a researcher is not necessarily motivated to provide full details, at least not until the claims to his ideas can be adequately protected.

It is interesting to note that academic and industrial researchers alike are employing all three means—patenting, publishing, and presenting—almost simultaneously when attempting to protect claims to their research findings. For example, the activity in high-temperature superconductors and cold fusion reveals more than one incidence where a researcher announced his work at a conference, submitted a paper for publication, and applied for a patent all within days, if not hours, of one another. Moreover, firms that do publish research typically have an internal review process for "scrubbing clean" a manuscript before it is sent to a journal editor or presented at a conference, in order to make certain it does not contain any information that management might view as proprietary. In this way, firms can receive the benefits that flow from divulging information without compromising confidentiality.

It is obvious that this increasing emphasis on assessing and monitoring the firm's external technological environment calls for empirical research that will illuminate the fundamental dynamics of the extra-organizational environment in fostering technological development. The concept of the technological community precisely attempts to do this.

2. TECHNOLOGICAL COMMUNITIES AS A LEVEL OF ANALYSIS

A number of scholars have recently pointed to the influence of communities of researchers in shaping technological progress (Constant, 1980; Thomson, 1988). In this study, the technological community is defined as the group of scientists and engineers, who are working on an interrelated set of technological problems and who may be organizationally and geographically dispersed but who nevertheless communicate with each other. In particular, the community level of analysis allows us to focus on the extra-organizational environment in studying technology development, as well as the actors shaping this development.

The community level of analysis complements current research on technological change. First, it turns attention away from the organizational or project levels of analysis, which have dominated in past studies of technological development, toward the external environment of the firm. Second, it focuses on the actors of technology development. Although economists and management scholars have demonstrated an interest in the process of technological innovation, their focus has mainly been on contextual factors influencing innovative performance. As a consequence, the actors involved in the process have received much less attention. In the same vein, the community concept turns attention away from all forms of interorganizational linkages, such as joint-ventures and alliances, in order to study information exchange behavior among technologists themselves. We conjecture that understanding this behavior is imperative if one wants to capitalize on it. In other words, we need to investigate to what extent communities are relevant loci of technological knowledge and information.

The analogy with the sociological writings on the functioning of scientific communities (Hagström, 1965; Crane, 1972; Hull, 1988) will be obvious. However, a technological community is not the same as a scientific community. For instance, a technological community can be truly interdisciplinary in nature; whereas, a scientific community often is demarcated by highly specific disciplinary boundaries. Moreover, technological communities are loosely-coupled systems in which the micro-motives of hundreds—perhaps even thousands—of individuals converge to one macro-objective (i.e. solving the problems related to a particular technology). Expressed in an alternative way, just as *"organizations are a means of achieving collective action in situations in which the price system fails"* (Arrow, 1974), technological communities could be hypothesized as a means of achieving collective action in situations in which the organization fails. Focused attention and shared values are two potential ingredients preventing the system from breaking down (Orton and Weick, 1990).

Given the scarcity of empirical data on the role of communities in technological development, this study sets out to examine how researchers function within a particular community with respect to the diffusion of knowledge.

3. Research Method and Data

In this paper we examine some of the behavioral characteristics of researchers within technological communities. In particular, we investigate the similarities and the differences in information exchange behavior for two important subsets of a community: academic researchers and industrial researchers. Much scholarly writing has focused on the differences that exist between academic and industrial research. We do not deny the likelihood of the existence of differences between both types of institutions. However, it has become generally accepted that both academic and industrial research have a prominent role in knowledge development, even in the realm of technological activity (Swann, 1988; Jaffe, 1989; Mansfield, 1991). Therefore, a detailed empirical analysis of both groups may yield valuable insights into the dynamics of this process.

Given the actor-oriented nature of the research, our first choice was to find a relevant community of researchers. Following sociologists' advise on the selection of a "strategic research site" (Bijker et al., 1987), the neural network research community was chosen. This community encompasses scientists and engineers working on the set of scientific and technological problems related to the development of a paradigm fundamentally different from traditional von Neumann computing. The field has known a turbulent history, and even today controversies persist as to the feasibility and ultimate usefulness of neural network computing (Minsky and Papert, 1988; Papert, 1988).

For the two-year period from 1988 and 1989, over 3,000 neural network researchers were identified worldwide through a careful analysis of the materials they published (i.e. journal articles, conference proceedings, and books). From this material we were able to specify the exact address for 2,037 researchers from 35 different countries. These researchers were sent a twelve-page questionnaire inquiring about (a) their current neural network activities; (b) their decision to start neural network research; (c) factors that might ultimately lead them to leave the field; (d) their information exchange behavior; and (e) their demographic characteristics. Given the difficulty in closely following-up on such a large-scale survey, we made use of electronic mail bulletin boards in order to reach neural network researchers. Finally, since 37 researchers had more than one address during the period considered, a total of 2,074 questionnaires were sent out. Of the 2,074 questionnaires, a total of 162 were returned undelivered. None of the undelivered questionnaires were among the 37 researchers with more than one address. A final response rate of 38.4% (720 of the 1875 questionnaires presumed delivered) was obtained.

A number of comparisons were carried out to see whether serious differences existed between the survey population and the respondent sample. The results of these comparisons are reported in Tables 1 and 2. In a geographic comparison of survey respondents and the survey population, there appears to be an adequate representation of the entire population. Researchers based in the U.S. are very heavily represented in both the respondent sample and the survey population. In an institutional comparison between the respondent sample and population, researchers were classified into three categories: academic, industrial and other. The last category is composed of researchers in a disparate collection of organizations, including a number of government managed and/or funded institutions not based at universities. Given the wide range of institutional variation across the nearly three dozen countries, it is difficult to begin analyzing this group without a more careful classification of institutional types; therefore, we will limit the present analysis to a comparison of respondents employed in academic and industrial institutions. No statistically significant difference appears between the respondent sample and the population.

Geographic Region	Respondent Sample (N=719)		Survey Population (N=2074)	
	N	% of total	N	% of total
North & South America	453	63.0	1393	67.2
Europe	181	25.2	444	21.4
Far East	73	10.2	209	10.1
Middle East	12	1.7	28	1.4

TABLE 1: *Comparison of sample and population by geographic region* (χ^2 = 5.24, n.s.)

Type of Institutional Affiliation	Respondent Sample (N=720)		Survey Population (N=2074)	
	N	% of total	N	% of total
Academic	452	62.8	1399	67.5
Industrial	177	24.6	459	22.1
Other	91	12.6	216	10.4

TABLE 2: *Comparison of sample and population by type of institutional affiliation* (χ^2=5.61, n.s.)

For the present analysis, this sample was reduced to those respondents who report their formal position title as faculty member, scientist, or engineer, and their employment locale as either university or industrial laboratory. Thus, students were left out of the analysis, as were respondents who could not be classified into one of the position categories or institutional types mentioned above. This reduced the sample to 401 cases: 286 academic researchers and 115 industrial researchers. From this sample a detailed statistical analysis on the behavior of both groups in the pursuit of their research agenda was conducted.

A summary of each respondent's self-reported position title and highest academic degree is presented in Table 3. The majority of academic respondents have a faculty position and hold a doctorate (80.4%), while only 10.8% have a position title of "scientist" and hold a doctorate. The majority of industrial respondents (59.6%) report their position title as "scientist" and hold a doctorate. Only a minority of "industrial scientists" do not have a doctorate (21 out of 89, or 23.6%). For the majority of "engineers" in industry, the opposite is true (19 out of 25, or 76%, do not hold a doctorate).

Overall, respondents who classify themselves as engineers are an absolute minority (28 out of 400, or 7%). The vast majority of respondents hold a doctoral degree (335 out of 400, or 83.8%). This pattern of education among researchers is certainly an indication of the scientific character of the new technology. *(Note: this level of education is not much different when considering the complete sample, i.e. 81.8% of the complete respondent set holds a doctoral degree or is in the process of obtaining one).*

Highest Academic Degree	Academic Affiliation by Position (N=286)			Industrial Affiliation by Position (N=114)	
	faculty	scientist	engineer	scientist	engineer
bachelor's	1	3	1	2	3
master's	2	16	2	19	16
doctorate	230	31	0	68	6

TABLE 3: *Respondent distribution according to institutional affiliation, highest degree and position.*

The distribution according to each respondent's major field of highest academic degree is given in Table 4. Electrical engineering is by far the largest category, and when joined with computer scientists, the combined total accounts for more than one-half of the respondents. The second largest category is physical science, with physicists accounting for the majority of respondents in this group. Biological sciences, mathematics, psychology, and neural networks each account for less than 10% of the total. *(Note: similar distributions hold for the complete sample.)*

Major Field of Highest Academic Degree	Respondents with an Academic Affiliation (N= 283)		Respondents with an Industrial Affiliation (N= 112)	
	N	% of total	N	% of total
Electrical engineering	99	35.0	57	50.9
Physical sciences	51	18.0	30	26.8
Computer science	44	15.5	10	8.9
Biological science & engineering	31	11.0	1	0.9
Mathematics	18	6.4	8	7.1
Psychology & cognitive science	15	5.3	3	2.7
Neural networks	12	4.2	1	0.9
Other	13	4.6	2	1.8

TABLE 4: *Major field of highest academic degree for academic and industrial respondents.*

Some final demographic sector comparisons are given in Table 5. These are: (a) the age of the respondent; (b) the number of years the respondent has been involved with developing neural network technology (EXPNN); and (c) the respondent's number of years of professional experience (EXPJOB). This last variable was defined as the time elapsed since the respondent's graduation. It is obvious that the number of years involved with neural network technology and the respondent's professional experience will not be completely independent. At the same time, though, they need not be strongly correlated. Some respondents may indeed have entered the neural network field only several years after graduating, while others may have entered long before graduating. (In fact, $r_{expnn.expjob}=0.42$; $p<.001$.)

Besides the fact that industrial researchers are, on average, younger than their academic colleagues, we also find their involvement with neural network technology to be more recent. While their professional experience is quite similar to that of academic researchers, the difference in EXPNN is interesting. Indeed, the majority of industrial researchers entered into the field only after it began to expand rapidly and, presumably, had become more legitimate. Prior to the early 1980s neural networks was judged harshly, and it is not unusual to find researchers who continue to have serious doubts (Papert, 1988). Only a handful of researchers worldwide were willing to pursue a neural network research agenda during the "wilderness years," as they are called in a recent report (DARPA, 1988). Thus, although industrial researchers have been present throughout, it has only been since 1984 that an increasingly significant subset of the total neural network community has started to form.

Variables	Academic			Industrial			t	p
	Mean	s.d.	N	Mean	s.d.	N		
Respondent's age	39.4	8.9	284	37.2	8.4	115	2.26	.012
Years of experience in neural networks (EXPNN)	7.5	6.9	277	4.5	4.6	114	4.93	<.001
Years of professional experience (EXPJOB)	10.8	8.7	286	9.9	7.4	115	1.08	n.s.

TABLE 5: *T-tests across institutional type for respondent age, years of experience with neural networks, and years of professional experience.*

An analysis of each respondent's first year of neural network research shows that 25% of the respondents entered the community prior to 1984, while 75% entered since that date (see Figure 1). Since 1984, the field clearly started rolling. As a consequence, we have chosen this year as a critical point in the community's evolution and have used it to separate the respondent sample into early and late entrants. A sensitivity analysis (using discriminant analysis techniques) indicates that the choice of a cut-off year to separate the two groups was robust as long as it occurred somewhere between 1980 and 1985.

Further analyses of variance, using sector of employment and highest degree as independent variables, show that respondents who hold a doctorate have been involved in neural networks for a longer period of time (EXPNN comparison, $F(1, 389)=4.1$, $p<.05$) and have had more years of professional experience (EXPJOB comparison, $F(1, 399)=4.9$, $p<.05$). No significant interaction effects were found.

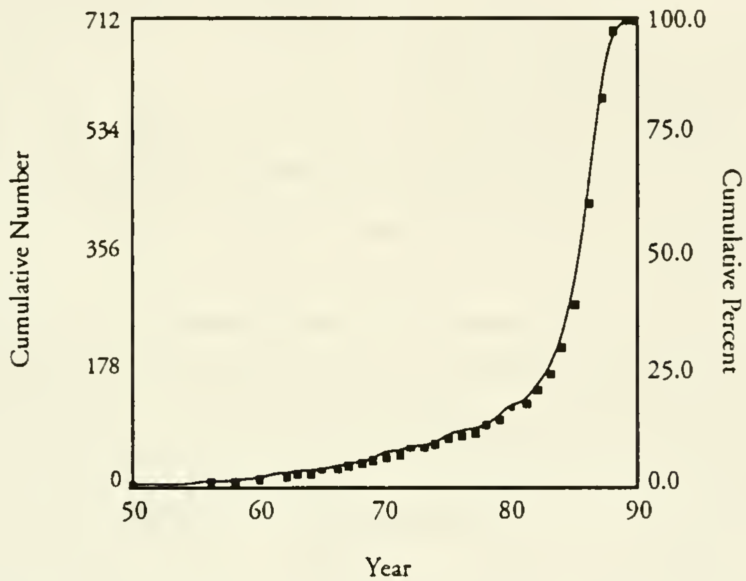

FIGURE 1: *Cumulative distribution of entries into neural network research by survey respondents*

4. INFORMATION AND KNOWLEDGE EXCHANGE AMONG NEURAL NETWORK RESEARCHERS

In this section we compare the information exchange behavior of academic and industrial researchers in the neural network community. When warranted, a distinction between early and late entrants is also taken into account.

4.1. *Communication behavior: general remarks*

The questionnaire investigated a number of issues related to the respondent's inclination to share information with the rest of the neural network community. The diffusion mechanisms include attending conferences, publishing articles, applying for patents, as well as directly communicating with researchers in other organizations. At first glance, it may seem odd to include patent applications in the analysis. However, to the extent that they are made publicly, patent applications do provide a means for communicating technical information. As outlined, the main focus is on comparing academic and industrial researchers. The original (unadjusted) results for a number of variables are shown in Table 6.

Indicator	Academic				Industrial			
	Early entrant		Late entrant		Early entrant		Late entrant	
Average number of neural network related...	mean	N	mean	N	mean	N	mean	N
conferences attended during last five years	11.08	88	5.11	186	7.25	12	5.14	101
publications during past five years	4.74	87	2.38	184	3.23	13	1.36	96
presentations during past five years	7.72	89	4.62	185	5.08	13	3.99	100
professional association memberships	3.13	86	1.97	183	2.54	13	1.78	94
patent applications	0.31	84	0.30	184	1.17	12	1.01	95

TABLE 6: *Averages for indicators of communal behavior for early and late entrants by institution type.*

The number of early entrants in industry is rather low compared to the three other subcategories considered. Taking the necessary caveats into account, analyses of co-variance were run using institutional type and entry period as independent variables, and the respondent's professional experience (EXPJOB) as a co-variate. The results, shown in Table 7, are not surprising. The entry period variable is almost always highly significant ($p<.001$), even after controlling for professional experience. The one exception is for the number of neural network related patents applied for by the respondent. The difference between early and late entrants is understandable: the former having been in the field longer. As for the patent situation, the emerging character of the field is a likely factor.

Focusing on institutional differences, we find that academic researchers present and publish more papers than their industrial colleagues ($p<.02$), but they hold less patents ($p<.001$). For these items, only main effects are present. As far as conference attendance and professional association membership are concerned, the situation is mixed. For instance, both industrial and academic late entrants report similar conference attendance rates, but this is not so for the early entrants (also notice the significant interaction effect, Table 7). As far as professional association membership is concerned, industry/academic differences do not attain statistical significance at all. Thus, in terms of information *acquisition* by means of conference attendance and professional association membership, researchers in both sectors show similar behavior. However, when it comes to information *diffusion* via publishing, presenting, and/or patenting the differences that could be expected are born out.

Indicator	EXPJOB (cov)	Academic/Industry (iv)	Early/Late Entry (iv)	Interaction
conference attendance	F(1,382)=4.9 *	F(1,382)=0.6 n.s.	F(1,382)=59.9 ***	F(1,382)=4.3 *
publications	F(1,375)=9.9 **	F(1,375)=9.7 **	F(1,375)=32.9 ***	F(1,375)=0.2 n.s.
presentations	F(1,382)=2.9 n.s.	F(1,382)=5.6 *	F(1,382)=45.2 ***	F(1,382)=3.4 n.s.
association membership	F(1,371)=15.4 ***	F(1,371)=2.1 n.s.	F(1,371)=28.3 ***	F(1,371)=0.6 n.s.
patent applications	F(1,370)=1.2 n.s.	F(1,370)=27.2 ***	F(1,370)=0.2 n.s.	F(1,370)=0.1 n.s.

TABLE 7: *ANCOVA comparison on communication behavior indicators by institutional type and entry period with professional experience as a co-variate.* (F-values: *p<.05; **p<.01; ***p<.001)

In subsequent analyses, we took the respondent's highest academic degree into account (dichotomized into a doctorate/non-doctorate independent variable). As might be expected, respondents with a doctorate report a greater extent of communal interaction than their colleagues who do not have a doctorate: they publish more articles (p=.04), they present more papers (p<.001), and they have more professional society memberships (p<.001). This is a clear illustration of the socialization that occurs while pursuing a doctorate. It also points to the differences between scientists and engineers as discussed by Allen (1988). When comparing respondents with and without a doctorate, no difference is found both in terms of the number of conferences attended during the past five years and the number of neural network related patent applications. When considering the institutional type and entry period as additional independent variables, no higher order interactions involving the academic degree variable are found. The doctorate/non-doctorate distinction only exerts main effects.

Lastly, we controlled for the education level of the respondents and examined whether or not there are sector differences pertaining to any of the five indicators discussed in Table 7. For non-doctorates, no statistical differences are found when comparing industrial and academic researchers, except for the number of patent applications. Non-doctorates in academic institutions report seldom having applied for patents (average number of applications = 0.08) compared to their industrial colleagues (average = 1.2). The difference is highly significant (p<.001). When comparing doctorates in academic and industrial institutions, we find more differences that are statistically significant. Doctorates in industry apply for more patents ($p<.001$), while their academic counterparts report more publications ($p<.001$), more conference presentations ($p=.025$), and more frequent conference attendance ($p=.019$). With respect to professional association membership, no statistically significant differences are found. Thus, when controlling for education level, our findings with respect to sector differences shown in Table 7 are clarified further.

4.2 *Amount and diversity of external communications*

The number of hours spent talking to researchers outside their organization does not differ significantly for academic (1.61 hours per week, N=256) and industrial researchers (1.40 hours per week, N=102). Controlling for the level of education does not significantly alter the results. Doctorates in universities spend 1.63 hours per week talking with researchers outside their institution, while doctorates in industry spend an average of 1.36 hours (n.s.). Non-doctorates in universities spend an average of 1.72 hours per week, compared with 1.36 hours for their industrial counterparts (n.s.). Moreover, when taking the other independent variables into account as well as the respondent's professional experience, we find neither significant main effects nor interaction effects. Thus, a remarkable degree of homogeneity exists within the community when comparing the amount of extra-organizational communication across institutional sectors, early and late entrants, doctorates and non-doctorates, and respondents with differing degrees of professional experience.

The respondents were further asked to categorize the number of researchers outside their organization with whom they regularly confer about neural network related issues. The results of a Mann-Whitney non-parametric test, shown in Figure 2, reveals no significant sector difference; that is, academic and industrial researchers report the same number of external communication partners (Mann-Whitney U=14141, $z= -1.54$, n.s.). As shown in Figure 3, the entry period variable yields a statistically significant difference (non-parametric Mann-Whitney U=10,500, $z= -4.02$, $p<.001$). Thus, even if the amount of outside communications (as measured in hours per week spent talking to external researchers) is similar for both groups, the external communication partners seem to be more diverse for the early entrants (where the number of communication partners is a proxy for this diversity).

Of course, it could be argued that this effect is attributable to the difference in the length of professional experience between early and late entrants. The longer one's professional career, the greater the opportunity one has to build a network of communication partners—even if a researcher is new to the field. An analysis of cohorts was performed in order to further investigate this issue.

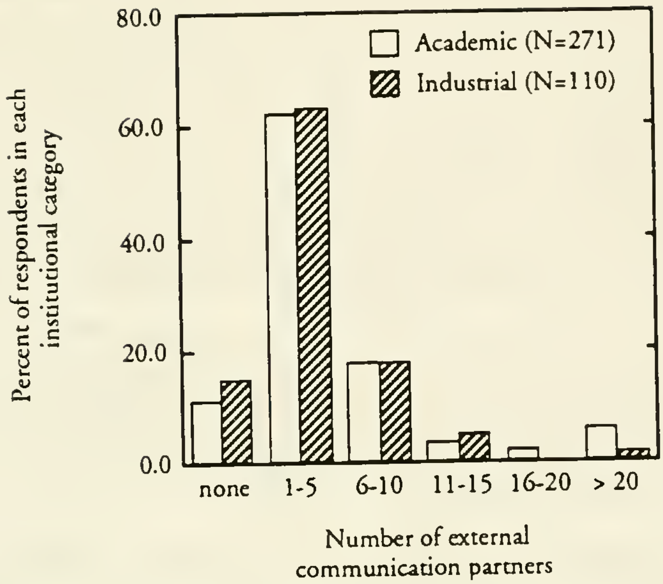

FIGURE 2: *External communication partners for academic and industrial researchers* (M-W U = 14,141; z = –1.54; n.s.)

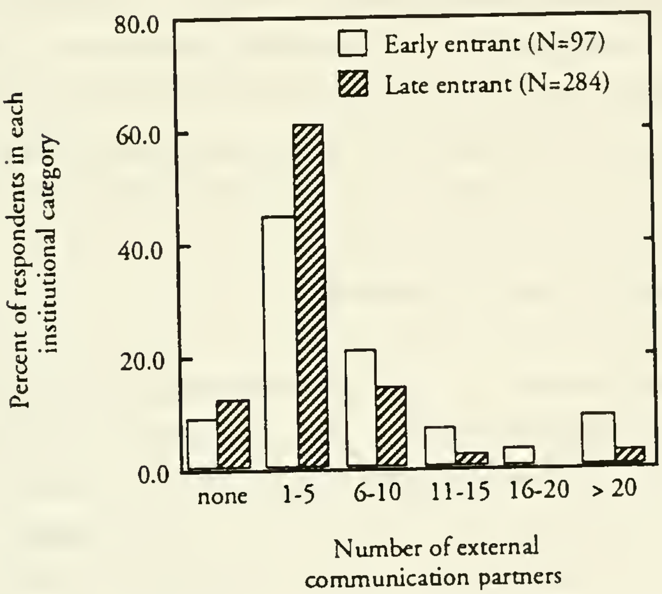

FIGURE 3: *External communication partners for early and late entrants* (M-W U = 10,500; Z = –4.02; p<.001)

The 401 respondents were partitioned into cohorts based on the EXPJOB variable. Within each cohort, early and late entrants were subsequently compared using Mann-Whitney non-parametric tests. The results of this analysis are mixed. In the respondent cohorts with professional experience of more than five years, the difference between early and late entrants never attains a p-value below 0.05. As a consequence, for respondents with more professional experience, the difference between early and late entrants as to the diversity of their communication partners is eliminated. For the cohort containing those respondents with five years or less professional experience, the difference between early entrants and late entrants is highly significant ($p<.001$). Thus, researchers who have been involved in neural networks a long time but have only recently obtained their highest degree—that is, those who enter the field as a student—are likely to have more communication partners than colleagues who have only just entered the community.

Along similar lines, the respondents were asked to name the neural network research teams outside their organization with whose work they are well-acquainted. Out of 110 industrial researchers who answered this question, 48 (43.6%) were unable to mention at least one such team. For the 277 academic researchers who answered this question, 109 (39.4%) were unable to do so. As a consequence, the null-hypothesis of no association between institutional type and familiarity could not be rejected (χ^2=0.435, n.s.). For those respondents in industry and academia who mentioned familiarity with at least one research team outside their organization, an analysis of co-variance was carried out similar to the ones reported above, i.e. with the sector and entry dichotomy as independent variables and the EXPJOB variable as a co-variate. We were not able to find any significant main effects nor any significant interaction effects from this analysis. Thus, both early and late entrants and academic and industrial researchers report the same level of familiarity (that is, an average of about 3.4 research teams for each group).

Furthermore, for the 62 industrial researchers and for the 168 academic researchers who mention some familiarity with at least one team, we examined similarities across institutional types. The vast majority of industrial respondents (56 out of 62, or 90.3%) mentioned at least one academic team; whereas only a minority of academic respondents (53 out of 168, or 31.5%) mention at least one industrial team (χ^2=30.2, $p<.001$). Finally, for each respondent who mention at least one team, we calculated the percentage of teams mentioned with which the respondent was actively involved in technical information exchange. Once again, we were unable to find statistically significant differences between sectors. Information exchange occurred with about one external team in two.

4.3. *Formal collaboration with other research teams*

Collaborative projects between researchers in different organizations were considered as yet another form of communal interaction. For 106 industrial respondents who completed the question, a total of 43 (40.6%) report that they are involved in at least one collaboration. For 277 academic respondents, 110 (39.7%) report having collaborations, resulting in a χ^2=.001, n.s. The average number of collaborations per respondent for the total sample (excluding those reporting no collaborations at all) is 1.73. Once again, no statistically significant differences could be found for the type of institution, the entry period, or their interaction.

For academic respondents, 78 (70.9%) do not have collaborations involving industrial partners. For the industrial respondents, only 16 (37.2%) report collaborations with researchers in other firms (χ^2=13.4, $p<.001$). Furthermore, with respect to the number of collaborations, we find that the large majority of academic respondents report collaborations with other academic researchers. Collaborations between academic and industrial researchers are a minority. The reverse is true for the projects mentioned by industrial respondents.

4.4. *Knowledge diffusion*

Respondents were asked to rank order five possible actions they might take after making an important advance in neural networks. They were able to choose between immediately publishing the result in a rapid publication journal, announcing it publicly at a press conference, seeking patent protection, assessing its potential commercial value, or disseminating it to other researchers in the field via telephone, fax or computer network.

Again, four groups were considered in the analysis according to institutional type and entry period. The results are shown in Table 8. As is clear from the data, some differences do exist between academic and industrial respondents. In general, industrial respondents are more inclined towards examining patent protection and commercial value. Within academic institutions, early and late entrants show similar behavior. This cannot be said for their counterparts in industry. The commercial orientation on behalf of the early entrants in industry is particularly noteworthy. We expected them to be more similar to academic early entrants, since both are pioneers in the field, however, the opposite is true.

Preference for ...	Academic		Industrial	
	Early entrant	Late entrant	Early entrant	Late entrant
publishing in rapid publication journal	1.42	1.46	2.43	2.15
disseminating to other NN researchers	2.44	2.73	3.79	3.44
seeking patent protection	3.25	3.04	2.79	2.17
assessing potential commercial value	3.63	3.53	1.64	3.19
announcing publicly at press conference	4.26	4.25	4.36	4.05
Kendall Concordance W*	0.50	0.44	0.48	0.28
Number of cases	36	93	7	65

TABLE 8: *Mean ranks on preference items for early and late entrants by institutional type* (1=highest priority; 5=lowest priority; *all significant below .01).

5. Discussion and Conclusion

In this paper we have attempted to demonstrate the usefulness of technological communities as a level of analysis for studying the diffusion of knowledge. Although our analysis is limited in the sense that only two subgroups of one particular community have been studied, we have been able nonetheless to point to several issues that are worthy of further attention.

First, the comparison of academic and industrial researchers highlights both similarities and differences that exist between both groups. It is reasonable to hold that different institutional types exert different kinds of constraints and influences on researcher behavior. Academic researchers may be more communally oriented than their colleagues in industry. Nevertheless, the empirical data presented in the paper shows that industrial researchers, even if they are not as open in their exchange of ideas and knowledge as their academic colleagues, recognize that the community may be a relevant locus of technological information and knowledge to them.

Second, the comparison of early and late entrants offers a useful starting point for further investigation into the dynamics underlying the emergence of new fields of technology. In particular, why do certain people become highly committed to a research agenda early on, when most of their colleagues consider the technology to hold little promise? Their dedication, or some might say stubbornness, may play a central role in the successful emergence of new technologies. Furthermore, investigation of pioneering researchers relative to the large majority of researchers who follow in their footsteps may offer important insights into this process.

Third, it is clear that the present data allow for more detailed analysis in several different directions, such as: the role of graduate students, the role of government researchers, and international comparisons of communal behavior. Work is now proceeding along all of these fronts.

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