NORTH-HOLLAND

Dismantling the Ivory Tower: The Influence of Networks on Innovative Output in Emerging Technologies

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ABSTRACT

In this article we examine how R&D networking affects an organization's innovative output. Using empirical data on 419 research organizations in transgene plant research over a 20-year period, we test several hypotheses relating their sociometric position in an R&D network to their innovative output. Attention is paid to the relative importance of in-house versus collaborative research. Least squares dummy variable models are used to analyze cross-sectional data across different time periods. The results show that (1) an organization's "network embeddedness" positively influences its innovative output; whereas (2) involvement in collaborative R&D has a curvilinear effect on innovative performance. © *1996 Elsevier Science Inc.*

Introduction

Networking in R&D has aroused increasing interest among students of the innovation process [1-4]. In the past decade organizations increasingly turned to collaborative R&D to support their innovative activities [5, 6]. Three major explanations are provided for this evolution. First, partners in the collaboration process benefit from mutual learning and knowledge exchange, which enables them to overcome the complex indivisible scientific problems none of them can solve individually [7-10]. Second, in many emerging fields, the cost of R&D is forcing firms to share scarce R&D resources. Hence, collaborations among government laboratories, universities, hospitals, new technology-based firms, and established firms have become a necessity [11]. Third, collaborative R&D allows the partners to internalize part of the positive externalities of their research activities under conditions of incomplete patent protection and technological spillover effects [12-15].

So far, much research has focused on the conditions under which R&D networks emerge. Transaction cost economics [16], evolutionary economics [17], game theory [4], and learning theory [6] have provided analytical or empirical frameworks to explain the

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Technological Forecasting and Social Change 53, 139-154 (1996)

655 Avenue of the Americas, New York, NY 10010

0040-1625/96/$15.00
PII S0040-1625(96)00036-4

growth of collaborative R&D. However, even though an increasing number of innovations are the result of network-like arrangements, only a few studies have explored the relationship between networks of collaborations and innovative performance [6, 18]. Especially in the case of more radical innovations, involving emerging technologies (i.e., demand-creating research), this relationship remains ambiguous at best [13]. The few existing models are rather limited in scope and they are primarily analytical. They suggest that toward the basic end of the R&D spectrum, collaboration enhances the innovative productivity of the firm [2, 4]. In this respect, Weelwright and Clark [19] point to the importance of participating in knowledge networks to complement in-house research as a necessary (but not sufficient) condition for generating successful technological breakthroughs. However, at the same time, many propositions on the necessity of R&D networks and alliances lack empirical support.

As a consequence, the aim of this article is to analyze the potential impact of positions in R&D networks on the innovative performance of a research organization. To this end, we test a theoretical model based on industrial economics [1, 2, 13] and social theory [20–22].

Technological Community as a Market of Ideas

Since we are concerned with demand-creating research that cannot satisfactorily be managed by a single organization or group of organizations, an appropriate level of analysis is required. Constant [23] and Thomson [24] both suggest that technological development takes place within a community of practitioners where traditions of practice develop. Gray [25] advocates a domain level of analysis to study interorganizational relations. The domain consists of "the set of actors (individuals, groups, or organizations) that become joined by a common issue or problem." Obviously, this domain-level approach can be applied to technological development as well. The domain then becomes the group of individuals and organizations committed to solve a set of interrelated scientific and technological problems. We have defined this group of individuals and organizations as the technological community [26], which essentially is a market of ideas that become embodied in publications and patents.

As far as the plant biotechnology community is concerned, four groups of actors have been discussed: universities, government-sponsored research laboratories, new biotechnology-based firms, and established firms (mostly seed firms, see [27]). Each actor attempts to maximize his innovative output, given his own strengths and weaknesses. The academic actors, for instance, may possess more fundamental research know-how than the established firm, but less financial and marketing resources. The new biotechnology firms may command less financial resources than academic or large industrial laboratories, but more entrepreneurial dynamism. But also within the same group, research organizations are different. Certain universities have a lot of expertise and experience, whereas others are relatively new to the field. Hence, collaboration may offer a promising avenue to overcome individual weaknesses and subsequently improve innovative output.

We consider the technological community to be a homogeneous goods industry with demand $Q = Q(q)$, where Q stands for the number of innovative ideas on the technoscientific problem (which is an indicator of industry output) and q is the quality of those ideas. Hence, on the market of ideas, the number of innovative ideas is a function of their quality. Demand meets supply at a quality q^*, above which an idea will be diffused across the community. The n actors in the technological community, whose in-house research efforts and external collaborations may all be unequal, try to maximize their market share on the market of ideas. Each of them is stimulated and constrained by the research ideas of all others. Indeed, each publication or patent (embodying the proliferation of ideas within the community) may provide new insights, though at the same time impede others from pursuing the same research results.

This dilemma is well known. For instance, the isolation of a part of the Hepatitis C virus genome by Chiron (Emeryville) which accounts for almost 90% of all non-A, non-B hepatitis in the late 1980s has encouraged a lot of research organizations to further explore the virus for diagnostic assays, vaccines, or therapeutic applications. However, it has impeded other actors like Mitsubishi Kasei (Yokohama, Japan), who announced to be close to its isolation one year before the Chiron publications, from publishing or patenting the bulk of their research efforts. Given these mechanisms, the market of ideas is assumed to behave similar to an industrial product market.

Publications as Proxy Measure for Innovative Output

Patent counts are frequently used as a measure of innovative performance (for a review, we refer to [28]). However, as far as fundamental research is concerned, patents have serious limitations. Moreover, in emerging fields such as plant biotechnology, patent regulations often are very fuzzy. Besides legal requirements such as the newness of an idea, ethical, political, and historical elements play a major role in the patenting process [29]. These issues not only refrain research organizations (especially universities) from applying for a patent, they also lengthen the time gap between the application and the patent grant. Searches on the American Patent Search and the World Patents Index showed that in the case of plant biotechnology, the average time lag between application and publication was more than 3 years. On the contrary, a random sample of 200 scientific articles revealed the time lag between first version received and publication date to be on average less than 6 months.

However, is each valuable idea published in the scientific literature? Are firms not reluctant to publish information because of secrecy imperatives? Nelson [3] points out that secrecy is much less important in emerging technologies (demand-creating research) than in product development (applied research). Furthermore, it has been shown that publishing after a patent application does not significantly hurt an organization's intellectual property rights [30]. A combined patent and publication search on transgene plants revealed that in 95% of the cases, the idea was published before the patent grant (though in the same year as the patent application). All topics patented were described in the literature. Thus, publications provide at least as much information as patents, while being much easier to collect.

But there is another advantage to publications which is still more important given the aims of our research. Where patents primarily serve as a means to protect intellectual property rights, publications perform a role as "signals of scientific competence" [6]. Actors in the technological community (i.e., universities, government research laboratories, new biotechnology firms, and established firms) have an incentive to diffuse these signals for various reasons. First, they improve the actor's professional standing in the community. This prestige position augments the actor's ability to recruit the best scientists in the field. A common example is the development of plant biotechnology research by Dr. Schneiderman at Monsanto (St. Louis, MO) in the 1980s [31–33].

Second, these signals may play an important role in attracting customers. Especially new biotechnology based firms value an article on the front cover of *Science* or *Nature* as the best reference for future research contracts. Major seed companies such as Sandoz, Limagrain, ICI Seeds, Rhône-Poulenc, Monsanto, and Ciba-Ceigy are collaborating with small biotechnology firms and universities with a reputation in the community. This form of dynamic complementarity is to a large extent driven by the publication market [34, 35].

Third, these signals have a symbolic importance to the financial stakeholders (i.e., private and public stockholders, venture capitalists, government, etc.). As long as no new technology-based products are commercialized, they are major criteria to "make stockholders happy and to attract new capital" [3].

Hence, we advocate that a research organization's yearly number of publications can be used as a direct measure of its innovative output in the technological community. In addition, an organization's yearly market share on the market of ideas (read: publications) serves as an indicator of its relative innovative performance in the technological community.

Determinants of Innovative Output: Research Cooperation, Network Embeddedness, and In-House Research

It is obvious that collaborative R&D takes on many forms. Industrial economics, for instance, views cooperation as a means to share research costs and to internalize positive spillover effects. Starting from symmetric oligopolistic models, industrial economics is not so much interested in whom the actors are cooperating with as it is interested in the extent to which the actors in the technological community are cooperating [2, 13, 18]. Social theory, on the other hand, approaches cooperation as a way of getting access to scarce resources and power [21, 22, 36, 37]. Consequently, its interest is directed toward whom the different actors are cooperating with (i.e., the different knowledge sources they have access to) and toward how power over these resources is dispersed across the actors in the community (i.e., who is dependent on whom). Hence, social theory focuses on the R&D organization's social embeddedness (i.e., the extent of its social capital) in the technological community as a determinant of its innovative output [21].

Under conditions of imperfect patent protection and in the presence of increasing returns to scale due to technical learning, industrial economists have proven that cooperation is beneficial to all the cooperating firms [2, 12]. Bozeman et al. [38] and Grossman and Shapiro [12] both show that this is especially the case with basic (i.e., demand-creating) research. Hence, in the case of basic research (e.g., transgene plant research), R&D cooperation may increase the innovative output of the actors in the technological community.

However, due to the longitudinal approach adopted in this article to study the evolution of innovative output and its relationship to R&D networking, we have to explicitly take into account the changing volume of collaborative activities from year to year in the community. For instance, organization ζ active in year x is involved in five R&D collaborations. In year x, we find a total of 35 collaborations in the community. In year $x + 5$, the total number of collaborations has reached 500; while organization ζ is still involved in 5 R&D cooperations. Clearly, this is a network position that strongly differs from the one in year x.

Hence, for each year of observation, we prefer to use an indicator of the relative position of the organization in the community R&D network. This indicator (defined as the organization's relative collaborative position) is calculated by dividing (for each observation period) the number of collaborations the individual members of the community are involved in by the number of collaborations of the organization that is having the highest number of collaborations for that observation period. Hence, the relative collaborative position indicator varies from 0 (no collaborations) to 1 (for the organization with the maximum number of collaborations) for each observation period. Given industrial economic theory just discussed, we hypothesize that:

> *H1:* The relative network position of an organization in the technological community will be positively related to its innovative output and its market share on the publication market.

In addition, many students of the R&D process stress the importance of in-house research to monitor, to evaluate, and to exploit external technical knowledge [7, 9, 39]. Collaborative and in-house R&D do not substitute for each other; rather they are complementary. Therefore, we create an index capturing the importance of collaborative R&D efforts in the organization's total R&D output. For each organization and for each observation period, the numerator of the index contains the number of publications that are the result of cooperative R&D, whereas the denominator contains the total number of publications (i.e., those resulting from in-house research as well as those resulting from collaborative R&D). Given the complementary nature of internal and external R&D, we hypothesize that:

> *H2:* The ratio of collaborative output to total output will have a curvilinear relationship to the organization's innovative output and its related market share on the publication market.

To measure the social embeddedness of an organization in the technological community, sociometric techniques are used [20, 40–42]. They allow us to compute several indicators of an organization's position in the community. As social theorists stress the importance of having access to a variety of resources, the first network indicator simply reflects the size of the network to which an individual organization belongs. To this end, we do not count the number of relations in which an organization is involved, but the number of distinct organizations to which the focal organization is related. When these contacts increase, the organization's exposure to knowledge sources increases. Access to multiple knowledge sources may in turn increase the innovative output of the focal organization:

> *H3:* The number of distinct organisations with which a focal organization cooperates will be positively related to its innovative output and its related market share.

Network size alone does not yet reflect the power or prestige an organization has within the technological community. Prestige increases with the demand for the focal organization's time and energy by other actors in the network. To this end, we assume that the relative network position a focal organization occupies in the community can serve as a proxy for its relative power or prestige [40, 41, 43]. Burt's prestige index provides a well-established measure of an organization's relative position in the network. Prestige is defined as the extent to which the focal organization is the object of exclusive relations from all alters, weighted by the relative position of all those alters [43]. Exclusive relations between ego and alter are computed on the basis of the number of relations between ego and alter divided by the total number of relations alter has with all others except with ego. Multiplication of the focal organization's exclusive relations by the power of their sources yields its absolute prestige position. In other words, prestigious research organizations are those organizations that have attained powerful network positions in networks with powerful others. To allow for longitudinal comparisons, the absolute prestige value is normalized using the value of the most prestigious actor as a scale parameter in the denominator. It then is straightforward to hypothesize that:

H4: The prestige of a focal organization in the technological community will have a positive relationship to its innovative output and its related market share on the publication market.

Finally, as discussed previously, in-house R&D still remains important to monitor and to evaluate external technical knowledge. Two frequently used indicators of internal R&D efforts are the number of researchers and annual R&D expenditures [9]. Of course, data on research expenditures are difficult to collect when performing a community-level study. Moreover, R&D expenditure data are subject to variations in reporting procedures and accounting rules. Therefore, the number of researchers is used as an indicator of organizational R&D efforts. For each research organization in the dataset, the cumulative number of researchers active in the technological community is calculated for each observation period. Of course, given our methodological approach based on bibliometric data (cfr. infra), we only take into account those researchers who visibly contribute to knowledge creation in the technological community. Drawing on previous research, we assume that these internal R&D investments increase the innovative output of a research organization.

H5: The cumulative number of researchers belonging a focal organization in the technological community will be positively related to its innovative output and its related market share on the publication market.

The cumulative number of researchers is used as a proxy measure for an organization's R&D efforts. This implies the existence of constant returns to scale associated with increases in R&D efforts. However, due to technical learning, organizations with a long history in a particular field may generate more output than those that are relatively new to the field. Hence, the longevity of the organization's association with the technology may positively influence its innovative output:

H6: The duration of an organization's association with a particular technology will positively relate to its innovative output and its related market share on the publication market.

Research Site

In the study, we have chosen the field of plant biotechnology (transgene plants) as a research site. Plant biotechnology is a subdomain of biotechnology, applying the technique of genetic engineering to plant varieties. The genetic engineering of transgene plants has resulted in three major application areas: (1) plant crop protection, (2) plant quality improvement, and (3) plant hybrids (for a review: see [44]). Interest in plant quality improvement was first aroused in the 1950s as a result of research into tissue cultures and the restrictions of tissue cultures. The emergence of genetic engineering in the 1970s, combined with the specification of the tumor-inducing plasmid (Ti-Plasmid) in 1974, caused a renewed interest in the field. More specific, the identification of the Ti-Plasmid laid the foundations of a field that would become known as plant genetic engineering in the 1980s.

The first plants to be genetically engineered appeared in 1983. Transgene plant research has shown three major foci of interest. Plant crop protection aims at developing virus-free plants with increased stress, herbicide, or disease resistance. Plant crop quality improvement aims at the engineering of proteins with increased nutritional value, control of ripening, prolongation of shelf life, and control of flower coloring. On the one hand, the production of hybrid seeds implies the conversion of open pollinated varieties to hybrids in order to provide farmers with superior quality seeds. On the other hand, it allows seed companies to protect the value they create through research and breeding. The first commercial products in all areas are predicted in the period 1994–1996. Thus, between the early 1980s and 1994, transgene plants have moved from being a scientific curiosity to a promising commercial activity (for a current state-of-the-art, we refer to [45]).

Data Collection and Methods

Journal articles, research notes, conference papers, and patents in a given field represent a detailed archival record of the research efforts performed by each organization in the domain. Moreover, whenever two or more research organizations jointly publish an article, a conference paper or a patent application, this can be identified as the outcome of a collaborative research effort (i.e., regardless whether this collaborative research effort is the outcome of an institutionalized agreement between two or more actors in the community or not). Operationalizing collaborative research in this manner has some major advantages: (1) as the publication conventions ensure a level of quality and authenticity, the research collaborations detected are assumed to attain a certain minimum quality threshold; (2) as the data are public, the data collection process can be easily replicated; and (3) bibliometric databases provide detailed information on both the research organizations and the individual researchers involved in each collaboration.

We used the databases of the Institute for Scientific Information (Philadelphia, U.S.) to identify publications related to the field of transgene plants. For the period before 1982, we used the ON-LINE version. From 1982 onward, the quarterly updated CD-ROM versions were used. Both databases were searched using a search strategy containing a Boolean combination of 18 key terms. The search strategy was verified with three independent experts. As the boundaries of a field are fuzzy to a certain extent, we extensively checked the completeness of the ISI databases. To this end, we compared the ISI documents for 1990 with a sample drawn from the biological abstracts database (provided by DIALOG). The ISI sample contained 189 unique documents whereas the DIALOG sample revealed the existence of 163 unique documents, 160 of which also appeared in the ISI sample. In addition, we checked our database against a sample of 100 hardcover articles selected by one of the experts: 80% of the publications in the sample were retrieved with the electronic search strategy.

The data collection procedure resulted in the identification of 1,792 unique source documents published between 1974 and 1993. It revealed the existence of 3,220 researchers employed at 419 research organizations that were active in the field over the 20-year period. For each research organization, we created a statistical database containing time-varying covariates. Thus, for each organization, the variables are recomputed each year of observation. Because the number of publications in the domain was very low during the initial period from 1974 to 1980 (32 publications), this period was collapsed into 1 year of observation. For a detailed description of the variables, we refer to Table 1.

DEPENDENT VARIABLES

As described above, we used the cumulative number of publications as a measure of innovative output. In our analytical approach, the explanatory variables computed for time period x are assumed to influence the dependent variable in time period $x + 1$. Hence, a 1-year time lag is observed in the computations of the dependent variable versus the independent variables. As a consequence, for 1993 (the last period of observation in the database) only data on the dependent variable are included in the analysis.

TABLE 1
Variables in the Least Squares Dummy Variable Model

Variable name	Explanation
Dependent variables	
Innovative output	Cumulative number of publications an organization has produced up to a given year of observation.
Market share	Cumulative number of publications an organization has produced up to a given year divided by the cumulative number of publications produced by all organizations still active that year.
Control variables at community level	
Number of publications	Cumulative number of publications each year of observation.
Herfindahl index	Herfindahl index of concentration of researchers among the various research organizations.
Density	Number of organizations active in the technological community [46]
$\text{Density}^2/1000$	Number of organizations $^2/1000$, i.e., contemporaneous density measure [46].
Percentage of connected organizations	The number of organizations connected to each other (clique) divided by the total number of organizations active in the field each year of observation.
Cooperative research covariates at organizational level	
Relative collaborative position	The number of collaborations each organization is involved in divided by the number of collaborations of the organization cooperating most in a given year.
Ratio collaborative output to total output	The cumulative number of publications that result from cooperative research divided by the total cumulative number of publications for each organization in the dataset. Range: 0 = all publications result from in-house research activities-to-1 = all publications are the result of collaborative efforts.
Prestige	This variable is an indicator of the prestige position of each organization relative to the most prestigious organization in the dataset. The absolute prestige position for each organization is computed according to Burt [43]. This absolute value for each organization is then divided by the prestige value of the most prestigious organization. Based on this definition, the prestige of an organization i increases with the demand of i's network time and energy.
Contacts	Number of other organizations in the community with which the organization has collaborated on the basis of co-authorships or co-inventorships.
Covariates measuring in-house research efforts	
Cumulative number of researchers	Cumulative number of authors/inventors at the organization for each observation period.
Time	Number of years the organization has been active in the community.

The market share of each organization on the market of publications is our second dependent variable. In addition to the absolute growth in innovative output at the organizational level, this variable captures the structural characteristics of the publication market. For each observation period, it is computed by dividing the cumulative number of publication counts for each organization in the community by the total number of publication counts in the technological community. Again, a 1-year time lag between the market share variable and the explanatory variables is taken into account. Unlike innovative output, market share on the publication market is directly affected by the entry and exit patterns in the technological community. To compute exits, we considered research organizations as having left the field if they had not contributed for more than two subsequent years. Also, it is important to note that when a domain grows because of new entries, incumbents have to publish proportionally more than the new entrants in order to maintain their previous market shares.

EXPLANATORY VARIABLES

Three variables are included that account for the degree of competition among organizations in the technological community. They provide measures of density, contemporaneous density [46], and concentration of resources among actors in the community [11, 47]. The density and contemporaneous density variables are based on population ecology theory. They are indicators of increased legitimacy or competition within a technological community due to changes in the number of organizations belonging to that community. Density is measured as the number of organizations active in the technological community during each year of observation. When increased levels of competition enhance organizational output, this variable is assumed to exert a positive influence on innovative output and market share. Contemporaneous density [i.e., density^2/1000] captures the second-offer effect of competition. It predicts that an increase in the level of competition enhances innovative output, though only at low levels of competition [46]. At high levels of competition, however, innovative output is constrained. Obviously, competition does not only result from changes in density. Also the concentration of scarce R&D resources among the actors in the community determines the level of competition. Therefore, we use the Herfindahl index of concentration to measure the dispersion of researchers among the different actors.

In addition to the three indicators of competition, we included one control variable for the total market size and one for the intensity of cooperation in the community. The first is operationalized by counting the total number of publications for each observation period. The second is calculated using the sociometric technique of clique detection [43]. For each observation period, the numerator contains the number of organizations that are in one way or another connected to each other, whereas the denominator contains all organizations in the community. Hence, the index stands for the level of information sharing in the community. Evolutionary economists [3] have argued that "everyone would be better off if everyone shared."

The variables related to H1 to H4 are described in Table 1 heading "cooperative research," whereas those related to H5 and H6 are described under the heading "in-house research." Each of those variables is subsequently used in the analyses.

Analysis and Results: Discussion

Pooled time series analysis was used to study the innovative output and market shares of the organizations in the transgene plant community [48–50]. This kind of analysis contains a variety of methods that can be used for studying cross-sections of data at different points in time. The cross-sections in our dataset are the different research organizations each year of observation. Heteroscedastic errors are produced, because it is not plausible to assume that the variance over the full pool is constant. Pooled time series methods use techniques to correct for autoregression and heteroscedasticity. As we assume that the direction of the relationship between our explanatory variables (see H1 to H6) and the dependent variable(s) remains constant for all cross-sections and all time periods, we may adopt a relatively simple model called the least squares dummy variable (LSDV) model [48, 49].

The LSDV model uses an intercept to capture the effects unique to the cross-sections and those that might be unique to time. The pool permits us to treat the unique effects of time as if time were a surrogate for systematic effects observed in time. To this end, the intercept is simply a characterization of the variance that attempts to minimize the bias in the true explanation. The intercept has been called specific ignorance, in contrast to our general ignorance, which is captured in the error term [49]. The basic model in our analyses can be written as follows:

$$Y_{nt+1} = \alpha_{nt} + X_{nt}\beta_k + u_{nt}$$

with

$$u_{nt} = \lambda_t + \mu_n + \xi_{nt}$$

for n = (1...N) cross-sections and t = (1...T) time series. The problems of autoregression and heteroscedasticity are avoided by incorporating the restriction:

$$\sum_t \lambda_t = \sum_n \mu_n = 0$$

The vectors of errors due to autoregression and heteroscedasticity [λ_t and μ_n] are fixed conditionally in the intercept; while the matrix of overall error terms ξ_{nt} is assumed to be random. X_{nt} is the matrix of covariates, and β_K is a vector of unknown regression parameters. We use the panel data module of the econometric software program LIMDEP to estimate the LSDV-model [51]. The model was estimated in a sequence of steps by adding sets of explanatory variables into the equation (see Table 2 for innovative output and Table 3 for effects on market share).

Models 1 and 4 estimate the effects of the competitiveness and cooperation variables at the community level on innovative output (model 1) and market share (model 4). Models 2 and 5 introduce the variables on cooperative R&D and networking that are related to H1 to H4. Finally, models 3 and 6 present the estimations with all variables included. For each model, three R^2 values are computed. The first one is the adjusted R^2 due to the explanatory variables. The second one stands for the variation explained by the explanatory variables and the group dummies, created to control for cross-sectional differences. Finally, the third value captures the variation explained by the explanatory variables and the dummies created for group and time effects. As can be seen in Tables 2 and 3, including the collaborative R&D and network variables enormously improved the overall quality of the model.

In models 1 to 3, the statistically significant negative sign of the contemporaneous density variable combined with the statistically significant and positive sign of the density variable implies an inverted U-shaped relationship between the intensity of competition (due to the number of organizations) and innovative output. This means that an increase in competition enhances innovative output at low levels of competition, though the organization's innovative output decreases at high levels of competition.

Interestingly, in models 4 to 6, both variables are statistically significant though in the reverse direction. This is explained easily, because the dependent variable in these models is affected by changes in entry and exit patterns (i.e., in organizational density). The signs should be interpreted as follows: at low levels of competition (i.e., when a technological community contains a small number of actors), a rather large innovative

TABLE 2
Estimation of Innovative Output Using the Least Squares Dummy Variable Model

Explanatory variables	Model 1	Model 2	Model 3
Degree of competition and cooperation (community level):			
Number of publications	0.007*	0.004	0.001
	(0.003)	(0.002)	(0.001)
Herfindahl index	−16.509	3.956	3.165
	(15.340)	(11.080)	(7.251)
Density	0.076‡	0.088‡	0.043‡
	(0.021)	(0.018)	(0.012)
$Density^2/1000$	−0.236†	−0.306‡	−0.120†
	(0.071)	(0.053)	(0.037)
Percentage of connected organizations	0.865	−3.518	−3.511
	(4.119)	(2.963)	(1.938)
Cooperative research indicators (organizational level)			
Relative collaborative position		−5.590	−11.423
		(23.590)	(15.680)
Ratio collaborative output to total output		−3.049‡	−0.615†
		(0.387)	(0.272)
Prestige		8.280‡	5.675‡
		(1.139)	(0.760)
Number of contacts		2.041‡	0.803‡
		(0.084)	(0.068)
In-house research indicators (organizational level):			
Cumulative number of researchers			0.394‡
			(0.012)
Time			0.063
			(0.073)
Scale parameter		−5.602‡	−3.893‡
		(1.510)	(0.937)
R^2 (X variables only)	0.005	0.693	0.856
R^2 (X variables and group effects)	0.714	0.869	0.940
R^2 (X variables, time and group effects)	0.639	0.860	0.940

Significances: * $0.05 < p < 0.01$; † $0.01 < p < 0.001$; ‡ $p < 0.001$. Standard errors of estimates between parentheses. Total number of research organizations = 419. Total number of 1,424 lines of observation.

output comes from the contributions of new entrants. Hence, an increase in competition decreases the market shares of the incumbents at low levels of competition. However, as a domain grows, relatively more innovative output is generated by the organizations already belonging to the technological community. As a consequence, new entrants contribute relatively less to the community. Therefore, at higher levels of competition, contemporaneous density positively affects market shares.

In addition, at the level of the community, the concentration of researchers across actors seems to affect only market shares, not innovative outputs. Its positive sign points to a concentration of researchers among fewer organizations having a positive relationship to market shares.

The results further indicate that three out of four hypotheses relating cooperative research and networking to innovative output receive support. The positive sign of the prestige and contacts variables ($p < .001$) indicate that social embeddedness in the technological community is positively related to an organization's innovative output (H3 and H4). This is also true, although less outspoken, for the market share dependent variable (see model 5).

TABLE 3
Estimation of Market Share Using the Least Squares Dummy Variable Model

Explanatory variables	Model 4	Model 5	Model 6
Degree of competition and cooperation (community level):			
Number of publications	0.0002‡	0.00001‡	0.00002‡
	(0.0000)	(0.00000)	(0.00001)
Herfindahl index	0.1135‡	0.07579†	0.08501‡
	(0.0258)	(0.02394)	(0.02287)
Density	−0.0003‡	−0.00021‡	−0.00024‡
	(0.0000)	(0.00004)	(0.00004)
$Density^2/1000$	0.0003†	0.00008	0.00056‡
	(0.0001)	(0.00011)	(0.00012)
Percentage of connected organizations	0.0232‡	0.00937	0.01534†
	(0.0069)	(0.00633)	(0.00613)
Cooperative research indicators (organizational level)			
Relative collaborative position		−0.78067‡	−0.47966‡
		(0.04489)	(0.05047)
Relative collaborative output to total output		−0.00720‡	−0.00425‡
		(0.00066)	(0.00089)
Prestige		0.00607†	−0.00014
		(0.00221)	(0.00244)
Number of contacts		0.00143‡	0.00056†
		(0.00016)	(0.00022)
In-house research indicators (organizational level):			
Cumulative number of researchers			0.00015‡
			(0.00004)
Time			−0.00112‡
			(0.00032)
Scale parameter	0.0208‡	0.01464‡	0.01983‡
	(0.0027)	(0.00289)	(0.00301)
R^2 (X variables only)	0.168	0.610	0.665
R^2 (X variables and group effects)	0.871	0.877	0.883
R^2 (X variables, time and group effects)	0.836	0.862	0.876

Significances: * $0.05 < p < 0.01$; † $0.01 < p < 0.001$; ‡ $p < 0.001$. Standard errors of estimates between parentheses. Total number of research organizations = 419. Total number of 1,424 lines of observation.

The negative sign of the ratio collaborative output to total output indicates that at least some in-house R&D capacity is beneficial to innovative output (as well as to market shares). Further inspection of the data shows that, depending on the panels studied, optimal balances for the ratio collaborative-to-in-house output do exist, pointing to a curvilinear relationship and thus supporting H2. This is shown in Figure 1.

This finding is also illustrated by the following descriptive data. The top 20% of the organizations in terms of innovative output realize, on average (i.e., for the observation periods considered in our panel), between 21% and 56% of their output as a result of collaborative research with very little variation across the organizations belonging to this category. The bottom 20% of research organizations in terms of innovative output, show much more dispersion with respect to collaborative research patterns. Either they tend to perform the bulk of their research in-house (i.e., they are social isolates) or, if not, they do it in collaboration with others. This means that the most productive organizations in terms of innovative output have been able to achieve a better balance between in-house and external R&D activities than their less productive counterparts. The only hypothesis not receiving support concerns the relationship between relative collaborative position and innovative output (H1).

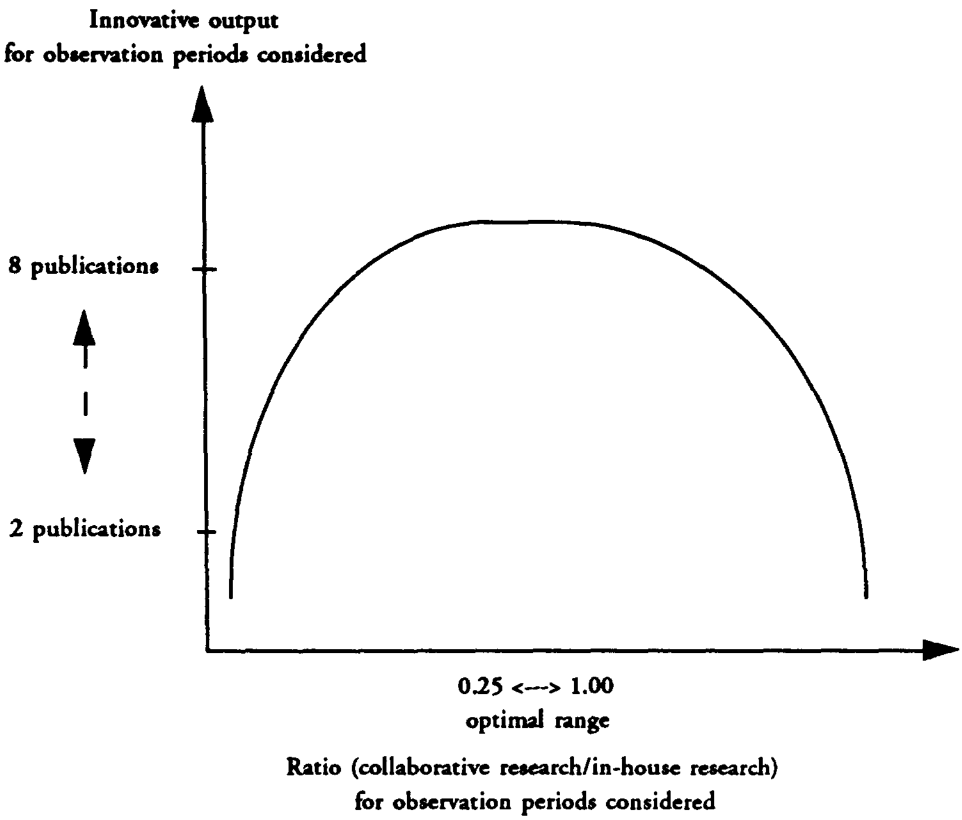

Fig. 1. Relationship between innovative output and the relative importance of collaborative research for the panels considered.

However, turning to market shares, a close look at models 5 and 6 reveals that the relative collaborative position is negatively related to an organization's market share. This seems puzzling at first. However, this result can be explained by the entry and exit patterns in the community. When a technological community matures, entry barriers build up. Therefore, an obvious way for new entrants to become involved in the field is through cooperation with incumbents [52]. As, in a proportional sense, incumbents must publish more than the new entrants to maintain their market share; those who publish a lot in cooperation with new entrants tend to lose market share.

Combining models 2 and 5 for the relative collaborative position variable, the data show that the majority of incumbents involved in frequent collaborations have the bulk of these collaborations with new entrants. However, these incumbents are not exceptionally productive (see model 2: a strong relative collaborative position does not significantly affect innovative output), whereas their collaborations with new entrants tend to decrease their market shares. Note that the number of collaborations is independent of the number of contacts. On the other hand, the statistically significant prestige index (models 2 and 3) indicates that exclusive collaborations with prestigious actors indeed influence innovative output. As a consequence, future analyses might include a variable controlling for the type of collaborations an organization is involved in. Organizations involved in a few joint research projects with incumbents should be more productive than organizations involved in many collaborations with one or more new entrants.

Furthermore, we find support for H5 relating the number of researchers to innovative output and market share. H6 relating time to innovative output does not receive support (model 3). Though, in model 6, the coefficient is statistically significant, its sign indicates that the time an organization is involved in the technological community is negatively related to its market share. This can be explained as previously. As the community grows over time [in 1986–87, the field experienced an explosive growth in terms of new entrants], it becomes increasingly difficult for incumbents to maintain their market shares even if their innovative output grows.

Conclusion

The empirical data described and analyzed in this article provide a longitudinal insight into the dynamic effects of networking on innovative output and market shares within a technological community. The pooled time series analysis, applied to the transgene plant community, demonstrates how collaborative R&D influences an organization's innovative output and even its share on a rapidly growing publication market. As alluded to, R&D networks are too complex a social structure to be understood solely in terms of the number of collaborations an organization is involved in. Therefore, future analytical models should include an indicator of the relative weight these collaborations have in the domain. Moreover, collaboration should be viewed as a complement to in-house research, not as a substitute for it.

The results reveal that there is an obvious need to embed organizational research activities in the larger technological community. It is the relative position an organization possesses in the field that influences its innovative output, not merely the number of collaborations it is involved in. Moreover, community-level variables affect the innovative output of the incumbents through technical breakthroughs, bandwagon effects, legitimation, competition, entry and exit patterns, and resource distribution.

To conclude, participation in R&D networks has been shown to improve an organization's innovative output. However, performing high-quality in-house R&D provides the best starting point for any kind of cooperation. As a consequence, the major contribution of community-level research is believed to be its ability to examine empirically in what manner and to what extent community-level phenomena such as R&D networks, researcher concentrations, etc., either constrain or facilitate the innovative performance of research organizations. Obviously, the present analyses and their results point to the many interesting research questions that lie ahead of us.

Bart Clarysse was supported by a grant from the ICM, Brussels, Belgium. Koenraad Debackere was supported by a grant from the Belgian National Fund for Scientific Research.

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Received August 1995; accepted 7 March 1996