# *A Structural Perspective on Organizational Innovation*

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*Sociologists contend that industries can be importantly characterized as sets of interlocking producer positions. This paper argues that this distinctively relational conception of a market represents a powerful framework for depicting and analyzing the process of technical change. The paper presents a method for using patent citation data to describe the positions of high-technology firms in a market-wide 'technological network'. It focuses on one property of a producer's position in this technological network—'crowding'—which represents the extent to which the firm specializes in areas of technology that are densely populated with other organizations. Four propositions are developed linking technological crowding to two firm-level measures of innovation: (i) the annual level of R&D expenditures, and (ii) the continuous time rate of patenting. The findings demonstrate that the positions innovators occupy in the technological structure of the market strongly affects their level of investment in R&D and rate of innovation.*

## 1. *Introduction*

The cogency of the sociological perspective on economic markets draws from the clarity of its conception and measurement of the positions occupied by producers. By precisely casting the producers in a market according to their locations in role structures (e.g. White, 1981), status orderings (e.g. Podolny, 1993), and market niches (e.g. Burt, 1983), sociological work has contributed to our understanding of such varied phenomena as the determinants of firm performance, the path to market clearing prices, the economic advantages and strategic constraints of occupying particular status positions, and the diffusion of corporate practices through communities of organizations.

Although progress has been made toward the development of a distinctively sociological understanding of markets, one of the most fundamental and





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influential domains of economic activity—the production of new ideas and innovations—has until recently escaped the attention of sociological analysis. True, scholars have spent many years grappling with some related questions. For instance, the absence of work on how market organization affects innovation belies the extensive effort devoted to the reciprocal relationship, namely the role of technological change in reconfiguring the structure of existing organizations (Thomson and Bates, 1957; Barley, 1986) and established industries (Tushman and Anderson, 1986; Barnett, 1990; Anderson and Tushman, 1990). There have also been many studies of the mechanisms that propel the diffusion of innovations through established social structures (Coleman *et al.*, 1966; Burt, 1987; Davis and Greve, 1997). Yet, in a period in which the ability to produce new technologies sustains organizational (and increasingly, economy-wide) performance, the relatively limited attention to the structural determinants of innovation is a fundamental omission in the sociological literature on organizations and markets.

This gap in the literature is especially notable because the phenomenon is inherently expressible in terms that are familiar to the sociological perspective on markets. In particular, the conception of a market as a collection of interrelated producer positions represents a powerful analytical framework for specifying the context in which innovation occurs. The reason for this is that the development of new technologies is a process that intrinsically produces linkages spanning organizational boundaries. The process of technical change is one in which new ideas are always extensions of antecedent ideas and are themselves candidates to become foundations for subsequent development (Schumpeter, 1942). Organizations participate in this process as the architects of ideas and innovations and, as a result, the actual technical relationships between discrete inventions imply both competitive and mutualistic connections between the enterprises engaged in the development of technology. Because of the intrinsic organizational interdependencies in the technology development process, relational measurements of firm positions and their characteristics—core strengths in the sociology of markets—are ideally suited to describing and modeling the factors that compel organizations to devote resources to the development of new technologies.

In this paper, I extend the social structural theory of technical change introduced in Podolny and Stuart (1995) and Stuart and Podolny (1996) to analyze innovation-related activities at the firm level. I begin by characterizing the positions of producers within a high-technology market, which is then followed by an empirical investigation of the links between technological positioning, the intensity of organizational searches for new technologies and the rate of innovation. I focus primarily on one property of producers' positions—'crowding'—which represents the extent to which an organization specializes in areas of technology that are densely populated with other firms (Stuart and Podolny, 1996). Crowded positions are tantamount to contested areas of technology: the producers in them lack differentiation because they have committed resources to the development and refinement of very similar ideas.

The paper's core prediction is that high crowding evokes effort on the part of producers to distinguish their activities from the initiatives of technologically adjacent organizations. This pursuit of differentiation assumes the form of investments in the development of technology. Thus, crowding is expected to incite organizational search. After proposing an organization-specific measure of technological crowding, I then present four propositions linking technological crowding to two firm-level variables: (i) annual research intensity (R&D spending), and (ii) the rate of innovation (measured as the continuous time rate of patenting).

## 2. *Technological Positioning and the Intensity of Organizational Search*

Through detailed descriptions of the circumstances surrounding the discovery of particular inventions, historians and sociologists of technology have demonstrated that the development of new inventions is significantly shaped by the sociotechnical and organizational contexts in which inventors work (Abernathy, 1978; Hughes, 1983; Tushman and Anderson, 1986; Latour, 1987; Basalla, 1988; Tushman and Rosenkopf, 1992). Corporate technological innovation is similarly intertwined with the organizational context. For instance, organizations typically draw ideas for new technologies from sources beyond their immediate boundaries, and these ideas often represent improvements to inventions developed by other organizations (Utterback, 1974; von Hippel, 1988). Therefore, viewed from the vantage point of any principal actor, the process of technological innovation entails the development of externally generated ideas and improvements to previously made discoveries.

The evolution of technology—like the progression of science—is thus an inherently cumulative endeavor, in which new inventions are amendments of, improvements to, or novel combinations of antecedent ones (Schumpeter, 1942; Elster, 1983; Basalla, 1988; Dosi, 1988). Podolny and Stuart (1995) argue that because technology development is a cumulative endeavor, it is possible to trace out the evolutionary links between 'discrete' inventions.

When this is done, a technological area can be viewed as an evolving network in which inventions are nodes and ties are the inter-invention ideational links that string together the nodes. Innovation occurs when new nodes (inventions) extend the frontier of the existing network. To attach a concrete image to this representation of the evolution of technology, a graphical picture of a technological network appears in Figure 1. In the figure, boxes are inventions and ties exist where a new node extends an antecedent one; thus, ties reflect technical extensions. Links in Figure 1 follow the direction of the time axis because technology always flows from antecedent to consequent. From the data in the figure, the developers of the inventions in the network are known (e.g. organizations A and B), as are the linkages that embed each organization's nodes into the network. With this information, a set of properties of each organization's 'position' or 'niche' can be specified.

I argue that organizations' positions in the technological network greatly influence the extent to which they choose to and are able to contribute to the evolution of the network in future periods. In this paper, I emphasize differences in the level of crowding across organizational positions and also consider the scope of organizations' participation across different segments of the technological network (i.e. a firm's level of generalism or 'niche width'), although one could certainly specify many additional properties of each organization's position in the network. For a number of reasons, high technological crowding at the firm level is expected to evoke an accelerated search for new technologies—an argument that has precedent and parallel explanations in the sociology of science (e.g. Merton, 1973) and a number of potential mechanisms in sociological work on structural equivalence (Lorrain and White, 1971; Burt, 1976) and competition (Hawley, 1950; Hannan and Freeman, 1989). As discussed in the conclusion, it also accords with some theories of the effects of competition in economics, particularly with the work on the ramifications of the spatial concentration of industries.

In developing the argument that competitive crowding promotes organizational search, it is helpful to begin with the assumption (shortly relaxed) that technological innovation is governed by the 'winner-take-all' quality that characterizes races for priority in science. In other words, I begin by assuming that the 'appropriability regime' in an industry is tight (Teece, 1986), implying that innovators are able to protect their proprietary technical developments from competitor imitation. This might occur because the relevant technologies are embodied in products (or processes) that are difficult to imitate or, more likely, because they are secured by strong intellectual property protection. When appropriability is tight, producers are able to

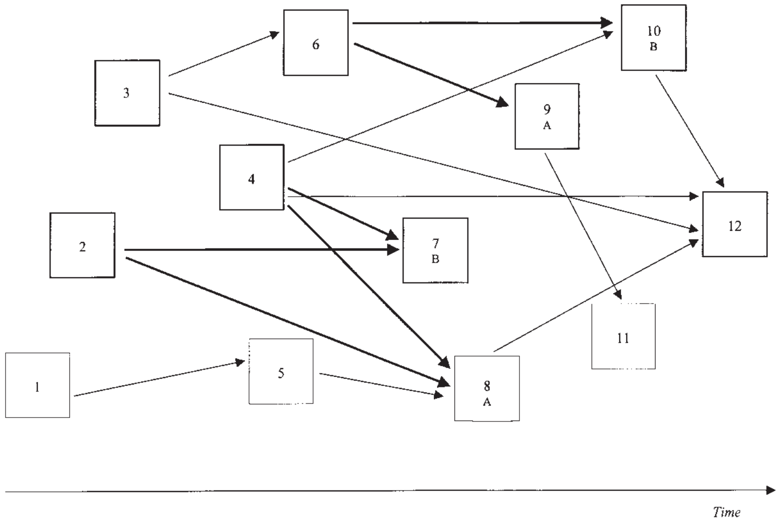


FIGURE 1. Hypothetical technological network.

safeguard their innovations from imitation and the economic rewards for being the first to innovate can be substantial.[1]

When the appropriability regime is tight, organizational innovation shares a core characteristic with the process of scientific progress: the largest share of the rewards from a new development accrue to the developer, and this makes priority in discovery a key organizational objective and produces a broadly similar set of competitive dynamics in the two domains. For this reason, much of the work on the effects of competition in scientific specialties is helpful in understanding the relationship between technological crowding and innovation. In the sociology of science, interest in competition's influence on scientific progress emerged with the observation that the histories of scientific disciplines are interlaced with fierce disputes over priority (i.e. controversies over who was the first to make a scientific discovery). Merton (1973, pp. 286–324) highlighted the frequency of independent, multiple

[1] Many of the analytical models of patent races in economics possess the feature that the winner reaps all of the rewards from the race (e.g. Grossman and Shapiro, 1987; Delbono and Denicolo, 1991). In other words, they assume that the first firm to patent is able to fully exclude others from using the discovery. Some of these models conclude that competition increases the intensity of organizational search as I will argue, while others assert that the presence of competing organizations reduces the aggregate level of R&D spending in equilibrium. The argument in this paper differs both in terms of the posited mechanisms and the importance it ascribes to the assumption that the sole prize is awarded to the first to innovate. In light of the empirical evidence that patents are often not successful at precluding competitors from imitating an innovation (see Levin *et al.*, 1987), it would seem important to develop arguments that are not highly sensitive to the assumption of tight appropriability conditions.

discoveries and the resultant altercations among scientists concerning the rightful allocation of credit for important scientific advances.[2] To determine the prevalence of concerns about priority, Hagstrom (1965) surveyed 1400 scientists, finding that about two-thirds had at some point in their careers been engaged in research that was anticipated by another scholar.

Although never placed under empirical scrutiny, one implication of Hagstrom's finding is that individual scientists in crowded fields will devote greater effort to their work (and produce faster) than comparably trained and equipped scientists in less crowded fields. The reason for this is that, in addition to the usual incentives to produce, scientists in crowded areas work under the constant threat that their research agendas and work-in-progress will be pre-empted by the findings of competing researchers. Drawing out this implication, Merton (1973, p. 330) wrote:

> Differences in the intellectual and social structure of scientific specialties probably affect the extent and intensity of competition for discovery within them. . . . Some fields are more 'crowded' than others in the sense that many workers are focusing on the same problems. In such specialties, competition tends to be particularly intense, and the tensions generated by the race for priority greater.

Thus, similar to my contention that the structure of competition in high-technology markets is a function of the crowding of innovative activity around the niches of producers, Merton argued that competition among scientists is a function of the intellectual organization of scientific fields. Moreover, as a stimulus for priority races, competition—a socio-scientific property—has been posited to speed the rate of scientific discovery.

There are many notable examples of crowding-induced innovation races among high-technology firms. Perhaps the most publicized of these have occurred in biotechnology.[3] For example, a crowding effect was evident in the

[2] A classic illustration of the salience of priority concerns in science is Watson's (1968) chronicle of the discovery of the helical structure of DNA. When describing the hunt, Watson expressed great concern that Linus Pauling would be the first to identify the structure of DNA. Watson and Crick's search was motivated not just by their belief in the scientific importance of the structure of DNA, but more immediately by the knowledge that Pauling and others were actively pursuing the very same discovery. Werth (1994) provides an enlightening ethnographic account of priority contests in an industrial context (the commercialization of a family of immunosuppressive drugs by biotech firms, university laboratories and pharmaceutical firms).

[3] It may not be a coincidence that drug discovery ranked as one of the industries in which patents are effective means of intellectual property protection in the Levin *et al.* (1987) appropriability survey. Because 'composition of matter' patents—those that apply to chemical compositions, drugs, gene sequences and vectors, and man-made (as opposed to naturally occurring) living matter—tend to be effective barriers to imitation, biotechnology is one of the industries in which patents do protect intellectual property, and this implies that the largest share of the rewards for innovating often accrue to the first to patent a new technology. Hence, discovery races take on particular salience in this industry.

worldwide search for a gene called *BRCA1* (BReast CAncer 1). In 1990 a prominent cancer researcher posited the location of a gene that would cause breast cancer if it was formed incorrectly. Scientists believed that *BRCA1*'s sequence could provide clues to the biological mechanisms behind breast cancer, and it could lead to the development of lucrative diagnostic products. In September 1994 *BRCA1* was sequenced by a team of scientists led by Myriad Genetics, a small biotechnology firm. The award for priority was the patent rights to the DNA sequence. Speaking of the four-year search, the CEO of Myriad Genetics stated, 'It was probably the most hotly contested race around—a dozen major research labs were looking for this gene' (Rhein, 1994).

Racing imagery has become ubiquitous in popular accounts of industrial innovation. Consider two recent headlines in the *Wall Street Journal*: 'Virus Chase: Five Teams Pursue Herpes Drug' and 'Battle Over Three-dimensional Graphics Takes Shape: Chip Firm S3 Wins Round Over Cirrus Logic, With Giants Poised to Strike'. These accounts describe organizations racing to achieve a set of technological milestones. Although each contest encompasses a separate group of organizations competing in a different technical arena, all races are thought to have been stimulated by the substantial benefits that can be captured by those who are first to reach sought-after milestones. Stated in terms of the network-based framework elaborated above, the presumption is that when an organization adds an important new node to the technological network, all other organizations are forestalled from contributing the identical node. Because only one organization can be the first to contribute any particular node, there is an overtly competitive race to extend the technological network, and the intensity of this competition is greatest in domains in which many organizations are poised to make similar accomplishments, i.e. in crowded areas of the technological network.

Crowding-induced innovation contests are driven by knowledge of the rewards accruing to the winners of technology races. Indeed, technological areas become crowded because firms are attracted to domains in which the remuneration for innovation is forecast to be substantial. Particularly in domains characterized by tight appropriability regimes, knowledge of the rewards for securing intellectual property rights for an innovation motivate organizations in crowded technological positions to invest heavily in the search for new technologies.[4]

[4] One might counter that there is a disincentive to invest in R&D among firms in crowded positions arising from the fact that the probability of being first to invent declines with the crowding around a niche (i.e. the probability of any one organization being first to a discovery falls as the number of competing searchers increases); in fact, this relationship is explicitly predicted below. My belief is that a number of factors militate against this disincentive. First, given the highly path-dependent and competence-

There are a number of additional benefits of investments in R&D even in circumstances in which intellectual property protection is not ironclad. First, the possibility of obtaining status and public recognition is an incentive to conduct organizational search. Just as the status-based rewards for discovery represent a core element of the system of credits in science, successful organizational innovators advance their reputations when they are the first to achieve significant technical milestones. As detailed accounts of the hunt for highly visible scientific or technological breakthroughs so often recount, the entry of additional actors into a technological area, while raising the competitive intensity of the area, also markedly augments the status that accrues to the developers of pivotal innovations in those areas (Watson, 1968; Werth, 1994). The decisions of multiple organizations to invest in the development of a particular set of technologies collectively generates attention and a sense of urgency for progress in that area. In turn, heightened attention to progress in crowded areas amplifies the recognition that accrues to those responsible for breakthroughs. Thus, particularly for organizations that compete in hotly contested technological areas, winning an innovation contest is a mark of skill and an occasion to publicize the organization's technological prowess. As a result, even in settings in which competitors can imitate a focal organization's innovations and so compromise its ability to reap the full profits from an innovation (i.e. in domains in which the appropriability regime is weak and the winner-take-all assumption is not defensible), the victors of technology races are routinely anointed by the press as innovation leaders. Thus, through gains in status, organizations can benefit from their technical achievements even if they cannot always fully preclude competitor imitation.

The status-based rewards earned by an organization for a major innovation are demonstrated by IBM's recent, 'break-through' development of semiconductor chips that use copper rather than aluminum as the interconnect metal.[5] A search of the Lexis/Nexis database revealed over 500 articles pertaining to IBM's innovation in a six-month period. The fact that public awareness of densely populated technology areas is already high only serves

dependent nature of organizational innovation (cf. Nelson and Winter, 1982; Dosi, 1988; Cohen and Levinthal, 1990; Stuart and Podolny, 1996), firms often do not have the option of moving between niches; thus, they either succeed at what they have historically done or they fail, which may entail the loss of sunk investments in manufacturing assets, research facilities and the like. Second, when appropriability conditions are imperfect, firms may capitalize on new technologies even when they are not the developers of them. However, it is now understood that an organization must possess absorptive capacity to comprehend and assimilate external developments (i.e. to capitalize on a competitor's advancement). Thus, the development of a technical knowledge stock produces the incentive to invest in R&D when an organization occupies a crowded niche (see Cohen and Levinthal, 1990).

[5] Copper conducts faster than aluminum and permits smaller line widths (distances) between circuits on a chip. By allowing for a higher density of circuits and speeding communication among them, copper interconnects promise faster integrated circuits.

to magnify the attention that is bestowed upon successful innovators in those domains.[6]

A final motivation for the proposition that high crowding will accelerate the search for new technologies can be attributed to the system of intellectual property protection and the nature of technological competition. With relatively few exceptions, product and process innovations tend to be protected by multiple patents: for example, a new semiconductor chip or a novel medical electronic device might be associated with dozens or even hundreds of patents. Because technological progress is cumulative and each new product or process improvement typically represents a vector of extensions to technologies developed by many different innovators, it is often the case that a focal organization may be excluded from the use of a particular component technology because the rights to it are held by a competing firm (patent infringement lawsuits and the like are the legal mechanisms of exclusion). There are two parts to the reasoning relating this consideration to technological crowding. First, because crowding increases when a focal organization concentrates on a heavily populated area of technology, the level of crowding affects the extent to which other firms have the capacity to interfere with a focal organization's undertakings: higher crowding implies that a greater number of firms are poised to exclude an organization from the use of a technology that is central to its endeavors. Second, the best defense against a competitor's effort to withhold the right to use an innovation is the capacity to retaliate in kind, i.e. to control a piece of technology that is essential to the competitor's initiatives. This power increases in the depth and quality of an innovator's stock of intellectual property; organizations that possess many and high-quality technical assets are well positioned to counter the infringement claims of their competitors. Therefore, organizations in crowded positions have the strongest incentive to engage in innovative search to develop and leverage the exclusionary power of a strong intellectual property base.[7]

[6] The desire of organizations to obtain status in high-technology markets may be quite rational from a net present value standpoint. High-status firms are able to attract top-quality scientists and technologists, they have greater ability to promote proprietary and open technical standards, they are often able to charge premium prices for their products and services, and so on. Due to benefits such as these, Podolny *et al.* (1996) found that high-status technology firms grew at a faster rate than otherwise comparable but lower-status firms. Stuart (1998) found that high-status semiconductor producers were better able to attract strategic alliance partners than their lesser-known competitors. Podolny (1993) discusses many of the generic advantages of status, with particular emphasis on the securities underwriting market.

[7] Grindley and Teece (1997) develop this line of reasoning in a case study of the electronics industry. They state (p. 8), 'Patents and trade secrets have become a key element of competition in high-technology industries. In electronics and semiconductors, firms continually make large investments in R&D in their attempts to stay at the frontier and to utilize technological developments external to the firm. Fierce competition has put a premium on innovation and on defending IP from unlicensed imitators. As IP owners have taken a more active stance regarding their patent portfolios, industry participants increasingly find it necessary to engage in licensing and cross-licensing . . . Firms that are high net users of others'

Based upon the preceding arguments, the level of niche crowding is expected to affect an organization's decision to invest in innovation. I make the following hypothesis:

*Hypothesis 1*
*The intensity of organizational search (level of R&D spending) is a positive function of the level of crowding around an organization's position in the technological network.*[8]

A variety of organizational and positional characteristics may mediate the relationship between crowding and R&D spending. One that I believe to be particularly significant is the scope of an organization's innovative competences. The width of an organization's niche refers to the extent to which the organization's activities are spread across the different segments of an industry's resource space: firms with broadly distributed activities are known as generalists, while those with narrowly focused positions are specialists. Conceptually, specialist organizations stake their life chances on their ability to dominate a small slice of an industry's resource space; they strive for excellence in a narrow range of activities, hoping to achieve technological superiority over the other organizations that compete in their domains. In contrast, generalists pursue scope economies by competing in multiple domains and implicitly hedge their bets by participating in many of the segments in a market (Freeman and Hannan, 1983; Carroll, 1985). Stated in terms of the technological network framework, specialists participate in narrowly circumscribed regions of the network, whereas the nodes of generalists are distributed throughout the network.

Niche width is likely to mediate the response to technological crowding because it influences the set of viable strategic options open to the firm. As an organization-level variable, crowding is a composite computed across the technical areas in which an organization focuses its efforts. When an organization with a narrow corporate scope is in a crowded area, all of its activities are in a single or small number of densely populated regions of the technology space. Because the external conditions confronted by a specialist pertain to the full range of corporate activities, I expect that a specialist's

patents have a choice. They must increasingly pay royalties, or they must develop their own portfolios so as to bring something to the table in cross-licensing negotiations.'

[8] Of course, increasing R&D spending is one among a set of potential responses to high crowding. Another response is to augment the investment in the complementary assets needed to commercialize new technologies, such as upgrading manufacturing assets or raising the level of marketing expenditures to obtain differentiation in a product market space. Because R&D spending adjustment is the most proximate of the predictable responses to the domain in which crowding is conceived and measured, I focus on it.

response to crowding (and other environmental conditions) is likely to be amplified. This will be particularly so when innovation is the activity in question because the path-dependent nature of the technology production function means that firms are unable to quickly shift the focus of their research. While the generalist possesses the option to shift its emphasis across the set of activities under the corporate umbrella in response to different conditions encountered by the components of its operations, specialists do not have this flexibility. Thus, I expect specialists to exhibit the strongest response to technological crowding.

*Hypothesis 2*
*The intensity of organizational search (level of R&D spending) induced by a high level of crowding around an organization's position in the technological network will be greatest if the organization is a specialist*

## 3. *The Rate of Innovation*

R&D spending is a measure of organizations' inputs to the innovation process. The argument thus far holds that firms in technologically crowded regions are relatively more concerned about having planned inventions anticipated by competitors and about being excluded from the use of core technologies that are controlled by competitors. They also stand to gain relatively more reputation-based rewards for developing important advances in their areas than do firms in crowded market segments. By contrast, organizations in crowded areas face the risk that their recent discoveries may be quickly leap-frogged and the possibility that planned inventions will be anticipated, and this creates a stimulus to invest in R&D.

As Elster (1983, p. 105) has argued, any theory capable of explaining the amount of innovative inputs (R&D spending) is also likely to be useful in predicting the rate of innovation. The difference between these two quantities is that it is possible to duplicate R&D efforts, while it is not possible for multiple actors to be the first to develop an identical technology. Referring again to *BRCA1* to illustrate the point, a number of organizations simultaneously invested in sequencing the gene, but only one organization was the first to identify (and patent) the sequence; in other words, the effort to sequence the gene was duplicated but the most widely pursued result (the sequence) was achieved first by a single enterprise. Still, it is almost certain that *BRCA1* was sequenced sooner than would have been the case had there not been an awareness among each of the competing research teams that other organizations were pursuing the gene.

The macro-level implication of this dynamic is that technology develops most rapidly in crowded fields. The fact that there are many concurrent searches taking place in crowded areas means that advances in those areas will be achieved quickly. At the same time, the micro-level implication, which follows from the posited effect of crowding on R&D spending, is that firms in crowded positions innovate relatively quickly. If firms in crowded areas spend more on research, they are likely to innovate at a greater rate even though some of their most intensively sought targets will be reached first by competitors.[9] Thus, following the reasoning that produced the prediction that firms in crowded areas invest more in R&D, I make the following hypothesis:

*Hypothesis 3*
*Organizations that occupy crowded positions in the technological network will have a high rate of innovation.*

There is also reason to believe that the level of crowding in a region of the technological network may moderate the relationship between R&D spending and the rate of innovation. Assuming a contest to develop important nodes in the network and thus to secure rights to a valuable intellectual property space, I would expect that any one organization will sometimes fail to succeed in its attempt to develop a cluster of technologies before another innovator has achieved the very same result. Moreover, the probability of failure may increase in the number of other organizations vying to achieve the same objective. Because crowded areas are characterized by a thicket of relatively undifferentiated research and development projects across competitors, the possibility of being pre-empted by competitors' advances is probably greatest in crowded areas.

This reasoning suggests that a given investment in R&D inputs will yield

[9] An anonymous reviewer was concerned that hypothesis 3 commits an ecological fallacy. The reviewer agreed that the sector-level rate of discovery will increase in the number of firms in the sector (e.g. if there are more gene sequencing firms, gene sequences will be identified sooner), but he/she was sceptical that the same result would apply at the firm level. A little formalization will clarify the argument. Allow $i$ to index firms, $RD$ to denote research spending, $A$ to signify technological crowding, and $TD$ to represent the time between discoveries (the waiting time). Suppressing time subscripts, I argue: $RD_i = f(A_i)$ (hypothesis 1); and $TD_i = f(RD_i) = f(A_i)$ (hypothesis 3; the rate of innovation will be explained by the factors that increase the intensity of organizational search). The reviewer questioned the relationship posited in hypothesis 3: $TD_i = f(RD_i)$. The basis for the objection was that if there are $N$ firms searching for a new discovery, $N - 1$ of the searches will end in failure and only one search will succeed (i.e. only one discovery will be made), regardless of the intensity of the $N$ searches. Yet $N - 1$ of the searches will fail only under the strictest definition of failure. It is true that only one organization will be first to achieve the most salient target, but because some discoveries are serendipitous and it is often possible to develop a number of variants and features of an innovation, the volume and rate of inventions should increase ($TD_i$ should decrease) in the intensity of search. Thus, even at the firm level, the rate of discovery should depend on the intensity of search.

more nodes in a sparsely populated area of the technological network as compared to the outputs that it will produce in a densely crowded region of the network, although the overall rate of innovation may be higher for firms in crowded technological positions due to their higher search intensities.[10] Even though there is probably no inherent carrying capacity for the number of new developments in a technological area, it is probably the case that latent discoveries vary in the extent to which they are suggested by the existing state-of-the-art (see Dosi, 1982). In fact, Hagstrom's (1965) survey demonstrated that scientists are routinely scooped by their competitors, and there is reason to expect that this dynamic occurs regularly in the development of technology and that the frequency of its occurrence is a function of technological crowding. Thus, I anticipate:

*Hypothesis 4*
*The productivity of a given quantity of R&D spending will depend upon the technological crowding of an organization's position: organizations that occupy crowded positions in the technological network will garner fewer inventions from each additional dollar of R&D spending.*

## 4. *Niche Overlap and Niche Width in a Patent Citation Network*

Following the ecological insight that competition can be equated with niche overlap (McPherson, 1983; Stuart and Podolny, 1996), I assume that organizations compete when they engage in very similar activities and therefore jockey for the same niche in a resource space. Hence, technological competition occurs with the greatest intensity where many organizations are committed to the development of the same technological areas. In this study, I measure niche overlap in terms of the linkages between the actual technologies developed by competing organizations. This is accomplished by

[10] There may be an effect that works at cross-purposes with the one that I posit in hypothesis 4. The knowledge-production process in high-technology industries is in one sense mutualistic: major technological accomplishments tend to disseminate quickly. As a result, when one organization solves an important technical problem, this advance can have the unintended consequence of facilitating the undertakings of that enterprise's nearest competitors. Because salient problems attract the attention of many organizations in crowded segments of the network, key problems are solved quickly in those areas. Hence, the innovations of competitors may stimulate new ideas and remove roadblocks that hamper the endeavors at a focal firm. My assumption is that firms in crowded positions are forestalled by their competitors more often then they are advantaged by competitors' work. The results will decide the question.

using a patent citation network to link organizations to specific technological activities (Podolny and Stuart, 1995).

## Patent Citations

Patent documents include a list of references (citations) to all previously granted patents that had made technological claims similar to those claimed in the application. In other words, patent citations are links between the ideas embodied in inventions, specifically connecting a proposed invention to the existing, patented inventions that are nearest to it in technical content. In the technological network framework articulated above, *patents are the nodes in the network (boxes in Figure 1) and patent citations are the ties (directed lines in Figure 1) that reveal technological relations between the nodes*.

The use of patent citation data to manifest evolutionary links between patented inventions has become common in the social sciences. Researchers have deployed these data to determine whether sets of organizations have been investing in the development of similar technologies. For example, Stuart and Podolny (1996) argued that patent co-citations (i.e. when two patents are linked by citations to a common, third patent) can be used to approximate the technological overlap of pairs of organizations. Economists have developed a similar use for patent citation data: to document technological knowledge spillovers between firms (e.g. Jaffe, 1986).

## US Semiconductor Patents

To test the hypotheses, I assembled a longitudinal database on a sample of semiconductor firms. All US semiconductor patents were collected for this analysis, and the industry was selected in large part because semiconductor firms routinely file for patent protection for their inventions. Suggestive evidence of the proclivity to patent exists in the fact that, with a single exception (the US government), the top ten holders of 1997 US patents were electronics firms that each patented heavily in microelectronics: IBM, Canon, NEC, Motorola, Fujitsu, Hitachi, Mitsubishi, Toshiba and Sony.

Because the United States is the world's largest technology marketplace, non-US-based firms regularly patent in this country (see Albert *et al.*, 1991). Attesting to this fact, Japanese firms made up seven of the ten largest holders of the US patents issued in 1997. I collected all post-1975 US semiconductor product, device and design inventions from the Micropatent Patent Abstract CD series. For each patent, I retained the date of application (recorded to the day), the assignee (the owner of the patent), and the list of US patents that were cited as prior art. Note, however, that patent protection in the chip industry is not thought to be extremely effective,[11] despite a series of well-documented changes in the early 1980s to strengthen patent protection in general and in the chip industry in particular.[12] Thus, the heavy incidence of patenting in the industry must be partially understood in terms of some of the alternative benefits of patents, although patents do remain useful in their traditional role as safeguards against the theft of intellectual property. The alternative benefits include: (i) patents are crucial bargaining chips in cross-licensing and strategic alliance negotiations (Grindley and Teece, 1997); (ii) a strong patent portfolio is a crucial deterrent against infringement lawsuits; (iii) patents are frequently used in incentive systems to motivate research staffs; and (iv) acquiring important patents entitle companies to bragging rights.[13]

The sample that I analyze includes all semiconductor companies tracked by Dataquest, an industry consultancy, during the period from 1986 to 1992. Dataquest compiles producer revenue figures from product shipment data. Because sales volume is an important control variable in the analyses, the sample was limited to the set of firms tracked by Dataquest.[14] The sample includes 150 companies, although some were founded during the analysis period. I identified corporate affiliations for all firms in the sample using annual reports and corporate directories. These were used to assign the patents of subsidiaries to the corporate parent. After identifying the firms that owned the 48 000 patents in the final database, I then created a series of annual patent citation networks to generate measures for the models.

[11] W. M. Cohen, R. R. Nelson and J. Walsh (1996), 'A First Look at the Results of the 1994 Carnegie–Mellon Survey of Industrial R&D in the United States', unpublished manuscript.

[12] A number of institutional changes supporting stronger patent protection were introduced during the early 1980s. The most important development was the creation of the Court of Appeals of the Federal Circuit (CAFC), a federal court with jurisdiction over patent cases. The CAFC has affirmed the standing of patents in the vast majority of cases appearing before it, thereby strengthening the property rights of patent holders. In addition, the Bayh–Dole Act of 1980 eased restrictions on patenting based on federally funded research, and the Semiconductor Chip Protection Act of 1984 established the copyrightability of semiconductor mask works.

[13] For example, in each of the past few years, IBM has been awarded more US patents than any other corporation and has received almost 9000 patents in the past five years. In each of these years, IBM has run a series of print advertisements announcing its technical prowess as evidenced by the fact that it was the recipient of the greatest number of patents among all for-profit corporations. IBM has also demonstrated the importance of patents as bargaining chips in the recent past: it has established a number of multi-million dollar patent cross-licensing agreements with some of its competitors, including 3Com, Dell Computer, Acer and EMC.

[14] Many of the organizations in the sample participated in multiple business lines (e.g. IBM, Siemens and Hitachi). While corporate-level sales figures could be ascertained from public sources for most firms in the sample, longitudinal semiconductor sales volume data are quite difficult to obtain. For this reason, I had to rely upon Dataquest for the revenue data.

## Measuring Technological Crowding

The technological overlap of any pair of organizations in a patent network such as the one displayed in Figure 1 can be thought of as the extent to which the members of the pair build upon the same antecedent patents. Following a large body of work in social network theory, two firms that build upon identical patents are 'structurally equivalent' in the technological network by virtue of the fact that their inventions are, from a structural vantage point, identically embedded in the network (Lorrain and White, 1971; Burt, 1976). As a general definition, two actors are structurally equivalent when they possess identical ties to the same third nodes.

Because patent citations represent technological similarities between inventions, a pair of organizations with a high frequency of patent co-citations are technological competitors.[15] Using Figure 1 as an example, the bold-faced ties in the figure therefore suggest that organizations A and B are direct competitors. These organizations focus on the same technological sub-fields, implying that they have developed similar technical expertise. Because they possess similar foci and are likely to be in pursuit of similar technologies, two structurally equivalent organizations are direct competitors. Using $\alpha_{ijt}$ to denote the extent to which organization $j$ occupies the niche of firm $i$ in period $t$, I define dyadic niche overlap as:

$$\alpha_{ijt} = \frac{\sum_p C_{ipt} C_{jpt}}{\sum_p C_{ipt}} \quad \text{where } i \neq j \tag{1}$$

and where $p = 1, \ldots, z$ indexes all existing patents, and $C_{ipt}, C_{jpt}$ is coded 1 if a patent of firm $i,j$ cites patent $p$ at time $t$, and 0 otherwise. Therefore, summing over $p$, $C_{ipt}C_{jpt}$ is incremented when the patents of organizations $i$ and $j$ cite a common patent, and the denominator is a count of organization $i$'s patent citations. In essence, each organization $j$ contributes to organization $i$'s crowding index the proportion of $i$'s patent citation that is also made by $j$ during $t$. To move from a dyadic overlap measure to a composite crowding score for organization $i$, I simply sum across $j$. Formally:

[15] It is important to stress that, by the novelty criterion (an invention must be novel to be patentable), no two patents are identical. Still, those that cite the same antecedent patents are relatively undifferentiated when compared to two patents that do not have redundant connections in the network. We know this to be the case because citations are mandated only when an antecedent invention made claims of novelty that are similar to those of a citing (subsequent) invention.

$$A_{it} = \frac{\sum_j \sum_p C_{ipt} C_{jpt}}{\sum_p C_{ipt}} = \sum_j \alpha_{ijt} \quad \text{where } i \neq j \tag{2}$$

The citation network can also be exploited to construct a measure of technological scope. If $n$ denotes the number of producers in the industry, each firm $i$ has $n - 1$ potential, direct competitors (i.e. firms such that $\alpha_{ijt} > 0$). I argue that a firm is a generalist if it has engaged in patenting that directly overlaps with many of the $n - 1$ potential competitors. To derive a measure of technological scope, I first constructed for each firm $i$ an $n - 1$ position vector with elements αijt for all $i \neq j$. Thus, the position vector for firm $i$ consists of the technological overlap scores between it and each of its alters. Based on this vector, I compute Shannon's (1948) inequality index—an entropy measure that is frequently used in population biology—as a measure of scope (see also Theil, 1970). This measure reflects both the degree and pattern of a firm's technological overlap with its competitors. The Shannon index for firm $i$ at time $t$ is:

$$G_{it} = -\sum_j P_{ijt} \log\left(P_{ijt}\right) \quad \text{where } i \neq j \tag{3}$$

and where $P_{ijt} = (\alpha_{ijt}/\alpha_{+jt})$. In other words, $P_{ijt}$ are the column stochastic elements on each firm's position vector for year $t$. Note that when any αjit = 0, the term inside the sum operator is also zero (the limit of $x \log x$ is 0 as $x$ approaches 0). Thus, a firm with no overlap across all $j, \ldots, n$ is the specialist archetype—it has a generalism score of zero (as do firms with only one direct competitor). At the other extreme, $G_{it}$ reaches a theoretical maximum at $\log(n - 1)$, which can be seen by maximizing (3) subject to the constraint that the $P_{jit}$ sum to 1. A value of $\log(n - 1)$ would indicate that all of a focal firm's competitors overlap its niche, and they do so in equal proportion. Note that $G_{it}$ increases when (i) *ceteris paribus*, there is an increase in the number of firms that contact $i$'s niche, and (ii) holding constant the number of firms that overlap $i$'s niche, there is a decline in the concentration of the overlap.[16]

Computing $\alpha_{ijt}$, $G_{it}$ and $A_{it}$ required a rule for how to update the variable as the patent network evolves. The lagged year is too short of an interval to summarize two organizations' activities overlap at year $t$; however, it would

[16] This measure appears quite consistent with the detailed descriptions of industry observers (see, for example, ICE's annual STATUS volumes) of the technological breadth of incumbents. In 1992, the firms with the highest values on the Shannon index were IBM, Hitachi, Texas Instruments, Fujitsu, Motorola and Mitsubishi. During the same year, Micro Linear, Kulite and Semikron were among the firms that had low values on this variable. I wish to thank Michael Hannan, who brought to my attention the Shannon index as a possible measure of technological scope.

introduce noise into the network-based variables to compute them on the basis of very old patents, since these will have lost their significance for current activities. Therefore, I used a five-year moving window to compute crowding and the Shannon index. The product lifecycle in the semiconductor industry was generally considered to be about five years during the analysis period, and this is the rationale for the duration of the window. Following equation (1), technological overlap at $t$ is computed from the patent co-citations between firm $i$ and all of its competitors between $t-5$ and $t-1$. However, to ensure that the results are not sensitive to the time window, all models were re-estimated with crowding and generalism defined over three- and seven-year moving windows.

# 5. *Methods*

## 5.1 Modeling the Intensity of Organizational Search

The predictions regarding the intensity of organizational search are tested in models of annual, *semiconductor-specific* R&D spending. I model the logarithm of annual semiconductor R&D spending. I estimate models of the form:

$$\log(\text{R\&D}_{it}) = \alpha + \beta 1 * \log(\text{Sales}_{it}) + \beta 2 * A_{it} + \beta 3 * G_{it} + \beta 4 * (A_{it} * G_{it}) + \gamma' \mathbf{X} + e_{it} \tag{4}$$

where $A_{it}$ is the crowding of organization $i$'s niche in the technological network at time $t$, $\text{Sales}_{it}$ is the semiconductor revenues of firm $i$, $G_{it}$ is the generalism index, $\mathbf{X}$ is a matrix of control variables, and $\gamma$ is a vector of parameter estimates. The first two hypotheses posit: $\beta 2 > 0$ (H1) and $\beta 4 < 0$ (H2).

The R&D intensity data are pooled cross-sections. I report OLS estimates of the regression model in equation (4) with and without firm fixed effects. The reported standard errors in the models without fixed effects are robust to heteroscedasticity and relax the assumption that repeated observations on the same firm are independent. The fixed-effects models incorporate a separate intercept for each firm in the model and thus remove all between-firm variance from the parameter estimates. These models assume that the correlation structure in the disturbance term in equation (4) can be decomposed into a firm-specific effect and a residual term that is uncorrelated across observations and is homoscedastic.

Time series data on R&D expenditures were available only for publicly traded firms (because these data were obtained from SEC filings). Also, because detailed business segment reporting is uncommon, *semiconductor* R&D numbers were only reliably available for dedicated producers. Hence, data availability restricted the analyses with R&D spending to the subsample of publicly traded, single-business semiconductor firms. The R&D subsample includes the 41 firms satisfying these criteria (all firms in SIC 3674 in the Compustat database).

## 5.2 Modeling the Rate of Innovation

The final two predictions are tested in continuous time event history models of the rate of patenting. In these models, the duration between events (the waiting time) is measured as the time elapsed between patent applications. If the firm has issued no patents through $t$, duration is the time since the firm was founded. The application dates on patents are recorded to the day.

I estimate the hazard rate using the semi-parametric Cox model.[17] In a Cox model, the hazard rate is the product of an unspecified baseline rate, $h(t)$, and a term specifying the influences of covariates in $\mathbf{X}$:

$$r(t) = h(t)\exp[\beta 1 * \text{Sales}_{it} + \beta 2 * A_{it} + \beta 3 * \text{RD}_{it} + \beta 4 * (A_{it} * \text{RD}_{it}) + \gamma' \mathbf{X}] \tag{5}$$

where the variables are defined as above. The final two hypotheses posit: $\beta 2 > 0$ (H3) and $\beta 4 < 0$ (H4).

The Cox model does not make parametric assumptions about the form of duration dependence in the hazard rate. This is advantageous because incorrect parametric assumptions may lead to biased estimates of the effects of covariates on the hazard rate (Blossfeld and Rohwer 1995). In the Cox model, the coefficient estimates in $\beta$ represent shifts in the baseline rate due to the covariates, under the assumption that all such changes are proportional [i.e. $h(t)$ does not depend on the covariates].

[17] The convention in the economics literature has been to model firm-level patent rates as annual counts. However, there are two compelling reasons to model the data as an event history. First, the exact day on which a patent application is filed is part of the published patent document. The hazard rate models I report use all of the information on the timing of the event, rather than aggregating the data over a year-long period. Second, the Poisson model and its derivatives (in the linear exponential family) assume that the rate of occurrence of an event is constant within observational units: these models assume that the probability of an event in one time is constant and independent of prior occurrences. Inspection of Nelson–Aalen non-parametric plots of the cumulative hazard of patenting show that this assumption is violated in the semiconductor patent data: there appears to be strong evidence of negative duration dependence in these data. Still, I also estimated annual patent counts employing the conditional fixed-effect negative binomial estimator proposed by Hausman *et al.* (1984), and this estimator yielded similar results.

## 5.3 Control Variables

All models control for firm size. There is considerable evidence suggesting scale economies in the innovation (and patent) production function. For example, a certain volume of patenting is necessary to justify the expense of in-house patent counsel. There is also a very large, empirical industrial organization literature on the relationship between the size of the firm and its ability to capture the value from R&D investments (see Cohen and Levin, 1989, for a review). Thus, it is necessary to account for firm size.

It is also important to control for a potential correlate of technological crowding: the level of market demand. R&D spending levels and innovation rates may be highly sensitive to changes in the level of demand in the market segment(s) in which particular firms operate. A plausible dynamic is that technological areas attract innovators when they are growing, and therefore crowding in the technological network may be driven by positive changes in market demand (this is the argument that market demand 'pulls' innovation). In other words, the level of market demand may be an omitted variable whose effect would be absorbed by the technological crowding coefficient. This explanation stands as a reasonable alternative to the posited mechanisms of crowding, so I include three control variables to allay concerns that the results are driven by changes in the level of product demand.

First, all models also include year dummy variables to account for economic conditions and other macro-level factors that have approximately constant effects on the organizations in the sample but vary over time. These dummies should absorb the effects of temporal changes that affect the level of R&D or rate of innovation in the industry as a whole. Second, I control for the growth rate of each firm's semiconductor revenues during the lagged year. The rationale for including this variable is that firms in niches in which demand is growing will on average experience high rates of sales volume growth. Therefore, including in the models the growth rate of the firm in the previous year should serve as a control for heterogeneity across organizations in changes in the demand for their products. Third, I use the patent data to derive endogenous technology 'clusters', where common cluster membership signifies participation in broadly similar areas of technology. The purpose of this is to control for differences in demand and other conditions across the major sectors of the industry.

To identify mutually exclusive technology groups, I used a patent co-citation matrix as a measure of association in a blockmodel (White *et al.*, 1976). I organized the alpha coefficients specified in equation (1) as a firm-to-firm matrix, denoted $\mathbf{M}$ [$= \alpha_{ijt}$], where the $\alpha_{ijt}$ are defined as above (the proportion of the patent citations made by the firm on the *i*th row that are also made by the firm on the *j*th column). Hence, the elements in the association matrix are the dyadic technological overlap scores for all pairs of organizations. I then compute the overall proximity of all pairs of firms by correlating the columns in the $2N \times N$ matrix, $(\mathbf{M}||\mathbf{M}')'$. The $(i,j)$th element in the resultant matrix $\mathbf{C} = \{r_{ij}\}$ is the correlation coefficient between the *i*th row and column and the *j*th row and column of the technological overlap matrix **M**. Finally, application of a hierarchical clustering algorithm partitioned the organizations into mutually exclusive clusters. This technique is performed for the first year of the empirical analysis and cluster memberships were held constant in subsequent years.[18]

A final control variable only appears in the patent rate models. One of the weaknesses of patent-based innovation indices is that the propensity to patent varies over firms. One source of variation is that some organizations simply choose not to patent all of their inventions. Another source is that some firms are more skilled than others at developing inventions. A third culprit is that some organizations will participate in underexploited technological areas in which there are abundant opportunities to innovate. To account for heterogeneity in firms' propensities and abilities to patent, I constructed a variable that reflects historical differences in patenting behavior: all models contain a (time-changing) count of the number of patents granted to each organization from 1975 until the start of the current spell. Including the number of times that the focal event has previously occurred for each firm is a method of controlling for unobserved heterogeneity in event models (Heckman and Borjas, 1980).

## 6. *Results*

Table 1 contains descriptive statistics for the variables in the four models. Turning to the multivariate analyses, Table 2 reports OLS estimates of the R&D spending models. The baseline model 1 includes year dummies, the growth rate of the focal firm's semiconductor business during the previous

[18] I chose to use a correlation coefficient instead of a Euclidean distance as the metric of pairwise equivalence among organizations ($\alpha_{ijt}$) to group organizations that have similar technological overlap patterns in the network, without capturing size differences between organizations (size differences are captured by the other control variables). Using the correlation coefficient will group organizations that innovated in similar technological areas even if they produced significantly different volumes of innovation. I used both Ward's method and average linkage to cluster the data. Ward's method minimizes the within-cluster sum of squares over all partitions; average linkage uses the average distance from objects in one clusters to those in other clusters as a cluster criterion. Respectively, I identified a six- and a five-cluster solution. I estimated all models with both sets of cluster memberships. The coefficients on all substantive variables are robust across both cluster solutions.

year, the size of the firm, and unreported technology cluster dummy variables. Both the size of the firm and it's recent growth rate have positive, statistically significant effects on R&D spending. The elasticity of R&D spending with respect to firm sales in the baseline model is 1.07, suggesting that R&D spending increases modestly more than proportionately with an increase in firm size (although the coefficient on sales declines as other covariates are entered and the corresponding coefficient in the baseline fixed effects model is shy of unity).

Model 2 adds the technological crowding variable, which has a positive, statistically significant, and substantively large effect. As predicted, organizations in crowded positions devote relatively greater resources to innovation. Based on model 2, a one standard deviation increase in the crowding variable leads to a predicted 30% increase in the level of R&D spending. The third model in Table 2 includes the Shannon generalism index and also the interaction between the Shannon index and the level of technological crowding. The main effect on the index is positive, implying that organizations with technical activities spread broadly across the segments in the microelectronics industry heavily invest in R&D. Because innovations result from novel syntheses or recombinations of existing technical knowledge, it is not surprising that generalists spend relatively heavily on R&D in an effort to capitalize on synergistic opportunities across the competences within the firm. Model 3 also offers support for the second prediction: it demonstrates a negative, statistically significant (but only at the 10% level) interaction between crowding and technological scope. Thus, it appears that the responsiveness of R&D spending levels to niche crowding is contingent on the scope of the firm: high crowding evokes greater R&D spending levels at low values of the Shannon index—in other words, among specialist enterprises.

The four remaining models in Table 2 report a comparable set of R&D spending models from a fixed-effects specification. Comparison of the results against the OLS parameters with robust standard errors demonstrates that support for the hypothesized effects remains strong even allowing for firm-specific intercepts. The first two hypotheses are supported, although the coefficient magnitudes are generally smaller in the fixed-effects specification. Finally, the hypotheses continue to be supported in model 7, which includes the lagged dependent variable. Including lagged R&D spending as a covariate eliminates concern about reverse causality, namely that it is in fact high R&D spending that produces high crowding and it is the temporal stability of this relationship that produces the coefficient on crowding in the models that omit the lagged dependent variable.

TABLE 2. OLS models of the Intensity of Organizational Search (log R&D)

| Variable | (1)[a] | (2)[a] | (3)[a] | (4)[b] | (5)[b] | (6)[b] | (7)[b] |
|---|---|---|---|---|---|---|---|
| Log sales | 1.073** | 0.987** | 0.954** | 0.852** | 0.837** | 0.838** | 0.623** |
| | (0.047) | (0.043) | (0.045) | (0.047) | (0.062) | (0.062) | (0.062) |
| Sales growth (lagged year) | 0.239** | 0.258** | 0.270** | 0.035 | 0.025 | 0.032 | 0.128** |
| | (0.118) | (0.106) | (0.103) | (0.038) | (0.035) | (0.035 | (0.037) |
| Technological crowding | | 0.200** | 0.240** | | 0.042** | 0.097** | 0.075** |
| | | (0.040) | (0.071) | | (0.021) | (0.036) | (0.033) |
| Shannon index (corporate tech. scope) | | | 0.186** | | | 0.115** | 0.079 |
| | | | (0.081) | | | (0.052) | (0.049) |
| Crowding × Shannon index | | | –0.054* | | | –0.047** | –0.035** |
| | | | (0.031) | | | (0.019) | (0.017) |
| Log R&D, lagged | | | | | | | 0.281** |
| | | | | | | | (0.053) |
| Year is 1986 | 0.018 | 0.039 | 0.014 | 0.006 | 0.048 | 0.066 | 0.081 |
| | (0.224) | (0.220) | (0.225) | (0.062) | (0.067) | (0.088) | (0.081) |
| Year is 1987 | –0.035 | –0.043 | –0.072 | –0.011 | 0.069 | 0.084 | 0.053 |
| | (0.218) | (0.215) | (0.224) | (0.062) | (0.073) | (0.093) | (0.086) |
| Year is 1989 | 0.003 | –0.035 | –0.068 | –0.031 | 0.078 | 0.096 | 0.033 |
| | (0.198) | (0.188) | (0.201) | (0.058) | (0.076) | (0.097) | (0.090) |
| Year is 1990 | –0.018 | –0.097 | –0.143 | 0.005 | 0.137 | 0.151 | 0.094 |
| | (0.181) | (0.164) | (0.178) | (0.059) | (0.082) | (0.104) | (0.096) |
| Year is 1991 | –0.010 | –0.060 | –0.106 | 0.007 | 0.161 | 0.174 | 0.084 |
| | (0.176) | (0.164) | (0.183) | (0.059) | (0.086) | (0.108) | (0.101) |
| Constant | –2.681** | –2.705** | –2.683** | –1.369** | –0.706** | –0.807** | –0.896** |
| | (0.392) | (0.387) | (0.406) | (0.236) | (0.264) | (0.273) | (0.251) |
| Observations | 221 | 221 | 221 | 221 | 221 | 221 | 221 |
| $r^2$ | 0.756 | 0.783 | 0.788 | 0.685 | 0.698 | 0.710 | 0.759 |

[a]OLS models with robust standard errors
[b]Fixed effects OLS models (reported $r^2$ is within-firm)

The patent rate results are presented in Table 3. The baseline model 8 contains the controls from the R&D intensity models and a time-updated count of the number of patents granted to each organization since 1975. The controls show that firm size increases the rate of patenting (the positive size effect remains in the model that includes R&D spending, demonstrating that there is a net effect of firm size even after controlling for investment in R&D). Organizations that grew quickly also patent at a higher rate, although the sales growth variable is statistically significant only at the 10% level. The occurrence dependence variable appears to have the desired effect of capturing the influence of unobservables which accelerate the rate of innovation. Note also that the controls in the baseline patent rate and R&D intensity models

TABLE 3. Cox Models of the Patent Rates of Semiconductor Firms

| Independent variables | Model (8)[a] | Model (9)[a] | Model (10)[a,b] |
|---|---|---|---|
| Semiconductor sales ($b.) | 0.146** (0.010) | 0.131** (0.010) | 0.439** (0.149) |
| Revenue growth rate at *t* {sales *t*/(sales *t* – 1)} | 0.038* (0.020) | 0.031 (0.020) | –0.012 (0.083) |
| Total number of patents since 1975 (in 100s) | 0.023** (0.002) | 0.028** (0.002) | 0.002 (0.013) |
| R&D spending year *t* | | | 0.006** (0.0017) |
| Tech. crowding of organization's position ($A_{it}$) | | 0.182** (0.019) | 0.192** (0.043) |
| Tech. crowding × R&D spending | | | –0.002** (0.0006) |
| Year is 1986 | –0.017 (0.034) | –0.035 (0.035) | –0.058 (0.107) |
| Year is 1987 | 0.111* (0.033) | 0.126** (0.033) | 0.104 (0.101) |
| Year is 1988 | omitted | omitted | omitted |
| Year is 1989 | 0.007 (0.031) | –0.010 (0.031) | –0.089 (0.095) |
| Year is 1990 | –0.074** (0.032) | –0.098** (0.032) | –0.020 (0.097) |
| Year is 1991 | –0.038 (0.030) | –0.0763** (0.0310) | 0.1382 (0.1022) |
| Number of organizations | 150 | 150 | 41 |
| Number of events | 13642 | 13642 | 2685 |
| Number of spells | 14448 | 14448 | 2888 |
| Log-likelihood | –121551 | –121505 | –12982 |

[a]Model includes unreported technology cluster dummies.
[b]Model includes only dedicated, US-based semiconductor firms (those in the R&D subsample).
*Significant at 10% level; **Significant at 5% level.

have similar effects. This is consistent with the view that the determinants of R&D spending should also be predictors of the rate of innovation.

Model 9 adds the technological crowding variable to test the third prediction that organizations in crowded positions innovate at a high rate. Once again, the coefficient on the crowding variable is in the hypothesized direction and is substantively and statistically significant. The technological crowding coefficient implies that a unit increase in the variable multiplies the patent rate by a factor of 1.31. Hypothesis 2 is therefore supported.[19]

The final model 10 tests the prediction that an increase in R&D spending has a smaller effect on the patent rate among firms in the most crowded positions. Model 10 includes R&D spending and a crowding-by-R&D interaction variable. The results indicate that the patent rate increases in R&D spending; they also show a positive, direct effect of crowding on the innovation rate even after controlling for R&D spending. As I elaborate in section 7, one potential explanation for the direct effect of crowding, even after controlling for R&D spending (and therefore the implicit, endogenous effect of crowding through R&D), is that firms in crowded positions shift their foci toward more incremental and short-term R&D projects (as opposed to projects that may not reach fruition for a number of years). This would have an immediate, positive effect on the rate of innovation, but possibly compromises the quality and quantity of innovation in the long term.

In support of the final prediction, the interaction between crowding and R&D spending is negative in model 10, showing that the impact of R&D on the patent rate is contingent upon the level of crowding. For example, if a firm with '0' crowding (a firm in a completely vacant position in the technological network) increases R&D spending by $25 m., it can expect a 16% increase in its baseline patent rate [= $\exp(0.006 \times 25)$]. This can be compared to the more meager 7% increase in the patent rate that follows a same-sized increase in R&D spending made by a firm at the mean level of crowding [= $\exp\{0.006 \times 25 - (0.002 \times 25 \times 1.77)\}$]. Hence, the effect of R&D spending on the patent rate depends significantly upon where a firm is situated in the technological network.

The negative coefficient on the crowding-by-R&D spending interaction is also helpful in ruling out an alternative explanation for some of the crowding-related effects. In particular, it is possible to argue that crowding proxies for the opportunities to innovate in the areas of a firm's activities. According to the line of reasoning, crowded areas are fertile because they are rich in technological spillovers: the fact that many other organizations are

[19] One of the shortcomings of patents as a measure of innovation is that the distribution of the 'importance' of patents is known to be highly skewed. However, there is one modeling strategy that may be employed to account for this heterogeneity. There is evidence that highly cited patents represent the most important inventions, suggesting that weighting patents by the number of citations they receive in subsequently issued patents will correct for differences in the importance of patents. Therefore, I performed the patent rate analysis defining the dependent variable to be an annual count of the number of patents received by an organization, weighted by the number of patent citations accruing to those patents in the four following years. Because it is necessary to allow for a minimum of four years for patents to accrue citations, this analysis was limited to the first two years of the data. The results for the citation-weighted patent count models were still consistent with the results reported in Table 3: technological crowding had a positive effect on the citation-weighted patent rate.

working in the area means that that there are ample opportunities to capitalize on competitors' advances (either because innovators are incapable of fully excluding others from utilizing their discoveries or because firms' advances open up new technical avenues for the organizations around them). However, it is hard to square this interpretation with the finding of a negative interaction between crowding and R&D spending.

## 7. *Discussion: Implications and Future Directions*

The findings reveal strong effects of technological crowding on the rate of innovation and the level of R&D spending. It is important to emphasize, however, that the results pertain only to innovation-related outcomes and do not necessarily inform the association between technological positioning and the life chances or performance of high-technology firms. There are many potential drawbacks of occupying a crowded technological position. First, organizations that concentrate on similar technological domains encounter one another further downstream where they compete in the same product markets. Second, organizations with overlapping technological niches are also likely to compete in the same factor markets (Hannan and Freeman, 1989). For example, they will enter the labor market demanding similarly-skilled technical personnel. Thus, Podolny *et al.* (1996) found that semiconductor firms in crowded positions had lower rates of growth than otherwise comparable producers. In addition, the results in this study show that R&D spending has a lower effect on the rate of innovation among firms in crowded areas of the technological network. On balance, organizations in sparse areas of technology innovate less quickly, but they also spend less on R&D and, if compared on other measures of performance, they may well surpass those of organizations in crowded niches.

At this juncture, it might be useful to link the focus of this study to the broader literature on high-technology industry dynamics, most importantly the evolutionary literature and the large body of work on technology cycles. Much of the work in this area elaborates the dominant design concept introduced by Abernathy (1978) and Abernathy and Utterback (1978). In this view, technology develops according to an evolutionary process driven by variation and selection. The early period of development (known as the era of 'ferment') is characterized by many competing technologies and lasts until a selection process produces a dominant design. The establishment of a dominant design marks the transition into a period in which technology evolves in a more orderly and incremental fashion along a well-defined trajectory (e.g. Dosi, 1982; Anderson and Tushman, 1990; Tushman and Murmann, 1998). This methodical development continues until it is disturbed by a subsequent technological discontinuity, followed once again by a selection process heralding the transition to a new dominant design. The basic claims of the evolutionary model (and a set of associated industry dynamics) have been strongly supported in many historical and case studies (Tushman and Murmann, 1998).

Although operating at a different level of analysis, the crowding concept mixes comfortably with the literature on dominant designs. The notion of a dominant design applies at the product or process level, or at the level of the component subsystem and associated linking mechanisms (Henderson and Clark, 1990). Thus, a dominant design is a technical property rather than an organizational characteristic, although organizational dynamics have been shown to vary significantly across the pre- and post-dominant design periods. Linking the two concepts, it is highly probably that crowding will be greater in the post-dominant design period, since this is the era in which widely accepted technical approaches serve as common foundations for all of the innovators in the market (in fact, crowding is precisely defined by the level of redundancy in technical foundations between a focal organization and all of its alters). Thus, the level of crowding will vary across the technology cycle, and a promising empirical direction would be to explore how the effects of crowding or other properties of the firm–environment interface vary across the stages of the technology cycle and impact transition rates between stages. Similarly, it would be useful to take a more macro view and to explore how network-level properties of the citation network (density, entropy, hierarchy, etc.) vary over the technology cycle and affect the transition into successive states.

I have focused on the effects of crowding levels across firms and over time. However, crowding may be an important property at a higher level of aggregation. While the actual correspondence between firm- and area-level crowding will depend upon the distribution of the activity of firms across different segments, the crowding of a sector can be analogously conceived as being inversely proportional to the amount of differentiation within it. Thus, although I have concentrated on the interorganizational competition that emerges when firms build upon a similar vector of foundational nodes in the patent network, it is a straightforward extension to investigate how the differences in the aggregate crowding in broad technological areas shape the rate and content of innovation at the area level.[20]

[20] If one chose to investigate the rate of innovation above the organizational level of analysis, one would then confront the task of identifying the boundaries around technological arenas. There are two approaches to the identification of boundaries. First, the endogenous approach uses one of a variety of network partitioning techniques to identify naturally occurring divisions in the data. Second, the exogenous approach utilizes a pre-existing taxonomy, such as the patent classification system, to distinguish among broad areas of technology.

It is instructive to imagine two market structures. In the first, innovation is spread evenly over the market terrain; from a network standpoint, there are relatively few indirect ties among the innovations comprising the market's technology base. In contrast, the second area is crowded: inventions form a clump in the center of the market and the nodes in the network appear to comprise a clique. The findings in this paper suggest that the rate of innovation is likely to be more rapid in the second market, because the actors in the sector will on balance hold more crowded positions.[21] In fact, this prediction is consistent with and analogous to certain theories of competition in economics, particularly work on the spatial concentration of industries. For instance, Porter (1990) argues that geographic concentration stimulates growth because the inter-firm rivalry stimulated by spatial proximity leads firms to invest in innovation and quickly adopt competitors' advances (see also Henderson, 1986; Glaeser *et al*., 1992).

This discussion suggests a broader study than the one I have performed: with the availability of the complete US patent system in electronic form, it is now feasible to conduct an analysis of the rate of knowledge production in all areas of technology (at least, all areas in which innovators routinely file for patent protection). Such a study has the potential to yield a general understanding of how the structural properties of semi-bounded areas of technological knowledge affects the rate of knowledge production. My belief is that characteristics of full fields of technology, such as the level of internal differentiation among the actors involved in developing them, will be strong predictors of the speed of technical change.

A second avenue for future research would be to explore how contextual variables such as crowding affect the characteristics of the technologies that firms develop. For example, it may be that organizations in crowded regions of the technological network forego searches for basic technological inventions in favor of more tractable and incremental discoveries, which can be brought to market in (relatively) brief periods of time. This choice of focus could stem from the rampant priority concerns felt by organizations in crowded niches—concerns that are surely amplified by the perceived need to create a unique identity in a product market by establishing a strong upstream position tied to one or more areas of technology. The paper's findings in fact hint at such a dynamic: crowding has a direct effect on the rate of patenting

[21] However, I would again expect that the patent rate per marginal R&D dollar will be lower in more crowded areas. As more triads in the area close (i.e. as more new patents include citations both to a given patent and the inventions cited as prior art of the focal patent), innovation may become more difficult. The reason is that many indirect ties in the citation network appear when clusters of innovation are tightly compacted from a technical standpoint. In other words, there is less room for new activity in such areas because there is very little technical distance between existing inventions.

even after controlling for the level of R&D spending, in addition to its indirect effect through its impact on R&D spending. My interpretation of this result is that firms in crowded positions adjust their focus toward nearer-term R&D projects, and hence crowding augments the rate of innovation net of its effect on the quantity of funds devoted to R&D. If correct, the implication is that incremental innovation occurs quickly in crowded fields, but it may do so at the expense of more fundamental innovation. With a longer observation period, it would be possible to investigate how the more distant history of environmental conditions experienced by an organization affects the firm's current-period productivity.

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