Aging, Obsolescence, and Organizational Innovation

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This paper investigates the relationship between organizational aging and innovation processes to illuminate the dynamics of high-technology industries, as well to resolve debates in organizational theory about the effects of aging on organizational functioning. We test hypotheses based on two seemingly contradictory consequences of aging for organizational innovation: that aging is associated with increases in firms' rates of innovation and that the difficulties of keeping pace with incessant external developments causes firms' innovative outputs to become obsolete relative to the most current environmental demands. These seemingly contradictory outcomes are intimately related and reflect inherent trade-offs in organizational learning and innovation processes. Multiple longitudinal analyses of the relationship between firm age and patenting behavior in the semiconductor and biotechnology industries lend support to these arguments.●

In an increasingly knowledge-based economy, pinpointing the factors that shape the ability of organizations to produce influential ideas and innovations is a central issue for organizational studies. Among all organizational outputs, innovation is fundamental not only because of its direct impact on the viability of firms but also because of its profound effects on the paths of social and economic change. In this paper, we focus on a ubiquitous organizational process, aging, and examine its multifaceted influence on organizational innovation. In so doing, we address an important unresolved issue in organizational theory, namely, the nature of the relationship between aging and organizational behavior (Hannan, 1998).

Evidence of how aging affects innovation should produce evidence relevant to competing theories of how age alters the internal features of organizations. Organizational ecologists have devoted the most sustained attention to the consequences of aging for organizational outcomes but have failed to reach consensus as to whether aging has negative or positive effects on organizational functioning (Hannan, 1998). While recent evidence suggests that there is a liability of aging (see Barnett, 1990; Barron, West, and Hannan, 1994; Ranger-Moore, 1997), there remains considerable empirical uncertainty about this relationship (Hannan et al., 1998). Moreover, there are debates in the ecology literature surrounding the mechanisms that underlie the observed effects of age on life chances (Barron, West, and Hannan, 1994; Hannan, 1998). Competing theories about the effects of aging on organizational survival reduce to contrasting claims about the effects of aging on internal organizational processes and on organization-environment fit, respectively, but the outcomes typically studied by ecologists—survival and growth—do not readily lend themselves to tests of these different mechanisms (but see Ranger-Moore, 1997). By studying the relationship between age and organizational innovation, we can shed light on some of the competing mechanisms posited in ecological theories and contribute scarce empirical evidence to the debate over the behavioral changes associated with organizational aging.

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Evidence clarifying the relationship between organizational aging and innovation also promises to improve our understanding of the organizational dynamics of high-technology markets and, in particular, the dynamics of technological leadership. At one extreme, aging may have uniformly positive consequences for innovative activity: on the foundation of accumulated experience, older firms may innovate more frequently, and their innovations may have greater significance than those of younger enterprises. In this scenario, technological change paradoxically may be associated with organizational stability, as incumbent organizations come to dominate the technological frontier, and their preeminence only increases with their tenure. At the other extreme, a consistently negative relationship between aging and innovation would imply that firms are increasingly unable to generate new or important innovations as they age. In this scenario, technological change progresses hand in hand with organizational turnover: technological leadership is ephemeral, and those at the forefront are quickly supplanted by new ventures. At first glance, reality does not conform neatly to either of these extremes. The positive effects of aging find their expression in the disproportionate patenting of well-established, Fortune 500 firms. At the same time, the putative negative effects of aging find their expression in the many tales of the displacement of technological leaders by upstarts (Abernathy and Utterback, 1978; Tushman and Anderson, 1986).

The relationship between aging and innovation is also relevant for the growing literature on the organizational determinants of technological innovation. Motivated by the insights of Schumpeter (1942), there is a vast but inconclusive body of empirical work on the effect of firm size in the industrial organization economics literature (reviewed in Cohen and Levin, 1989). In the administrative literature, there has been a great deal of work evaluating the ability of different internal systems and structures to spawn new ideas and speed the commercialization of inventions (Burgelman, 1983). To our knowledge, however, there have been very few systematic, large-sample studies of the relationship between organizational age and the propensity of firms to produce technological innovations.

That older, established organizations often encounter difficulty in keeping up with externally generated technical advances—especially when such developments represent radical changes from prior approaches—is widely accepted in the evolutionary literature on technical change. This idea is grounded in part in past historical studies of technological trajectories and industrial evolution (Abernathy, 1978; Abernathy and Utterback, 1978). Thus, a number of industry histories and case studies have demonstrated that periods of technological ferment in an industry (where new product introductions are frequent and alternative product forms compete for market acceptance) are followed by periods of relative stability in which innovation consists largely of incremental improvements to a widely adopted product architecture, often called a dominant design. These studies have also demonstrated that the radical innovations that spawn new technological fields often emerge from small, entrepreneurial firms (Abernathy and Utterback, 1978; Tushman and Anderson, 1986; Rosenbloom and Christensen, 1994) and that the innovative capabilities of established organizations are generally better suited to producing incremental innovations along existing technological trajectories. Thus, particularly in periods of radical technical change, it has been demonstrated that established organizations often are unable to adapt their activities to incorporate major, external advances.

Our argument differs from these studies in two respects. First, rather than making categorical distinctions between industry incumbents and entrants or radical and incremental technological change, we view the innovative capabilities of firms as falling along a continuum defined by firm age. Aging leads to predictable changes in the nature of firm-level innovative activity, many of which occur independent of the broader innovative context. Second, although innovation at the firm level is governed in part by an industry-level clock, whereby the passage of time heralds different economic and technological contexts for innovation in an industry (i.e., the industry lifecycle), our emphasis is on how innovation processes at the firm level are governed by the firm's own internal clock, which leads firms facing the same industry-level constraints to respond differently as a function of differences in their ages. Our goal is to use the literature on organizational ecology, evolutionary theory, and learning theory to derive testable propositions of aging as an obsolescence process for a variety of aspects of organizational innovation and to present empirical analyses that document the impact of age on these different facets of corporate technological innovation in a large sample of firms. Our analyses are performed on samples of firms drawn from two high-technology industries: semiconductors and biotechnology.

EFFECTS OF AGING ON INNOVATION

Innovation at the organizational level is governed by collections of organizational routines and search strategies (Cyert and March, 1963; Nelson and Winter, 1982; Hannan and Freeman, 1984). Routines are repositories of organizational knowledge (March, 1988), and it is through their combination that organizations generate outputs. It is also through their combination that organizational frictions arise, as a result of coordination problems, breakdowns in control, and so on. In general, an organization's performance reflects a combination of its ability to refine and effectively coordinate its organizational routines, which we denote as organizational competence, and the extent to which those routines are well-suited to the state of the environment, which we label environmental fit.[1] A firm with routines that are well-tailored to environmental demands (high fit) may nonetheless perform poorly if the organization suffers from an inability to coordinate its routines effectively or experiences excessive bureaucratization (low competence). Conversely, a highly efficient firm may fail in the absence of demand for the outputs that its routines are designed to create. In trying to unpack the relationship between organizational aging and innovation, we frame the discussion in terms of this distinction: how aging might affect organizational competence (vis-à-vis innovation) versus the

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We use both of these terms narrowly throughout the paper. Organizational competence refers to the capacity of the firm to produce innovations, regardless of the broader acceptance or quality of these new technologies. Environmental fit refers to the match between the firm's innovations and the current state of the art, as well as to the receptivity of other producers to the organization's new technologies.

consequences of aging for the fit between organizational routines and environmental demands.

Organizational Competence

A number of scholars have argued that aging leads to decreases in the efficiency with which organizations carry out their routines and, hence, to a decline in organizational competence. Barron, West, and Hannan (1994) suggested that a positive relationship between aging and organizational mortality may be due to the development of impediments to effective action, including taken-for-granted understandings, political coalitions, and the like. With respect to innovation, Cohen and Levinthal (1989, 1990) suggested that a firm's ability to use its existing knowledge base for further innovation depends critically on the patterns of communication and distribution of knowledge within the firm. Thus, if aging leads to increased rigidity and an ossification of communication patterns, firms may produce fewer innovations as they age.

Other scholars maintain that organizational competence improves over time. In positing a liability of newness, Stinchcombe (1965) suggested that older organizations may be more efficient than younger firms because they have more (cumulative) production experience, possess stronger relationships with vendors and customers, have a more experienced workforce, and so on (see also Hannan and Freeman, 1984). Organizational learning theorists also have argued that experience with a set of routines enhances an organization's competence, in part by improving the reliability with which routines are implemented (March, 1991). With respect to the production of technological innovations, Cohen and Levinthal (1990) showed that the accumulation of knowledge enhances organizations' ability to recognize and assimilate new ideas, as well as their ability to convert this knowledge into further innovations. Similarly, Tushman and Anderson (1986), Henderson (1993), and others have argued that established firms possess information-processing routines that facilitate incremental innovation along existing technological trajectories. Thus, if the passage of time leads to an accumulation of foundational knowledge, organizational competence will increase with age.

The distinction between these two arguments parallels the competing perspectives offered by two theories of aging in organizational ecology, namely, the liability of newness (Stinchcombe, 1965; Hannan and Freeman, 1984) and the liability of senescence (Barron, West, and Hannan, 1994). As Hannan (1998) showed, both of these arguments can be cast as special cases of a general framework relating organizational outcomes to the cumulation of knowledge, internal frictions, and the quality of external ties. The two theories differ in their expectations concerning how aging affects each of these components of organizational behavior. Empirically, these arguments suggest that the net effect of aging on organizational competencies depends on the relative magnitude of the gains from experience with a set of routines and the losses due to various forms of organizational sclerosis.

With respect to the production of innovations, the gains from experience with the innovation process should outweigh any negative consequences of bureaucratization. Abstracting for the moment from the quality and significance of their output, organizations should become more adept at producing innovations as they age, for two reasons. First, as Cohen and Levinthal (1990: 136) noted, the background knowledge required for innovative activity is cumulative: new ideas are more efficiently assimilated if a solid base of knowledge has been established (see also Nelson and Winter, 1982; March, 1991). Moreover, the cycle between innovation and the accumulation of knowledge within the organization tends to be self-reinforcing, such that organizations with a larger knowledge base are more likely to pursue the innovative opportunities that further contribute to the accumulation of knowledge (Cohen and Levinthal, 1990). Second, older high-technology firms will have perfected the routines, structures, incentive programs, and other infrastructure that are needed to develop new technologies and bring them to market. In short, high-technology firms that have survived a long period of time are likely to have developed the competence to innovate, particularly in their established innovative domains. This leads us to expect the following:

Hypothesis 1: Organizational age will be positively associated with the rate of innovation.

Our predictions about the effects of age are premised on holding size constant. Many scholars have argued that large size is associated with high levels of complexity and bureaucracy (Blau and Schoenherr, 1971) and a decline in organizational responsiveness that leads to reduced levels of innovation (Aldrich and Auster, 1986). Conversely, a different view suggests that large organizations may invest a greater proportion of their slack resources in innovation because they possess the market power to appropriate the returns from innovating (Schumpeter, 1942). Thus, Cohen and Klepper (1996) argued that large firms are likely to spend more on research and development (R&D) and shift their R&D mix toward process innovation because they have a greater production volume over which to benefit from process improvements. In either case, our expectation that older organizations will have high competence (as well as all subsequent hypotheses) is premised on empirical models that control for firm size.

Organization-environment Fit

Organizational age gauges not just the length of a firm's operational experience but also the duration of its exposure to environmental changes (Carroll, 1983). The effect of aging on organization-environment fit therefore depends on the rate of adjustment of internal organizational routines relative to the pace of environmental change (Hannan and Freeman, 1984). Organizations may be able to adapt only imperfectly to environmental changes. The gap between organizational competencies and environmental demands may therefore increase with time, such that aging will be associated with organizational obsolescence (Barron, West, and Hannan, 1994), particularly in industries where significant developments in technology can require a different set of knowledge and skills than that possessed by established firms (Clark, 1985; Tushman and Anderson, 1986).

Support for this claim can be found in a number of literatures. Organizational ecologists suggest that the combined influences of imprinting, inertia, and environmental change render obsolete the core technologies of old organizations (Barron, West, and Hannan, 1994; Aldrich and Auster, 1986; Ranger-Moore, 1997). Stinchcombe (1965) argued that the core technologies, structures, and processes of organizations reflect the early decisions of a firm's founders and the prevailing practices at the time of founding (see also Hannan, Burton, and Baron, 1996). If organizations are relatively inert (Hannan and Freeman, 1984; Delacroix and Swaminathan, 1991; Amburgey, Kelly, and Barnett, 1993), then important early decisions and practices will persist as organizations age. When the external environment changes significantly over time, the forces of imprinting, coupled with organizational inertia, generate a decline in organization-environment fit as the accreting drift of the environment results in a relatively large, cumulative shift away from the activities of the organization.

Evolutionary theories (Nelson and Winter, 1982) reinforce the notion that core organizational routines are subject to inertial pressures. These theories subscribe to a Markovian conception of adaptation, in which organizational change is seen as the product of searches for new practices in the neighborhood of an organization's existing routines (Cyert and March, 1963; Stuart and Podolny, 1996), or what Nelson and Winter (1982: 211) described as local search. Local search occurs for myriad reasons. Most importantly, individual decision makers within organizations are boundedly rational and heavily anchored in past experiences when they evaluate alternative courses of action. Also, patterns of behavior stabilize as formal structures and routines become institutionalized over time (Cyert and March, 1963). To preserve their privileged positions, dominant political coalitions inside the firm often have strong incentives to insure that the firm continues to focus on activities and market niches that require their expertise (Pfeffer, 1981; Burgelman, 1994). Incumbent personnel also have career interests at stake if they have developed expertise specific to the areas in which an organization has previously focused, particularly if this expertise if of little value to other organizations. Similarly, the necessity of serving existing customers often hampers the ability of an organization to perceive and pursue emerging market opportunities (Rosenbloom and Christensen, 1994). Although the retention of routines and the entrenchment of interests may facilitate smooth and stable organizational functioning, they also interfere with the capacity of the organization to adjust to changing environments (Nelson and Winter, 1982). Thus, as organizations age, they gain history and routines that limit their flexibility by restricting the range of organizational action.

Organizational learning theories suggest that firms may become less likely to change as they age precisely because their competencies improve as they accumulate experience in a particular domain of activity. Experience in existing activities, if accompanied by improvements in the performance of those tasks, may increase the appeal of existing courses of action (Levitt and March, 1988). Cohen and Levinthal (1990) argued that if organizations have not previously acquired knowledge in a rapidly evolving technological area, they quickly lose the ability to assimilate and exploit new information in that domain. This type of lockout occurs for two reasons. First, when firms lack detailed knowledge of a particular set of technologies, they do not appreciate the significance of new technological opportunities in related areas. Second, even if such opportunities are recognized, the lack of sufficient background knowledge impedes organizations' ability to capitalize on new developments to generate innovations (Cohen and Levinthal, 1990: 137). Particularly in high-technology markets, where the ability to innovate hinges on heavy investments in competence building in particular areas of technology, long-established competencies are likely to stand in the way of adaptation to major changes in technological regimes (Abernathy and Utterback, 1978; Tushman and Anderson, 1986; Henderson and Clark, 1990; Burgelman, 1994).

These arguments suggest that the core technologies of firms in changing environments will become obsolete as they age. As Barron, West, and Hannan (1994) noted, obsolescence is due to changes in external circumstances over time; it is not caused by a decline in internal organizational efficiency. In fact, if environments were stable, the organization-environment fit would not diminish over time. In changing environments, however, the improvement in organizational competence that accompanies the accumulation of production experience paradoxically exacerbates the decline in organization-environment fit, because the organization becomes better at performing routines that are less and less valued by the environment. In this sense, innovative firms may succumb to competency traps, which occur when "favorable performance with an inferior procedure leads an organization to accumulate more experience with it, thus keeping experience with a superior procedure inadequate to make it rewarding to use" (Levitt and March, 1988: 322). Competency traps ensnare organizations because prior innovative successes reinforce established routines even as the technological frontier shifts to new areas.

The obsolescence argument suggests a number of hypotheses about how age affects the quality and nature of the innovative outputs that firms develop. First, older firms are more likely to exploit their established innovative domains than to move into new fields of innovative activity. If older firms have specific areas of innovation in which they have encountered repeated successes in the past, they can be expected to harvest in those areas in the future because of the organizational tendency to exploit areas of established competence. Moreover, if older organizations are slow in changing because of inertia, they will be unhurried in moving beyond prior areas of innovation. Similarly, if more experienced firms with long-standing routines are less likely than younger companies to experiment with nonlocal investments in technology, then a firm's innovative activity may increasingly become insulated from external technological developments and thus take the form of refinements to its areas of prior innovation. In short, an obsolescing organization follows a firm-specific innovation trajectory (cf. Dosi, 1982). This leads to our second prediction:

Hypothesis 2: When compared with young companies, older firms will show a greater tendency to build on their previous innovative activity.

A closely related manifestation of an age-related decline in organization-environment fit would be a tendency for the current-period innovative activities of older organizations to build on older technological foundations. If inertial tendencies are strong, then older firms would be slow to update their areas of concentration. Hence, because they are less flexible, older firms may be less likely to incorporate the technological advances of other firms into their activity, effectively ceding the development of newer and potentially more influential areas of technology to start-up organizations. These ideas lead us to a third prediction:

Hypothesis 3: As firms age, their current-period innovations will elaborate and refine older areas of technology.

A final indication of the fit between a firm's innovative activities and the current technological environment is the influence of the organization's innovations on its technological community. If obsolescence is a concomitant of age, then as firms age, their innovative outputs may become increasingly mismatched with current environmental demands and irrelevant to the innovative activities of the other firms in a technological community. In this sense, age, experience, and accumulated competencies can be considerable disadvantages when compared with inexperience and youth, particularly with respect to their influences on the organization's ability to adapt to or develop major technological changes (Abernathy, 1978; Tushman and Anderson, 1986; Henderson and Clark, 1990; Henderson, 1993). Routines that are nurtured in the course of a firm's experience with developing and refining older scientific or technological principles simply become outmoded. If older organizations are more likely to hold on to such routines and to work in older areas of technology, or if they are slow to incorporate the most recent technological advances into their developmental work, we expect the following:

Hypothesis 4: In the broader industrial community, the innovations of older firms will be less influential on subsequent technology development than will those of their younger counterparts.

METHOD

We assembled large samples of firms from two very different high-technology areas, semiconductors and biotechnology, to test the predicted effects of firm age on innovative activity. There are many differences in the fundamental nature of the underlying technologies in these two businesses, in the types of firms that populate them, in their market dynamics, and in the maturity levels of the two areas of technology. Rather than focus on a single industry, we collected data on two very diverse contexts. Consistent findings across two very different industries would show that our arguments have general application.

The semiconductor industry originated with the discovery of the point contact transistor at Bell Labs in 1947 (see Tilton, 1971; Wilson, Ashton, and Egan, 1980, for histories of the early industry). Although the industry has grown large and global in scope over the past fifty years, it is arguably still changing quickly. The pace of technological change continues to be rapid and relentless, a condition evidenced by the fact that research and development (R&D) expenditures by industry incumbents routinely exceed 10 percent of revenues. The members of the industry include many of the largest and most influential firms in the worldwide economy—companies such as IBM, Intel, Philips, and Fujitsu—as well as many young and small dedicated producers. The sample that we analyzed contains all semiconductor producers for which we were able to gather annual sales volume data during a seven-year period (1986–1992). This sampling criterion was imposed because of the importance of sales volume as a control variable in the statistical models. As research in organizational ecology has demonstrated, inferences drawn about the effects of organizational age in models that fail to control for firm size may be spurious due to the correlation between age and size (Barron, West, and Hannan, 1994). In addition, there is a rich body of work in the industrial organization literature that suggests that firm size is likely to influence a number of the outcome variables that we model. Dataquest, a consulting and information services firm, was the source of the revenue data. The Dataquest database was supplemented with sales figures from the Integrated Circuit Engineering Corp.'s annual reports. All together, there were 150 companies in the sample, although some were not present for all years. Two-thirds of the firms in the sample had headquarters in the U.S.; the remainder were divided between Europe, Japan, and other Southeast Asian nations. As a whole, the sample accounted for 90 percent of the total, worldwide semiconductor production volume in 1991.

Our sample of semiconductor firms reflects certain trade-offs in research design created by the necessity of including sales data. First, the sample excludes very small, private firms that do not appear in the Dataquest database. This means that young firms may be underrepresented in our sample. Second, the sample is characterized by a survivor bias: it does not contain organizations that were founded and failed before the first year we were able to acquire data, although this should introduce a conservative bias to our analyses. Because the semiconductor industry is technology driven and success is at some level tied to innovative ability, one might expect that the more accomplished innovators on balance experience lower failure probabilities. If so, then the level of support for our predictions about the adverse consequences of aging on environmental fit will likely be weakened by the survivor bias in the semiconductor sample.

The biotechnology sample was created by randomly selecting 250 dedicated biotechnology firms that were listed in the *Corporate Technology Directory* in 1988. Due to inconsistencies across data sources in reported founding dates and/or firm sizes, our sample for analysis was reduced to 237 firms observed during an eight year period (1987–1994). Our data sources suggest that very few biotechnology firms failed prior to the start of our observation window, which gives us confidence that there is little if any survivor bias in the biotechnology sample.

Although the microelectronics and biotechnology industries share certain similarities (for instance, they are both among the most innovation-intensive industries in the economy), the two differ in myriad ways. First, contemporary biotechnology is a more recent endeavor: the industry is often claimed to have originated in 1973 with the discovery of recombinant DNA and, two years later, of hybridoma technology (Kenney 1986, provides a useful overview of the core biotechnologies and the early history of the industry). Commercial activity in biotechnology took off only after 1980, thanks to changes in patent law and the astonishingly successful initial public offering of Genentech in that year. Second, the nature of the underlying technology differs fundamentally; whereas semiconductor innovation derives from the physical and material sciences, biotechnology is at the intersection of molecular biology, immunology, genetics, and chemistry. Third, the semiconductor business is importantly shaped by confederations of producers banding together to promote technology standards. In contrast, standards and network externalities do not affect biotechnology industry dynamics. The biotechnology industry is populated primarily by small and dedicated producers staffed with Ph.D. scientists, whereas the semiconductor industry contains many diversified, multi-billion-dollar companies. Because they are small and specialized enterprises, all but a few dedicated biotechnology firms rely heavily on external organizations, such as pharmaceutical and chemical companies, to fund their internal development efforts and to assist in the manufacture, distribution, marketing, and sales of their innovations (Barley, Freeman, and Hybels, 1992). In fact, many biotechnology companies have no revenues other than royalty payments from strategic alliance partners. Although semiconductor firms have also taken on many strategic partners of late and sometimes outsource chip fabrication, the larger producers have tended to perform many segments of the value chain in house. Whereas the contemporary semiconductor industry has globalized, the United States remains the center of biotechnology. In short, the two industrial contexts differ on many rudimentary dimensions. Consistent effects of aging on innovation across the two contexts would strengthen our confidence in the validity and generalizability of the findings.

The empirical analyses require a number of measures of the innovative activities of the firms in the two industry samples. To construct these measures, we gathered data on semiconductor and biotechnology inventions patented in the U.S. As a requirement of the patent application process, an inventor must submit a list of citations to all previously granted patents that made technological claims similar to those that are claimed in the current application, acknowledging the existing, patented inventions that are nearest in technical content to the proposed inventions. Patent citations are an integral part of the application process because they establish the scope of patents under evaluation: inventors can only stake property rights for the novel aspects of their inventions. To establish their unique contributions, patent applicants must recognize all patented precursors, in addition to emphasizing the original elements of their pending inventions. In the process of reviewing applications, one of the duties of the Patent Examiner is to verify that the list of references to previous patents, known as the "prior art," is complete. When a patent application is granted, the patent issues with the final list of prior-art citations. The Patent Examiner's prior-art search serves as a safeguard for the integrity of the citation process.

While some scholars have been critical of the use of patent data in social science research (see Levin et al., 1987), in particular because the proclivity to patent varies across industries, there are two reasons why interindustry differences in patenting activity should not jeopardize the results from our study. First, because we analyze the samples from each industry separately, our coefficients cannot be influenced by uncontrolled cross-industry variance in the proclivity to patent. Second, firms in both the semiconductor and biotechnology industries actively patent, particularly as the strength of U.S. intellectual property protection has increased. With one exception (the U.S. government), the top 10 patent holders in the U.S. in 1997 were electronics firms that each patented heavily in microelectronics: IBM, Canon, NEC, Motorola, Fujitsu, Hitachi, Mitsubishi, Toshiba, and Sony. Similarly, biotechnology is identified in Levin et al.'s (1987) study as one of the industries in which intellectual property protection is particularly strong.

For the analysis, we collected all U.S. biotechnology and semiconductor patents assigned to the firms in each of our industry samples, as well as all patents that were cited by or subsequently cited those patents. We chose to collect U.S. patents because the United States is the largest technology marketplace in the world. To gain intellectual property protection in a particular country, the inventor must file for a patent in that country. Because the U.S. is a large and central market for both semiconductors and biotechnology, it is standard practice for non-U.S.-based firms to patent in this country (Albert et al., 1991). Our source for the patent data is the Micropatent "Patent Abstracts" CD series, which includes all U.S. patents from 1975 to the present.

For the sample of dedicated biotechnology firms, we searched the U.S. patent system for the names of all 237 firms in our sample. The semiconductor sample required us to employ a more complex procedure to gather patent data because some of the firms in microelectronics were broadly diversified into other industries. Searching on firm names would cast a net that would capture all of the patents of the firm, whereas our objective was to isolate an organization's activity in microelectonics. To do this, we identified approximately 2,400 distinct patent classes that contained semiconductor product, device, and design inventions. We retrieved the 50,000 patents issued in these classes between 1975 and 1994 from the Micropatent CDs. Next, after constructing detailed corporate ownership trees, we matched the patents in the 2,400 patent classes to the 150 firms in our sample. Once the patents of the firms in the two industry samples were compiled, we added information as needed from a database containing the entire U.S. patent system (see below).

Measures

Patent-based measures of innovation. We used the patent data to derive four measures of innovation to test our hypotheses. We tested hypothesis 1, that older organizations will produce a greater number of innovations, by modeling the rate of patenting as a function of firm age and other covariates. The three remaining analyses employed patent citation data, which enabled us to construct measures of the importance of firms' inventions, the temporal proximity of firms' inventions to the most current technological developments, and the intertemporal stability in the focus of firms' innovative activities. To test hypothesis 2, that firms will innovate in the technological areas in which they have worked in the past, we distinguished new patents that were closely related to a firm's prior innovative activities from inventions that were technologically distant from the firm's past activities. We differentiated between two types of patents that can be issued to a firm: *self-citing* patents, which include one or more citations to the firm's prior patents and are thus related to prior endeavors, and *non-self-citing* patents, which do not build on the firm's earlier patented inventions and thus are a departure from a focal firm's previous innovative activity.

Conditional on the firm having been granted at least one patent, we treated these outcomes as competing risks in an event-history framework. In competing risks models, the transition rate to a particular destination state (e.g., issuing a self-citing patent) can be decomposed into the overall rate of transition (the patent rate) times the probability of the destination state, given that the transition has occurred (Petersen, 1995: 482). Our hypothesis is that firm age should increase the rate of issuing self-citing patents. We do not have a strong prediction about how age will affect the rate of developing non-self-citing patents. On the one hand, a firm that suffers from poor organization-environment fit may have difficulty generating patents that do not build on its own prior work, suggesting a negative effect of age. On the other hand, the increased efficiency associated with the refinement of organizational routines may lead to a positive effect of age. It is therefore possible that aging will increase both the rate of issuing self-citing and non-self-citing patents. If obsolescence processes are operating, however, the relative tendency to self-cite should increase with age. We therefore expect that the age effect on issuing self-citing patents will be stronger than the increase in the rate of non-self-citing patents.

We tested hypothesis 3, that old firms will be less likely than young firms to incorporate the most recent technological developments into their previous innovative activities, by measuring the age of the foundations of each firm's current-period innovations (i.e., the age of the prior art cited by a firm's current-period patents). Because patent citations are tantamount to technological building relationships (Jaffe, Trajtenberg, and Henderson, 1993), firms that cite new patents are elaborating on the most contemporary areas of technology. Conversely, firms that cite old prior art are working in mature areas of technology. We predict that the patents of older firms will include longer citation lags (the time elapsed between the application dates of the cited and citing patent).

Previous studies have shown that highly cited patents cover innovations that experts in a technological area perceive to have been the most important inventions in that area (Albert et al., 1991). Therefore, patent citations reveal community-wide perceptions of the relative importance of patented technologies (see Trajtenberg, 1990). We therefore tested hypothesis 4, about the effect of organizational age on the importance of firms' innovations, by investigating how the age of a firm at the time it develops a patent affects the rate at which the patent is cited in the future. These analyses exclude all citations that a firm makes to its own, previously issued patents.

Firm age. The age of the firms in the semiconductor sample was measured as the difference between the current year and the time that the firm first entered the industry. For dedicated semiconductor firms, the date of first entry is the firm's incorporation date. For entrants from other industries, the date of entry is the first year that the firm began producing semiconductor devices. We used the date of first entry into the industry for these firms because virtually all entrants established new organizations (subsidiaries) on or shortly after their initial entry into the industry. Because the biotechnology sample consists of dedicated producers only, the age clock for the firms in this sample always begins at incorporation. Our models include both a monotonic and quadratic organizational age term to allow the models to determine if the effect of age on a focal outcome is linear or if the second derivative of age is positive or negative with respect to the different patent-based outcome measures.

Environmental change. Because of the substantial rate of change in high-technology industries such as microelectronics and biotechnology, the quality of the organization-environment fit should diminish with firm age. Our models implicitly assume that environmental change is not cyclical during the periods studied. Lacking good measures of the pace of change in the environments for the two industries, we were unable to make a different assumption. Because our analyses cover a relatively short period of time, however, we believe that the assumption of a linear path of change is reasonable. Moreover, our knowledge of the two industries suggests that although innovation has been rapid in both domains, neither one has experienced a radical or competence destroying technological change in the periods spanned by our data.[2]

Firm size. We included time-varying measures of firm size in our models, for two reasons. First, previous research has shown that models of age effects that fail to control for size yield biased estimates of the effects of age on organizational

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Tushman and Anderson (1986: 442) defined competence enhancing discontinuities as inventions that result in "sharp price-performance improvements over existing technologies" and competence destroying discontinuities as inventions that require fundamentally different skills and knowledge. No such radical changes occurred in semiconductors in our study period. Because of the nature of the technology, it is difficult to use the price-performance ratio as a metric of the importance of an invention in biotechnology. Perhaps the most significant shift in biotech in the period of our analyses was the growing importance and influence of genomics, but this area did not emerge in full force until just beyond the end of our sampling period.

outcomes, due to the typically strong positive correlation between the two variables (Barron, West, and Hannan, 1994). Because large organizations are often more bureaucratic and less entrepreneurial than small enterprises (Blau and Schoenherr, 1971; Abernathy, 1978; Aldrich and Auster, 1986), we expected that size would have a negative effect on the importance of firms' innovations. Second, controls for firm size are particularly important in studies of patenting behavior in light of the literature in economics on the association between firm size and innovation rates. This literature has explored the hypothesis, credited to Schumpeter (1942), that large firms generate a disproportionate quantity of innovation (Cohen, Levin, and Mowery, 1987; Cohen and Klepper, 1996). Economists have posited a number of potential explanations for this relationship, including capital market imperfections that preclude small firms from raising sufficient funds to support large R&D programs, the existence of scale economies in the R&D function, and the superior capacity of large firms to appropriate the returns generated by their discoveries.

We operationalized size in the microelectronics sample as the total volume of semiconductor sales of each firm in each year as provided in Dataquest; the sales measure reflects a firm's turnover in semiconductors only, not corporate-wide sales. The size of biotechnology firms was operationalized as the total number of employees of the firm in a year. Because many biotechnology firms do not have any revenues and their assets are usually intangible, the best measure of firm size in this industry is a headcount (Powell, Koput, and Smith-Doerr, 1996). Since we included only dedicated biotechnology firms in the sample, the corporate-level size data accurately reflect a firm's scale of operations in biotechnology. The source for these data was the annual Corptech directories.

Additional measures. For two reasons, all of the models we report include a calendar time trend (*year*). First, the volume of patenting increases over the observation window in both industries, and this temporal pattern would be captured by the age (and size) variables in the absence of the time trend. Second, the industry lifecycle model described above suggests that the actual composition of organizational innovation is likely to change as a consequence of the maturation of the industrial context. Even though the time interval we analyzed is relatively short, it is still necessary to incorporate the time trend.

In the citation-rate analyses, we controlled for the total number of patents previously applied for by each firm because this variable should capture differences between organizations in their quality threshold for patenting. We reasoned that the cost of patenting may vary across organizations and that this in turn would create differences in the quality threshold that an invention must surpass for the organization to decide to file for a patent. Our operating assumption was that, other things being equal, firms that have applied for many patents have lower costs of patenting. We therefore expected that the lagged patent count would have a negative effect on the rate at which patents are cited because, other things being equal, firms that have patented extensively in the past are likely to have a lower cost of patenting and are therefore more willing to patent lower-quality inventions.

In addition to our firm-level measures of size and number of patents (both at the time the patent was applied for), the citation-rate analyses include three characteristics of the patent itself. We included the age of the patent (i.e., the time elapsed since patent issuance) and a quadratic patent-age term to control for possible dependence of the citation rate on the amount of time the patent was available to the broader technological community (cf. Podolny and Stuart, 1995). We also included a series of dummy variables for the patent's major class as controls for differences in citation rates across broad technological domains.

Two additional covariates were included in the models estimated on the biotechnology sample (because we were able to obtain the necessary data only in this setting). First, the biotechnology models are reported with and without a control for the annual R&D expenditure levels of publicly traded firms. We were not able to obtain R&D spending for semiconductor firms or for privately held biotechnology firms. Therefore, the results including biotechnology R&D exclude the predominantly young, private firms in the sample. We report the biotechnology results without R&D both to allow comparisons with the findings from the semiconductor analyses and to avoid any sample selection bias.[3] Second, we included an indicator variable denoting if the chief executive officer of the biotechnology firm changed. The rationale for including this variable was that a change in senior-level leadership may be associated with a conscious, board-level decision to change the direction of the firm. Even when CEO changes result from mandatory retirements or volitional departures, replacing senior leaders may enable major alterations in the innovative foci of a firm. Therefore, we included this variable to learn whether leadership changes altered the innovation-related manifestations of aging.

Analysis

With the exception of the analyses of the age of the prior art cited in a firm's patents, all of our analyses employ event-history techniques. While previous studies in economics have modeled yearly patent counts (e.g., Hausman, Hall, and Griliches, 1984), our data sources specify the precise day on which patent applications were received by the Patent Office. We have opted to use event-history analysis, rather than the count models commonly employed by economists, for two reasons. First, in all of our nonparametric and parametric analyses of firm-level patenting rates, we found strong evidence of a rapid decline in the patent rate with the passage of time since the firm's last patent was issued. This violates a basic assumption of the Poisson distribution, which is the basis for event-count models. Specifically, the Poisson distribution assumes that the underlying rate of event occurrence is constant within a time period (e.g., King, 1989: 50). In addition, our data contain right-censored event histories. While there are awkward ways to accommodate right censoring using count models, they typically involve discarding information on the censored cases. By contrast, the hazard

3
Because many of the firms in our semiconductor samples were diversified, privately owned, or foreign-owned, we were unable to gather industry-specific, annual R&D expenditures for many of them, but we were able to collect the annual R&D expenditures of a small subset of firms in the industry (about one-third of the firm years in the full sample). Among publicly traded, dedicated, U.S.-based semiconductor producers, the correlation between R&D spending and sales was very high—0.978. Therefore, in the semiconductor sample, we are confident that size is a sufficient control for R&D spending.

rate models we employ incorporate information on both uncensored and censored cases. Therefore, event-history techniques are used throughout, although we have been able to reproduce all of the findings we report using a fixed effects negative binomial estimator (Hausman, Hall, and Griliches, 1984). All models were estimated in Stata 6.0.

The first two predictions were tested using patent-rate models. If we define T as the duration elapsed until a change in state, the instantaneous (hazard) rate of issuing a patent at time t is defined as

$$r(t) = \lim_{t' \to t} \frac{\Pr(t \leq T < t' \mid T \geq t)}{t' \to t}.$$

In the patent-rate models, duration is measured as the time elapsed since the last patent application date or, if the firm has issued no previous patents, the time since the firm was founded. The application dates of patents are recorded to the day. Although we do not model the full history of patenting of every firm, the data are left-truncated, not left-censored. Because we know the date of the most recent pre-sample-period patent for each firm and the date all firms were founded, we were able to measure duration for the initial spell of each firm correctly. Similarly, we were able to measure all covariates accurately.

We modeled the hazard rate using semiparametric Cox models (Cox, 1972). 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 X:

$$r(t) = h(t)\exp(\beta X).$$

The advantage of using a Cox model is that one does not need to make parametric assumptions about the form of duration dependence in the hazard rate. 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 β measure shifts in the baseline rate due to the covariates in X, under the assumption that all such changes are proportional—in other words, that h(t) does not depend on the covariates. For our analyses, the Cox model is appropriate: there is little theory to suggest how the transition rate should depend on the time elapsed since the previous patent (thus making parametric assumptions more difficult), and there is no reason to believe that the proportionality assumption is violated. To increase our confidence in the results, however, we also estimated piecewise-constant rate models, which generated nearly identical results.

Patent age. This variable was constructed by averaging the age of all patent citations (the difference between the current year and the year in which a cited patent was applied for) made in the patents of each firm in each year. Average citation age, which is defined for a firm in a year only if the firm had at least one new patent in that year, is continuous and approximately normally distributed. We therefore estimated models using OLS but corrected for autocorrelation of the disturbances within firms by using a fixed-effects estimator (Tuma and Hannan, 1984). Adding fixed effects for firms assumes that the correlation structure in the disturbance term can be decomposed into a firm-specific effect and a residual term that is uncorrelated across observations and is homoscedastic. Because of the inclusion of firm dummy variables, the estimated coefficients represent within-firm effects and so implicitly control for differences across firms in the technological areas in which they specialize. In addition to the other covariates, the citation age models include annual period effects.

A separate issue presents itself in the citation age models, namely, the possibility of sample selection bias (Heckman, 1976). The citation age measure is necessarily missing for a firm in any year in which the firm does not patent. To control for any biases such selection might induce, we used a generalization of the Heckman correction procedure suggested by Lee (1983). We used estimates from an event history patent-rate model to generate a predicted probability that a firm will patent at age t; this corresponds to the probit selection equation in the Heckman procedure. These predicted probabilities are then used to generate the following:

$$\lambda_{it} = \frac{\phi\{\Phi^{-1}[F_i(t)]\}}{F_i(t)},$$

where $F_i(t)$ is the survivor function for firm i at time t, ϕ is the standard normal density function, and Φ^{-1} is the inverse of the standard normal distribution function (Lee, 1983). We then include the time varying λ as a covariate in the fixed-effects models of citation age.

The final analysis concerned the effect of age on the importance of a firm's innovative outputs. Here, we inferred importance from the extent to which a firm's patents were cited in subsequently developed inventions. We performed this analysis at the level of the individual patent: we assumed that each patent is at risk of being cited by other firms from the time that it is issued and onward. These data were modeled at the patent level and as a continuous time event history because the patents in our database were issued at different points in time and so were at risk of being cited by future patents for different time intervals. We estimated Cox models of the citation rate and treated citation as a repeatable event. Duration was defined as the time elapsed since the issuance of the patent (if the patent had not been cited) or the time since last citation. Each time a patent is cited, it reenters the risk set with duration reset to zero. Firms are represented in this analysis proportional to their patent rate; virtually all firms are represented more than once. This will typically lead to inflated *t*-statistics for the effects of firm-level characteristics. We therefore present robust variance estimates that adjust for clustering at the firm level (Lin and Wei, 1989).

RESULTS

Firm-level descriptive statistics and bivariate correlations for the two samples are presented in table 1. These statistics make apparent the differences between the semiconductor and biotechnology industries in terms of patenting activity and average firm age. In both samples, there is a moderately high correlation between firm size and the total number of patents; the correlations involving firm age are more modest.

Table 2 displays a series of univariate statistics corresponding to each of the four predictions. This table splits the firms in each industry into four age categories and then presents category-specific means of the rate of patenting, the rate of self-citation patenting, the average age of the patents cited by each firm's patents, and the rate at which each of the patents of the firms in an age range are cited by patents developed by other organizations. In this table, all rates were computed by dividing the observed number of events (e.g., the number of patents) by the number of years that the firms in the age range were at risk of experiencing the event. Consistent with our predictions, the rate of patenting and of self-citation patenting increases sharply with firm age in both samples. Similarly, the age of the foundations of firms' current-period innovations (mean citation age) increases precipitously with firm age. Lastly, there is a monotonic decline across the age categories in the rate at which firms' patents are cited by the patents of other organizations. Our predictions find strong support in the univariate statistics; we then tested them in multivariate analyses.

We began by analyzing the relationship between aging and the rate at which firms in the two samples produced new innovations. Tables 3 and 4 present Cox-model estimates of the firm-level patent rate in the two samples. In addition to firm age and age-squared, the models include time-varying

Table 1

Descriptive Statistics and Correlations for Firm-level Data

Means and standard deviations

	Semiconductor (N = 150)		**Biotechnology (N = 237)**	
Variable	**Mean**	**Φ**	**Mean**	**Φ**
Firm size	350.07	762.47	121.32	310.54
Patents at entry to sample	94.91	246.72	2.11	6.06
Patents issued during sampling period	130.51	295.29	8.62	19.38
Firm age	18.54	12.26	4.31	3.48
Log R&D*	–	–	1.51	1.49
CEO change	–	–	0.09	0.29

Bivariate correlations†

	1	**2**	**3**	**4**
1. Size	–	0.758	0.439	–
2. Patent total	0.670	–	0.490	–
3. Firm age	0.242	0.292	–	–
4. Log R&D	0.555	0.549	0.321	–
5. CEO change	–0.022	0.007	–0.042	0.012

*The R&D measure is restricted to public biotechnology firms only.

† Correlations for the semiconductor industry are above the main diagonal; for biotechnology, they are below. Correlations are from the pooled cross-section time series data: N = 985 for semiconductor and N = 1,628 for biotechnology. Correlations involving R&D in biotechnology are restricted to public firms; N = 678.

Table 2

Characteristics of Patenting Activity by Age Groups*

Age	Overall patent rate	Self-citing patent rate	Mean citation age	Citation rate
Semiconductor industry				
0–12 Years	1.794	0.877	5.139	0.676
12–24 Years	9.255	3.731	5.548	0.621
24–36 Years	34.248	12.899	5.773	0.573
36+ Years	71.174	28.250	6.164	0.411
Full sample	17.920	9.350	5.596	0.556
Biotechnology industry				
0–4 Years	0.505	0.101	7.452	0.388
4–8 Years	0.980	0.329	7.870	0.356
8–12 Years	1.538	0.592	7.779	0.271
12+ Years	2.279	0.959	9.126	0.258
Full sample	1.151	0.723	7.931	0.320

* The predicted rates are computed by dividing the observed number of failures by the total duration at risk (in years). The rates of issuing self-citing patents are contingent on the firm having at least one patent.

measures of firm size (sales in semiconductors and total employees in biotechnology), a time trend, and a time-varying count of the number of (semiconductor or biotechnology) patents issued to each firm prior to the beginning of the spell. Including the frequency of occurrence of the focal event is a common method of controlling for unobserved heterogeneity (Heckman and Borjas, 1980). The occurrence dependence variable should control for the time-constant effects of unobserved factors (such as managerial ability) that produce variance in organizations' abilities or opportunities to patent.

The results in tables 3 and 4 show that older firms innovate at a higher rate. This supports our claim that as firms age, they gradually refine the organizational routines and competencies that underlie the production of innovations. In the semiconductor industry, a one-year increase in firm age leads

Table 3

Cox Models of Firm Patent Rates, Semiconductor Industry*

	Overall Patent Rate		Competing Risks Model			
			Non-self-citing		Self-citing	
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Size/1000	0.331••	0.329••	0.383••	0.382••	0.255••	0.260••
	(0.008)	(0.008)	(0.009)	(0.009)	(0.013)	(0.013)
Cumulative firm patents/100	0.416••	0.414••	0.096••	0.096••	0.899••	0.907••
	(0.014)	(0.014)	(0.018)	(0.018)	(0.021)	(0.022)
Year	–0.045••	–0.042••	–0.027••	–0.026••	–0.095••	–0.102••
	(0.004)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)
Firm age	0.029••	0.040••	0.027••	0.032••	0.040••	0.016
	(0.001)	(0.005)	(0.001)	(0.006)	(0.002)	(0.011)
Firm age squared/1000		–0.206•		–0.086		0.429•
		(0.098)		(0.118)		(0.201)
Log-likelihood	–149,176	–149,174	–98,100	–98,100	–50,409	–50,407
Events	17,470	17,470	11,519	11,519	5,912	5,912
Spells	18,445	18,445	18,095	18,095	18,095	18,095

• $p < .05$; •• $p < .01$.
* Standard errors are in parentheses. Π^2 test for equality of age coefficients in models (3) and (5): 24.40 (1 d.f.).

Table 4

Cox Models of Firm Patent Rates, Biotechnology Industry*

	Overall Patent Rate				Competing Risks Model: Non-self-citing				Competing Risks Model: Self-citing			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Size/1000	0.215••	0.153••	–0.098	0.153••	0.348••	0.306••	–0.048	0.304••	–0.141	–0.252•	–0.262•	–0.252•
	(0.043)	(0.045)	(0.055)	(0.045)	(0.048)	(0.049)	(0.062)	(0.049)	(0.103)	(0.109)	(0.122)	(0.109)
Cumulative firm	0.468••	0.940••	0.743••	0.940••	0.373••	0.703••	0.578••	0.703••	0.977••	1.410••	1.184••	1.410••
patents/100	(0.071)	(0.096)	(0.113)	(0.096)	(0.087)	(0.114)	(0.141)	(0.114)	(0.149)	(0.191)	(0.204)	(0.191)
Year	0.016	–0.010	–0.043••	–0.010	–0.025	–0.036•	–0.065••	–0.035•	0.047	0.016	–0.006	0.016
	(0.013)	(0.013)	(0.014)	(0.013)	(0.015)	(0.015)	(0.017)	(0.015)	(0.025)	(0.025)	(0.028)	(0.025)
Firm age	0.023••	0.302••	0.212••	0.302••	–0.008	0.204••	0.192••	0.203••	0.037••	0.389••	0.276••	0.389••
	(0.008)	(0.028)	(0.041)	(0.028)	(0.010)	(0.035)	(0.051)	(0.035)	(0.014)	(0.064)	(0.077)	(0.064)
Firm age		–15.358••	–11.809••	–15.362••		–11.624••	–12.799••	–11.601••		–16.908••	–11.184••	–16.907••
squared/1000		(1.557)	(2.154)	(1.557)		(1.955)	(2.782)	(1.954)		(3.196)	(3.709)	(3.197)
Log R&D			0.250••				0.356••				0.022	
			(0.030)				(0.037)				(0.053)	
CEO change				–0.016				–0.066				0.012
				(0.081)				(0.099)				(0.151)
Log–likelihood	–12,291	–12,217	–9,357	–12,217	–8,381	–8,355	–6,379	–8,355	–3,431	–3,409	–2,834	–3,409
Events	1,899	1,899	1,521	1,899	1,303	1,303	1,044	1,303	525	525	451	525
Spells†	3,563	3,563	2,227	3,563	2,843	2,843	2,077	2,843	2,843	2,843	2,077	2,843

• $p < .05$; •• $p < .01$.

* Standard errors are in parentheses. Π^2 test for equality of age coefficients in models (5) and (9): 6.35, 1d.f.

† The models including R&D (models 3, 7 and 11) are restricted to public firms only.

to a 3-percent increase in the patent rate; in biotechnology, the corresponding increase is 2 percent. Model 2 in both of the tables adds a quadratic age term to determine whether the effects of age are monotonic. There is some evidence of a weakly nonmonotonic age effect in the semiconductor sample. By contrast, patenting rates among biotechnology firms increase with age up to a point and then decline, generating an inverted-U shape. The point of inflection, or maximum effect on patenting, is at approximately 10 years of age.

We assessed the robustness of these results by including, in models 3 and 4 in table 4, measures of the R&D expenditures of (public) biotechnology firms and an indicator for recent CEO turnover. Firms with greater R&D expenditures have higher patenting rates; however, a change in firm leadership does not affect patenting rates. Most importantly, the effects of age remain highly significant and imply the same substantive result: patenting rates increase with age, at a decreasing rate. One might counter this claim with the argument that the increased patenting rates of older firms may be due to greater investments in a patenting infrastructure within the firm, if these investments lower the marginal cost of new patent applications. Since building such an infrastructure requires a certain degree of organizational slack, however, such investments should be strongly correlated with firm size, which is included as a control variable. Moreover, the models control for occurrence dependence with the lagged patent count, yet the positive effect of age persists. Net of firm size and the lagged patent count, the effects of age are strong and highly significant.

While we controlled for what we believe to be the most important firm-level determinants of innovative activity, a skeptic might still claim that the aging results we observe are due to the influence of unmeasured variables correlated with firm age. In least squares regression, such complications are often dealt with by including firm-specific dummy variables to control for any unmeasured characteristics. To our knowledge, however, there is no analogue to the fixed-effects estimator in an event-history framework. Therefore, we also estimated fixed-effects negative binomial models of counts of the number of patents applied for by each firm in each year. The results (available upon request) support the conclusions drawn from the hazard-rate models in tables 3 and 4: organizational age has a significant, positive effect on the patent rate in both samples.

Our remaining analyses show that the fit between an organization's outputs and environmental demands appears to decline as firms age. The first manifestation of this decline can be found in the fact that the innovations of older firms are more likely to consist of extensions of their established innovative domains, which suggests a positive association between firm age and patent self-citation rates. In addition to presenting models of the overall patenting rate, tables 3 and 4 present estimates from models in which we decomposed the overall patent rate into two competing risks: self-citing and non-self-citing patents. Since a firm can only issue a self-citing patent if it already possesses patents, these analyses are restricted to spells occurring after the firm's first patent.

In the semiconductor industry, age increases the rate at which a firm applies for both types of patents. There is no evidence to suggest a nonmonotonic effect of age. Firm age has a greater effect on the rate of self-citation patenting than it does on the rate of non-self-citation patenting. This difference is statistically significant: a Wald test of the equality of the age coefficients yields a χ^2 of 24.4 with 1 degree of freedom, which can be rejected easily at the 1-percent level. Thus, as semiconductor firms age, they grow increasingly more likely to build on their prior areas of activity than to branch into new technological domains.

The pattern of results is even more striking in the biotechnology sample. Here, firm age has a strong, positive effect on the rate of self-citation patenting. The effect of firm age on issuing a non-self-citing patent, by contrast, is statistically indistinguishable from zero. This difference is again statistically significant, yielding a χ^2 of 6.35 for 1 degree of freedom. As in the case of the overall patent rate, the rates of issuing both non-self-citing and self-citing patents exhibit nonmonotonic relationships with firm age; the patenting rates follow an inverted-U shape. Furthermore, the inclusion of controls for R&D spending and CEO turnover does not substantially affect the relationship between age and patenting. A firm's volume of R&D investments appears to increase the rate of generating patents in innovative domains that are new to the firm, but they have no impact on the propensity to create patents that extend the firm's existing work. A change in CEO leadership does not affect patenting rates.

These results are consistent with our claim that as firms age, they become increasingly likely to generate innovations that exploit existing competencies. The qualitative implications of these models are shown in figures 1 and 2. Figure 1 plots the predicted multiplier of the hazard rate for the two types of patenting in the semiconductor industry, based on the age coefficients in models 3 and 5 of table 3. As age increases, the relative tendency to issue self-citing patents increases. Figure 2 plots the hazard rate multipliers for biotechnology, based on the age effects in models 6 and 10 in table 4. There is clear evidence that as the age of biotechnology firms

Figure 1: Predicted effects of age on the patent rate in the semiconductor industry.

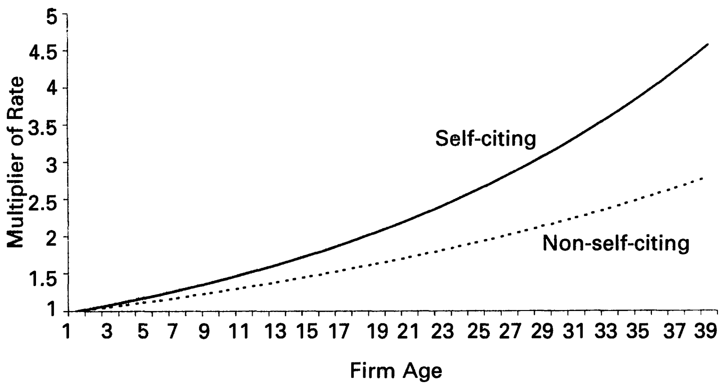
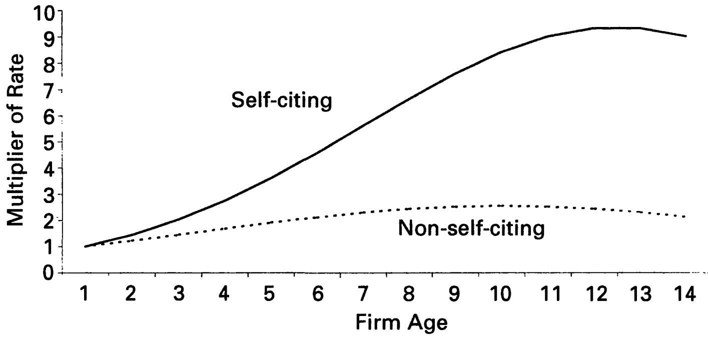


Figure 2: Predicted effects of age on the patent rate in the biotechnology industry.



increases, their propensity to generate patents based on their own prior innovations, as opposed to working in new innovative domains, increases dramatically.

We further hypothesized that as firms age, they would tend to work on refinements of older areas of technology. The extent to which firms have incorporated recent technological developments into their own innovations can be measured by the average age of the patents that they have cited as prior art. Table 5 presents estimates from fixed-effects models of the mean citation lag for all of the patents applied for by a firm (on a yearly basis), including Lee's (1983) correction for sample selection bias. In both the semiconductor and biotechnology industries, the age of the prior art cited increases significantly with firm age. Because the firm-specific dummies were included, the increase in the age of cited prior art can be attributed to the consequences of aging for

Table 5

Fixed-Effects OLS Models of the Average Age of Prior Art Cited in Patents Issued*

	Semiconductor		Biotechnology			
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Size/1000	–0.265 (0.300)	–0.258 (0.300)	–0.176 (0.785)	–0.166 (0.786)	0.092 (0.716)	–0.164 (0.786)
Cumulative firm patents/100	–0.050 (0.070)	–0.068 (0.078)	0.779 (1.052)	0.650 (1.076)	0.609 (0.992)	0.773 (1.054)
λ	0.056 (0.061)	0.056 (0.061)	–0.392 (0.441)	–0.382 (0.442)	–0.375 (0.412)	–0.400 (0.442)
Firm age	0.241•• (0.045)	0.205• (0.084)	0.428•• (0.135)	0.296 (0.262)	0.490•• (0.175)	0.430•• (0.135)
Firm age squared/1000		0.854 (1.650)		7.358 (12.522)		
Log R&D					–0.345 (0.385)	
CEO change						0.314 (0.589)
R^2	0.09	0.09	0.08	0.08	0.11	0.08
Spells†	517	517	451	451	295	451

• $p < .05$; •• $p < .01$.

* Standard errors are in parentheses. λ is an adjustment for sample selection bias as in Lee (1983). All models include dummy variables for annual period effects (estimates not shown).

† The models including R&D (models 3, 7 and 11) are restricted to public firms only.

the firm's innovative activity, rather than to cross-sectional differences in firm ages or between-firm differences in technological foci. This further reinforces our claim that as firms grow older, their outputs become increasingly dated. Older firms trail behind the technological frontier, focusing their innovative activities instead on well-established rather than up-and-coming technological domains.

Finally, we argued that older firms are likely to produce innovations that have a lesser impact on their technological communities than do those of young firms. This would manifest itself in a lower citation rate to the patents of older firms. Tables 6 and 7 present estimates from Cox models of the citation rate of all patents issued to the firms in our samples, with standard errors adjusted for clustering at the firm level. Model 1 in table 6 shows that in the semiconductor industry, firm age at the time of patent application has a significant negative effect on the rate at which the patent is used as a foundation for the work of other innovators. Patents issued by older semiconductor firms garner less attention from external actors. The effect of firm age on citation rates in biotechnology does not conform to our expectations, however, as is apparent from the first four models in table 7. For models estimated on the full sample of biotechnology firms,

Table 6

Cox Models of the Citation Rate to Patents Issued to Firms in the Semiconductor Industry*

	All patents		Non-self-citing	
Variable	(1)	(2)	(3)	(4)
257: Active solid-state devices (e.g., transistors, solid-state diodes)	0.235•• (0.040)	0.232•• (0.040)	0.267•• (0.038)	0.264•• (0.038)
307: Electrical transmission or interconnection systems	0.288•• (0.039)	0.283•• (0.040)	0.281•• (0.036)	0.277•• (0.037)
364: Electrical computers and data processing systems	0.103• (0.046)	0.104• (0.045)	0.144•• (0.052)	0.144•• (0.052)
365: Static information storage and retrieval	0.095•• (0.031)	0.090•• (0.030)	0.115•• (0.033)	0.110•• (0.032)
395: Information processing system organization	0.208•• (0.047)	0.214•• (0.049)	0.219•• (0.053)	0.223•• (0.054)
438: Semiconductor device manufacturing: process	0.365•• (0.029)	0.364•• (0.030)	0.407•• (0.042)	0.406•• (0.042)
Size/1000	0.053•• (0.016)	0.059•• (0.015)	0.045•• (0.016)	0.050•• (0.015)
Cumulative firm patents/100	–0.006 (0.004)	–0.006 (0.003)	–0.007 (0.005)	–0.007• (0.004)
Patent age	0.832•• (0.021)	0.839•• (0.021)	0.831•• (0.019)	0.838•• (0.019)
Patent age squared	–0.113•• (0.005)	–0.113•• (0.005)	–0.113•• (0.004)	–0.113•• (0.004)
Year	0.007 (0.007)	–0.001 (0.009)	0.012 (0.010)	0.004 (0.012)
Firm age	–0.008•• (0.003)	–0.032• (0.013)	–0.009•• (0.003)	–0.032• (0.014)
Firm age squared/1000		0.469 (0.259)		0.490 (0.294)
Log-likelihood	–308,088	–308,071	–200,235	–200,220
Spells	50,169	50,169	34,112	34,112

• $p < .05$; •• $p < .01$.
* Standard errors are in parentheses.

Table 7

Cox Models of the Citation Rate to Patents Issued to Firms in the Biotechnology Industry*

Variable	All patents (1)	(2)	(3)	(4)	Non-self-citing (5)	(6)	(7)	(8)
128: Surgery	0.001	−0.008	−0.065	−0.007	0.016	0.010	−0.086	0.010
	(0.162)	(0.161)	(0.155)	(0.157)	(0.174)	(0.173)	(0.169)	(0.171)
424: Drug, bio-affecting	−0.048	−0.053	0.042	−0.050	−0.152	−0.155	−0.108	−0.153
. . .compositions	(0.124)	(0.122)	(0.150)	(0.121)	(0.152)	(0.151)	(0.210)	(0.150)
435: Molecular biology and	−0.312•	−0.317•	−0.343•	−0.317•	−0.278•	−0.280•	−0.365•	−0.281•
microbiology	(0.126)	(0.124)	(0.157)	(0.124)	(0.135)	(0.134)	(0.178)	(0.133)
436: Analytical and	−0.315	−0.316	−0.180	−0.323	−0.409	−0.410	−0.196	−0.413
immunological testing	(0.258)	(0.256)	(0.251)	(0.257)	(0.281)	(0.280)	(0.255)	(0.280)
514: Drug, bio-affecting	−0.277•	−0.277•	−0.111	−0.277•	−0.215	−0.215	−0.070	−0.217
. . .compositions	(0.127)	(0.128)	(0.119)	(0.128)	(0.138)	(0.139)	(0.145)	(0.140)
530: Natural resins or	−0.479••	−0.481••	−0.430••	−0.484••	−0.465••	−0.466••	−0.478••	−0.470••
derivatives; etc.	(0.128)	(0.127)	(0.128)	(0.129)	(0.142)	(0.142)	(0.155)	(0.145)
536: Organic	−0.633••	−0.638••	−0.533•	−0.634••	−0.604••	−0.606••	−0.547•	−0.604••
compounds	(0.204)	(0.203)	(0.216)	(0.202)	(0.221)	(0.220)	(0.249)	(0.220)
Size/1000	−0.178••	−0.182••	−0.049	−0.179••	−0.125•	−0.127	0.050	−0.124
	(0.057)	(0.063)	(0.116)	(0.061)	(0.060)	(0.066)	(0.138)	(0.064)
Cumulative firm	−0.231	−0.235	−0.104	−0.229	−0.138	−0.142	−0.009	−0.137
patents/100	(0.150)	(0.150)	(0.160)	(0.149)	(0.192)	(0.192)	(0.189)	(0.189)
Patent age	0.879••	0.879••	0.895••	0.880••	0.852••	0.853••	0.870••	0.853••
	(0.048)	(0.048)	(0.058)	(0.048)	(0.054)	(0.054)	(0.064)	(0.054)
Patent age squared	−0.089••	−0.089••	−0.087••	−0.089••	−0.084••	−0.084••	−0.083••	−0.084••
	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)	(0.012)	(0.011)
Year	−0.098••	−0.098••	−0.118••	−0.101••	−0.095••	−0.095••	−0.114••	−0.097••
	(0.026)	(0.026)	(0.031)	(0.028)	(0.029)	(0.029)	(0.035)	(0.031)
Firm age	0.029	0.042	0.147••	0.042	0.018	0.026	0.181••	0.026
	(0.015)	(0.038)	(0.054)	(0.038)	(0.017)	(0.041)	(0.058)	(0.041)
Firm age		−0.655	−4.661	−0.653		−0.372	−7.259••	−0.372
squared/1000		(1.288)	(2.447)	(1.288)		(1.279)	(2.600)	(1.280)
Log R&D			−0.111				−0.125	
			(0.058)				(0.070)	
CEO change				0.070				0.055
				(0.109)				(0.133)
Log-likelihood	−18,206	−18,205	−12,463	−18,205	−13,780	−13,780	−8,847	−13,781
Spells	4,420	4,420	3,326	4,420	3,349	3,349	2,409	3,349

• $p < .05$; •• $p < .01$.

* Standard errors are in parentheses.

† The models including R&D (models 3 and 7) are restricted to public firms only.

our estimates suggest a positive but nonsignificant effect of age on the citation rate.

Occasionally, firms have been suspected of filing for a set of closely related patents to obtain an intellectual property blanket for a particularly important technology. This may lead firms to patent relatively marginal inventions that are unlikely to be of interest to the broader technological community. Because the citation rate models are estimated at the patent level, this phenomenon could lead us to find that old firms develop less important inventions when, in reality, they simply file for a large number of patents for marginal inventions to secure broad intellectual property coverage for certain discoveries. The final sets of models in tables 6 and 7 report citation-rate models that are restricted to the subsample of patents that, at the time of issuance, do not include self-citations to any of the firm's previously issued patents. By excluding all patents that make one or more self-citations, we should largely eliminate marginal patents filed for the purpose of filling in small holes in an intellectual property estate. The firm age coefficients, however, are essentially unchanged in the citation-rate models that exclude all such patents.

Firm size. As shown in table 3, large firms patent at a higher rate than smaller ones in the semiconductor industry. A positive effect of firm size is also evident in the biotechnology patent-rate models in table 4 but disappears in the model that controls for R&D spending. Results in tables 6 and 7, however, show that size has discrepant effects on the importance of firms' innovations across the two samples: in biotechnology, the patents of large firms are less well-cited on a per-patent basis, but the innovations of large semiconductor firms are more likely to be cited by the patents of other organizations. One possible explanation may be that technologies in that market are interdependent due to the need for compatibility among users of semiconductor devices. Therefore, the success of a new microelectronics technology may depend as much on the social capital and reputation of the firms sponsoring an innovation as it does on the underlying technical specification of a device (Tushman and Rosenkopf, 1992; Wade, 1995; Podolny and Stuart, 1995). Because resources in such highly interdependent markets are often distributed on the basis of reputations and promises, large and prestigious firms (e.g., Intel) are often able to attract other innovators as adopters and elaborators of their technologies even if their innovations are not superior from a technological standpoint. By contrast, there are no such network externalities in biotechnology.

DISCUSSION

The results of this study provide strong support for our argument that aging has two seemingly contradictory consequences for organizational behavior, and specifically for innovation. On the one hand, experience with a set of organizational routines leads to gains in the efficiency with which these routines are executed. On the other hand, in rapidly changing environments, the fit between organizational capabilities and environmental demands declines with age.

Our evidence shows that as organizations age, they generate more innovations: the competence to produce new innovations—or at least patents—appears to improve with age, but these gains in organizational competence come at a price, namely, an increasing divergence between organizational competence and current environmental demands. Most impressively, the results are generally consistent across two very diverse technological contexts, semiconductors and biotechnology. Moreover, in the biotech sample the effects are generally consistent with our theory even though the industry is quite young: the mean age of the firms in the sample is only 7.3 years, but the posited effects are already evident.

Of course, some of the findings are open to alternative interpretation. For instance, although there is considerable evidence that the patent-citation rate is a valid measure of the importance of the technology the patent represents, it is possible that patents are also cited at a lower rate when their owners succeed at excluding potential competitors from entering their areas of activity. If this were the case, then older firms might garner fewer patent citations because they have so dominated a technological area that others choose not to enter or perhaps are deterred from entering out of concern for competitive retaliation. Because individual findings may be interpreted in more than one way, our empirical strategy has been to establish a series of findings consistent with the obsolescence argument. Thus, considered as isolated findings, the results in each of the tables may not be accepted as strong evidence of an age-related decline in organization-environment fit. When the pattern of results is considered together, however, we feel that the evidence for the existence of an obsolescence process is persuasive.

The apparent paradox that organizations improve the functioning of their routines just as they lose touch with environmental demands is readily resolved with arguments about the trade-offs necessary for effective organizational learning (March, 1991). Gains in the efficiency of organizational routines are achieved by making simplifying assumptions about the state of the environment (Cyert and March, 1963). These assumptions may be formulated early in the firm's life and therefore may reflect the state of the environment near the time of founding (Stinchcombe, 1965). Unless routines are updated to reflect changes in the environment, the organization's capabilities will drift out of alignment with environmental demands. As a growing literature has established, however, introducing significant changes in organizational routines is risky, as it upsets existing balances of power and patterns of interaction, which may create short-term performance problems. Therefore, in the absence of compelling evidence of the inferiority of existing routines, firms are unlikely to substantially modify seemingly successful procedures. Rather, changes in the blueprints for behavior will tend to be incremental.

A number of unresolved empirical issues remain, and the results suggest some exciting possibilities for future research. One is the largely undocumented link between innovation and firm survival and, hence, based on the results we have reported, the indirect link from age to innovation to survival. We began this paper by describing two extremes, one in which aging had uniformly positive consequences for organizational innovation and another in which aging impeded the ability to innovate. We suggested that those two scenarios had direct implications for the emergent demography of organizations in high-technology industries. Yet the coupling between organizational survival and the innovation outcomes we have analyzed is not at all transparent. Although our results have demonstrated that the inventions of older firms tend to be less well matched to the current demands of the technological field than those of younger ones, this disadvantage could be overcome if older firms possess stronger relations with vendors, buyers, and strategic partners or if they enjoy higher status and a superior reputation. In short, it would be useful to study the joint effects of age and innovation outcomes in models of organizational mortality or growth. Due to the positional advantages that older firms may have accrued (Hannan, 1998), age may have a negative effect on mortality in models that control for measures of the organization-environment fit.

Another promising avenue for future research concerns the intersection between industry- and firm-level maturation processes. At the level of the firm, our arguments suggest that the ultimate impact of aging on organizational performance depends on whether the gains in competence due to experience are negated by the decline in performance due to poor organization-environment fit. At the field level, evolutionary models of technical change suggest that the pace and content of technical development tend to vary systematically with the maturity of a technological area. Studies have shown that the early period of a new area of technology is often characterized by technological ferment but that the pace of change slows after the emergence of a dominant design (Abernathy, 1978; Abernathy and Utterback ,1978; Dosi, 1982; Tushman and Anderson, 1986). At that point, innovation becomes more incremental, and process innovation increases in importance relative to product innovation. Coupling the insights of the evolutionary model with our arguments suggests that the slope coefficients on firm age in the models of organization-environment fit are likely to vary across levels of industry maturity. If the pace of change in the environment is sufficiently subdued (as may be the case later in an industry's lifecycle), the efficiency advantages that accrue to older organizations give them a competitive advantage over younger firms. The coefficients on the age variable in the models of organization-environment fit may then approach zero. In this respect, the effects of aging on organizational performance are contingent on the organization's context. The time period spanned by our data is too short to allow us to explore this contingency empirically, but it seems a promising direction for future research.

One of the limitations of patents as an innovation index is that these data do not allow us to examine how organizational age affects the commercialization of new technologies. Case-based evidence and the popular press suggest that older firms often experience great difficulty in shepherding inventions from the R&D lab into the marketplace when the inventions differ substantially from the firm's established areas of business. Perhaps the most celebrated example of this failure is Xerox, whose Palo Alto Research Center (PARC) is credited with having developed many of the seminal technologies used in personal computing, graphical displays, and computer networking (Hiltzik, 1999). Unfortunately, Xerox failed to capitalize on most of the developments at PARC, although it did patent a number of the PARC discoveries. This case suggests that analyses of patent data may understate the adverse consequences of aging on the organization-environment fit, since Xerox successfully established a satellite R&D lab that developed many revolutionary technologies, but the organization as a whole failed to understand and assimilate PARC's developments. In terms of research avenues, this case suggests the importance of exploring the aging process with other measures of innovation.

More generally, our findings raise a number of questions about the general consequences of aging for organizational functioning and dynamics and of the effects of aging on innovation in particular. One intriguing issue is the relationship between organizational aging and the demography of the organizational workforce. For example, differences across firms in the pattern of recruitment and turnover over time may mediate the relationship between aging and organizational innovation. On one hand, high levels of turnover, particularly in key roles, may dilute the institutional memory of the organization. Firms with high turnover levels therefore might not see the gains in competence associated with aging. On the other hand, high levels of turnover also expose the firm to a greater variety of external influences (Baty, Evan, and Rothermel, 1971; Sørensen, 1999), which may make it easier for the firm to stay abreast of new technological developments. Although we observed no immediate effects of CEO turnover on the patent-based outcome measures in this study, our analysis of this possibility is incomplete because of the short time frame of our data, which precluded experimentation with different lag structures. Similarly, we ran a series of unreported models looking at the impact of changes in firm headcount on the measures of organization-environment fit. Here, as well, we found no significant effects on the patent-based outcome measures, although this analysis was also handicapped by our inability to incorporate multiyear lags. A particularly promising avenue for future research would be to examine how the sources and timing of recruitment, rather than simply the volume of hiring, moderates the effects of aging.

Another issue is the managerial implications of the age-related decline in organization-environment fit. As Barnett and Carroll (1995) noted, organizational theories have for some time been polarized according to their perspective on the adaptability of organizations. Our own perspective is that the mismatch between older firms' capabilities and the environment's demands poses a particularly difficult problem for managers because it develops incrementally and is hard to detect. This is in part because the increasing mastery of existing routines disguises the gradual divergence between the organization's areas of competence and the environment's demands. Although inertia is clearly a powerful force in high-technology firms, further study of the role of management practice in moderating the age-innovation relationship would be fruitful.

Finally, the increasing gap between the organization's innovative capabilities and the technological frontier creates opportunities for new firms whose internal routines are better aligned with the current state of technological development. Students of technical change have long observed that many major innovations are pioneered by young, entrepreneurial firms. The success of such start-ups is to a large extent contingent on the inability of established firms to enter important, emerging market niches and out-compete the new ventures. This suggests that age-related obsolescence in established organizations is a necessary condition for the surge in entrepreneurial activity in high-technology industries and that organizational aging is an important source of dynamic change in high-technology markets.

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