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THE EFFECT OF THE INNOVATIVE ENVIRONMENT ON EXIT OF ENTREPRENEURIAL FIRMS

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To foster 'creative destruction,' entrants must survive the turbulent conditions they face in their first crucial years in the industry. We investigate how the external knowledge milieu of an entrant, conceptualized as its innovative environment, causes systematic variation in survival patterns. We test our model from 3,431 firms in 33 industries over 80 years. We depict the innovative environment along two knowledge-related dimensions, namely technology regime and technology intensity. While the aligned state of the innovative environment, where product innovation exists in tandem with abundant innovation opportunities, promotes entrant survival, we find that this beneficial effect is more pronounced for small entrants due to a possible mitigation of scale disadvantages.

The entry of new firms, the reorganization and rationalization of existing firms, and subsequent exits are all recognized as evolutionary forces that shape competitive dynamics within markets. Such forces are unleashed when entering firms introduce innovations that are based on new technological knowledge or customer insights (Hayek, 1945; Schumpeter, 1934). Knowledge, therefore, is the genesis of entrepreneurial entry (Venkataraman, 1997). However, although contemporary perspectives have typically focused on the strategic benefits of knowledge that is internal to a firm, the evolutionary and innovation literatures suggest the intriguing possibility that knowledge conditions in the external environment of an entrant may also carry important implications for its survival. In this paper, we draw attention to how knowledge shapes the external milieu, or the innovative environment of an entering firm, and examine the implication of different types of such environments for entrant survival.

Studying the root causes of survival of industry entrants is fundamental to understanding whether entering firms will survive in the focal market long enough to have a discernible effect on it. By influencing the rate at which economically valuable knowledge is created (Arrow, 1962), entrepreneurial entry impacts economic welfare and growth (Acs *et al*., 2003). Thus, as agents of change, entrants can profoundly influence the

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social diffusion of innovations. However, the vulnerability of a large number of entrants to liabilities of newness and smallness has been emphasized (Freeman, Carroll, and Hannan, 1983; Stinchcombe, 1965). In fact, empirical findings of endemic entrant failure (Huyghebaert and Van de Gucht, 2004) vindicate Geroski's (1995) claim that entry is often times easier than survival. Of particular concern is whether the pattern of change in markets resembles a 'revolving door,' where the majority of entrants exit soon after they enter, rather than 'creative destruction,' where entrants displace old firms that have lost their ability to create value. However, our understanding of the forces governing change in an industry and the conditions under which small, new firms can survive is limited. As Shane (2001) wrote, there is a need to explore variance in the exit rates of entrants to accurately determine the level of entrepreneurial churn in an industry.

Previous research suggests that it may make particular sense to study the confluence of entry timing, demographics, and industry in order to further our understanding of the phenomena of entrant survival. First, both organizational ecology and economics research indicates that early-year survival depends on an entering firm's size (Audretsch and Mahmood, 1995; Freeman *et al.*, 1983). Second, studies also indicate that entrant survival may be influenced by the technology regime, or the evolutionary stage, of the industry at the time of entry (Agarwal, Sarkar, and Echambadi, 2002). In this vein, evolutionary scholars examine how the relevance of a particular type of knowledge base to innovation changes as the industry progresses through its life cycle, and how such transformations impact competitive advantage that accrues to different types of firms (Gort and Klepper, 1982; Nelson and Winter, 1982; Suarez and Utterback, 1995; Tushman and Anderson, 1986). Third, there are indications that the scientific nature of an industry, as captured by its technology intensity, may impact competitive dynamics within industries and thereby influence entrant survival (Geroski, 1990; Klevorick *et al.*, 1995; Zahra, 1996). For example, investments in knowledge-producing activities may push out the technological frontier of an industry, and create more innovation opportunities for new entrants (Kamien and Schwartz, 1982; Mansfield, 1968; Silverberg, Dosi, and Orsenigo, 1988).

In other words, previous research suggests that patterns of entrant survival may vary across time (*when*), industry (*where*), and size (*how*) of entry. Although there may arise intriguing possibilities when considered in conjunction, the interplay among these temporal, spatial, and scale dimensions of entry and their joint implications on entrant survival have been largely unexplored. In this paper, we attempt to address this lacuna in research. Towards this end, we propose that two of these dimensions—technology regime (which relates to timing of entry) and technology intensity (which relates to the industry where entry is occurring)—comprise interrelated knowledge-based dimensions of an entrant's *innovative environment*. Technology regime is related to the comparative importance of knowledge that is possessed by entrants to that of incumbents with respect to applicability to innovation. Technology intensity, on the other hand, relates to cross-sectional differences in the 'inventive potential' of industries (Rosenberg, 1974) and innovation opportunities that are made possible by knowledge investments in an industry (Romer, 1986). Within this framework of the innovative environment where entry takes place, we investigate how entrant size shapes survival patterns. We report tests of our hypotheses using longitudinal data on 3,431 firms that entered 33 industries between 1908 and 1991.

THEORETICAL FRAMEWORK

Knowledge and the innovative environment

According to the knowledge-based view of the firm, the generation, combination or recombination, and exploitation of knowledge (Conner and Prahalad, 1996; Kogut and Zander, 1992) underlies all firm organizations. While contemporary work tends to view knowledge predominantly through the lens of competitive advantage (Barney, 1991; Grant, 1996), the entrepreneurship literature has long acknowledged knowledge to be the fountainhead of innovative entry of new firms (Venkataraman, 1997). When entrepreneurs seek to reap the economic value of unique and idiosyncratic knowledge stemming from technological breakthroughs and/or customer insights, they enter a market with their innovations (Hayek, 1945; Schumpeter, 1934). Typically, the emphasis in the strategy literature is on knowledge that a firm possesses, and which is thus *internal* to a firm. However, rich research streams on industry evolution and on innovation have emphasized that knowledge that is *external* to a firm may impact entry and exit patterns.

Our interest lies in being able to predict patterns of firm survival, which we define as continued operations in the focal industry. While the equivalence between economic performance and survival has been questioned (Gimeno *et al*., 1997), we justify our focus on survival, or on its corollary of exit, on the basis of theory, precedence and context. First, it has been argued that well-performing firms survive, while poor performers exit the market (Penrose, 1952; Winter, 1984; Williamson, 1991). Accordingly, seminal studies in population ecology (Freeman *et al*., 1983), IO economics (Geroski, 1995), and strategy (Agarwal *et al*., 2002) have considered firm survival as a valid organizational outcome. Moreover, in the present context where we wish to study entrepreneurial churn as a precursor to new entrants being able to fulfill their larger role as change agents, continued survival during the initial years of heightened mortality is a first-order condition which takes precedence over any other parameter of performance.

The evolutionary view suggests that the type of knowledge that underlies technological innovation undergoes transformation over time as an industry matures (Gort and Klepper, 1982; Nelson and Winter, 1982). Accordingly, competitive conditions and survival advantages change over time as an industry evolves. Complementary research on innovation and technological progress highlight how spillovers from knowledge investments create differences in innovation opportunities across industries (Arrow, 1962; Jaffe, 1986; Mansfield, 1968; Romer, 1986; Rosenberg, 1974). These perspectives on temporal and cross-sectional differences in knowledge conditions suggest that their roles as complementary factors together determine the *innovative environment* facing an entrant. The first, *technology regime*, relates to the potential relevance of entrant vs. incumbent knowledge, while the second, *technology intensity*, relates to innovation opportunities available to entrants in the industry. We define and discuss each dimension of the innovative environment, and then draw conclusions about their joint impact on entrant survival and exit.

Technology regime

Scholars in economics, organizational ecology, and strategy argue that evolutionary processes shape the type of knowledge that forms the foundation behind firms' innovative actions in an industry (Gort and Klepper, 1982; Hannan and Freeman, 1989; Nelson and Winter, 1982; Tushman and Anderson, 1986; Utterback and Abernathy, 1975). While emphasizing these dynamics of innovation, Nelson and Winter (1982) further propose the notion of 'regimes of technological change' as a way to describe the knowledge bases underlying firms' innovation processes, as well as the modal properties of their learning processes and sources of knowledge (Dosi, 1982). Following Schumpeter's (1934) identification of historical phases of economic development, Nelson and Winter (1982) distinguish between 'entrepreneurial' and 'routinized' technology regimes. During the initial entrepreneurial regime of an industry, the stock of industry-specific knowledge is low, and knowledge that is critical to innovation lies outside established incumbent routines, thus favoring entrants rather than incumbents (Gort and Klepper, 1982). As the industry matures into a routinized regime, innovation is increasingly determined by accumulated stocks of non-transferable, internalized, market-based expertise. Therefore, while an entrepreneurial regime facilitates innovation by new firms, the routinized, experience-based regime helps innovation by industry incumbents (Dosi, 1982; Gort and Klepper, 1982; Winter, 1984). In other words, the knowledge-based advantage of entrants over incumbents reverses over time, as do *ex ante* prospects for making technical advances.

We note that technology regimes are analogous to Tushman and Anderson's (1986) 'era of ferment' and 'era of incremental change.' The concept of regime is also consistent with work on competitive density, legitimation, and competition in organizational ecology (Hannan and Freeman, 1989). Further, Gort and Klepper (1982) describe five stages of a product or technology life cycle, and Klepper and Graddy (1990) divide this life cycle into three stages. Integrating the different literature streams, Agarwal *et al*. (2002) note that the entrepreneurial regime (which they call the 'growth phase') and the routinized regime (the 'mature phase') are separated by a major change in competitive conditions, which suppresses entry into the observed industry. Regardless of differences in the naming and numbering of stages of industry evolution, the notion that knowledge-based advantage changes sides over time appears consistently in the relevant scholarly literature. Entrants have an innovation advantage over established firms in an initial period, but established firms have the innovation advantage in a later period. Here, we refer to periods in the knowledge history of industries as technology regimes.

Technology intensity

We conceptualize technology intensity as the degree to which the industry invests in creative activities that increase the stock of scientific knowledge and its use in new applications. Research suggests that technology intensity reflects not only the munificence of innovation opportunities within the industry, but also the ability of firms to appropriate economic returns from new developments (Klevorick *et al*., 1995). Investments in knowledge-generating activities not only have a 'spillover' effect on innovation opportunities (Arrow, 1962; Mansfield, 1968), but more importantly, technology-intensive industries can sustain higher rates of technological opportunities because even though firms may be rapidly exploiting prevailing opportunities, new ones are being created equally rapidly (Allen, 1977; Jaffe, 1986). The inherent relationship of investments in knowledge-producing activities with opportunities for innovation has implications for entrepreneurial entry and the pattern of change in an industry.

First, technological opportunities are a by-product of knowledge investments. Knowledge spillovers from scientific discoveries stimulate technological opportunities, which in turn create an impetus for innovation and entrepreneurial entry (Acs *et al*., 2003; Levin and Reiss, 1988). Investments in knowledge-generating activities thus create positive externalities and growth opportunities (Arrow, 1962; Mansfield, 1968; Romer, 1986). In other words, the public good aspect of knowledge and associated spillover effects in the industry implies that technology intensive environments are likely to have a greater magnitude of innovation opportunities that entrepreneurial entrants can take advantage of (Acs *et al*., 2003). For instance, recent work indicates that, due to the permeable nature of organization boundaries, technological investments by incumbent firms create entrepreneurial opportunities for their employees (Agarwal *et al*., 2004; Klepper, 2002).

Second, technology intensity increases the number of ways in which an entrant's offering can be differentiated from existing products (Blair, 1972; Comanor, 1967). Scientific and market breakthroughs from knowledge investments tend to engender products constantly increasing in sophistication (Shaked and Sutton, 1987). Often, these scientific breakthroughs result in opportunities to create new markets that are ignored by existing firms but exploited by entrants (Christensen, 1997). According to Comanor, expenditures in research 'foster and promote a rapid rate of new product introduction, which then serves to facilitate the achievement of differentiation' (Comanor, 1967: 646). Not surprisingly, therefore, it has been noted that high-technology industries, or those characterized by high investment in scientific know-how, experience more entrepreneurial activity and foster faster new product and process innovation (Acs and Audretsch, 1988; Geroski, 1990; Zahra, 1996). Since rapid innovation tends to 'deconcentrate' markets (Blair, 1972; Geroski and Pomroy, 1990), it seems that technology intensity may have implications not only for the entry of innovators, but also for their survival.

The innovative environment and entrant survival

We combine the two complementary dimensions of the innovative environment discussed above, namely, technology regime and technology intensity, to define four states of the innovative environment facing an industry's potential entrants. Figure 1 shows these four states. We name the entrepreneurial regime of high-technology-intensity industries *the aligned environment* (Cell I), since in this state entrants possess a knowledge advantage and innovation opportunities are abundant. In direct contrast, *the nonaligned environment* (Cell IV), or the routinized regime of low-technology-intensity industries, represents conditions in which entrants lack a knowledge advantage and have fewer innovation opportunities. The other two states are partially aligned, since entrants either have either fewer innovation opportunities (Cell II) or a knowledge disadvantage (Cell III).

Entrants in the aligned (Cell I) environment are likely to enjoy a better survival rate than those in any other quadrant. Unlike entrants in either

		Technology Intensity	
		High	Low
Technology Regime	Entrepreneurial	***I: Aligned Environment:*** Entrant Knowledge Advantage More Innovation Opportunities	***II: Partially-aligned Environment*** Entrant Knowledge Advantage Fewer Innovation Opportunities
	Routinized	***III: Partially-aligned Environment*** Entrant Knowledge Disadvantage More Innovation Opportunities	***IV: Nonaligned Environment*** Entrant Knowledge Disadvantage Fewer Innovation Opportunities

Figure 1. The innovative environment facing entrants

the nonaligned Cell IV or the partially aligned Cell III, firms that enter in Cell I experience the entrepreneurial regime of an industry. As discussed above, during this period, the stocks of industry-specific knowledge and routinized information that would favor incumbents are relatively low (Acs and Audretsch, 1988). In Cell I, the knowledge advantage the entrepreneurial regime confers is further reinforced by the presence of innovation opportunities conferred by the technology intensity of the industry, thus providing entrants in the aligned environment an advantage over the firms entering the partially aligned Cell II. As discussed above, positive spillovers of technology and increased scope for differentiation in industries with high technology-intensity permit entrants to seize innovation opportunities (Kessides, 1991) or occupy strategic niches (Porter, 1980), thus increasing their probability of survival. In short, entrants into an aligned environment can benefit from the synergy of relevant knowledge and abundant opportunities.

On the other hand, the nonaligned Cell IV represents a hostile environment for entering firms, because they not only face an unfavorable technology regime, but are also starved of innovation opportunities. The routinized regime implies that incumbents have the knowledge advantage *vis-à-vis* entrants, and the low technology intensity implies that there are few opportunities for enjoying spillover or differentiation benefits. As a result, these entrants are disadvantaged with respect to both dimensions of innovative environment.

In the partially aligned Cells II and III, the situation is less clear. In Cell II, knowledge conditions are favorable because the entrepreneurial regime prevails, but technological opportunities are lacking because technology intensity is low. In Cell III, technological opportunities abound because technology intensity is high, but knowledge conditions disadvantage entrants because the routinized regime prevails. Clearly, these partially aligned environments are not as good as Cell I, but are preferable to Cell IV. Differentiating between the entrant conditions in Cells II and III requires judging the relative importance of the two dimensions. On the one hand, if appropriate knowledge is a precursor to exploiting market opportunities, Cell II is likely to be better for entrants than Cell III. On the other hand, if abundant market opportunities will allow entrants to occupy market niches left vacant by incumbent organizations, even though these entrants have knowledge disadvantages, Cell III appears more favorable than Cell II for entrants. Therefore, because there are strong theoretical arguments in both directions, we treat Cells II and III similarly in our hypothesis below, and leave the resolution as an empirical issue.

Hypothesis 1: New entrants into an aligned innovative environment are less likely to exit the market than new entrants into nonaligned *innovative environments. New entrants into partially aligned environments will have intermediate likelihoods of exit.*

Entry size and the innovative environment–survival relationship

In the above discussion, we did not distinguish among the firms that enter a new industry. In essence, we treated entrants as homogeneous, since our focus was the innovative environment they face. We now turn to a key entry characteristic of a firm—one that has received significant attention—the size or scale of entry. We posit that size may moderate the relationship between innovative environment and entrant survival.

Studies in organizational ecology (Freeman *et al*., 1983; Hannan and Freeman, 1984) and industrial organization (Dunne, Roberts, and Samuelson, 1988; Sutton, 1997) indicate a positive relationship between firm size and survival. Organizational ecologists propose that the liability of smallness stems from three factors: the selection processes that favor the structural inertia of larger organizations (Hannan and Freeman, 1984), their access to capital and trained manpower and their legitimacy with external stakeholders (Baum and Oliver, 1991). In economics, size advantage emanates from market power (Bain, 1956) and minimum efficient scale considerations (Jovanovic, 1982; Mansfield, 1962). Thus, small entrants suffer a liability of smallness because they are likely to lack production and procurement economies, institutional support and linkages (Baum and Oliver, 1991; Stinchcombe, 1965), refined routines, and the ability to produce outputs of consistent quality (Hannan and Freeman, 1984).

Since small entrants lack the additional cushion of size that is available to large entrants the receptivity of an environment becomes particularly important, and an aligned innovative environment may be necessary for high levels of survival. Given the vulnerabilities of small entrants, an environment that is not only rich in innovation opportunities, but also gives them a knowledge advantage is likely to facilitate their survival more than any other type of environment. On the other hand, large entrants may additionally find other states of the innovative environment, particularly the partially aligned ones, favorable to their survival prospects, because they do not have the liability of smallness. Their larger scale of entry and access to deep pockets and resources may shield them in an environment that lacks perfect alignment of the dimensions that facilitate entry and entrant survival. While entering an aligned environment would certainly benefit large entrants, their scale of entry may mitigate the disadvantage of either few innovation opportunities or no entrant knowledge advantage. Our next hypothesis reflects this difference in the innovative environment–survival relationship for small and large firms.

Hypothesis 2: Entry size moderates the relationship between innovative environment and likelihood of exit such that the aligned innovative environment will be more crucial for small entrants than for large entrants.

METHOD

Data

We used longitudinal data on firm entry and exit from 1908 to 1991 in 33 manufacturing industries to test our hypotheses. The *Thomas Register of American Manufacturers*, our source of information for firm-level data, is a buying guide for the full range of products manufactured in the United States (Lavin, 1992: 129). Researchers in economics, strategy, and marketing have relied on the guide to study issues related to the diffusion of innovations and market evolution (see Gort and Klepper, 1982; Klepper and Simons, 2000; Robinson and Min, 2002). The publishers of the *Thomas Register* seek to obtain the complete representation of domestic manufacturing activity by analyzing a broad range of industry newsletters as well as start-up ventures in university incubators. Moreover, the guide does not charge a fee for inclusion, which further fosters its completeness and accuracy.

The 33 manufacturing industries included in our study are drawn primarily from the Gort and Klepper (1982) study of 46 industries that resulted from product innovations. We designated the first year that an industry appeared in the *Thomas Register* as the year of an innovation's commercial introduction.[1] The Gort–Klepper study tracked only the

[1] Gort and Klepper (1982) supplemented the *Thomas Register* with other sources for some of their products. As a result, their year of commercialization sometimes preceded the year a product was first listed in the *Thomas Register*. However, since the number of firms that entered in the early years for the

number of firms existing in these industries, and their data are censored at 1973. We developed the data independently and extended the time period through 1991. As a result, several of the industries in the Gort–Klepper study could not be used for new data development. Some industries (e.g., nylon, computers) experienced substantial changes in definition over the years for which we conducted the analysis. Other industries (e.g., DDT, cryogenic tanks) were omitted due to their discontinuation over the years for which the analysis was extended. Still other categories (e.g., streptomycin, penicillin) were discarded in favor of the broader industry group of antibiotics. A few industries were not included in the analysis owing to time limitations on the development of data. Finally, two new industries—contact lenses and video cassette recorders—were included since they gained prominence after the Gort–Klepper study was published. The final set of 33 industries (see Table 1) compares favorably with the number of industries investigated by other historical studies (cf., for example, Sultan, Farley, and Lehman, 1990).

Two sets of research assistants independently made lists of the firms that entered and exited each industry from its first listed year through 1991. In addition to the names and addresses of firms, the

few products for which Gort and Klepper (1982) had additional information is very small, we do not expect our reliance on the *Thomas Register* for the systematic identification of the year of commercialization to yield substantively different results.

Table 1. List of industries in the sample

Industry name	Year of commercial introduction	Onset of routinized regime[a]	Technology intensity	Number of entrants in industry	Number of firms that exited industry within 5 years of entry
Antibiotics	1948	1968	High	66	17
Artificial Xmas Trees	1938	1962	Low	56	19
Ball-point Pens	1948	—	Low	226	85
Betaray Gauges	1956	1971	High	19	3
Cathode Ray Tubes	1935	1967	High	122	41
Combination Locks	1912	1942	Low	93	33
Contact Lenses	1936	—	High	73	15
Electric Blankets	1916	1963	Low	47	11
Electric Shavers	1937	1949	Low	58	31
Electrocardiographs	1942	1975	High	41	8
Freezers	1946	1966	Low	132	45
Freon Compressors	1935	1980	Low	74	29
Gas Turbines	1944	—	High	138	35
Guided Missiles	1951	1966	High	386	90
Gyroscopes	1915	1978	High	121	36
Heat Pumps	1954	—	Low	117	38
Jet Engines	1948	1965	High	79	14
Microfilm Readers	1940	1977	High	94	31
Nuclear Reactors	1955	1965	Low	82	24
Outboard Motors	1913	1974	Low	119	45
Oxygen Tents	1932	1965	High	48	16
Paints	1934	1967	Low	221	36
Phonograph Records	1908	1927	Low	237	88
Photocopying Machines	1940	1971	High	94	34
Piezoelectric Crystals	1940	1964	High	93	27
Polariscopes	1928	1959	High	42	12
Radar Antenna Assemblies	1952	1966	High	113	38
Radiant Heating Baseboards	1947	1965	Low	46	6
Radiation Meters	1949	1967	High	65	24
Recording Tapes	1952	—	Low	160	54
Rocket Engines	1958	1966	High	38	4
Styrene	1938	1980	Low	89	23
Video Cassette Recorders	1972	—	Low	44	12

[a] Six industries in the study did not exhibit the onset of entry barriers for the period under investigation.

following firm-specific data were collected: year of entry, year of exit, asset size, and diversification index. The year of entry (exit) was designated as the first year that the firm was listed (delisted) in the *Thomas Register* in the industry records. The asset size was obtained from the entry year listing. Information on diversification was obtained by consulting the annual firm index volumes of the *Thomas Register* for the year preceding a given firm's industry entry to see if the firm had produced in any other manufacturing category prior to its entry in the focal industry. We then compared the data from the two sets of assistants to reconcile discrepancies, rectify mistakes, and ensure the accuracy of our records. For example, before classifying an event as an entry or as an exit, we verified data from successive years. We compared the names, addresses, and other relevant information of firms to ensure that an actual entry/exit had occurred, and excluded the cases in which existing firms had merely been renamed or relocated. Identifiable mergers were treated as the continuance of the larger firm and the exit of the smaller firm (Mansfield, 1962).[2] Additionally, we obtained information on the R&D intensity of the industries from the Survey of Industrial Research and Development conducted by the National Science Foundation.

Our data provide several advantages. First, they represent a great number of industries that resulted from product innovations, and these industry histories span almost the entire twentieth century. These features lend a potential for generalizability lacking in single-industry studies. Second, our use of objective, historical data from industry directories ensures that our study does not suffer from potential self-report bias of survey-based data. Third, using data recorded at the time of event occurrence enables us to better study time-related effects without the fear of survivor bias. Finally, future replication and validation studies are feasible, since our data were compiled from secondary data sources.

Variable definitions

Entrants are defined as firms who are less than 5 years old in the focal industry. The 5-year time span has been used in earlier studies of entrant survival (e.g., Baldwin, 1995; Robinson and Min, 2002), and is consistent with our focus on early-year survival patterns. Our final dataset consists of 3,431 firms for a total of 14,173 firm–year observations. Table 2(a) concisely describes the

[2] Coding firm exits in this manner, while consistent with other studies (Dunne *et al*., 1988; Robinson and Min, 2002), leads to the fundamental question: Does every merger/acquisition indicate a firm's failure, or do some reflect only success? Although redefining risks of exits that allow this delineation might prove extremely useful, data limitations did not allow us to make this distinction. Moreover, a check revealed that less than 3 percent of our exits were attributable to identifiable mergers, leading us to believe that our substantive results would not vary as a result of this limitation.

Table 2(a). Operationalization of key variables appearing in the model

Variable name	Variable description
Firm exit	= 1 if the firm exited; = 0 if the firm survived
Technology regime	= 1 if the firm entered in the entrepreneurial regime; = 0 if the firm entered in the routinized regime
Technology intensity	= 1 if the firm entered a high-technology industry; = 0 if the firm entered a low-technology industry
Small size at entry	= 1 if the firm entry size is in the smallest two asset categories; 0 if the firm entry size is in the 3rd, 4th, and 5th asset categories
Age	The number of years since the time of firm entry into the industry
Age^2	A squared term of age to account for nonlinear effects of age
Diversifying entrant	= 1 if the firm existed in some other industry prior to entry in focal industry; = 0 if the firm is a *de novo* entrant
Density	The number of firms in the industry at the time of founding relative to the peak number of firms in the industry
Consumer good	= 1 if the firm entered a consumer industry; = 0 otherwise
Lagged entry rate	The 1-year lagged values of entry rate
Lagged exit rate	The 1-year lagged values of exit rate
Post-World War II	= 1 if the firm entered the industry post-World War II; = 0 otherwise

Table 2(b). Means, standard deviations, and correlations of key variables

	Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1	Firm exit	0.07	0.26	1										
2	Technology regime	0.69	0.46	0.03	1									
3	Technology intensity	0.44	0.50	0.02	0.07	1								
4	Small size at entry	0.68	0.47	−0.03	−0.06	−0.04	1							
5	Density	0.62	0.27	−0.02	−0.19	0.06	0.06	1						
6	Diversified entrant	0.64	0.48	0.04	0.03	0.07	−0.21	0.04	1					
7	Post-World War II	0.89	0.32	0.03	−0.16	0.17	−0.03	0.30	0.18	1				
8	Consumer good	0.52	0.50	−0.02	0.12	−0.30	0.06	−0.05	−0.11	−0.12	1			
9	Age	2.80	1.40	−0.01	0.05	0.01	−0.02	−0.04	0.02	0	−0.01	1		
10	Age^2	9.81	8.40	0	0.04	0.01	−0.02	−0.04	0.02	0	−0.01	0.98	1	
11	Lagged entry rate	0.17	0.31	0	0.16	0.04	−0.03	−0.33	−0.01	−0.15	−0.03	−0.24	−0.21	1
12	Lagged exit rate	0.06	0.06	−0.05	−0.08	−0.03	0.02	0.09	−0.02	−0.09	0.03	−0.03	−0.03	0

$n = 14{,}173$ observations

measurement of the variables in the study, and Table 2(b) provides the corresponding descriptive statistics and correlation matrix.

Dependent variable: firm exit

Our dependent variable, firm exit, is coded as 1 if a firm exited the focal industry in a given year, and 0 otherwise. Since firms exiting the focal industry may still be in existence in other industries, we refrain from using the term 'firm failure' synonymously with firm exit. For example, for a firm that exited 3 years after entry, the dependent variable took the value of 0 for the first 2 years and the value of 1 in the third year. For a firm that survived for 5 years after its entry, which is the survival period of interest in this study, the dependent variable is coded 0 for all five yearly observations. As noted in Table 2(b), about 7 percent of firms exited in any given year.

Key explanatory variables

The three explanatory variables in our study are technology regime, technology intensity, and firm size at time of entry in the focal industry. While technology intensity and size may also be measured on a continuous scale, we use dichotomous category values for all three variables in our analysis. We are motivated to do so in light of our category-based research framework, combined with a methodological need to interpret three-way interactions (Gruber, 1994), as detailed in the following section.

Technology regime

Industry evolution studies have used patterns in the number of firms, net entry, and gross entry, as depicted in Figure 2, to distinguish among the stages of the industry life cycle (Agarwal *et al*., 2002; Gort and Klepper, 1982; Klepper and Graddy, 1990). We base our measure of technology regime on Agarwal *et al*.'s (2002) work because it differentiates the entrepreneurial and the routinized regimes on the basis of gross entry rates, rather than net entry (gross entry less gross exit), or on the basis of number of firms (Gort and Klepper, 1982; Klepper and Graddy, 1990). Agarwal *et al*.'s measure of gross entry satisfies the important condition that the operationalization of life cycle regimes for a study investigating firm exit rates not be functionally related to the dependent variable of firm exit.

Accordingly, we define the entrepreneurial regime as the period extending from the commercialization of an innovation to the significant reduction in entries (that is, the large hill in the gross entry pattern depicted in Figure 2), and the routinized regime as the period after that point (that is, from the period of low/zero entry to the subsequent resurgence, as depicted in Figure 2). Statistically, to distinguish between two consecutive intervals, we determine the delineating year between the two regimes using the generalized discriminant analysis procedure first used by Gort and Klepper (1982). Briefly, this methodology allows us to distinguish between any two consecutive intervals by examining the data on annual gross entry rates for each industry. To determine the delineating year, we first partition the entry rate series into three

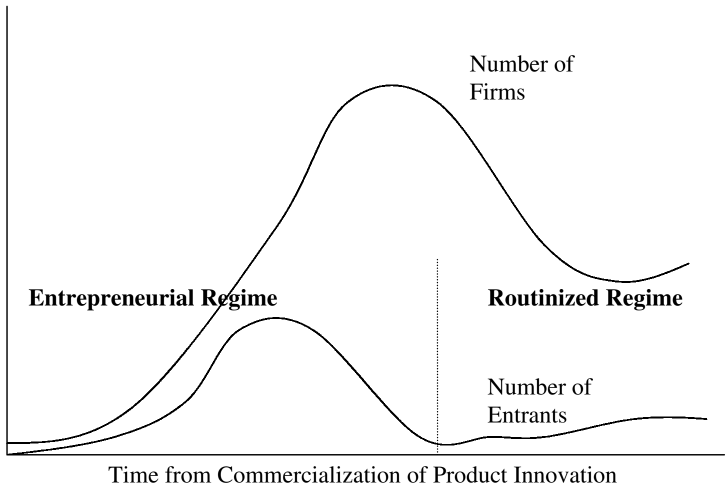

Figure 2. Stylized patterns of entry and number of firms over the industry life cycle

categories—the first and third categories contain the years where the gross entry rates clearly reflect the entrepreneurial and routinized regimes. Periods for the 'in-between' years are then optimally classified based on mean values. The Appendix describes in detail the application of this procedure to distinguish the two regimes.

Table 1 identifies the delineating year between the two regimes for each industry. We conducted numerous sensitivity tests to ensure that our results were robust to changes in the year that separated the regimes. Also, since six industries did not experience the onset of routinized regimes by the end of our sample period, we conducted robustness checks to ensure that the results were not sensitive to the inclusion or omission of these industries. Consistent with the patterns depicted in Figure 2, the descriptive statistics in Table 2(b) show that 69 percent of all firms entered during the entrepreneurial regime of the industries.

Technology intensity

Technology intensity captures the investment in knowledge-producing activities in an industry. Accordingly, we base our measure on total (company, federal, and other) industrial R&D funds allotted as a percentage of sales. These figures are provided at the three-digit SIC (Standard Industrial Classification) level in the Survey of Industrial Research and Development. For the 1987–97 period, the average R&D intensity for all manufacturing industries in the United States was 4.7 percent. We define those industries in our sample that were above the average R&D intensity as high-technology-intensity industries and those that were below the average as low-technology-intensity industries. An examination of the R&D intensity values of the industries in our sample revealed a distinct clustering at the low and high ends of the scale, suggesting that the use of this dichotomous measure did not result in a loss of significant information.

Since technology intensity is a critical independent variable in our analysis, we conducted robustness checks to ensure the validity of our operationalization. In accordance with Robinson and Min (2002), we experimented with a labor-based measure for R&D intensity, using Hadlock, Hecker, and Gannon's (1991) classification, and obtained similar results. We also examined whether the categorization results changed when the dividing line was specified differently. The use of the median value of R&D intensity to split the sample into high- and low-technology-intensity industries resulted in identical categorization results. Finally, we compared the R&D intensity of our sample to the R&D intensity of all industries at the 3-digit SIC level, and used the sample mean and median as alternative dividing lines. Our categorization results were virtually identical for alternate specifications, thereby indicating that our dichotomous measure of R&D intensity possessed adequate face validity.

We note that our measure of technology intensity across industries does not vary over time, since the temporal dimension is being captured in the technology regime, or life cycle, measure. Although industries may undergo periods of peaks and troughs in the amount of effort and resource they devote to knowledge-generating activities, cross-industry variations in technology intensity seem to be relatively robust. As Klevorick *et al.* note, '[A] striking characteristic of industries that are commonly thought to be rich in technological opportunities is that high R&D intensities and high rates of technical advance tend to be sustained over time' (Klevorick *et al.*, 1995: 188). Accordingly, we believe that, although not without limitations, a time-invariant measure of technology intensity is adequately valid. As reported in Table 2(b), 45 percent of the firms entered high technology-intensity industries.

Firm size

Firm size at the time of entry is measured by its asset size as listed by the *Thomas Register* in the year a firm entered a relevant market. Although firm size has been otherwise measured in a variety of ways, such as by employees, sales, asset value, the empirical results have so far demonstrated that all of these definitions of firm size provide very similar results (Child, 1972; Chandy and Tellis, 2000).

Each firm's asset values are reported in nominal, or at current dollar value, asset categories in the *Thomas Register*, and the data span over 80 years, so there was a need to control for inflation. Accordingly, we recorded the asset value of each firm in the year it entered the industry of interest, and converted it to 1982 U.S. dollars to obtain a real dollar value. On the basis of their real adjusted values, the firms were then classified into five asset categories. Fifty percent of the firms had assets less than \$2.8 million; 12 percent had assets between \$2.8 to \$5.5 million; 5 percent had assets between \$5.5 to \$8.3 million; 32 percent had assets between \$8.3 and \$11 million; and less than 1 percent of the firms had assets greater than \$11 million. The size distribution based on asset size is consistent with the distribution by employee size reported by Chandy and Tellis (2000), and is also generally representative of manufacturing industries.

Given the bimodal distribution in the size of firms, and since our hypotheses concern the differing impact of the innovative environment on firm survival for small and large firms, we classified the firms in the two lowest asset categories, with real value less than \$5.5 million, as small; and classified all other firms as large. Robustness checks revealed that the effect of size on survival was the same whether we used the all five asset classes, or the dichotomous measure of small vs. large. The latter was chosen for ease of exposition and analysis. Further, when we tested an alternative operationalization of large firms, dropping the third asset category (\$5.5 million to \$8.3 million) from the large firm category, our results did not change. To corroborate our empirical operationalization of size, we also experimented with an alternative classification. Defining small firms as those below the 60th percentile of the size distribution of the firms in their decade of entry produced largely similar results, thus demonstrating the robustness of our operationalization. The descriptive statistics in Table 2 show that small entrants accounted for approximately 68 percent of the firms operating in any given year.

Control variables

In addition to the above variables of interest, we include several firm- and industry-level controls to account for both fixed and time-varying effects. Our firm-level controls included the firm's age, and a diversification dummy. A quadratic specification for age is used to allow for nonlinear effects of age. We further include a diversification dummy (1 = diversified, 0 = otherwise) to control for differences between diversified and *de novo* entrants. Our industry-level controls included the measure of founding density, or the number of firms at time of entry, because the organizational ecology literature suggests that firm exit varies with the number of firms in a given population. Given that our study encompassed many industries, there were differences in numbers of entrants per industry, as revealed in Table 1. To accommodate these differences and to enable cross-industry comparisons, we computed a relative measure of density by dividing the number of firms in an industry in any given year by the maximum number of firms observed in the industry, which is represented by the peak of the number-of-firms curve depicted in Figure 2. Further, we used a dummy variable to distinguish between consumer goods and component or industrial goods, because the demand conditions facing firms in each type may differ. To control for temporal differences, we calculated lagged entry and exit rates in an industry. Entry (or exit) rates are computed as the number of entrants (or exits) in a year divided by the total number of firms that existed in the industry in the preceding year. We used 1-year lagged values rather than contemporaneous values for entry and exit rates to avoid concerns of endogeneity of population level entry and exit rates with our dependent variable of firm-level exit. We also included a dummy variable to differentiate between firms that entered before and those that entered after World War II, because the war was a major economic event that significantly altered the business environment in the United States. For example, historical evidence suggests that after World War II large firms instituted organizational features that better supported radical innovation (Chandler, 1956).

Model specification and estimation

We tested our hypotheses by examining entrant hazard rate, which is the probability of a firm not surviving another year after a particular age. Although several discrete- and continuous-time analysis techniques are available (Allison, 1995), we chose the random-effects complementary log-log model to control for unobserved heterogeneity among industries that our control variables may not have captured. As described by Allison (1995), the complementary log-log distribution is preferable to other distributions (e.g., logistic), because it accommodates for the possibility that exits can occur at any point during a given year, even though the exits are recorded only at yearly intervals. Also, we use random effects to control for unobserved heterogeneity because fixed effects models are not available in the existing statistical packages. Unconditional fixed effects estimates are biased, and a sufficient statistic allowing the fixed effects to be conditioned out of the likelihood does not exist. To ensure robust results, we tested additional model specifications, including the probit, logistic, and Cox proportional hazards, and our results were consistent across specifications.

The empirical analysis of our hypotheses required testing contingencies or interactions along the following three distinct dimensions: technology regime, technology intensity, and size. Given the complexities of interpretation, and collinearity problems associated with three-way interaction models, we employed the variant of a technique developed by Gruber (1994) in the economics literature. The technique categorizes firms into exclusive groups depending on the values taken by each dichotomous independent variable of interest. These n groups are then represented by $(n-1)$ dummy variables, the last group being the control group. This method nests traditional interaction models and enjoys several advantages, particularly with respect to three-way interactions. First, these models did not suffer from potential multicollinearity because Gruber's technique uses independent variables to classify observations into mutually exclusive groups; moreover, in this study, these groups depended on size and innovative environment. Second, Gruber's technique allowed the investigation of differences in firm exit in different environments, at different sizes, and permitted the immediate comparison of the probability of the survival of each group relative to the control group. Thus, the technique circumvents problems in the interpretation of the coefficients of interaction terms in traditional three-way interaction analysis, and prevents the need for additional subgroup analysis. Third, Gruber's technique provides a generalized and unrestricted model against which the validity of models that suggest the survival probabilities in *any two of the groups* to be the same can be easily tested using likelihood ratio tests.

For the test of Hypothesis 1, we specify the following model:

$$h(t) = \gamma_1\ T_1 + \gamma_2\ T_2 + \delta \boldsymbol{X}_{it} \tag{1}$$

where:

$T_1 = 1$ for entrants into the aligned innovative environment (Cell I in Figure 1), and 0 otherwise;
$T_2 = 1$ for entrants into partially aligned environments (either Cell II or Cell III in Figure 1), and 0 otherwise;

and $\boldsymbol{X}_{it}$ represents the vector of control variables for firm i at time t.
In Equation 1 the underlying control group consists of entrants into the nonaligned environment (Cell IV in Figure 1). The coefficients γ_1 and γ_2 can then be interpreted as showing the difference in firm exit of each group of firms from that of the control group.

For the test of Hypothesis 2, we use two different models. First, we conduct a subgroup analysis and test the innovative environment–firm exit relationship shown in Equation 1, for small and large entrants separately. Second, we estimate the full model for the three-variable interactions in which eight groups are represented by seven dummy variables. Thus, the model is specified as:

$$h(t) = \beta_1 * G_1 + \beta_2 * G_2 + \beta_3 * G_3 + \beta_4 * G_4 + \beta_5 * G_5 + \beta_6 * G_6 + \beta_7 * G_7 + \alpha X_{it} \quad (2)$$

where:

$G_1 = 1$ for large entrants into the aligned innovative environment (Cell 1), and 0 otherwise;
$G_2 = 1$ for large entrants into the entrepreneurial regimes of low-technology-intensity industries (Cell 2), and 0 otherwise;
$G_3 = 1$ for large entrants into the routinized regimes of high-technology-intensity industries (Cell 3), and 0 otherwise;
$G_4 = 1$ for large entrants into the nonaligned innovative environment (Cell 4), and 0 otherwise;
$G_5 = 1$ for small entrants into the aligned innovative environment (Cell 1), and 0 otherwise;
$G_6 = 1$ for small entrants into the entrepreneurial regimes of low-technology-intensity industries (Cell 2), and 0 otherwise;
$G_7 = 1$ for small entrants into the routinized regimes of high-technology-intensity industries (Cell 3), and 0 otherwise;

and X_{it} represents the vector of control variables. In Equation 2, the control group consists of small entrants into nonaligned environments (Cell 4). The coefficients β_1 through β_7 can then be interpreted as showing the difference in firm exit of each group of firms from that of the control group.

RESULTS

Table 3 provides the results of our analysis for Hypothesis. Model 1 in Table 3(a) reports the coefficients for the two groups defined in Equation 1 relative to the control group. Our results reveal that the coefficient of the aligned environment is negative and significant ($\gamma = -0.13$; $p < 0.05$), implying that entrants into aligned environments (Cell I in Figure 1) have higher survival rates than nonaligned environment entrants (Cell IV in Figure 1). The relative magnitudes of the coefficient estimates of the aligned and partially aligned environments indicate that survival rates in the aligned environment are higher than those in the partially aligned environments. Also, as posited, Model 1 reveals a difference in the survival rates of entrants into partially aligned environments (Cells II and III in Figure 1) and nonaligned environments (Cell IV in Figure 1) ($\gamma = -0.05$; $p < 0.05$), implying that entrants into partially aligned environments also have higher survival rates than nonaligned environment entrants. Together, these results indicate support for Hypothesis 1.

Table 3(a). Estimates of probability of firm exit in innovative environments

	Model 1	Model 2
Intercept	−1.17* (0.08)	−1.16* (0.08)
Aligned environment (Cell I)	−0.13* (0.03)	−0.13* (0.03)
Partially aligned environment	−0.05* (0.02)	—
Entrepreneurial, low-technology-intensity (Cell II)	—	−0.08* (0.03)
Routinized, high-technology-intensity (Cell III)	—	0.02 (0.04)
Age	0.16* (0.04)	0.16* (0.04)
Age^2	−0.02* (0.007)	−0.02* (0.01)
Diversified entrant	−0.11* (0.02)	−0.11* (0.02)
Density	0.19* (0.05)	0.18* (0.05)
Consumer good	0.05** (0.03)	0.05** (0.03)
Lagged entry rate	0.10* (0.04)	0.10* (0.04)
Lagged exit rate	0.85* (0.18)	0.82* (0.19)
Post-World War II	−0.08* (0.04)	−0.09* (0.04)
Log likelihood	−3559.45	−3556.47
Number of observations	14173	14173

Routinized, low-technology-intensity is used as the baseline group.
Standard errors are given in parentheses.
Significant at: * 0.05 level; ** 0.10 level

Table 3(b). Results from the tests of restrictions of Table 3(a)

	Chi-square[a]	Significance
Likelihood ratio test from pooling the aligned and partially aligned environments in Model 1	10.07*	Significant
Likelihood ratio test from pooling the aligned and entrepreneurial low-technology-intensity environments (Cell II) in Model 2	4.06*	Significant

[a] computed as −2[difference between unrestricted and restricted log likelihood]
* Significant at 0.05 level

Because we characterize two distinct types of environments as partially aligned, we conducted additional analysis to ascertain differences in survival rates between the aligned and each of the two partially aligned environments. The results from Model 2 in Table 3(a) indicate that although survival rates are highest in the aligned environment (Cell I) ($\gamma = -0.13$; $p < 0.05$), entrants into the entrepreneurial, low-technology-intensity environment (Cell II) are better off ($\gamma = -0.08$; $p < 0.05$) than either nonaligned entrants (Cell IV) or entrants into routinized, high-technology-intensity environments (Cell III) ($\gamma = 0.02$; $p < 0.10$). We next verified that the survival probability in the aligned environment (Cell I) differed statistically from the survival probabilities in either partially aligned environment (Cells II and III). We tested for the invariance of the survival coefficients, in two separate sets of comparisons, between the (a) aligned environment (Cell I) and the partially aligned environments (Cells II and III); and between the (b) aligned environment (Cell I) and the more advantageous of the two partially aligned environments, namely, the entrepreneurial regime with low-technology-intensity industries (Cell II). The likelihood ratio tests reported in Table 3(b) illustrate that the aligned environment could not be pooled with the partially aligned environments ($\chi^2 = 10.70$; $p < 0.05$) or even with the more advantageous partially aligned environment (Cell II) ($\chi^2 = 4.06$; $p < 0.05$), thereby reconfirming support for Hypothesis 1. Clearly, entrants into aligned environments (Cell I) are advantaged over all other entrants.

Table 4(a) provides the results for Hypothesis 2, which we tested by conducting a subgroup analysis for small and large entrants (as depicted in Models 1 and 2, respectively). Our

Table 4(a). Estimates of probability of firm exit in innovative environments for small and large entrants

Variable	Model 1 (small entrants)	Model 2 (large entrants)
Intercept	−1.17* (0.10)	−1.22* (0.15)
Aligned environment (Cell I)	−0.14* (0.04)	−0.13* (0.05)
Entrepreneurial, low-technology-intensity (Cell II)	−0.06 (0.04)	−0.12* (0.04)
Routinized, high-technology-intensity (Cell III)	0.05 (0.05)	−0.04 (0.08)
Age	0.19* (0.05)	0.11 (0.08)
Age^2	−0.03* (0.01)	−0.01 (0.01)
Diversified entrant	−0.12* (0.03)	−0.02 (0.05)
Density	0.17* (0.06)	0.20* (0.09)
Consumer good	0.07* (0.03)	−0.01 (0.05)
Lagged entry rate	0.12* (0.05)	0.06 (0.08)
Lagged exit rate	0.71* (0.23)	1.01* (0.34)
Post-world war ii	−0.09* (0.05)	−0.08 (0.08)
Log likelihood	−2521.43	−1026.249
Number of observations	9681	4492

Routinized, low-technology-intensity is used as the baseline group.
Standard errors are given in parentheses.
* Significant at 0.05 level.

Table 4(b). Results from tests of restrictions for Models 1 and 2 in Table 5(a)

	Chi-square[a]	Significance
Small firms		
Likelihood ratio test from pooling firms in the aligned and the entrepreneurial, low-technology environments (Cell II)	5.31*	Significant
Likelihood ratio test from pooling firms in the aligned and the routinized, high-technology environments (Cell III)	13.94*	Significant
Large firms		
Likelihood ratio test from pooling firms in the aligned and the entrepreneurial, low-technology environments (Cell II)	0.05	Not significant
Likelihood ratio test from pooling firms in the aligned and the routinized, high-technology environments (Cell III)	3.92*	Significant

[a] computed as −2[difference between unrestricted and restricted log likelihood]
* Significant at 0.05 level

results reveal that for small entrants only the aligned environment has a negative and significant coefficient ($\gamma = -0.14$; $p < 0.05$), while both the partially aligned environments have statistically insignificant negative coefficients. In contrast, for large entrants, the coefficients are negative and significant for both the aligned environment ($\gamma = -0.13$; $p < 0.05$) as well as the entrepreneurial, low-technology-intensity environment ($\gamma = -0.12$; $p < 0.05$). The likelihood tests reported in Table 4(b) show that for small entrants the aligned environment cannot be pooled with either partially aligned environment ($\chi^2 = 5.31$ and 13.94 for Cell II and Cell III, respectively; $p < 0.05$). However, for large entrants, not only are the coefficient values almost the same for the aligned and the entrepreneurial, low-technology-intensity environments; but furthermore, the likelihood test fails to rule out the possibility that the two environments can be pooled ($\chi^2 = 0.05$; $p > 0.10$).

To ensure that the results are not sensitive to the assumptions inherent in the subgroup analysis, we analyzed the full model with three-way interactions, and Table 5 presents the results. The results are consistent with those reported in Table 4. Further, the analysis presented in Table 5 enables the tests of pooling small and large entrants within an innovative environment. In particular, we conducted likelihood tests to confirm that in the aligned environment the exit rates of small entrants are not significantly different from those of large entrants ($\chi^2 = 0.09$; $p > 0.10$). Thus, the aligned environment mitigates any scale disadvantages that small entrants may experience. However, in the entrepreneurial, low-technology-intensity environment (Cell II), the likelihood test disallows the possibility that small and large entrants can be pooled together ($\chi^2 = 3.94$; $p < 0.05$), because large entrants have significantly lower exit rates.

To interpret the magnitude of the coefficients, we calculated marginal effects associated with above analysis. This enables us to compute the differences in the estimated values of the exit rates across size and innovative environment. Using the nonaligned environment as the control group, we calculated the percentage differences in the exit rates for small and large firms in each of the other innovative environments. We obtained the initial predicted probabilities of exit, by holding the other control variables at their means. Thereafter, we normalized the predicted probability of the baseline group to 0, and adjusted the other probabilities for the other groups accordingly. Table 6 gives these results. Small entrants experienced a 32 percent decline in exit rates in the aligned environment relative to the nonaligned environment; but in all other environments the differences in exit rates are not statistically significant. For large entrants, exit rates are statistically equal, that is, 27 percent lower in the aligned environment and 29 percent lower in the entrepreneurial, low-technology-intensity environment. Together, the results show that entering the aligned environment

Table 5. Estimates of probability of firm exit in different environments across different firm sizes

Variable	Model 3
Intercept	−1.16* (0.08)
G_1: Large entrant in aligned environment (Cell I)	−0.13* (0.05)
G_2: Large entrant in entrepreneurial, low-technology intensity (Cell II)	−0.14* (0.05)
G_3: Large entrant in routinized, high-technology intensity (Cell III)	−0.02 (0.07)
G_4: Large entrant in routinized, low-technology intensity (Cell IV)	−0.01 (0.06)
G_5: Small entrant in entrepreneurial, high-technology intensity (Cell I)	−0.14* (0.04)
G_6: Small entrant in entrepreneurial, low-technology intensity (Cell II)	−0.06 (0.04)
G_7: Small entrant in routinized, high-technology intensity (Cell III)	0.04 (0.05)
Age	0.16* (0.04)
Age^2	−0.02* (0.01)
Diversified entrant	−0.10* (0.03)
Density	0.18* (0.05)
Consumer good	0.04* (0.03)
Lagged entry rate	0.10* (0.04)
Lagged exit rate	0.81* (0.19)
Post-World War II	−0.09* (0.04)
Log likelihood	−3554.32

Standard errors are given in parentheses.
Significant at: * 0.05 level; ** 0.10 level

Table 6. Differences in probabilities of exit across different environments for small and large entrants

Innovative environment	Small entrants	Large entrants
Aligned environment (Cell 1)	32% lower*	27% lower*
Entrepreneurial, low-technology-intensity (Cell 2)	12% lower	29% lower*
Routinized, high-technology-intensity (Cell 3)	11% higher	2% lower

The values in this table are computed based on the marginal effects from the analysis in Tables 4 and 5. The nonaligned environment is the baseline group.
* Differences significant at the 0.05 level.

is the only way that small entrants can enhance their odds of survival, while large entrants have at least one other environment that increases their probability of survival. Thus, we find support for Hypothesis 2.

It is important to note that our results indicate that for large entrants, entering during the entrepreneurial regime increases survival, irrespective of technology intensity. Alignment brings large entrants no added advantage over and above the beneficial effect of the entrepreneurial regime. Their survival rates are regime-variant, not technology-intensity-variant. However, for small firms, it is only in the aligned environment that their survival is significantly enhanced.

DISCUSSION AND CONCLUSION

Although new entrants have been celebrated as agents of innovation and change, recent empirical findings reaffirm their high levels of vulnerability to exit during the early years of their existence (Huyghebaert and Van de Gucht, 2004). While such findings resonate with existing theoretical arguments related to liabilities of newness and size (Stinchcombe, 1965), what is less well understood are factors that determine variance *within* the exit rates of new entrants (Shane, 2001). In other words, understanding how certain entry conditions may provide a protective umbrella to small new entrants, and therefore mitigate their early year vulnerabilities seems salient since it will inform us about entrepreneurial churn, a phenomenon regarding which we have limited knowledge.

Our theoretical framework and empirical finding focuses on this gap, and draws attention to how the external knowledge environment of entry influences a new entrant's likelihood of early exit, or conversely survival. Our typology of the innovation arena of an entrant is based on two knowledge-related dimensions of an entrant's environment: technology regime and technology intensity. While the former reflects the temporal dimension of the external knowledge environment, the latter mirrors its cross-sectional component. By complementing the temporal element of an entrant's entry environment, namely the evolutionary stage of the industry's life cycle in which it enters, with a cross-sectional characteristic of the industry, namely its technology intensity, we intersect evolutionary literature with that on technological progress. On one hand, evolutionary research seeks to explain 'the movement of something over time, or to explain why that something is what it is at a moment of time in terms of how it got there' (Dosi and Nelson, 1994). Adopting a dynamic approach, evolutionary scholars emphasize temporal changes in both competitive conditions and the nature of knowledge that underlies innovation over the life cycle of an industry. On the other hand, research on technological progress concerns itself with trying to explain what causes cross-sectional differences in the 'inventive potential' or the richness of innovation opportunities across industries (Rosenberg, 1974; Klevorick *et al*., 1995). Adopting a knowledge spillover perspective (Arrow, 1962; Mansfield, 1968; Jaffe, 1986; Griliches, 1979), it is generally argued that resources devoted to knowledge-generating activities in an industry endogenously determine the technological opportunities available within an industry (Romer, 1986; Lucas, 1988).

Integrating the two perspectives, we propose that the innovation setting of an entrant may be characterized by a typology of *alignment* (or the lack thereof) based on technology regime and technology intensity. We hypothesize that firms entering aligned innovative environments, where entrants have both a knowledge advantage and ample technological opportunities, will enjoy a survival premium denied to firms entering other environments (Hypothesis 1). Further, we expect the size of entry to impact the relationship between innovative environment and survival relationship in such a way that the aligned state of the innovative environment will be more critical for small than for large entrants (Hypothesis 2). We test our hypotheses with data on 3,431 entrants in 33 industries over the years 1908–91. Using this longitudinal and comprehensive dataset allowed us to test the hypotheses in a manner precluded by the use of cross-sectional data, which can have survivor bias and data-censoring problems.

We found support for both hypotheses. Entrants into aligned environments had significantly lower exit rates than entrants into all other environments. Further, we found that entrant size conditioned the innovative environment–survival relationship such that alignment of the two dimensions of innovative environment is a necessary condition for the enhanced survival levels of small entrants, but not for large entrants. Our analysis allowed us to discern the effect of each of the two dimensions of innovative environment on the survival rates of small and large entrants. In the context of the first dimension, technology regime, our results are in support of the general arguments derived from industry evolution theories; that in general, firms that enter during the entrepreneurial regime have a distinct survival advantage as compared to those that enter during the routinized period of the industry's life cycle (Agarwal and Gort, 1996; Suarez and Utterback, 1995). However, our findings indicate that this result is not unequivocally true for all types of entrants. In line with our theoretical predictions, we find that small entrants are benefited by entry into the entrepreneurial regime *only* when the industry they enter is one that is technology intensive and characterized by high levels of R&D investment. Thus, our results demonstrate how the knowledge intensity of the industry and scale of entry together form boundary conditions on the effects of technology regimes on entrant survival.

Our study has several potential contributions. First, we shed light on a phenomenon that is central to our understanding of competitive evolution, and thus critical to scholarship in the domains of entrepreneurship and strategic management. To truly act as agents of change that reshape markets and help diffuse innovations through society, new entrants need to be able to survive the initial years when they are especially vulnerable to exit due to liabilities of newness. Otherwise, in sharp contrast to the utopian Schumpeterian vision of creative destruction, entrepreneurial churn may resemble a revolving door since entrants are likely to exit soon after they enter. Our study integrates insights from evolutionary and innovation literatures to suggest that a confluence of knowledge conditions in the external environment helps entrants by providing them with an innovation advantage *vis-à-vis* incumbent firms. We thus attempt to explain such variations in entrant survival rates through our framework of the firm's innovative environment.

Second, while much of strategy literature is dedicated to examining knowledge that is internal to a firm, we draw attention to the important role played by the external knowledge environment on entrant performance. In developing our theoretical rationale on how technological intensity relates to innovative opportunities in an industry, we draw on insights from Kenneth Arrow's pioneering work on knowledge spillovers and endogenous growth theory research conducted by Paul Romer and colleagues. By merging considerations of how investments in innovation create in turn more innovation into an evolutionary life cycle approach, our study points to the increasing relevance of a co-evolutionary approach to strategy research.

Third, our findings contribute to the under-researched area of technology intensity. Quite intriguingly, there has been little empirical investigation of the relationship between technology intensity and entrant survival. A notable exception is Audretsch and Mahmood (1995), who conceptualized an industry's technology intensity as equivalent to entry barriers and reported a positive relationship between exit rates and technology intensity. However, their research was cross-sectional in nature, and temporal differences in the innovation environment were ignored. Our marked departure is on two fronts: one, in line with endogenous growth theory, our work proposes that technology intensity may be actually reflective of *lower* barriers to entry/survival due to higher innovation opportunities in the industry; and two, we demonstrate the importance of considering both evolutionary dynamics and scale issues in considerations of how technological intensity may impact entrant exit.

Fourth, although our hypotheses and findings point to size as a key entrant characteristic, we find that the distinction between start-up, or *de novo* entry, and diversifying entry as an important factor that influences exit. We conducted additional analyses to check for the effects of innovative environment on the subgroup of *de novo* entrants, and found the results to be consistent with our overall results. Small *de novo* entrants in particular benefited from aligned environments, enjoying higher survival rates than small *de novo* entrants in all other environments. Large *de novo* entrants found the entrepreneurial regime conducive to their survival. To the extent that entrepreneurial entry is associated with size as well as start-up status, our results imply that small firms are benefited by innovative environments that do not penalize their scale disadvantage.

From a practitioner perspective, our work indicates that the timing of entry decision seems contingent on the type of industry being considered and the amount of resources the entrepreneur has at her disposal. Our study explains conditions where small entrants may be able to benefit from spillovers of technology investments, and situations where small entrants may be more competitive. Also, firms that deal with a portfolio of investments in start-ups may find our findings of value in that our research points out to the innovative environment being a criterion along which they may consider delineating their portfolio.

Although we tested our hypotheses using data from several industries, thus increasing the generalizability of our results, several study limitations stem from the data constraints of a multi-industry study. First, entrant size was a dichotomous measure based on asset values. Given the key role of entrant size, collecting the size data using an alternative measure, such as number of employees or sales volume, would greatly enhance the validity of the results. We believe the similarity of substantive results using alternative measures (Child, 1972; Chandy and Tellis, 2000) partly mitigates this concern. Further, our data indicated a bimodal distribution of size that allowed us to use 'small' and 'large' as broad categories, obviating the need for multiple measures of asset size. Still, the analysis would have been stronger without this data limitation.

Similarly, though we included important control variables capturing inter-firm and inter-industry differences (for instance, age, diversifying entrant, consumer good, and entry after World War II), and applied an estimation technique that accommodates unobserved heterogeneity, including additional firm- and industry-level control variables would further increase the validity of our results. Third, in view of prior research findings, our measure of technology intensity is time-invariant, in that each industry is characterized as highly technology intensive, or not, for its entire life cycle. Our technology regime variable is dynamic, and partially captures differences in technology intensity over time; however, a time-variant measure of technology intensity would have enabled us to explicitly test the validity of the assumption that industry technology intensity remains stable over time, and would have allowed us to capture dynamics not attributable to industry evolution alone.

The above limitations provide further avenues for potential future research. For instance, variables such as market share and financial performance may be investigated, in addition to survival, as in this paper. Another fruitful area of research would be the analysis of how the two dimensions of entrepreneurial entry (size and *de novo* status) affect entrant survival in conjunction with the two dimensions of innovative environment (technology regime and intensity). Finally, our data could also be used to test for chronological differences in the size–survival relationship, while controlling for temporal differences arising due to industry evolution. The data would need to be extended to adequately represent industries that were in the routinized regime in the early part of the 20th century and those in the entrepreneurial regime in the later part of the 20th century, so that effects of time that are not confounded by the selection of industries could be discerned.

In summary, our paper refocuses attention on knowledge that is *external* to firms as being an important determinant of their performance, as is internal knowledge. Further, we integrate two strands of research that have developed largely parallel to each other, creating a new theoretical construct relating to the innovative environment facing industry entrants. Our paper thus extends each strand via an integrative model that shows the importance to entrant survival of the *alignment* of two aspects of innovative environment. Finally, by focusing on the differing impact of innovative environment on small and large entrants, we provide support for the importance of the *fit* between the resource characteristics of firms and the environments that firms enter.

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REFERENCES

Acs ZJ, Audretsch DB. 1988. Innovation in large and small firms: an empirical analysis. *American Economics Review* **78**: 678–690.

Acs Z, Audretsch DB, Braunerhjelm P, Carlsson B. 2003. The missing link: the knowledge filter and endogenous growth. Working paper, presented at the *DRUID's* Knowledge Conference, June 2003.

Agarwal R, Gort M. 1996. The evolution of markets and entry, exit and survival of firms. *Review of Economics and Statistics* **78**: 489–498.

Agarwal R, Echambadi R, Franco A, Sarkar MB. 2004. Knowledge transfer through inheritance: spinout generation, development and survival. *Academy of Management Journal* **47**(4): 501–522.

Agarwal R, Sarkar MB, Echambadi R. 2002. The conditioning effect of time on firm survival: an industry life-cycle approach. *Academy of Management Journal* **45**(5): 971–994.

Allen T. 1977. *Managing the Flow of Technology*. MIT Press: Cambridge, MA.

Allison PD. 1995. *Survival Analysis Using the SAS System: A Practical Guide*. SAS Institute: Cary NC.

Arrow K. 1962. The economic implications of learning by doing. *Review of Economic Studies* **29**: 155–173.

Audretsch DA, Mahmood T. 1995. New firm survival: new results using a hazard function. *Review of Economics and Statistics* **76**: 97–103.

Bain JS. 1956. *Barriers to New Competition*. Harvard University Press: Cambridge, MA.

Baldwin JR. 1995. *The Dynamics of Industrial Competition: A North-American Perspective*. Cambridge University Press: Cambridge, MA.

Barney JB. 1991. Firm resources and sustained competitive advantage. *Journal of Management* **17**(1): 99–120.

Baum JA, Oliver C. 1991. Institutional linkages and organizational mortality. *Administrative Science Quarterly* **36**: 187–218.

Blair J. 1972. *Economic Concentration*. Harcourt, Brace & Jovanovich: New York.

Chandler AD. 1956. Management decentralization: an historical analysis. *Business History Review* **30**: 111–174.

Chandy RK, Tellis GJ. 2000. The incumbent's curse? Incumbency, size and radical product innovation. *Journal of Marketing* **64**: 1–17.

Child J. 1972. Organization structure, environment, and performance: the role of strategic choice. *Sociology Review* **6**: 1–22.

Christensen C. 1997. *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*. Harvard Business School Press: Boston, MA.

Comanor WS. 1967. Market structure, product differentiation, and industrial research. *Quarterly Journal of Economics* **81**(4): 639–657.

Conner KR, Prahalad CK. 1996. A resource-based theory of the firm: knowledge versus opportunism. *Organization Science* **7**: 477–501.

Dosi G. 1982. Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. *Research Policy* **11**(3): 147–162.

Dosi G, Nelson RR. 1994. An introduction to evolutionary theories in economics. *Journal of Evolutionary Economics* **4**: 153–172.

Dunne T, Roberts MJ, Samuelson L. 1988. Patterns of firm entry and exit in U.S. manufacturing industries. *RAND Journal of Economics* **19**(4): 495–515.

Freeman J, Carroll GR, Hannan MT. 1983. The liability of newness: age dependence in organizational death rates. *American Sociological Review* **48**: 692–710.

Geroski PA. 1990. The effect of entry on profit margins in the short and long run. *Anales d'Economie et de Statistique* **15–16**: 333–353.

Geroski PA. 1995. What do we know about entry? *International Journal of Industrial Organization* **13**: 450–456.

Geroski PA, Pomroy R. 1990. Innovation and the evolution of market structure. *Journal of Industrial Economics* **38**(3): 299–314.

Gimeno J, Folta TB, Cooper AC, Woo CY. 1997. Survival of the fittest? Entrepreneurial human capital and the persistence of underperforming firms. *Administrative Science Quarterly* **42**(4): 750–783.

Griliches Z. 1979. Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Econometrics* **10**(1): 92–116.

Gort M, Klepper S. 1982. Time paths in the diffusion of product innovations. *Economic Journal* **92**: 630–653.

Grant RM. 1996. Toward a knowledge-based theory of the firm. *Strategic Management Journal*, Winter Special Issue **17**: 109–122.

Gruber J. 1994. The incidence of mandated maternity benefits. *American Economic Review* **84**(3): 622–641.

Hadlock P, Hecker D, Gannon J. 1991. High technology employment: another view. *Monthly Labor Review* **114**(7): 26–30.

Hannan MT, Freeman J. 1984. Structural inertia and organizational change. *American Journal of Sociology* **49**: 149–164.

Hannan MT, Freeman J. 1989. *Organizational Ecology*. Harvard University Press: Cambridge, MA.

Hayek FA. 1945. The use of knowledge in society. *American Economic Review* **35**(September): 519–530.

Huyghebaert N, Van de Gucht L. 2004. Incumbent strategic behavior in financial markets and the exit of entrepreneurial start-ups. *Strategic Management Journal* **25**(7): 669–688.

Jaffe A. 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. *American Economic Review* **76**(5): 984–1001.

Jovanovic B. 1982. Selection and the evolution of industry. *Econometrica* **50**(3): 649–670.

Kamien M, Schwartz N. 1982. *Market Structure and Innovation*. Cambridge University Press: New York.

Kessides IN. 1991. Entry and market contestability: the evidence from the United States. In *Entry and Market Contestability: An International Comparison*, Geroski PA, Schwalbach J (eds). Blackwell: Oxford; 23–48.

Klepper S. 2002. The capabilities of new firms and the evolution of the U.S. automobile industry. *Industrial and Corporate Change* **11**(4): 645–666.

Klepper S, Graddy E. 1990. The evolution of new industries and the determinants of market structure. *RAND Journal of Economics* **21**(1): 27–44.

Klepper S, Simons K. 2000. Dominance by birthright: entry of prior radio producers and competitive ramifications in the U.S. television receiver industry. *Strategic Management Journal*, Special Issue **21**(10/11): 997–1016.

Klevorick A, Levin RC, Nelson RR, Winter SG. 1995. On the sources and significance of interindustry differences in technological opportunities. *Research Policy* **24**: 185–205.

Kogut B, Zander U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science* **3**: 383–397.

Lavin MR. 1992. *Business Information: How to Find It, How to Use It* (2nd edn). Oryx Press: Phoenix, AZ.

Levin RC, Reiss PC. 1988. Cost-reducing and demand-creating R&D with spillovers. *RAND Journal of Economics* **19**(4): 538–556.

Lucas RE. 1988. On the mechanics of economic development. *Journal of Monetary Economics* **22**: 3–42.

Mansfield E. 1962. Entry, Gibrat's law, innovation and the growth of firms. *American Economic Review* **52**(4): 1023–1051.

Mansfield E. 1968. *Industrial Research and Technological Innovation: An Econometric Analysis*. Norton Press: New York.

Nelson RR, Winter SG. 1982. *An Evolutionary Theory of Economic Change*. Harvard University Press: Cambridge, MA.

Penrose ET. 1952. Biological analogies in the theory of the firm. *American Economic Review* **42**: 804–819.

Porter M. 1980. *Competitive Strategy*. Free Press: New York.

Robinson WT, Min S. 2002. Is the first to market the first to fail? Empirical evidence for industrial goods businesses. *Journal Marketing Research* **39**(1): 120–128.

Romer P. 1986. Increasing returns and long-run growth. *Journal of Political Economy* **94**(5): 1002–1037.

Rosenberg N. 1974. Science, invention and economic growth. *Economic Journal* **84**(333): 90–108.

Schumpeter JA. 1934. *The Theory of Economic Development*. Harvard University Press: Cambridge, MA.

Shaked A, Sutton J. 1987. Product differentiation and industrial structure. *Journal of Industrial Economics* **36**(2): 131–146.

Shane S. 2001. Technology regimes and new firm formation. *Management Science* **47**(9): 1173–1190.

Silverberg G, Dosi G, Orsenigo L. 1988. Innovation, diversity and diffusion: a self-organization model. *Economic Journal* **98**(393): 1032–1054.
Stinchcombe AL. 1965. Social structures and organizations. In *Handbook of Organizations*, March JG (ed). Rand McNally: Chicago, IL; 142–193.
Suarez FF, Utterback JM. 1995. Dominant designs and the survival of firms. *Strategic Management Journal* **16**(6): 415–430.
Sutton J. 1997. Gibrat's legacy. *Journal of Economic Literature* **35**(1): 40–59.
Sultan F, Farley JU, Lehman DR. 1990. A meta-analysis of applications of diffusion models. *Journal of Marketing Research* **27**(1): 70–77.
Tushman ML, Anderson P. 1986. Technological discontinuities and organizational environments. *Administrative Science Quarterly* **31**: 439–465.
Utterback JM, Abernathy WJ. 1975. A dynamic model of process and product innovation. *OMEGA* **3**: 639–656.
Venkataraman S. 1997. The distinctive domain of entrepreneurship research: an editor's perspective. In *Advances in Entrepreneurship, Firm Emergence, and Growth*, Brockhaus JKR (ed). JAI Press: Greenwich, CT; 119–138.
Williamson OE. 1991. Strategizing economizing and economic organization. *Strategic Management Journal*, Winter Special Issue **12**: 75–94.
Winter SG. 1984. Schumpeterian competition in alternative technological regimes. *Journal of Economic Behavior and Organization* **5**: 287–293.
Zahra SA. 1996. Governance, ownership, and corporate entrepreneurship: the moderating impact of industry technological opportunities. *Academy of Management Journal* **39**(6): 1713–1735.

APPENDIX: GENERALIZED DISCRIMINANT PROCEDURE USED TO IDENTIFY ENTREPRENEURIAL AND ROUTINIZED REGIMES

To distinguish between the entrepreneurial and routinized stages, we examined the dataset of the annual gross entry rates for each industry, which were typically characterized by a large 'hill' separated from a later period of little or no entry. To determine the break year for each industry, in which gross entry rates slowed, we first partitioned the series into three categories. Categories A and B contain the years when the gross entry rate clearly reflects the entrepreneurial and routinized stages, respectively. The series of the T consecutive in-between years of the third category are then labeled $x_1,\ x_2,\ \ldots,\ x_T$. The problem was then to choose an optimal dividing year j such that observations $x_1,\ x_2,\ \ldots,\ x_j$ would be classified in the period before entries become numerous, and $x_{j+1},\ x_{j+2},\ \ldots,\ x_T$ would be classified in the period after entries become numerous. This can be accomplished using the following three-step procedure:

For each $j = 1, 2, \ldots, T$, we computed

$$d_1(j) = \sum_{i=1}^{j} x_i/j \qquad (1)$$

$$d_2(j) = \sum_{i=j+1}^{T} x_i/(T-j)$$

The choice of the dividing year was limited to those values of j for which

$$|d_1(j) - \mu_1| \leq |(\mu_1 - \mu_2)/2| \qquad (2)$$

$$|d_2(j) - \mu_2| \leq |(\mu_1 - \mu_2)/2|$$

where μ_1 and μ_2 represent the mean rates of gross entry for the entrepreneurial and routinized categories. If there were no values of j satisfying Equation 2, then all observations were classified in the entrepreneurial stage if $|d_1(T) - \mu_1| < |d_1(T) - \mu_2|$ and in the routinized stage. The rationale behind this step was that the mean of the observations classified into each of the two stages is closer to the sample mean of the observations initially classified into its respective stage, rather than to the mean of those placed into the other stage.

If multiple values of j satisfied Equation 2, then we selected the value of j from this set that maximized $|d_1(j) - d_2(j)|$.

This step ensured that, among the classifications that would satisfy Step 2, the classification that was chosen maximized the difference between the means of the points classified into the two alternative stages.