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NICHE WIDTH REVISITED: ORGANIZATIONAL SCOPE, BEHAVIOR AND PERFORMANCE

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Although strategy research typically regards firm scope as a positional characteristic associated with performance differences, we propose that broad contemporary scope also provides insight into the routines that govern firm behavior. To attain broad scope, firms must repeatedly explore outside the boundaries of their current niche. Firms with broad niches therefore operate under a set of routines that repeatedly propel them into new market segments, expanding their niche. These niche expansions, however, involve risky organizational changes, behavior that disadvantages generalists relative to specialists, despite the positional value of broad scope. Empirical analyses of machine tool manufacturers and computer workstation manufacturers support this conjecture: (i) generalists introduce new products at a higher than optimal rate, thereby increasing their exit rates; and (ii) generalists also more frequently launch new models with novel features or targeted at new consumer segments rather than improving only incrementally on existing products, further accelerating their odds of failure. After adjusting for these behavioral differences, broad niche widths reduce exit rates, suggesting that they provide positional advantages. The paper discusses how this phenomenon may help to explain the diversification and multi-nationality discounts. Copyright © 2006 John Wiley & Sons, Ltd.

INTRODUCTION

Researchers from a variety of perspectives have highlighted the scope of the firm (i.e., its niche width) and its influence on performance as an important issue in organizational theory and strategy. Within individual markets, for example, managers confront the question of product variety (e.g., Kekre and Srinivasan, 1990; Sorenson, 2000): Should firms develop a broad portfolio of products tailored to heterogeneous customers, or limit variety to exploit economies of scale? A closely related line of research in organizational ecology examines whether firms should draw on a wide range of resources or focus their activities (Hannan and Freeman, 1977; Freeman and Hannan, 1983). And at the corporate strategy level, a substantial literature on diversification attempts to isolate if and when the dispersion of activities across multiple markets benefits performance (e.g., Rumelt, 1982).

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In these various lines of research, the theories forwarded to relate firm scope to performance typically focus on this dimension as a positional characteristic of the organization. In other words, the firm gains an advantage (or disadvantage) because of the number and types of products it offers and/or resources it uses (i.e., due to its position in product or resource space). Firms with broad product lines, for example, can charge higher prices or garner greater market share because they produce goods and services that better fit the diverse preferences of different segments of consumers (Pigou, 1920; Perloff and Salop, 1985). Firms with valuable resources, especially those difficult to trade, enter new markets to exploit their excess capacity (Penrose, 1959). By leveraging such resources across multiple markets, these firms gain scope economies and cost advantages over single market competitors (Teece, 1982). Taking a more dynamic view, ecologists meanwhile point to the fact that generalists—firms with broad scope—adjust more easily to the demands of shifting environmental conditions, thereby improving their survival chances (Hannan and Freeman, 1977).

Although the positional advantages associated with scope undoubtedly play an important role in determining firm performance, firms with broad scope also *behave* differently from those with narrow scope, potentially in ways that significantly affect performance. Indeed, the very fact that firms differ in scope implies that these organizations vary with respect to the underlying codes, or routines, that govern their behavior. Just as the vast majority of firms start small, the vast majority of firms also begin life with narrow scope, as specialists, operating in a single market with limited geographic purview. To expand beyond this position, an organization must repeatedly extend outside of its original niche, testing its acumen in new markets. Thus, organizations with broad scope—generalists, diversified firms, and multinational corporations—differ not only in the positions that they have obtained, but also in the behaviors that have brought them there.

Although firms might wish, ideally, to discontinue expansion after achieving an optimal range of activities, enacting such a strategy is difficult. Firms cannot easily rewrite their organizational codes upon reaching advantaged positions; rather, exhibiting the second principle of inertia—bodies in motion tend to stay in motion—the very routines that allowed the firm to achieve an advantageous scope inextricably lead the firm into risky (and potentially detrimental) expansions in the future. Firms with broad niches thus suffer a behavioral disadvantage relative to more focused rivals.

Delving into these nuances in the relationships between organizational scope, firm behavior, and performance requires more detailed data than researchers typically use in studies of firm scope. In particular, we need information not just on the boundaries of firms, but also on their product entries over time. Two unusual and complementary datasets covering all U.S. machine tool manufacturers from 1975 to 1995 and all U.S. computer workstation manufacturers from 1980 to 1996 contain the necessary information. Our empirical analyses focus on how the product entry behavior of machine tool and computer workstation manufacturers varies according to firm scope, as well as how those actions affect firm performance—in this case, the likelihood of firm failure. We find that: (i) specialists introduce fewer new products than generalists; (ii) the products that specialists introduce more likely embody incremental improvements on existing technologies than exploratory ventures into new markets and niches; and (iii) after controlling for the debilitating effects of excessive product introductions, wider niche widths increase survival rates. Generalists thus appear to enjoy a positional advantage that partially offsets their behavioral disadvantage.

The implications of our findings reach beyond simply refining niche width theory in organizational ecology; our approach may also lead to a better understanding of some perplexing empirical findings in the study of organizations. For example, studies of diversified firms frequently find that investors trade their securities at a discount to the market (Lang and Stulz, 1994; Berger and Ofek, 1995). Recent refinements of this research, however, demonstrate that diversification itself does not depress stock prices; rather, investors discount the equity of the types of firms that tend to diversify (Campa and Kedia, 2002; Villalonga, 2004). After correcting for this selection bias, diversifying firms may even trade at a premium (Villalonga, 2004, 2005). Ushijima (2002) has shown that a similar relationship exists for international expansions; firms with a high probability of expanding abroad trade at a discount, but actual foreign investments appear to increase firm value.

Like generalists, diversified firms and multinational enterprises reach these positions through a series of moves. Though the end states that they come to occupy may benefit the firms, reaching these positions (i.e., becoming diversified or expanding internationally) entails substantial risk. Our results suggest that investors may discount the value of these firms because the exploration-oriented organizational codes at their cores cannot ensure reliable ongoing performance.

NICHE WIDTH THEORY

Before embarking on the exposition of our theoretical propositions, let us first define clearly what we mean by 'niche width.' Following Hutchinson (1957), Hannan and Freeman (1977) defined an ecological niche as all combinations of resource types and levels in which a population can survive. For a commercial organization, one might think more concretely about what sources of capital, labor, and material inputs the firm requires, as well as which consumers might purchase its goods and services. Though initially identified at the level of the organizational population, subsequent empirical research and theoretical extensions have shown that the concept also has validity at the level of an individual organization (Podolny, Stuart, and Hannan, 1996; Hannan, Carroll, and Pólos, 2003). One can therefore think of the organizational niche as the range of resource types and levels within which a particular firm can survive.

Niche width is one means of classifying these resource spaces. In particular, organizational ecologists define firms as specialists if they can only survive within a limited range of resources. Generalists meanwhile can draw sustenance from a wide range of resources—technologies, customers, employee skills, and other factors of production—to survive (Hannan and Freeman, 1977). Specialists perform better within a narrow range of environmental conditions because they consistently use their resources closer to full capacity. Generalists, by contrast, carry 'excess capacity' in the sense that their resources exceed those needed for routine tasks; they only operate at full potential when called upon to deal with unanticipated fluctuations in the environment.

Operationally, specialists and generalists have typically been distinguished according to the breadth of the markets in which they participate because this information corresponds closely to the underlying resources on which the organization draws. For example, Freeman and Hannan (1983) coded restaurants as being generalists if they offered a relatively broad menu, had at least one chef and offered in-restaurant seating. Baum and Singh (1994) defined niche width in the day-care industry in terms of the ages of children served, as this range indicates the types of care-givers an organization must employ, and the kinds of activities and material resources it uses. Similarly, studies of the automobile industry identify niche width according to the range of engine sizes produced, a relevant measure of the underlying technologies, customer segments, and design capabilities of the firm (e.g., Dobrev, Kim, and Hannan, 2001). Our analyses follow this tradition of using the range of product characteristics to assess niche width. We nonetheless refine it to consider not just the range, but the entire distribution of products offered by firms. In other words, two firms might have equivalent ranges on some product characteristic, but if one has a tightly grouped set of products with a single outlier, we consider it more of a specialist than a firm spreading its offerings evenly across the product space. In the machine tool industry, we focus on the variety of different classes of machine tools manufactured by each firm, while in the computer workstation market we use the variation in machine prices to assess niche width.

Although the range of product characteristics enjoys wide acceptance as a measure of niche width, not all accounts define the scope of the firm according to product range. Many studies instead use organizational size. For example, several studies in resource partitioning—through the use of concentration ratios—implicitly classify generalists according to size (e.g., Carroll, 1985). Some researchers even use this criterion explicitly; for example, Swaminathan (2001) identified specialist wineries as those producing small quantities, but with a reputation for high quality, while he labeled the large, mass producers, generalists. Though size almost certainly correlates positively with being a generalist, defining the two as equivalent strikes us as problematic; size also reflects the historical success of the organizational form. We therefore concentrate on product-range based definitions of niche width.

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Niche width and organizational behavior

A number of perspectives on organizational behavior treat the firm, more or less, as a set of routines. Evolutionary approaches discuss the firm as a collection of relatively stable routines that govern behavior (March and Simon, 1958; Nelson and Winter, 1982). Similarly, ecological perspectives emphasize that organizations begin with a set of core structural features: (i) a mission and goals; (ii) forms of authority and bases for exchange among the organization and its members; (iii) technology; and (iv) marketing strategy; which remain largely unchanged over their lifetimes (Hannan and Freeman, 1984; Carroll and Hannan, 2000, provides a major restatement). These core elements remain relatively stable because deeply ingrained tacit elements of the organization, such as culture and informal relationships, support them. Change therefore requires renegotiating political agreements, unlearning behaviors that have become habitual, and modifying both core and peripheral features of a firm's structure (Cyert and March, 1963; Nelson and Winter, 1982). Consequently, the routines present in a firm's infancy continue to shape its behavior in important ways throughout its lifetime (Stinchcombe, 1965).

With few exceptions, organizations begin life as small, single-market (frequently single-product) firms. Regardless, firms differ even at this early stage in their founders' aspirations and visions, the resources garnered to begin business, and the allocation of decision making and operational responsibilities. Firms that develop broad niches likely have, at their core, routines that encourage employees to push the boundaries of the firm (e.g., a mission that emphasizes growth and innovation, or defines a firm's business in terms of general needs, rather than specific markets and customers). Firms also enter with an endowment of technologies, marketing strategies, and supporting human and organizational resources that vary in their suitability for different niche widths; certain individuals possess more fungible skills and some technologies allow a broader range of application (Hannan and Freeman, 1977). These differences in routines and resources lead some firms to expand while others do not.

Although differences in propensities to expand probably exist within the firm from its early formation (though do not become apparent to outside observers until acted upon), the strength of these tendencies may also adjust over time. In particular, the act of engaging these routines strengthens them. Firms remember routines by 'doing' more of a particular activity, giving organizational behavior a strong path-dependent character (March, 1991). Positive feedback can further accentuate these differences, even when actors do not understand the causes of success and failure. Studies of individual and organizational behavior commonly find that positive outcomes following an action increase its likelihood in the future (Thorndike, 1927; Levitt and March, 1988). Even without apparent rewards, merely acting in a particular manner in the past often increases the tendency toward that course of action in the future as individuals become more comfortable with it (Bandura, 1986). Over time, these behaviors become 'locked-in' as individuals and organizations require overwhelming evidence to justify changing behaviors after forming beliefs about the appropriateness of these routines (Hastie, 1984).

These factors suggest that an organization that has become a generalist will continue to expand and diversify. Consider two organizations of the same age, one of which has remained a specialist while the other has become a generalist. To reach this state, the generalist almost by definition has taken more actions, such as introducing new products, to expand its resource niche. On the one hand, the generalist's expansion efforts reflect initial differences in its underlying routines. To the extent that these routines remain stable, they will continue to push the generalist beyond its boundaries. But the very act of engaging in these expansions also increases their likelihood in the future as managers and employees become accustomed to product innovation as a mode of operation. Moreover, to the extent that product introductions represent a risky action, those that survive will more likely have experienced positive outcomes from their earlier product introductions, further increasing their propensity to engage in these actions in the future. Combined, these processes imply a strong inertial tendency for generalists to continue introducing new products at a high rate. Consistent with this expectation, empirical studies of resource partitioning commonly observe that generalists tend to become larger and more general over time (Carroll and Hannan, 2000). Thus, we predict:

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Hypothesis 1: Generalists introduce new products at a higher rate than specialists.

The simple introduction rate of new products, however, does not completely explain the differences between generalists and specialists; over time, generalists also introduce a wider variety of products than specialists. A specialist could introduce a large number of products into a particular niche yet remain tightly focused. Only organizations that introduce products outside their narrow existing niches become generalists. Just as behavioral inertia propels generalists to introduce more products, it should also lead them to introduce more products outside their existing niches (i.e., products that require new resources or attract new customers) more frequently:

Hypothesis 2: Generalists introduce products outside their existing niches at a higher rate than specialists.

Generalists also probably introduce more innovations that push the frontiers of current technology and product performance. Significant product and process innovations require firms to depart from what they have done in the past. In some cases—often referred to as competence-destroying innovations—new technologies draw on existing resources to such a limited extent that even large incumbents find it difficult to survive (Tushman and Anderson, 1986). But even when firms can continue to use their existing resources, the adoption of new technologies typically requires firms to develop new routines, to hire employees with new skills, and to court new customers. Like other forms of niche expansion, technological innovation therefore requires firms to depart from what they have done in the past. Since routines that encourage such departures govern the operations of generalists, we expect them to adopt these new technologies more rapidly:

Hypothesis 3: Generalists adopt innovations at a higher rate than specialists.

Niche width and organizational performance

These differing behavioral paths also influence the viability of the organization. Product innovations, niche expansions, and the adoption of new technologies all represent risky activities on the part of the firm, even when these moves appear sensible in terms of strategic positioning. Barnett and Carroll (1995) argued that researchers must decouple the content and process of organizational change. Even when change involves shifting to a position that fits the environment better, the process of reaching that position can still prove hazardous. Organizations must learn new skills, recruit different types of personnel and develop relationships with unknown external parties, each of which the organization must do without any degree of certainty about whether it will succeed. As a result, even in the case of sensible shifts in strategy, the process of change often hurts the organization in the short run—increasing its likelihood of failure and reducing its profitability—until it has integrated into its internal systems the changes necessary to accommodate these strategic shifts. Firms that survive this process may nonetheless benefit from these changes in the long run.

In one of the first empirical tests of this proposition, Barnett and Freeman (2001) studied the effects of product introductions on the survival chances of semiconductor manufacturers. They found that when one decouples the process and content of innovation, the process of introducing new products to the market increased the likelihood of firm failure, even though having a large set of up-to-date products improves the viability of semiconductor manufacturers (see also Dowell and Swaminathan, 2000, for evidence from bicycle manufacturers). Barnett and Freeman argue that this effect stems from the difficulty of implementing manufacturing processes for the new products and training sales forces to market them. Frequent product innovations in a short span of time exacerbate this process, as firms must begin assimilating a new product before successfully digesting the previous one. Product introductions may also divert attention from supporting a firm's existing products, and thereby threaten their performance (Roberts and McEvily, 2005). Designing, developing, and distributing new products disrupts established routines, and hence increases a firm's likelihood of failure, even though by updating and expanding its product portfolio a firm can ultimately attain a better market position:

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Hypothesis 4: Product introductions increase failure rates in the short run.

Generalists and specialists, however, probably differ in the degree to which they suffer from new product introductions. Niche expanding moves (i.e., those that enlarge the set of resources a firm requires) disrupt the firm's activities even more than product introductions into established niches. Novel technologies may entail modifications to the core elements of a firm's product designs and manufacturing processes, as well as to the routines used to sell and support its products (Tushman and Anderson, 1986). Employees hired to bring new skills into the organization need time to assimilate the firm-specific knowledge and norms that enable efficient and reliable collective action (Stinchcombe, 1965; Hannan and Freeman, 1984). And the more the customer demands and technological opportunities that a firm targets depart from its experience, the longer it will take to eliminate the bugs in these routines (Abernathy and Clark, 1985). Diversification also places greater strain on an organization's existing resources because it reduces the value of a firm's prior experience in fine-tuning and developing new routines (March, 1991; Barnett and Carroll, 1995).

Since niche expansion and innovation temporarily disrupt existing routines and demand new roles, procedures, and relationships, firms that more frequently introduce new products that push the firm into new regions of the resource space likely face a higher risk of failure (Dowell and Swaminathan, 2000; Barnett and Freeman, 2001). As noted above, generalists also engage in the niche expansions and technology adoptions that necessitate more extensive changes to existing competencies and routines. As a result, one might expect that generalists would encounter greater difficulty when introducing new products and require additional time to assimilate them into their systems:

Hypothesis 5: Product introductions increase the exit rates of generalists more than specialists.

Although the performance of generalists and specialists may vary as a result of their positional differences, we contend that these firms also vary with respect to their behavior, in a manner relevant to firm performance. In particular, differences in the goals, routines, and resources present at an organization's founding lead to varying paths of niche expansion. Firms with highly reliable routines adopt a conservative approach, rarely pushing outside of the niches in which they have experience. Other firms expand more frequently. Those successful in these expansions may enjoy positional advantages from their broader niche widths, but the process of getting there is fraught with risk.

TWO CONTRASTING SETTINGS

We test these hypotheses in two very different settings: machine tool manufacturing (1975–95) and computer workstation manufacturing (1980–96). Machine tool manufacturing is a mature industry; many of the firms active in the industry trace their roots to the 19th century. Though firms compete to some extent on innovation, products enjoy long life cycles and older products often compete successfully for years against machines offering the latest innovations. Computer workstation manufacturing, by contrast, is a relatively new industry dominated by recent startups. The rapid rate of innovation in the core components of these systems requires manufacturers to update their product lines frequently to remain competitive. Not only do these industries provide two independent settings for testing our hypotheses, but also, to the extent that firms in both settings behave similarly, the contrasting characteristics of these industries allow us to exclude a wide variety of alternative context-specific explanations.

We begin by describing each industry in more detail and then turn to a discussion of our variable construction, estimation, and results.

Machine tool manufacturing

Though historians do not know when the first machine tool appeared, artifacts dating to periods as early as 1200 BC show evidence of having been 'turned'—that is, having a core hollowed out by a sharp rotating device, such as a drill or blade (Rolt, 1965). Despite this long history, modern machine tools began appearing more recently, at the end of the 18th century, when the steam engine created demand for precision manufacturing equipment; in 1775, John Wilkinson developed an extremely

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precise horizontal boring machine, which made the steam engine possible.[1]

Though British inventors focused on creating machines to improve the quality of craft production, machines developed during the American industrial revolution increased speed and economized on labor, valuable features in a sparsely populated country. Eli Whitney pioneered America's machine tool industry. After securing a government contract in 1798 to produce 10,000 army muskets, Whitney single-handedly built all the machinery necessary to produce the weapons. His system popularized the concept of interchangeable parts, in which one could mass-produce parts, and then reliably assemble guns from randomly selected components. In 1818, he developed the first milling machine. Shortly thereafter, other American inventors, including Isaac Singer (sewing machines), Cyrus McCormack (harvesters), and Henry Ford (automobiles), developed machine tools for their industries following Whitney's example. From 1895 to today, the automobile industry has been the largest consumer of machine tools and, with the defense sector, has been the primary force driving the direction of innovation in the machine tool industry.

Our machine tool data come primarily from the *AMT Members Directory*, 1975–95. This directory lists the products manufactured by its members and includes both American and non-American manufacturers of machine tools. In total, we identified 564 machine tool manufacturers and observed them for a total of 5572 company-years. We also used the American Machine Tool Distributors' Association (AMTDA) *Membership Directory* from 1975 to 1995 to corroborate the exit data. Our historical research and interviews with industry experts suggest that, together, the AMT and AMTDA directories cover nearly 100 percent of the manufacturers of U.S. machine tools.[2] In extending and assessing the reliability of these data, we referenced *Huebner's Directory of Machine Tool Specifications* (1980, 1982), *Reynolds RMT Redbook, Ward's Industrial Directory*, the *Million Dollar Directory*, and the *D&B Metalworking Directory*.

Owing to the amount of effort required to gather data on product introductions and their performance attributes, we limited our analysis to two categories of metal-cutting tools. Specifically, we focused on Category 8 (which includes horizontal and vertical milling machines, horizontal boring machines, and horizontal and vertical machining centers) and Category 12 (which includes horizontal and vertical lathes, chucker and bar machines, and turning centers). These two categories constitute nearly 90 percent of all metal-cutting tool shipments. Within these categories, we found 2869 product introductions advertised in *American Machinist* from 1975 to 1995.[3]

Computer workstation manufacturing

By contrast, the birth of the computer workstation industry is a recent event. Apollo launched the first workstation, the DOMAIN, in 1980. This new machine combined several recently developed technologies into one machine: a 32-bit microprocessor, a high-speed local area network (LAN), large shared virtual memory resources, and Winchester hard drives. Together these elements brought the power of mainframes to desktop computing.

Although today workstations have relatively homogeneous characteristics, early machines varied greatly in the specifics of their configurations. Manufacturers used a variety of off-the-shelf and customized microprocessors. Some companies used existing operating systems, such as UNIX, while others developed their own proprietary operating systems. Manufacturers even disagreed on the best means of producing graphics. Some systems produced images by defining a series of lines

[1] Steam engines required large cylinders of precise interior size to prevent steam from leaking between the cylinder and the piston. Wilkinson's machine tool solved this problem by enabling the manufacture of much more accurate parts than had previously been possible.

[2] To verify our interpretations of the technologies and market segments, we interviewed several industry experts: Anderson Ashburn, the longest serving editor (about 25 years) of *American Machinist* and founding editor of the industry Blue Books; Anthony Bratkovich, Engineering Director, AMT; Joe Jablonowski, previously editor of *American Machinist* and now editor of *Metalworking News*; Ralph Nappi, Director, AMTDA; and Mark Rogo, who has managed a variety of machine tool businesses over the last 30 years.

[3] Checks of these advertisements against Mark Rogo's private library of machine tool product specifications suggest that nearly all new cutting machines introduced into the U.S. market receive advertising coverage in *American Machinist*, though these ads sometimes neglect to provide complete product characteristic data. We therefore used Rogo's archive to complete missing information where necessary.

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on the screen (raster-based graphics), while others defined images one pixel at a time (bit-mapping).

Because of this variety, defining workstations according to any particular feature would force hindsight of the evolution of the product onto the sample. We therefore identified workstations according to a set of general attributes. In particular, we included all distributed computing machines intended primarily for the use of a single individual. In doing so, we usefully distinguish workstations from three other classes of computing machines: terminals, servers, and personal computers. Terminals lack significant local processing capabilities. Servers can operate in distributed computing environments, but they typically do not serve a single user. And personal computers, while intended for a single user, do not share resources across machines.[4]

Using this definition, we identified all workstation manufacturers and all of the products they introduced between 1980 and 1996 using *Data Sources*. To assess the completeness of these data and to supplement the information appearing in them, we also referenced the corporate reports of all public companies and reviewed advertisements and product announcements in *IEEE Graphical Computing and Applications*.[5] The final dataset includes all organizations in North America producing computing machines classified as workstations between 1980 and 1996, 677 company-years and 2721 product-years representing the market histories of 175 companies and 1276 products in North America.

Measures

Specialism

In the behavior models, the primary independent variable of interest is the niche width of the firm. This measure should reflect the breadth of the routines, or capabilities, available to the firm. Prior studies have often relied on qualitative descriptions of alternative business models or organizational forms to categorize firms as being either specialists or generalists (e.g., Freeman and Hannan, 1983). Those that have developed continuous measures typically code the range of the values on some product characteristic; for example, Dobrev, Kim, and Hannan (2001) use engine size for automobile manufacturers. Although these measures, when appropriately chosen, provide information on firms' underlying capabilities, they remain course-grained measures at best of this variety. We therefore refine this conceptualization further by computing measures of niche width based on the entire distribution of product offerings.

For machine tool manufacturers, we calculated the Herfindahl concentration ratio across the 12 categories of machine tool products:

$$\text{Machine tools: } specialist_i = \sum_k s_{ik}^2$$

where s denotes the proportion of firm i's total products classified in segment k (though not included in the equation, these time-varying measures also all have implicit indices for time). The measure ranges from 0 to 1, with 1 indicating the highest level of specialization. Product segments provide an appropriate basis for measuring the degree to which incumbents compete as specialists, as each corresponds to a different set of customer requirements and exploits a unique set of technologies (Roy and McEvily, 2004, detail the specific competencies required for each class of machine). Firms serving a greater number of product categories enact more general strategies and operate with a wider variety of resources simultaneously.

For computer workstation manufacturers, we calculated the relative variance of the prices as a measure of specialization:

$$\text{Computer workstations: } specialist_i = 1 - \frac{\sum (p_{ij} - \overline{p}_i)^2 / N_i}{\max\left[\sum (p_{ij} - \overline{p}_i)^2 / N_i\right]}$$

where p represents the list price of product j and N is the total number of products offered by the firm (again, all terms have implicit indices for time). Intuitively, we compute the variance in product prices for each firm and then normalize it by dividing through by the largest variance in prices for any firm in that year. This process yields a measure with a minimum of 0 (generalist) and a maximum of 1 (specialist). As general machines, workstations do not have the same type of distinct

[4] See Sorenson (2000, 2003) for additional details regarding the construction of the sample.

[5] Although we identified additional systems from 1980 to 1982, *Data Sources* appeared to have completed coverage from 1983 onward.

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product types as machine tools; most differentiation across products is vertical (e.g., faster) rather than horizontal. Many firms nonetheless specialize in a narrow range of workstation quality, oftentimes customizing these machines for the needs of a particular segment of consumers, such as engineers using CAD/CAM software or publishers using workstations for electronic typesetting. Prices, moreover, should reflect firm capabilities as the challenges involved in producing the cheapest machine possible differ greatly from those associated with maximizing performance. Consumers in these segments also differ in the channels through which they purchase and their expectations for service.

Product introductions

We examined the effects of these variables on three different product outcomes: (i) the proportion of new products a firm introduces each year; (ii) the proportion of these new products a firm introduces outside of its existing niche each year; and (iii) the likelihood that its new products incorporate new technologies.

Proportion new products counts the number of distinct new models divided by the total number of products offered by the firm. Product listings with the same name and the same characteristics as products available in early years do not count as new models for this measure. We expect that generalists bring a greater proportion of new products to market. Because the measure is a proportion and only ranges from 0 to 1, OLS regression produces biased estimates. We therefore use tobit regression to estimate the parameters (for a review of tobit estimation, see Maddala, 1983).

Proportion out of niche counts the number of products that a firm introduced outside its existing niche divided by the total number of new products offered by the firm. In the case of machine tools, we treat the niche as the range of engine sizes (in HP) produced by the firm. Within product categories, motor size changes represent risky moves because they typically require the firm to develop a range of new architectural competencies. For example, the relative positions of the spindle and gears change in a smaller machine. Machine tools of different sizes also typically target distinct customers and metal-cutting applications. We therefore count any new product with an engine size below the previous minimum level or above the previous maximum as an out-of-niche expansion. If the firm introduces many new products in a year outside of its prior niche boundaries, all of them count as out-of-niche (not just the extreme values that define the new boundaries). In computer workstations, we define the niche boundaries as the cheapest and most expensive products offered by the firm in the prior year and calculate our measure accordingly. As noted above, these moves often reflect attempts to reach new customer segments.[6] Despite already covering a larger share of the market, we expect generalists to introduce a larger proportion of products outside of their existing niches. We also model these proportions using tobit regression.

Technological adoption—in machine tool manufacturing, numerical and computer numerical controls (CNC) represented a major new component technology. Though first introduced in the 1960s, U.S. machine tool manufacturers adopted this technology slowly—their lack of flexibility, high costs, and unreliability meant they did not diffuse to any notable degree until the early 1970s (Ehrnberg and Jacobsson, 1997). CNC diffused even more slowly in the United States, with 1975 marking the beginning of its expansion. Roy and McEvily (2004) argue that CNC is a radical (i.e., competence-destroying) innovation in the industry. To incorporate CNCs into machine tools, firms had to acquire skills in electronics, microprocessor technologies, and software—a substantial departure from their largely mechanical skill base. CNC production also required extensive organizational changes, as well as the acquisition of upstream and downstream capabilities; for example, clients could no longer service their own machines, so manufacturers had to build service departments to support customers using CNC machine tools.

For computer workstations, we consider the adoption of any new operating system or microprocessor a major technological adoption. New operating systems often require either the development of new hardware drivers or the redesign of the system to eliminate incompatible hardware (see

[6] One might worry that price changes in the computer industry simply stem from the downward price trajectories in the market over time (such as in personal computers). In our study period, however, this effect probably accounts for few of our niche expansions. Notably, 62 percent of our expansions come from higher-priced machines (typically with new capabilities), and even many of the expansions beyond the lower end of the price range clearly reflect the introduction of stripped down (i.e., entry-level) models.

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Kernighan and Morgan, 1982, for the difficulties of porting UNIX). Similarly, as Anderson (1995: 38) notes: 'Designing a computer around a microprocessor is not a trivial exercise;' the adoption of a new processor typically entails not just a change in this chip but also complementary changes in nearly every other subsystem of the machine. Though staying competitive requires workstation manufacturers to integrate such new components frequently, the process is not without peril.

In the case of machine tool manufacturers, we model adoption as a discrete time failure rate model with logit regression, with the adoption of a new technology representing a failure. In nearly every case, once a machine tool manufacturer adopts CNC it incorporates it in all of its new models going forward (19 exceptions out of 564 cases).[7] We therefore treat these adoptions as one-time events. Computer workstation manufacturers frequently introduce products in a single year with a variety of microprocessors and operating systems. We therefore estimated adoption as the proportion of new products offered incorporating either a new operating system or a new microprocessor, again using tobit regression. We expect that generalists more frequently adopt these new technologies.

Control variables

All of the models control for a variety of other factors that may influence product introduction behavior and firm performance. For example, firm age may hinder adaptation to radical innovations (Sørensen and Stuart, 2000). It has also been linked to the likelihood of exit in many previous studies, though its effect has varied from study to study (see Hannan, 1998, for a review). We measure *age* as the difference between the current year and the year in which the firm entered the market. To control for potential differences between early and late entrants to the market, we also included the *entry year* in the models (defined with the first observation year = 0; 1823 for machine tools and 1980 for computer workstations).

Scale also importantly influences firm behavior and performance. We include three controls to capture different types of potential scale effects. Firm *size*, the sales of the firm (in logged 1995 dollars), helps to control for economies of scale and the fact that innovation may not cost large firms much more even though they can enjoy the benefits of those innovations across a larger number of units. Meanwhile, *market share* captures both scale effects and returns to market power.[8] Market power may in turn increase the incentives for innovation if it allows firms to capture the value of these innovations more easily. And the *number of machine tools/workstations*, a count of the number of products firms currently sell, is a measure of the potential advantages or disadvantages of product variety (Sorenson, 2000).

The models also include controls for basic ecological processes. Competition for resources becomes more intense as the number of organizations in a given niche rises. We measure *density*, or the number of competitors, as the number of companies competing in the industry. Following the normal procedure in organizational ecology, we include the squared density term as well to account for the fact that rivals may have both legitimating as well as competitive effects on other organizations in the population (Carroll and Hannan, 2000). In addition to influencing performance, firms may actively adjust their product entry strategies in response to this competition. Variable definitions appear in Table 1, while Tables 2 and 3 report descriptive statistics and correlations for the variables used in the models.

Table 4 reports our estimates of the correlates of new product introductions in the machine tool industry. Model 1 estimates what factors influence the rate at which a machine tool manufacturer introduces new products into the market. As expected (Hypothesis 1), specialists introduce products at a much slower rate than generalists. Even after controlling for size, a one standard deviation decline in the degree of specialism corresponds to an 87 percentage-point increase ($= -2.42 \times -0.36$) in the rate of product introductions. Models 2 and 3 then investigate which firms bring more innovative products to market. The estimates from Model 2 reveal that generalists more frequently engage in product segment niche expansion—through the introduction of products

[7] Treating these partial cases as either adoptions or non-adoptions does not substantively affect the results.

[8] For machine tool manufacturers, we compute market share as total firm sales divided by U.S. machine tool consumption. For workstation manufacturers, market share is the ratio of firm workstation sales to the sum of workstation sales across all manufacturers.

Table 1. Variable definitions

Machine tool manufacturers	
Proportion new products	# new products/total # of products
Proportion segment (HP) niche expansions	# new products above max HP ($t-1$) or below min HP ($t-1$)/total # of products
Technological expansions (CNC/NC machine)	0/1 indicator for adoption of CNC/NC technology
Density	Count of machine tool manufacturers
Age	Current year − year firm entered market
Entry year	Year firm entered market − 1823
Size (logged sales)	ln (firm sales in 1995 dollars)
Market share	Firm sales/sum across all firms (firm sales)
Number of machine tools	Count of product offerings
Specialist (product diversity)	Herfindahl concentration measure across product categories
Average product age	Average age of products at beginning of period
Firm exit	Firm discontinues production of machine tools
Workstation manufacturers	
Proportion new products	# new products/total # of products
Proportion niche (price) expansions	# new products above max. price ($t-1$) or below min. price ($t-1$)/total # of products
Technological expansions (operating system/processor)	# new products with operating system or processor not previously used by firm/total # of products
Density	Count of computer workstation manufacturers
Age	Current year − year firm entered market
Entry year	Year firm entered market − 1980
Size (logged sales)	log (sales in 1995 dollars)
Market share	Workstation sales/sum across all firms (workstation sales)
Number of workstations	Count of product offerings
Specialist (relative price range)	Variance of product prices
Average product age	Average age of products at beginning of period
Firm exit	Firm discontinues production of computer workstations

with smaller or larger engines than their existing product line—despite the fact that these firms already cover a larger range of the potential market (supporting Hypothesis 2). Model 3 meanwhile indicates that specialists less frequently introduce products with the new CNC control technology (an expansion of their technological niches), consistent with Hypothesis 3.

The control variables also indicate that many other firm characteristics have consistent effects on product innovation behavior. Firms release products at a slower rate and introduce products that are less novel as they age. Later entrants also interestingly appear less innovative. Larger firms, measured either in terms of absolute or relative (i.e., market share) scale, tend to introduce new products and niche-expanding products at higher rates. So, if we considered size a measure of niche width, as many other researchers do, these results would also support Hypotheses 1, 2, and 3.

The intensity of competition appears to have a particularly interesting effect on product introduction behavior. Although the proportion of new products introduced in a year declines with density, the proportion of these products outside of the firm's existing niches rises with density. It appears that competitive crowding may push firms to allocate resources to expanding their niches in search of less-contested regions of product space. In this sense, one might consider our findings the first direct evidence for the micro-processes underlying the 'density delay' effect proposed by Carroll and Hannan (1989).

Table 5 reports parallel models for new product introductions in the computer workstation industry. Model 4 considers what covariates affect the proportion of new products offered by a workstation manufacturer. As with machine tools, specialists introduce new workstations at a slower rate—a one standard deviation increase in specialism reduces the expected proportion of new products by 18 percentage points (supporting Hypothesis 1). From Models 5 and 6, we can see that specialists also introduce a smaller proportion of new products outside of their existing niche (i.e., with list prices above their current maximum or below their current minimum price), and adopt new operating systems and microprocessors at a

Table 2. Descriptive statistics

	Mean	SD	Min	Max
Machine tool manufacturers				
Proportion new products	0.31	0.41	0	1
Proportion segment (HP) niche expansions	0.11	0.32	0	1
Technological expansions (CNC/NC machine)	0.43	0.50	0	1
Density	205.10	12.11	175	223
Age	40.90	36.00	0	172
Entry year	121.20	37.20	0	172
Size (logged sales)	1.77	1.72	0	8.88
Market share	0.01	0.04	0.00	0.75
Number of machine tools	3.71	3.71	0	40
Specialist (product diversity)	0.58	0.36	0	1
Average product age	4.93	5.04	0	31.80
Firm exit	0.03	0.28	0	1
Workstation manufacturers				
Proportion new products	0.44	0.44	0	1
Proportion niche (price) expansions	0.34	0.40	0	1
Technological expansions (operating system/processor)	0.67	0.46	0	1
Density	50.93	16.30	2	76
Age	2.98	2.99	0	14
Entry year	7.50	4.15	0	14
Size (logged sales)	16.33	2.31	9.39	22.77
Market share	0.02	0.06	0.00	0.65
Number of workstations	3.93	6.44	1	47
Specialist (relative price range)	0.74	0.28	0	1
Average product age	1.31	1.45	0	10
Firm exit	0.18	0.38	0	1

slower rate, consistent with Hypotheses 2 and 3. Although innovativeness declines with age in the computer workstation industry, the other control variables do not have consistent effects.

Performance

We use survival to assess organizational performance. Though one might consider other measures, at least three factors point to survival as an important and useful measure. First, firms rarely exit a market when earning substantial profits and expecting those profit streams to continue. Exit may therefore offer a more accurate assessment of performance than accounting-based measures that firms frequently manipulate. Second, our theoretical development regarding the effects on performance concerns the risk involved in a firm's actions, a factor more closely related to the likelihood of failure than to mean profitability. Third, in both samples, more than half of all firms remain private and therefore do not report detailed financial data; hence, as a practical matter, survival is one measure of performance that we can observe for all firms. In both industries, an incumbent fails when it no longer offers products in that industry. We also code three additional events that might explain why a firm no longer offers products: (i) bankruptcy; (ii) divesture from the business by a diversified corporation; and (iii) merger with another company or acquisition by a company wishing to enter the industry. The third type of event may or may not leave the existing company largely intact, though operating under a different name. News reports and trade journals allowed us to determine whether a merger or acquisition resulted in substantial organizational change (and hence to decide whether to treat these events as exits).

We analyze the exit rate of machine tool and computer workstation manufacturers from the market using continuous time survival analysis methods. In particular, we estimate a piece-wise exponential model because it allows for flexible modeling of age dependence and can accommodate the left- and right-censoring found in our sample (Guo, 1993).[9] The models include two variables to

[9] Per Guo's (1993) suggestion, we also included a dummy variable for left censored cases.

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Table 3. Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11
Machine tool manufacturers											
1 % new products											
2 % niche expansions	0.19										
3 CNC/NC adoption	−0.03	−0.04									
4 Density	0.02	−0.05	0.01								
5 Age	−0.37	−0.23	0.19	−0.17							
6 Entry year	0.40	0.07	−0.21	0.09	−0.02						
7 Size	−0.31	0.00	0.23	−0.03	−0.01	−0.59					
8 Market share	−0.10	0.15	0.09	−0.39	−0.43	−0.38	0.59				
9 # machine tools	−0.51	−0.04	0.18	−0.06	0.06	−0.55	0.55	0.40			
10 Specialist	−0.58	−0.11	0.10	−0.05	0.26	−0.29	0.19	0.04	0.12		
11 Product age	−0.73	−0.15	−0.08	0.00	0.43	−0.27	0.13	−0.04	0.36	0.30	
12 Firm exit	0.08	0.08	0.05	−0.03	0.09	−0.03	0.01	0.09	0.03	−0.06	−0.11
Workstation manufacturers											
1 % new products											
2 % niche expansions	−0.05										
3 OS/CPU adoption	0.48	−0.32									
4 Density	−0.12	−0.10	−0.01								
5 Age	−0.34	−0.42	0.01	0.24							
6 Entry year	0.13	0.14	0.03	0.44	−0.48						
7 Size	0.04	−0.49	0.16	−0.05	0.31	−0.28					
8 Market share	0.05	−0.36	0.13	−0.21	0.24	−0.35	0.59				
9 Number of workstations	0.05	−0.72	0.24	0.07	0.46	−0.14	0.54	0.52			
10 Specialist	−0.07	−0.48	−0.21	0.12	−0.22	0.29	−0.42	−0.35	−0.40		
11 Product age	−0.67	0.09	−0.28	0.17	0.42	−0.14	−0.13	−0.11	−0.11	−0.12	
12 Firm exit	−0.08	−0.12	0.30	0.11	0.09	0.09	−0.15	−0.13	−0.10	−0.04	0.31

test for the effects of new product introductions: the proportion of new products introduced this year and the proportion introduced in the previous year. A higher proportion of new products should increase exit rates. And if the disruptive effects of product introductions dissipate over time, lagged introductions should have less of an effect than those in the current year (Barnett and Carroll, 1995; Barnett and Freeman, 2001).[10] The models also include the same control variables as the product introduction models, plus the *average product age* (in years). Irrespective of the process effects of introducing new products, we would expect older product lines to increase failure rates as it becomes increasingly difficult for firms to compete in the product market.

The results in Table 6 provide evidence from the machine tool industry consistent with our fourth and fifth hypotheses. Although specialists exit less quickly overall (see Model 8), this effect appears to result entirely from behavioral differences. After controlling for the number of product introductions in Model 9, the specialist positional advantage essentially disappears. Product introductions have a deleterious effect on firm performance, which specialists avoid to some extent by bringing new products to market less frequently. Each 10 percent replacement of the product line by a firm in a year corresponds to a 10.6 percent rise in the firm's likelihood of exit. However, the insignificant and small value of the lagged term suggests that firms can recover relatively quickly, in less than 1 year, from these disruptions. Model 9 still does not account for the different types of product introductions though. In Model 10, we allow for product introduction to influence specialists and generalists differently (by including an interaction term between the product diversity measure and the proportion of new products). As expected—since specialists more frequently engage in incremental change—even when specialists do introduce new products, these

[10] We use the lagged proportion of introductions instead of the entry clock suggested by Barnett and Freeman (2001) to test for adjustment effects for two reasons: (i) we find it easier to interpret; and (ii) in the computer workstation industry, most firms introduce products every year so we have few cases available, in which a clock would increment, to identify the adjustment effects.

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Table 4. Models of machine tool product introductions

	Model 1 H1	Model 2 H2	Model 3 H3
Estimation method	Tobit	Tobit	Logit
Dependent variable	Proportion new products	Proportion out of HP niche	CNC/NC machine
Age	−0.042***	−0.035***	−0.089***
	(0.003)	(0.004)	(0.026)
Age squared/100	0.009***	0.004***	0.018*
	(0.001)	(0.001)	(0.007)
Entry year	−0.029***	−0.029***	−0.066**
	(0.027)	(0.004)	(0.026)
Density	−0.076**	0.538***	−0.302
	(0.029)	(0.043)	(0.198)
Density squared/1000	0.002**	−0.013***	0.711
	(0.001)	(0.001)	(0.495)
Size (logged sales)	0.139***	0.010	0.196*
	(0.009)	(0.009)	(0.096)
Market share	−0.007	0.068***	0.144*
	(0.008)	(0.010)	(0.070)
Number of machine tools	−0.088***	−0.013***	−0.084*
	(0.003)	(0.004)	(0.033)
Specialist (product diversity)	−2.42***	−0.107*	−3.86***
	(0.059)	(0.048)	(0.413)
Proportion new products		0.893***	1.25
		(0.067)	(0.894)
Constant	13.7	−51.2	40.6
	(2.94)	(4.56)	(19.8)
Log-likelihood	−3750.5	−1890.7	−358.9
R^2/pseudo R^2	0.42	0.15	0.31

3316 product introductions; two-sided t-tests: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

introductions have less of a negative impact on the firm (as little as half the negative impact faced by generalists). Once we control for the behavioral effects of product introductions, we can see that generalists enjoy a positional advantage in the machine tool industry.

The control variables in these models appear to have reasonable effects. Exit rates rise with product age, as firms become less competitive relative to the product frontier. Density has the expected non-monotonic effect—initially lowering and then raising exit rates. Early entrants enjoy lower failure rates, suggesting some form of early mover advantage. And large firms fail less frequently. Perhaps surprisingly, however, firms with greater market share fail at a higher rate. This effect, however, almost certainly reflects the effect of foreign entrants. Between 1975 and 1985 foreign manufacturers dramatically increased their share of the U.S. market, largely at the expense of the largest domestic producers (Finegold *et al.*, 1994).

Table 7 provides a similar set of models for computer workstation manufacturers. The baseline estimates (Model 11) show the expected effects of density dependence and size dependence. Here too, we see evidence of an early mover advantage: firms that enter earlier in the industry's history enjoy lower failure rates. Model 13 introduces the measure of new product entries. As expected in Hypothesis 4, new product introductions accelerate exit. Each 10 percent replacement of a firm's product line results in a 20 percent increase in the likelihood of failure. As in the machine tool industry, these deleterious effects appear short-lived. Products that have been on the market for a year actually reduce exit rates, though the positive effect of average product age suggests that these benefits do not last long. And consistent with Hypothesis 5, specialists (those with less variance in the prices of their offerings) suffer less from the introduction of new products. Again, after controlling for these behavioral effects, generalists appear to enjoy a positional advantage.

Table 5. Models of computer workstation introductions

	Model 4 H1	Model 5 H2	Model 6 H3
Estimation method	Tobit	Tobit	Tobit
Dependent variable	Proportion new products	Proportion out of price niche	Proportion new OS/CPU
Age	−0.735***	−0.160***	−0.103**
	(0.063)	(0.024)	(0.034)
Age squared/100	0.053***	0.012***	10.02***
	(0.005)	(0.002)	(0.311)
Entry year	−0.033	−0.017	0.002
	(0.021)	(0.009)	(0.002)
Density	0.018	0.006	−0.018
	(0.018)	(0.008)	(0.010)
Density squared/100	−0.016	−0.007	0.152
	(0.017)	(0.007)	(0.098)
Size (logged sales)	0.078**	−0.036**	−0.028
	(0.029)	(0.013)	(0.020)
Market share	−0.022*	0.015**	0.011
	(0.011)	(0.005)	(0.007)
Number of workstations	0.034***	−0.042***	−0.018***
	(0.010)	(0.004)	(0.006)
Specialist (relative price range)	−0.649*	−0.735***	−0.447**
	(0.263)	(0.104)	(0.146)
Proportion new products		−0.237***	−0.111
		(0.057)	(0.145)
Constant	−0.044	2.30	2.12
	(0.528)	(0.242)	(0.392)
Log-likelihood	−708.6	−385.9	−384.3
R^2/pseudo R^2	0.16	0.37	0.09

1276 product introductions; two-sided t-tests: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

DISCUSSION

Our results provide strong evidence that specialists differ from generalists not only in position, but also in behavior. To attain broad scope, firms must repeatedly explore outside the boundaries of their current niche. This suggests that proto-generalists enter with a set of resources, a mission, and rudimentary routines geared toward growth and a wider range of operation. The enactment of these expansionary actions strengthens these initial differences in resources and routines, hence further perpetuating generalists' tendency to expand. As a result, firms with broad scope continually extend the boundaries of their niches. Our empirical analysis of machine tool and computer workstation manufacturers supports this thesis: (i) specialists introduce fewer new products; (ii) when they do launch new models, they tend to offer machines that improve only incrementally on existing models rather than exploring new features; and (iii) specialists adopt new technologies at a slower rate.

Since expansion entails potentially hazardous organizational change for any firm, these behavioral differences disadvantage generalists relative to the specialists against which they compete. Given the importance of innovation in both industries, however, the prescription to avoid introducing new products does not seem tenable. Imagine trying to sell a 5-year-old computer! In fact, our results do not suggest that firms should never introduce new products; both machine tool and computer workstation manufacturers suffer as their average product ages increase. Taking both the detrimental *process* effects of product introductions and the beneficial *positional* effects of having up-to-date products into account, Figure 1 shows the total effects of product introductions on exit (from Models 9 and 13), assuming that firms maintain the total number of offerings in their product line and replace the same proportion of their oldest machines with new machines each year.[11]

[11] If firms replace the same proportion of products each year, then the proportion of products introduced in any year equals

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Table 6. Piecewise exponential models of exit from the machine tool market

Variable	Model 7	Model 8	Model 9	Model 10
Age <6 years	22.6*	22.3*	15.2	5.07
	(9.06)	(9.07)	(9.18)	(9.11)
6–25 years	22.3*	22.0*	14.7	4.58
	(9.07)	(9.08)	(9.19)	(9.11)
26–50 years	24.9**	24.5**	17.1	7.06
	(9.08)	(9.08)	(9.20)	(9.13)
50+ years	27.5***	27.2**	20.5*	10.5
	(9.08)	(9.09)	(9.21)	(9.13)
Density	−0.346***	−0.341***	−0.320***	−0.228*
	(0.092)	(0.092)	(0.095)	(0.093)
Density squared/1000	0.009***	0.008***	0.007***	0.006*
	(0.002)	(0.002)	(0.002)	(0.002)
Entry year	0.086***	0.085***	0.110***	−0.111***
	(0.004)	(0.005)	(0.006)	(0.007)
Size (logged sales)	−0.209**	−0.204**	−0.177**	−0.164*
	(0.067)	(0.067)	(0.061)	(0.066)
Market share	0.151***	0.147***	0.132***	0.135***
	(0.037)	(0.038)	(0.037)	(0.039)
Number of machine tools	−0.055***	−0.056***	−0.019	−0.007
	(0.016)	(0.016)	(0.015)	(0.015)
Average product age	−0.034***	−0.033***	0.027***	0.016*
	(0.006)	(0.006)	(0.006)	(0.007)
Specialist (product diversity)		−0.273*	0.197	1.93***
		(0.119)	(0.223)	(0.572)
H4: Proportion new products ($t = 0$)			1.01***	1.04***
			(0.251)	(0.265)
H4: Proportion new products ($t = -1$)			−0.181	−0.172***
			(0.104)	(0.102)
H5: Specialist × proportion new products ($t = 0$)				−0.560*
				(0.222)
Specialist × proportion new products ($t = -1$)				−0.178**
				(0.061)
Left censored	−1.87***	−1.86***	−2.52***	−2.69**
	(0.175)	(0.176)	(0.167)	(0.175)
Log-likelihood	−824.9	−822.8	−792.7	−770.1
LR test		4.2*	60.2***	45.2***

563 firms, 191 failures; two-sided t-tests: * $p < .05$; ** $p < 0.01$; *** $p < 0.001$

the lagged proportion of products introduced. And if we assume that firms generally remove their oldest products from the market when they introduce new ones, and that they replace a constant proportion of products year to year, then the average product age is one half the inverse of this proportion (i.e., one half of the inverse of their product introduction rate). For instance, a firm that replaces 10 percent of its product line annually has an average product age of 5 years—one-half of its product life cycle (it takes 10 years for this firm to renew its product line if it replaces 10% of it each year). For example, for machine tool manufacturers, we use the following formula: multiplier of exit $= \exp\ (1.01t - 0.181t + 0.027/2t$, where t represents the constant product introduction rate. (Note: these coefficients reflect Model 9; for workstations, we use the corresponding coefficients from Model 13.) To ease the comparison across populations, we normalize the predicted rates so that the exit rate minimizes at a value of one in Figure 1 (by dividing through by the minimum predicted value across the observed range of data).

As one can see, the optimal rate of product introduction is not zero: in the machine tool industry, manufacturers minimize their likelihood of exit by replacing 12.8 percent of their product lines each year, while for computer workstations manufacturers the estimates suggest an optimal rate of 40.7 percent (a difference consistent with the idea that the workstation industry experiences higher average rates of innovation than the machine tool industry).

Since firms must introduce some new products to remain competitive, the question then becomes: Do generalists introduce too many new products? It appears so. Figure 2 compares the optimal product introduction rates to the observed rates

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Table 7. Piecewise exponential models of exit from the workstation market

Variable	Model 11	Model 12	Model 13	Model 14
Age <2 years	0.480	0.000	−0.259	−0.517
	(0.866)	(0.914)	(0.904)	(0.891)
2–4 years	0.651	0.174	−0.139	−0.404
	(0.926)	(0.970)	(0.989)	(0.976)
5–9 years	0.411	−0.067	−0.781	−1.11
	(1.07)	(1.11)	(1.18)	(1.17)
10+ years	2.26*	1.83	1.91	1.59
	(1.12)	(1.16)	(1.03)	(1.02)
Density	−0.128**	−0.120**	−0.101***	−0.095***
	(0.039)	(0.039)	(0.028)	(0.028)
Density squared/100	0.114**	0.108**	0.093***	−0.087***
	(0.035)	(0.035)	(0.026)	(0.026)
Entry year	0.142***	0.143***	0.154***	0.150***
	(0.039)	(0.039)	(0.032)	(0.032)
Size (logged sales)	−0.022	−0.017	−0.068	−0.066
	(0.016)	(0.017)	(0.038)	(0.037)
Market share	−0.330*	−0.349*	−0.443	−0.417
	(0.152)	(0.154)	(0.302)	(0.290)
Number of workstations	−0.013	−0.010	−0.059*	−0.058
	(0.031)	(0.031)	(0.030)	(0.032)
Average product age	0.262***	0.267***	0.421***	0.434***
	(0.065)	(0.065)	(0.091)	(0.091)
Specialist (relative price range)		−0.321	0.335	2.18*
		(0.192)	(0.191)	(1.09)
H4: Proportion new products ($t = 0$)			1.83***	2.01***
			(0.206)	(0.206)
H4: Proportion new products ($t = -1$)			−0.559**	−0.530*
			(0.206)	(0.219)
H5: Specialist × proportion new products ($t = 0$)				−0.746*
				(0.295)
Specialist × proportion new products ($t = -1$)				−0.207
				(0.251)
Log-likelihood	−159.9	−158.5	−146.3	−143.3
LR test		2.8	24.4***	6.0*

175 firms, 122 failures; two-sided t-tests: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

(the upper panel for machine tool manufacturers and the lower panel for workstation manufacturers). Our calculations for the optimal rate (the solid line in each panel) follow those described above except that we use the estimates from Models 10 and 14 that account for how the effect of product introductions varies as a function of the firm's degree of specialization.[12] As the line shows, the optimum (stable) rate of product introduction, in both settings, rises with the degree of specialization. Firms with narrower scope (specialists) typically introduce more incremental products, reducing the adjustment costs associated with these introductions, which in turn allows them to replace a larger percentage of their old products with new ones without risking failure.

Generalists then should ideally introduce products at a lower rate than specialists. But they do not. Within each two-tenths of the range of the specialist variable, the points with error bars describe the average observed rate of product introduction for firms with that level of specialization, along with the 95 percent confidence intervals surrounding it. As one can clearly see, in both cases generalists (those with low levels of

[12] Specifically, we take the partial derivative of the product introduction related components with respect to the rate of product introduction. For example, for machine tool manufacturers, Model 10 gives us: $1.04t - 0.172t - 0.560st - 0.178st + 0.027/2t$, where s represents specialist. The partial derivative is: $1.04 - 0.172 - 0.560s - 0.178s - 0.014/t^2$. By setting this equal to zero and solving for t, we can calculate the optimal product introduction rate as a function of s.

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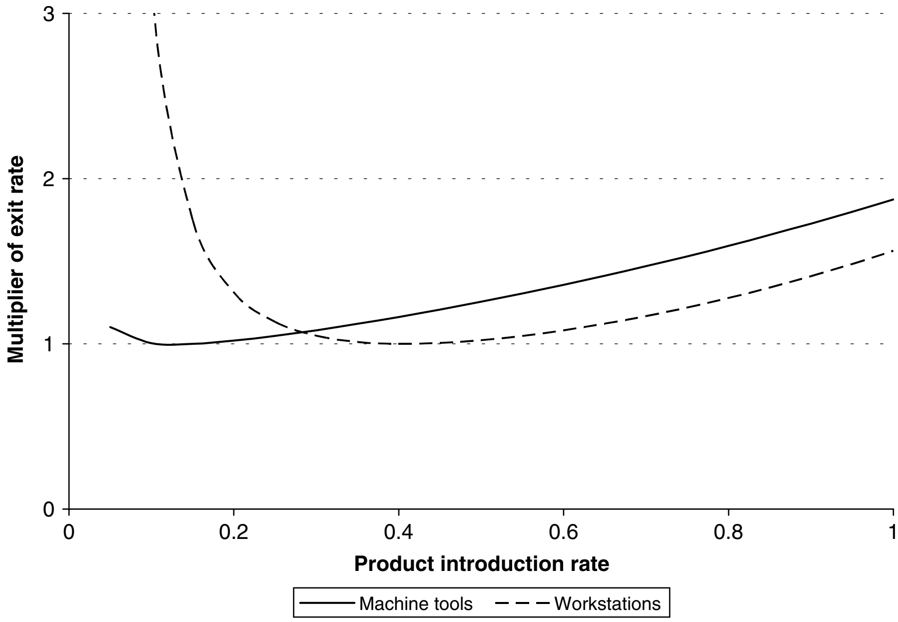

Figure 1. The overall effect of product introductions on firm exit

specialization) introduce new products at rates significantly above the optimum, while specialists, on average, replace their product lines at rates significantly below the ideal. After accounting for the effects of these behavioral differences on performance, it is clear that generalists do enjoy a positional advantage relative to specialists but that they do not benefit from this advantage as much as they could because they engage in riskier product strategies.

On the face of it, our results may appear to contradict Dobrev, Kim, and Carroll (2003). They find that generalists suffer less from changes in niche width, a result that they attribute to the better ability of firms with broad niches to adapt. We suspect that the same would hold true in our data. Conditional on the number of niche-expanding changes made, generalists likely absorb these disruptions better than specialists. We, however, focus on the unconditional behavior of generalists and specialists (i.e., the fact that generalists expand outside their niche at a much faster rate than specialists and suffer the consequences). Both effects can easily coexist. Indeed, our attempts to replicate their results (unreported) in these industries found support for this effect.

At least three potential alternative interpretations merit consideration. First, although we highlight the importance of routines in determining firm behavior, incentives may also play a role in the differential innovation patterns across generalists and specialists. Much of the literature on innovation contends that scale and scope economies in R&D influence a firm's incentives to innovate. Scale economies in R&D may encourage large firms to innovate but to invest in relatively incremental improvements (Cohen and Klepper, 1992). Diversified firms, on the other hand, may invest more heavily in basic R&D because they can more likely find an application for their discoveries within their existing portfolio of businesses (Nelson, 1959). Although the results of our innovation models appear consistent with this interpretation, and we lack direct evidence on the incentives facing firms, the fact that excessive product innovation accelerates firm failure favors our account, rooted in differences in routines, since incentives-based explanations rely crucially on the idea that such behavior *improves* firm performance.

A second alternative interpretation might reframe our performance results as reflecting a tradeoff between risk and return. Risky product strategies might increase firm failure rates but perhaps those that survive earn greater profits. In a series of unreported analyses, we attempted to gain some traction on this question by estimating the determinants of sales growth. Though the introduction of new products does appear to accelerate growth

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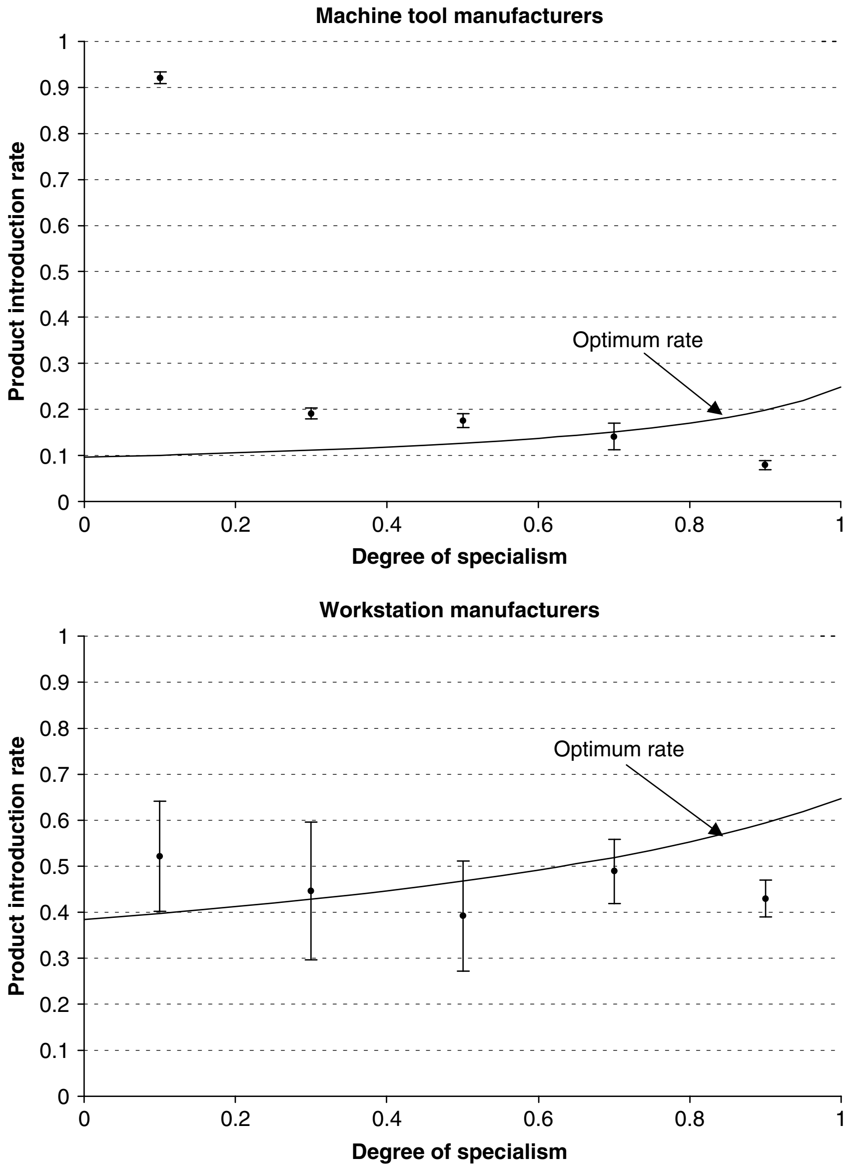

Figure 2. Actual vs. optimal (stable) rates of product introduction

rates, we could not find any evidence that specialists and generalists differ in the magnitude of these effects. In other words, generalists do not appear to benefit from increasing sales as a result of their riskier niche-expanding and new technology-incorporating product introductions. Our samples, however, do not allow us to examine this issue convincingly. Private firms, for which accounting data are not available, dominate our samples, particularly of specialists.

Finally, our results on the negative effects of product introductions on performance might reflect environmental conditions rather than individual firm processes. If product turnover increases during the same periods that major innovations increase the general level of uncertainty in the market, then our results might reflect an overall increase in failure rates during these turbulent periods rather than detrimental effects to product introductions. To address this possibility, we reran the models with calendar year fixed effects. Although the inclusion of these terms reduced the magnitude of the effects of product introductions (by 35% for machine tool manufacturers and 24% for computer workstation manufacturers), the deleterious process effects of product turnover remain highly significant. We nonetheless cannot exclude the possibility that finer-grained (e.g., monthly) periods of turbulence might account for our results.

Our findings speak importantly to a variety of issues. Most proximally, our results have implications for research on niche width. Research that fails to account for the differing actions taken by specialists and generalists may misattribute heterogeneity in performance to the relative positions of these firms. Sorenson (2000), for example, found that firms with a large number of product offerings enjoy higher survival rates in the computer workstation industry. Regardless, subsequent research by Dowell and Swaminathan (2000) in the bicycle industry and Barnett and Freeman (2001) in semiconductors, as well as our own results, suggest that his results probably underestimate this advantage because his findings confound the beneficial effects of product variety with the detrimental effects of getting there (i.e., introducing new products).

Perhaps the most interesting extension of these findings, though, applies to the large literature on corporate diversification. Here, our results suggest an explanation for some perplexing empirical results. Recent developments in this literature suggest that diversification itself does not depress equity prices; rather, investors appear to devalue the stock of firms whose attributes suggest they have a high probability of diversifying (Campa and Kedia, 2002; Villalonga, 2004). After correcting for this selection, Villalonga (2004, 2005) finds that diversification itself may even generate an equity premium, a result that Ushijima (2002) mirrors in his study of international expansions. Like generalists, diversified firms and international firms reach these positions through a series of moves (i.e., niche expansion). Though the end states that they occupy may benefit the firms, reaching these positions (i.e., becoming diversified or internationalizing) entails substantial risk; moreover, behavioral inertia will likely lead these firms to continue these risky activities. Investors, therefore, may discount the value of these firms because the exploration-oriented organizational codes at their cores cannot ensure reliable ongoing performance.

Inertia resides at the core of our argument, and in this sense, we bring niche width theory back in line with ecological research on structural inertia (Hannan and Freeman, 1984). Niche width theory has generally assessed the benefits of being a generalist or a specialist without regard to how firms arrive at these positions. Structural inertia theory, on the other hand, implies that the paths that firms take to reach a particular position matter. Firms typically start small and grow with an imperfect understanding of how their resources and routines fit various environments. Generalists arise from those firms founded with codes that lead them to push the boundaries of their existing niche. Structural inertia implies that these routines have lasting effects both on firm behavior and performance that have not yet been articulated in niche width theory. More generally, we believe that the fact that positions and paths might provide insight into firm behavior and performance potentially offers a fruitful route for future research.

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