TEMPORAL ROUTINES FOR GENERATIONAL PRODUCT INNOVATION IN COMPUTER SOFTWARE

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ABSTRACT

This study uses a routines-based theoretical lens to examine time-based pacing of generational product innovation in the applications software industry. We develop a temporal routines model to explain the effect of time since previous innovation on generational product innovation. The model further suggests that organizational size moderates the time-pacing relationship. Employing event history analysis, we examined forty-six organizations competing in four segments of business productivity software from 1994 to 1998. We found empirical evidence consistent with our temporal routines model, indicating that software organizations, particularly larger organizations, employ temporal routines for generational product innovation.

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Time-based pacing of innovation has drawn recent interest from academics (Brown and Eisenhardt, 1997; Bluedorn, 2002) and practitioners (*Economist*, 2003). Time-based pacing typically involves generational forms of innovation. A generational product innovation represents a significant advance in the technical performance of an existing product (Lawless and Anderson, 1996). In turn, time-based pacing of innovation refers to releasing new generations of a product in a consistent pattern, such as releasing a new generation every 18 months. Generational product innovations are often central to technological decision-making in organizations and have an important effect on organizational performance (Brown and Eisenhardt, 1997). As an example, the inability to successfully manage generational product innovation contributed to the failure of Lotus 1-2-3 in applications software (*InfoWorld*, 1985, 1988a) and to the decline of the Ford Taurus as the leading sedan in the automobile industry (*Automotive News*, 2003).

In prior theory-building research, Brown and Eisenhardt (1997) provide a rich understanding of the performance consequences from employing time-based pacing of generational product innovation. However, we have limited understanding as to why organizations employ time-based pacing of innovation. The purpose of this study is to develop our understanding of why organizations might employ time-based pacing of generational product innovation and to demonstrate that time-based pacing exists in practice. We use a routines-based theoretical lens (Nelson and Winter, 1982) to examine this phenomenon, viewing time-based pacing of innovation as a particular form of modification routine. Further, we examine organizational size as a core determinant of the employment of temporal routines for generational product innovation. This study contributes to our understanding of innovation as a routine process. Our empirical context focuses on four business productivity segments of the U. S. microcomputer software industry from 1994 to 1998, including computer-aided design (CAD), desktop publishing, spreadsheets, and word-processing. We undertake event history analysis, offering a comparison of results using discrete-time and continuous-time approaches.

THEORY AND HYPOTHESES

From the perspective of routines-based theory, organizations function according to a set of routines, in contrast with traditional economic theory that assumes that organizations adaptively optimize their behavior. Routines are repetitive patterns of organizational behavior (Nelson and Winter, 1982). More specifically, a routine is an executable capability for repeated performance in a particular context (Cohen, et al., 1996). We consider routines as involving both automatic action patterns that proceed without managerial choices and action patterns that involve deliberate choices to maintain the routines.

Routines are often viewed in a hierarchy of operating and modification types. Operating routines are standard patterns of organization activity in a given context. Modification routines are patterns of activity that systematically change the operating routines of an organization (Nelson, 1991; Nelson and Winter, 1982). This study aligns with the tradition of examining routines in the form of self-sustaining operating and modification types. Nelson and Winter (1982) provide the self-sustaining condition as a basic assumption of the evolutionary model, highlighting that routines become established among organizational members. Nelson and Winter (1982) refer to this establishment as a de facto contract, or "routine as truce."

We consider routines-based research in two categories: (1) research that examines organizations as a portfolio of routines, and (2) research that examines a particular routine within organizations (Hannan and Freeman, 1989; Cohen, et al., 1996). In the first category, researchers focus on the process by which organizations function according to a set of routines (i.e., Cyert and March, 1992/1963; Karim and Mitchell, 2000). In the second category, researchers focus on a particular routine, which is composed of sub-level routines and resources (Pentland and Rueter, 1994; Feldman, 2000). This study falls into the latter group, as it addresses a particular routine.

Our focal routine is the temporal routine for generational product innovation. At the business unit level, the product of interest represents a core component in the organization's operating routines. A generational product innovation represents a significant change in the product and, correspondingly, in the product-related components of the organization's operating routines. As such, a temporal routine for generational product innovation is a particular type of modification routine, where changes to the product and the product-related components of a set of operating routines occur on a consistent basis across time.

We initially outline the boundary conditions, assumptions, and concepts that shape our research. We then turn to specific hypotheses.

Boundary conditions, assumptions, and concepts

Two boundary conditions define the scope within which our theoretical perspective will consider the phenomenon of time-based pacing. First, we concentrate on routines involving product change, where products produced by one set of organizations (producers) are employed as inputs for production by another set of organizations (organizational customers). Although all products do not need to be sold to organizations, our argument emphasizes organizations as a significant base of customers for the producers.

Second, our argument focuses on products that are interdependent with other components in the operating routines of producers and their organizational customers. In this sense, routines are complex systems composed of sub-level components (Simon, 1962; Nelson, 1991). The second condition implies that the addition of a new product, or change in an existing product, results in non-trivial disruption costs for one of more operating routines within the organization. For example, consider the producer of a computer software application. When the producer changes the product (i.e., releases a new version), a corresponding series of changes are required within the organization (e.g., customer support training). In a recent study, Mukherjee, et al. (2000) found evidence consistent with the idea that variation in a set of inputs results in disrupted performance of the routine.

Within these boundary conditions, our argument requires several assumptions. Foremost, the argument hinges on the assumptions of routines-based theory (Nelson and Winter, 1982). The argument also requires two additional assumptions.

First, we assume that organizations have favorable perceptions of change to an existing product. In studying the automobile industry, Abernathy (1978) observed that important functional improvements are made in the early stages of product life. These functional improvements provide substantial value to customers (Abernathy, 1978). While Abernathy's research supports the value of early-stage innovation, we suggest greater generality of the assumption. In particular, we expect organizations to have favorable perceptions of product change in environments with significant technological opportunity.

Second, we assume that producers will make changes to an existing product in line with the preferences of their existing customers. Resource dependence theory supports this assumption. According to this theory, organizations are interdependent with resource providers in the external environment, and resource providers influence the behavior of their resource-dependent organizations (Pfeffer and Salancik, 1978). Research by Clayton Christensen extends resource dependence theory, highlighting that the demands from an organization's existing customers drive its resource allocation decisions. In particular, this research found that the preferences of firms' existing customers strongly shape the path of technological innovation in the hard disk drive industry (Christensen and Bower, 1996).

The argument builds on three core concepts: generational product innovation, time since previous innovation, and organizational size. To define the generational product innovation concept, we refer to Henderson and Clark (1990) and Lawless and Anderson (1996). Henderson and Clark (1990) define product innovations along two dimensions: (1) degree of change in core design concepts, and (2) degree of change in the linkages among core components. The first dimension focuses attention on the extent to which core product attributes are reinforced relative to being overturned, while the second dimension focuses on the extent to which the product architecture changes. This study focuses on product innovations in which the core design concepts are reinforced and the product architecture is unchanged. Henderson and Clark (1990) refer to this type of innovation as an incremental innovation.

According to Lawless and Anderson (1996), a generational product innovation is a particular form of incremental innovation. The researchers state that generational innovations have two focal characteristics. First, the innovation represents a significant advance in the technical performance of an existing product. Lawless and Anderson (1996) describe a generational innovation as an advance within a technology regime. Second, most generational product innovations are backward-compatible, such that older generations tend to compete alongside newer generations (Lawless and Anderson, 1996).

Alternatively, some researchers have described architectural innovations as generational innovations (Henderson and Clark, 1990, footnote 1; Henderson, 1993). Similar to incremental innovations, architectural innovations reinforce the core design concepts of the product. However, with architectural innovations, the linkages between the core concepts also change (Henderson and Clark, 1990). In this study, we do not include architectural forms of innovation within our definition of generational product innovation. This allows greater focus in developing our conceptual argument. Further, in our empirical context, architectural product innovations typically represent entry into new technological markets (i.e., Windows) for existing organizations. Therefore, we treat these innovations as new market entries.

To clarify the definition of generational product innovation, we present an example from the AutoSketch family of CAD microcomputer software. In this example, we classify the introduction of AutoSketch 3.0, which followed AutoSketch 2.0 (both DOS products), as a generational product innovation. Relative to AutoSketch 2.0, AutoSketch 3.0 contained new features that improved its performance, particularly its ease of use and ease of learning. As one example, AutoSketch 3.0 added a new text editor that allowed users to import and export text. In turn, we classify the introduction of AutoSketch for Windows as an architectural product innovation. In summary, a generational product innovation is a significant advance in the technical performance of an existing product; the core concepts of the product are reinforced within an existing architecture (Henderson and Clark, 1990; Lawless and Anderson, 1996).

The notion of time since previous innovation draws from the organizational ecology literature (Amburgey, et al., 1993; Baum, 1999). We define this concept as the elapsed time since the previous product innovation of the same type. With respect to generational product innovation, previous product innovation of the same type refers to either the initial introduction of the product on the market or the most recent generational product innovation introduced to the market.

Organizational ecology researchers have argued for a negative effect of time since previous innovation on the likelihood of another innovation of the same type (Amburgey, et al., 1993). The focal argument is that, by local search in time, organizations are most likely to employ recently-used modification routines (Amburgey, et al., 1993; Cyert and March, 1992/1963). Therefore, as the elapsed time since a previous innovation increases, the organization is less likely to introduce an innovation of the same type (Amburgey, et al., 1993; Baum, 1999).

Returning to the AutoSketch product example, after the organization's initial release of AutoSketch, the time since previous innovation increments by one for each time period until the firm releases a generational product innovation (AutoSketch 2.0). In the first period following the release of AutoSketch 2.0, the time since previous innovation resets to one. The time count then increments by one for each period, until the organization releases another generational product innovation. In summary, we define time since previous innovation as the elapsed time since the previous product innovation of the same type.

In defining organizational size, we refer to innovation research in the industrial organization economics and organizational ecology literatures. These literatures focus on two dimensions of organizational size: external to the organization and internal to the organization. Both dimensions arise in industrial organization economics and organizational ecology, but industrial organization economics places greater emphasis on the external dimension (Scherer, 1980), while organizational ecology places greater emphasis on the internal dimension (Baum, 1999). Incorporating both dimensions, organizational size represents the magnitude of an organizational unit.

From the external perspective, researchers often operationalize organizational size as the volume of sales for a given organizational unit (Cohen and Levin, 1989). In industrial organization economics, the external perspective reflects a market-based orientation. Schumpeterian researchers present several conceptual arguments for a positive effect of size on innovation. These arguments include (a) size correlates with available financial resources in imperfect markets, suggesting that larger organizations have greater ability to undertake innovation, and (b) size provides scale economies, such that larger organizations can justify greater investment in specialized resources for producing innovations or justify greater investment in process innovations from a cost-spreading perspective (Scherer, 1980; Cohen and Klepper, 1996). At the same time, though, more traditional industrial organization economics researchers expect a negative effect of size on innovation, based on reduced competitive incentives (Scherer, 1980). In parallel, organizational ecology researchers also use the external perspective to present arguments for both positive and negative effects of size on innovation (Haveman, 1993).

From the internal perspective, researchers typically operationalize organizational size as the number of employees in the organizational unit. In both organizational ecology and industrial organization economics, the internal perspective reflects a bureaucratic orientation. From this perspective, researchers in organizational ecology expect a negative effect of size on innovation. These arguments suggest that larger organizations have greater diffusion of control and decision-making, such that changing organizational structure is more difficult in larger organizations (Hannan and Freeman, 1984; Haveman, 1993). Researchers present a similar argument in industrial organization economics, suggesting that managerial control declines as organizations increase in size. In addition, individual scientists have reduced incentive for innovation if their ability to capture the rewards of innovation decreases with increasing size (Cohen and Levin, 1989).

In the AutoSketch example, organizational size refers to the magnitude of the business unit that governs the development, production and support for the AutoSketch product. From the external perspective, organizational size is the volume of sales of the AutoSketch product. From the internal perspective, organizational size is the number of employees involved in the development, production and support of the AutoSketch product. Our argument draws on both internal and external dimensions of organizational size, and consistent with prior research, we expect significant overlap between the respective measures. Because of the key role of customer pressure in our argument, though, we place greater emphasis on the external dimension.

Hypotheses

Hypothesis 1 predicts the presence of temporal routines for generational product innovation within organizations. For this argument, we must address both (a) demand for generational product innovation and (b) demand for consistency in the release of generational product innovations. Recall that we assume that organizational perceptions of change to an existing product are favorable. In particular, we consider two sources of pressure for generational product innovation. First, there is exogenous pressure for product change based on technological and market opportunities in the environment (e.g., innovations in foundational technologies).

Second, there is endogenous pressure for product change that emanates within the operating routines of existing customers. From our boundary conditions, as organizations make changes to components within their existing operating routines, there are disruptions due to interdependencies among the components of the operating routine. In efforts to maintain their existing routines, organizations attempt to smooth out the induced disruptions, or frictions (Nelson and Winter, 1982). By searching locally for solutions to the friction problem, organizations seek subsequent improvements, or modifications, to the most recently-changed component (Cyert and March, 1992/1963). Therefore, as customer organizations adopt new or modified products, they generate pressure for subsequent changes to the product.

In addition to demand for generational product innovation, there is demand for consistency in the release pattern. One of Nelson and Winter's (1982) central assumptions is that organizations behave according to a set of routines. Establishing a routine for innovation at the organization level requires reliability in the delivery of inputs, including timeliness. Organizations require this reliability to address temporal interdependencies and resource allocations (e.g., human resources across phases of a project), both within and across departments (March and Simon, 1958). By establishing temporal routines for innovation, producers have greater ability to coordinate the complex task of innovation (Cyert and March, 1992/1963; Brown and Eisenhardt, 1997). These forces serve as an internal source of pressure for producers to create temporal routines for developing generational product innovations.

In parallel with pressures for producer routines, organizational customers face internal pressures to create routines for adopting generational product innovations, especially in cases where adopting a changed product invokes substantial disruptions. These disruptions reflect systemic changes that are required elsewhere in the organization as a result of the adoption of the changed product. The requisite changes result from linkages among the focal product, complementary assets and services, and organizational employees with related responsibilities. While computer software programs are a prime example (e.g., integrated with hardware and other software), many goods and services have similar linkages. Given the associated disruptions, by establishing adoption routines, organizational customers facilitate planning and coordination.

The benefits of adoption routines at customers and the preference for development routines at producers reinforce each other, leading to a strong propensity toward temporal reliability in the release of new products. The reinforcement comes from both the supply side and demand side of the market. From the supply side, the presence of producer routines and consequent tendency for regular product introduction will encourage organizational customers to develop systems suited to adopting innovations on a regular basis (e.g., "adopt every new generation of the product at the time of release"). From the demand side, the existence of adoption routines leads customers to encourage temporal reliability in the release of generational product innovations (Amburgey and Miner, 1992). Thus, the innovation routines of producers and the adoption routines of their organizational customers support one another, resulting in temporal alignment of generational product innovation.

Note the presence of incentives for temporal alignment still permits heterogeneity across organizations. In cases where there is a consistent cycle on the supply side (e.g., "introduce every year at the major trade show") coupled with strong pressures for a particular adoption cycle on the demand side (e.g., “adopt every summer when activity is slower”), then a market will tend to converge to a single generational product innovation pattern. Often, though, the technical and adoption pressures will allow variety in cycles. For example, some customers may develop adoption routines that are multiples of other customers’ routines, possibly with greater flexibility (e.g., “adopt every other generation of the product within several months of its release”). Thus, while a certain degree of variation is present, the primary force of the argument is that producers exhibit temporal regularity in generational product innovation.

The temporal alignment of routines helps explain why producer routines for innovation exist in competitive markets, despite seeming market pressures for producer flexibility. Since routines provide value to both producers and organizational customers, markets welcome time-based pacing of innovation, particularly under conditions in which innovation adoption requires substantial adjustment costs. Further, once the temporal routine becomes established, there is pressure for producers and organizational customers to maintain the established norm, in the sense of "routine as truce". Figure 1 describes the expected relationship for Hypothesis 1.

> Hypothesis 1. Generational product innovation will have an inverted-U relationship with time since previous innovation, first increasing and then decreasing beyond a threshold.

Next we address the effect of organizational size on temporal routines for generational product innovation. Specifically we consider internal pressure and customer pressure as leading to greater temporal consistency for the release of generational product innovations in larger organizations. We present these two types of pressure as elements of a larger argument that focuses on the costs of coordinating change in an innovation routine.

First, consider internal pressure. As organizations become larger, coordination among agents, whether individuals or departments, plays an increasingly important role in organizational activity. As part of the innovation routine at the organization level, departments develop routines that are consistent with the organization-level routine (Nelson, 1991; Winter, 1995). This suggests that change in the routine at the organization level requires changing department-level routines as well as reestablishing post-change linkages among the department-level routines.

Assuming that larger organizations have greater numbers of departments, they face greater costs of coordinating change based on the number and interactions of department-level routines (Simon, 1962). Therefore, as organizations become larger, disrupting an established routine becomes more costly from a coordination perspective. Alternatively, in smaller organizations, coordination among agents plays a relatively less important role. In smaller organizations, there is less need to establish the routine for coordination purposes, and if established, the cost of disrupting the routine is smaller relative to larger organizations.

Second, consider customer pressure. We assume that, for planning and coordination purposes, organizational customers establish change routines in line with the innovation routines of producers. This assumption that organizational customers follow producers in establishing change routines acknowledges the significant internal pressure behind innovation routines, which constrains the ability of producers to adapt their routines in response to variations in customer preferences. Given this producer-customer linkage of routines, as producers change their innovation routines, their organizational customers face significant pressure to change their routines.

If producers are sensitive to their impact on customer routines, they will attempt to communicate and/or negotiate changes in innovation routines with their organizational customers. In applications software, the development of this producer sensitivity was particularly clear in the case of Lotus. For instance, due to compatibility problems, an early generational product innovation for Lotus 1-2-3 (Release 2) caused major disruptions for organizational customers (*InfoWorld*, 1985). The resulting customer pressure led to increased sensitivity regarding the producer-customer innovation linkage (*InfoWorld*, 1989), both in terms of content (i.e., inter-generational compatibility) and timing (i.e., communications involving release schedules).

Since larger organizations have greater numbers of organizational customers, they face greater costs of coordinating intended changes in their innovation routines. Therefore, we expect greater adherence to innovation routines in larger organizations. Figure 2 describes the expected relationship for Hypothesis 2.

> Hypothesis 2. The greater the organizational size, the more positive the initial effect of time since previous innovation on the likelihood of generational product innovation. Beyond a threshold, the greater the organizational size, the more negative the effect of time since previous innovation on the likelihood of generational product innovation.

Taken together, these hypotheses suggest that organizations employ temporal routines for generational product innovation. Moreover, as organizations increase in size, they are more likely to employ these routines.

DATA AND METHODS

The empirical context focuses on business productivity segments of the U. S. microcomputer software applications industry from 1994 to 1998. We examine organizations in four segments: computer-aided design (CAD), desktop-publishing, spreadsheets, and word-processing.

Appropriateness of the empirical context

We consider applications software relative to the boundary conditions and assumptions that we stated earlier. The trade press for the software industry provides supporting evidence for the boundary conditions and assumptions.

The first boundary condition limits the scope of the theoretical argument to situations in which products are produced by one set of organizations (producers) and are employed as inputs for production by another set of organizations (organizational customers). This condition recognizes that corporate customers are a significant presence in markets for business productivity software products.

The second boundary condition limits the scope of the argument to products that, upon adoption, become interdependent with other components in the operating routines of producers and organizational customers. This condition implies that the addition of a product, or change in the product, results in non-trivial disruptions for one or more operating routines. In the applications software industry, there is substantial support for the assertion that the addition of, or change in, a software product results in non-trivial disruptions to existing operating routines for adopting organizations. According to one administrator, the upgrade process is a "logistical nightmare." Another remarks that "the cost of the package is peanuts compared to the amount of administrative time involved in an upgrade" (*InfoWorld*, 1988b). Specific examples include downtime associated with new bugs, revision of training programs, logistical costs of installation, increases in support questions following an upgrade, and hardware upgrades that software upgrades may induce (i.e., *InfoWorld*, 1988b).

The first assumption states that organizational perceptions of changes to an existing product are favorable. This assumption is valid for software applications. As an example from the demand side of product change, Wordstar was an early leader in the market for word-processing software. At one point, an industry observer noted that "Wordstar users have been practically begging Micropro for a new update of their favorite word processor..." (*InfoWorld*, 1987). On the supply side, Cringely (1996: 226) notes that producers immediately begin revisions to their product releases in order to fix bugs and stay current with the technology. Researchers observe that, in the case of Microsoft, persistence with upgrades has contributed to success in the marketplace (Cusumano and Selby, 1995; Liebowitz and Margolis, 1999).[1]

The second assumption states that producers will make changes to an existing product in line with the preferences of their existing organizational customers. This assumption is appropriate for product innovations by many organizations in the application software industry. When releasing generational product innovations, organizations often highlight the role of existing customers in shaping the innovation process. Representative comments include "the new release of Total Word incorporates improvements requested by our customers" offered by Vickie Boddie, president of Volkswriter (*Computer Reseller News*, 1990), and "639 user enhancement requests have been incorporated into WordPerfect 6.0 for DOS" (*Business Wire*, 1993). Perhaps the strongest statement in support of this assumption is offered by John Walker, founder of Autodesk and co-author of AutoCAD: “Any doubts about the veracity of our claim 'our development agenda is taken directly from the list of user-requested features' can be easily dispelled by comparing [our user-requested] wish list with the features in AutoCAD releases up to the present day” (Walker, 1994).

Further, microcomputer software is a component within a larger, complex technological system. While not a boundary condition or assumption, this factor suggests an additional source of pressure for temporal routines from complement producers. These complements include microprocessors, other computer hardware (e.g., memory, storage), and operating system software.

Data

We obtained the starting point of the dataset from PC Data (now NPD INTELECT), a market research firm that specializes in information technology markets. The dataset from PC Data includes monthly product sales data in four segments of business productivity computer software from 1994-1998. The four segments are CAD, desktop publishing, spreadsheets, and word processing. These segments are based on stand-alone applications and do not include sales from integrated software suites. PC Data personnel told us that their data represent the following annual percentages of the U.S. retail software market during the five years from 1994 to 1998: 33%, 60%, 70%, 80%, and 80%. In addition, we supplemented the dataset with extensive archival research.

Below, we describe the construction of the CAD segment dataset. We employed a similar process for the other three segments.

We constructed a CAD market segment that assumed that products are substitutes in terms of functionality. The initial PC Data database had two limitations that prevented the initial comparison of products as substitutes. First, PC Data reported the product data at a stock-keeping unit. Therefore, when multiple formats or versions existed within a product family, we aggregated the individual products into one representative product family. For example, we aggregated Turbo Cad, Turbo Cad 5.0, and Turbo Cad Academic into a representative Turbo Cad product family. The Turbo Cad product family represents the product offering from the Turbo Cad organization. In many cases, the organizations in this study are business units within larger firms.

Second, the PC Data database included products that are not substitutes. For example, PC Data listed add-on products and products that are similar in content but different in functionality alongside traditional products. To address this issue, we constructed more precise market segments with the assistance of secondary data sources. This construction proceeded in two phases: (1) reducing the PC Data database into a set of products that perform similar functions, and (2) segmenting the remaining products into competitively-equivalent markets.

The first phase of construction required the identification of products that perform similar functions. This categorization relied on the primary classification by PC Data, which represents the industry standard. We then narrowed the PC Data list of products to a more precise set, using secondary data sources to confirm product similarity. We primarily accessed secondary data sources through information databases, such as Dow Jones Interactive, Infotrac, and Proquest. Specific referenced publications included *Business Wire, Computer Graphics World, Home Office Computing, InfoWorld, MacUser, MacWEEK, PC/Computing, PC Magazine, PC Week, PR Newswire, The Software Encyclopedia, Windows Magazine,* and *Windows Sources*. Company web pages were also accessed as needed and available.

The second phase of construction further segmented products into competitively-equivalent markets. This ensured comparison within distinct market segments. We segmented the product markets by format and tier of market. First, in terms of format, the categorization focused on operating platform. During the 1994-1998 empirical window, there was a clear market distinction between products for IBM-compatible and Macintosh computers. Within the IBM-compatible system, two dominant operating platforms were present: DOS and Windows. Therefore, we segmented the products into three respective operating platforms: (1) DOS for IBM-compatible, (2) Windows for IBM-compatible, and (3) Macintosh. Second, market tier refers to the feature/price level within a product category (e.g., high-end, low-end). We used product comparison reports in the trade press from 1988-1998 to guide segmentation by market tier.

Based on these reports, we divided the CAD market into high-end CAD software for the microcomputer (approximately $3000 in list price) and low-end CAD software (less than $1000 in list price). However, only certain high-end CAD products are sold through the retail channel that PC Data tracks. Therefore, this study does not analyze the high-end CAD segment. Our review of product comparison articles in the trade press revealed a lack of clear segmentation within the sub-$1000 products. We found product comparisons based on sub-$1000, sub-$500, sub-$400, and sub-$250 segments. As a result, we plotted the sub-$1000 products by list price and searched for the presence of identifiable clusters. The highest frequency of products had a list price of $500, with numerous products above and below $500. Therefore, we judged the sub-$1000 market to be the most appropriate level for analysis and did not further segment the data. Examples of products in this segment include AutoCAD LT, MiniCAD, and TurboCAD.

The final stage of archival research involved tracing the innovation history of each product family. We used these histories to identify the cumulative number and timing of generational product innovation releases. The tracing process included a review of every issue of *InfoWorld*, a weekly industry trade publication, from 1981-1990. Our initial year, 1981, is an appropriate beginning period because IBM introduced its personal computer in that year (Langlois, 1992; Cringely, 1996), leading 1981 to be labeled as the beginning of the second era in microcomputing (Cringely, 1996). The tracing process involved archival searches with secondary data sources via information databases and company web pages. Consistent availability of product innovation data via information databases began in approximately the mid-1980s. Therefore, the combination of reviewing *InfoWorld* from 1981-1990 and searching information databases from their earliest available dates (typically the early 1980s) through the end of 1998 provided a comprehensive approach to gathering archival data. Finally, if necessary and available, we contacted companies directly to help resolve any uncertainties.

In addition to the CAD segment, we analyzed the desktop publishing, spreadsheets, and word-processing segments. The dataset construction process was similar for the three remaining segments. Guided by the trade press, we identified two market segments for desktop publishing: high-end (approximately $500-$900 in list price) and low-end (approximately $100-$300). However, PC Data did not list a well-known low-end desktop publishing product. Therefore, this study does not analyze the low-end segment. We identified a single segment for spreadsheets, with list prices in the range of $100 to $600. For the word-processing category, we identified two segments: high-end (approximately $350-$700 in list price) and low-end (approximately $50-$250). There was very little innovation activity in the low-end word processing market, and the category itself largely disappeared by the end of 1998. Due to lack of variance on the dependent variable, this study does not analyze the low-end of the word processing market.

Operational variables

There are three focal variables in the empirical model. The dependent variable is generational product innovation, and the explanatory variables are the time since previous innovation and organizational size. Control variables include age, cumulative number of product innovations, market concentration, market size, market generational product innovations, and operating system platform. After data collection, we calculated the operational variables using a series of Visual Basic macro programs within a Microsoft Excel spreadsheet. In addition to the standard calculation procedures, where appropriate, the process involved the development and execution of recalculation procedures to check the calculations.

Dependent variable. We operationalized generational product innovation (GenProdInnov) by a binary variable (1 for the month in which a generational product innovation release occurs, and 0 otherwise).[2] Overall there were 72 generational product innovation events among 46 organizations competing in four segments of microcomputer applications software from 1994 to 1998.

In identifying generational product innovations, we focused our attention on whether a release represented a significant advance in technical performance, relative to the existing product. One concern associated with this measure was to ensure that generational releases are distinguished from minor bug-fix releases. In both cases, we expect the technical performance of the product to improve (Lawless and Anderson, 1996), but we assume the significance of the advance to be much smaller in the bug-fix release. Further, while generational release dates can be identified with archival data, the trade press does not publish many of the bug-fix release dates. To address the significance of technical advance, we reviewed trade press information for individual product innovation releases.

To distinguish generational product innovations from other types of innovation within the applications software context, we focused on three dimensions: (a) the number and magnitude of feature additions/enhancements, (b) the numbering convention for the product innovation release (i.e., Version 1.0, 1.01, 1.1, 2.0), and (c) the pricing schedule for the product innovation release (e.g., upgrade list price relative to full list price). Through historical observation of the trade press, we found that the latter two dimensions typically reflect the first dimension. Examining trade press information with particular attention to these three dimensions provided a heuristic guide for distinguishing generational product innovation releases from bug-fix releases. As an example, for the price dimension, a useful guide was whether the upgrade list price was greater than or less than 10% of the full list price.

Our objective was to triangulate in determining whether a product release was classified as a generational product innovation. We examined multiple accounts in the trade press with attention directed to the three aforementioned dimensions. For the majority of product releases, data was available on all three dimensions, and the evidence on these dimensions was consistent (either toward a generational product innovation classification or against it). When the evidence was conflicting across dimensions, or when trade press information was missing for a particular dimension, our classification was based on the majority of evidence for the three dimensions.

Explanatory variables. Time since previous innovation (TimeSinceInnov) is the elapsed time since previous product innovation. The previous innovation may be the initial product release or the most recent generational product innovation. We represented time since previous innovation with a monthly clock, which started at one for the first month following the month in which an innovation occurred (the initial innovation or a generational product innovation). The clock increased by one for each month until the first month after a new generational product innovation was released; at this point, the clock reset to one.

We operationalized the organizational size measure (OrgSize) as the total number of product units sold by the organization, lagged one time period and logged. The organization size measure was lagged to address potential simultaneity, and we used its logarithm based on our expectation that the effect diminishes with increases in organizational size. For calculation purposes (i.e., zero as a nuisance value), we added one to the lag of organizational size prior to taking its logarithm. Since we study the interaction between the explanatory variables, for interpretative purposes, we centered the organizational size and time since previous innovation variables (Aiken and West, 1991).

Control variables. Age of the organizational unit (Age) is the number of months since the initial release of the product. Some researchers have argued that, over time, organizations develop routines that inhibit change (Hannan and Freeman, 1984). Other research suggests that organizations become more fluid with age. In attempts to reconcile this work, Singh and Lumsden (1990) suggest that the effect of age on organizational change depends on whether the change is core or peripheral. However, a recent review of empirical work in this area highlights mixed findings on the age-change relationship, beyond consideration of the core-peripheral reconciliation efforts (Baum, 1999).

Cumulative number of previous innovations (TotPrevInnov) is a count measure, which increases by one for each introduction of a generational product innovation. The cumulative number of generational product innovations is a measure of repetitive momentum (Amburgey and Miner, 1992; Amburgey, et al., 1993). In this case, increases in cumulative innovation lead to greater experience with innovation, which suggests increased likelihood of future innovations (Amburgey and Miner, 1992). Reviewing empirical studies, Baum (1999) found strong support for a positive effect of repetitive momentum on innovation.

We used a Hirschman-Herfindahl Index to measure market concentration (MktConc), using market share in terms of unit sales. The index is defined as the sum of the squared values of products' market share (Curry and George, 1983). A large body of work in industrial organization economics examines the effect of market concentration on innovation (Cohen, 1995; Cohen and Levin, 1989). This stream of research provides alternative arguments about the relationship. Some researchers argue for a positive effect. This argument suggests that in concentrated markets, rivalry has greater certainty. Moreover, less certainty regarding extent of rivalry could reduce incentives for innovation (Schumpeter, 1942). Others argue for a negative effect, suggesting that greater market concentration leads to less direct competitive incentive for investment in innovation (Hennipman, 1954; Scherer, 1980).

A market size (MktSize) variable recorded the total number of product units sold in a given market, lagged one time period and logged. We added one to the lag of market size prior to taking its logarithm because in a few instances (e.g., late 1998), a given month had zero product sales for an application category on the DOS platform. Arguments for an effect of market size on innovative activity include firms' positioning themselves in emerging niches (Porter, 1980) or firms' trying to reinvigorate declining markets (Miller, 1990). Researchers have found significant effects of market size on competitive behavior (Miller and Chen, 1994; Bayus and Putsis, 1999).

Market generational product innovation (MktInnov) is a binary variable that indicates whether any peer organizations within a market released a generational product innovation in the previous time period. We employed a binary variable due to the few instances in which more than one innovation release by peer organizations occurred in the previous time period. Institutional theorists have argued that organizations imitate the behavior of their peers (DiMaggio and Powell, 1983). In addition, researchers of competitive rivalry suggest that organizations are likely to respond to competitive moves by peer organizations (Chen, 1996). Relative to this measure, we highlight that in the applications software industry, there tends to be significant levels of signaling and transparency associated with innovation releases. Thus, we expect that peer organizations have knowledge of upcoming innovation releases prior to the actual event.

We included dummy variables for operating system markets (DOS, WIN), using effect-coding: DOS organization-month observations (1 for DOS, 0 for WIN), Windows organization-month observations (0 for DOS, 1 for WIN), and Macintosh organization-month observations (-1 for DOS, -1 for WIN). As such, a negative effect for either the DOS variable or the WIN variable indicates a respective likelihood of generational product innovation that is significantly below the average likelihood. The average likelihood is taken across DOS, Windows, and Macintosh platforms for all organization-month observations.

A market density (MktDens) variable recorded the total number of organizations operating in a market, lagged one time period. We included this variable in a selection equation for our discrete-time (probit) analyses, rather than in the focal equation. As we discuss in the next section, the discrete-time analysis involves simultaneous estimation of two equations. With this approach, the selection equation requires at least one unique variable. While many of the variables in the focal model and selection model were common, we included market density as unique to the selection equation. The variable draws from density dependence research in organizational ecology (Hannan and Freeman, 1989). Researchers argue for a curvilinear effect of density on survival. Due to institutional legitimacy, increases in density initially increase the likelihood of survival. Then beyond a threshold, due to competitive interactions, increases in density decrease the likelihood of survival (Hannan and Freeman, 1989; Baum, 1999). Since the empirical analysis focuses on a developed industry state, and to minimize the number of variables in the model given a limited number of selection events, we included only a linear effect for density, expecting a negative effect of density on survival based on the competitive interactions argument.

Table 1 provides descriptive statistics and correlations. In the analyses, the total number of observations was 2617 organization-months: 2592 uncensored observations (indicating that the organization remained on the market throughout the month) and 25 censored observations (indicating that the organization did not remain on the market beyond that month).

Models and analyses

We used both discrete and continuous time approaches for the analysis. While we expect similar findings, each approach offers distinct advantages. With the discrete-time approach, we employ a more favorable means of accounting for the potential of selection bias. With the continuous-time approach, we incorporate historical time effects through the distribution. We perform both sets of analyses to examine the sensitivity of our results.

Discrete time approach. The discrete-time approach applied a probit model with selection. Since organizations may select out of a market during the time window of data, the model needs to account for the potential of survival bias in the estimates. As such, we employed a probit model with selection (van de Ven and van Praag, 1981), which extends from Heckman (1979). This model estimates the two equations (focal equation and selection equation) simultaneously using maximum likelihood. We used the heckprob command in the Stata statistical software package to perform the analyses.

As an illustration of survival bias, consider the following scenario. Suppose that the objective is to understand the effect of organizational size on the likelihood of generational product innovation. Further suppose that (1) organizational size has positive effects on the likelihood of generational product innovation and the likelihood of survival, and (2) the likelihood of generational product innovation is higher among surviving organizations than among otherwise identical organizations that are failing. In this scenario, the marginal effect of organizational size has two elements: its influence on the likelihood of survival and its influence on the likelihood of generational product innovation among the surviving organizations. Under these conditions, without controlling for selection, the model would overstate the marginal effect of organizational size on the likelihood of generational product innovation (Greene, 2000). For more information regarding sample selection bias, see Greene (2000) and Heckman (1979).

Several factors influenced our choice of the probit technique: censoring, a repeated-event dependent variable, variation within and across organizations, and infrequency of event occurrences. In event history studies, censoring is often a concern. In this study, left-censoring refers to organizational activity prior to the start of the data window, and right-censoring refers to activity after the end of our data window. Left-censoring is not a large concern because generational innovations are repeated events and, with archival research, we were able to collect pre-window data for the occurrence of earlier events (Allison, 1984). This is also known as left truncation. Here, the primary limitation associated with left-truncation was that the empirical window begins at a relatively-mature stage of the industry.

Allison (1995) argues that discrete-time probit or logit models are appropriate techniques for event history studies, given right-censored cases and time-varying covariates. Probit and logit models are standard approaches to analyzing binary choices. The models differ in their assumptions about the distribution of the error term. Probit models assume a cumulative normal distribution, while logit models assume that the cumulative distribution is logistic. However, these models typically yield similar results, as the difference in distributions is small, with the exception of the tails (Maddala, 1992). In further support of discrete-time probit and logit models, Petersen (1995: 499) comments that "if the probability of an event in each time interval is small, then the coefficients obtained from a discrete-time specification for most models will be quite close to those obtained from a continuous-time specification." In this study, on average, the probability of an event in any time period is small (0.027).

Standard probit and logit models may be complicated by the longitudinal nature of the study. The unobserved factors within organizations may lead to correlated error terms if additional controls are not implemented. But statisticians and econometricians have found that ignoring the error correlations and using a standard probit model with pooled data yields consistent, albeit inefficient, estimates (Maddala, 1987; Robinson, 1982). As such, Maddala (1987) has recommended the use of the standard probit with pooled data prior to the use of more elaborate models.

Of the more elaborate discrete-time models, two offer potential interest: (a) fixed effects logit model, and (b) random effects probit model (Maddala, 1987; Verbeek, 2000). A fixed effects logit model controls for an effect of each organization, emphasizing within-organization variation. For this study, the major disadvantage of this approach would arise from the relatively-small number of generational product innovation events occurring within organizations during the window of data. As such, there is likely to be low power associated with the use of a fixed effects logit model.

The second option, the random effects probit model, is more favorable but also has limitations. Relative to the pooled probit model, the random effects approach yields more efficient estimates. The common form of the random effects probit is the Gauss-Quadrature model, which handles unbalanced panel data well. Its primary disadvantage is the assumption that the random effects are uncorrelated with the explanatory variables, which does not hold in many cases. The Chamberlain model, a correlated random effects approach, provides a more flexible technique. It allows the random effects to depend on current, future, and past explanatory variables (Maddala, 1987). Unfortunately, the Chamberlain model is not well-suited for unbalanced panel data.

Given the above factors, we selected the standard probit model with pooled data as the most appropriate discrete-time technique; we also incorporate selection into the model (Allison, 1995; Maddala, 1987; van de Ven and van Praag, 1981). As an improvement to the standard pooled probit model, we clustered observations at the organization-platform level (e.g., Microsoft Word on the Macintosh operating platform) using the robust option to calculate standard errors. This approach provides better estimation of the standard errors, versus an assumption of independence across observations.

Continuous time approach. For the continuous-time approach, we used parametric analysis. Historical time is the time axis for the analyses. As suggested by our hypotheses, we have chosen to model duration dependence through covariates (i.e., time since previous innovation), leaving only historical time effects to model through the distribution. Further, using historical time as the time axis eases the comparison of our continuous-time and discrete-time approaches. Beginning with our discrete-time formation of the dataset, the explanatory and control variables are updated monthly. The selection (OnMkt) and generational product innovation variables (GenProdInnov) are also updated monthly. Following Petersen's (1991) approximation to minimize time aggregation bias, we set the selection and innovation events to the mid-point in their months of occurrence.

As we transition to the continuous-time approach, one of the first issues to address is controlling for survival bias. While the discrete-time probit model can estimate the focal and selection equations simultaneously, similar models are not available for continuous time. Therefore, we used Lee's (1983) generalization of the Heckman (1979) two-stage estimator. Using the same set of explanatory variables for the probit selection equation, we first estimated a separate selection model. For the selection model, we compared five different parametric models: exponential, Weibull, Gompertz, log-normal, and log-logistic. Among the first three models, we found that the exponential model provided the best fit according to the AIC criteria. Further, we observed that the Weibull and Gompertz models could not exclude the exponential distribution at a 95% confidence level. We also estimated log-normal and log-logistic models, finding that the log-normal model had the most favorable AIC score while the log-logistic model had the least favorable AIC score (of the five models). Next we compared the overall fit of the exponential and log-normal models using the Cox-Snell residuals, finding that the exponential model clearly provided a better fit than the log-normal model. Therefore, we used the exponential distribution for the selection model. Next we calculated the following estimate of lambda (Lee, 1983):

$$\lambda = [\phi(\Phi^{-1}[1-F(t)])]/F(t)]$$

with ϕ as the standard normal density and Φ as the standard normal distribution. We then included the lambda estimate in the focal model (GenProdInnov) to control for survival bias. We do not report the results of this model, as they were substantively similar to the probit selection equation.

Next we proceeded to the generational product innovation model. Again we used the robust option to calculate standard errors, clustering the observations at the organization-platform level. We estimated the same five parametric models as in the selection model. In a nested comparison, we found that the Weibull outperformed the exponential model (p=0.06), finding a monotonically increasing hazard for the Weibull specification. Based on the AIC criterion, we found the following three models as most favorable (in order): log-logistic, log-normal, and Weibull. As a further comparison, we examined the overall fit of the log-logistic and Weibull models using the Cox-Snell residuals. The model fits were similar, with a slightly better fit for the log-logistic model.

Both the log-logistic and Weibull findings are consistent with a maturing markets perspective of innovation rates. This perspective suggests that, as markets develop, innovation rates proceed along an S-curve. In the initial stages of market development, innovation rates increase at an increasing rate, followed by rates that increase at a decreasing rate (with decreasing innovation rates likely in later stages). With the log-logistic parametric model, we found an innovation rate that follows an S-curve pattern; within our data window, the pattern was largely the upper portion of the curve. With the Weibull parametric model, we found an innovation rate that follows a monotonically increasing pattern, consistent with the upper portion of an S-curve pattern.

Given similar findings between the log-logistic and Weibull models, we decided to present the Weibull model for two reasons. First, the Weibull estimates can be displayed in a hazard metric, as opposed to an accelerated failure time metric, which aligns more directly with our stated hypotheses and facilitates comparison between the discrete-time and continuous-time approaches. Second, the Weibull model provides more conservative results relative to our hypotheses.

RESULTS

Table 2 presents the results for the discrete-time (probit) model. The focal equation has generational product innovation as the dependent variable. These results are presented above the selection equation results in Table 2. The dependent variable for the selection equation is whether an organization remains on the market. We operationalized selection (OnMkt) as a binary variable (1 if the organization's product remains on the market throughout the end of the time period, and 0 otherwise). Table 3 presents the results for the continuous-time model, employing a Weibull distribution. We report the results in a hazard metric. Following Lee (1983), the analyses included a lambda estimate from a separate selection model to control for survival bias.

To test the hypotheses, we examined three nested models. Since we employ the clustering/robust option to calculate standard errors, we were not able to conduct incremental likelihood ratio tests. Model 1 is the baseline model, which has a set of control variables and intercept term. To assess Hypothesis 1, Model 2 added two measures to the baseline model: (a) time since previous innovation, and (b) the square of time since previous innovation. Our test for Hypothesis 1 focuses on the coefficient for the square of time since previous innovation (TimeSinceInnovSq). Note that, with TimeSinceInnovSq in the model, the TimeSinceInnov coefficient represents the effect of time since previous innovation on generational product innovation when TimeSinceInnov = 0 (its mean, since the variable is centered).

Model 3 examined the consistency of the evidence with respect to Hypothesis 2. Model 3 added two interaction terms: (a) organizational size and time since previous innovation, and (b) organizational size and the square of time since previous innovation. Our test for Hypothesis 2 focuses on the coefficient for the interaction between organizational size (OrgSize) and the square of time since previous innovation (TimeSinceInnovSq). The interpretation of the OrgSize*TimeSinceInnov coefficient follows from the previous discussion of the interpretation of the TimeSinceInnov coefficient in Model 2. In Tables 2 and 3, given the predicted directions of our hypotheses, we present one-tail test results.

The presence of temporal routines for generational product innovation

Model 2 examined the empirical evidence for Hypothesis 1. This hypothesis focuses on the presence of temporal routines for generational product innovation. We expect a negative effect for the square of time since previous innovation. We found strong support for Hypothesis 1 from both the probit and Weibull models. The coefficient for TimeSinceInnovSq is negative and significant in the probit ($p<0.001$) and the Weibull ($p<0.01$) models. Also, note that the

TimeSinceInnov coefficient is positive, which indicates that the inverse-U shaped relationship peaks to the right of the mean of time since previous innovation.

In examining the control variables across the probit and Weibull models, we generally found similar results with some differences in significance levels: a negative effect for the DOS platform ($p<0.05$ on probit, not significant on Weibull), a positive effect for the Windows platform ($p<0.10$ on probit, not significant on Weibull), a negative effect for market concentration ($p<0.05$ on probit, $p<0.01$ on Weibull), and a negative effect for organizational age ($p<0.001$ on both). Of particular interest was the effect of organizational size (positive and $p < 0.001$ on probit, negative and not significant on Weibull). In the following section, we discuss the different findings for organizational size.

Between the probit and Weibull approaches, we also observed differences in selection bias. One difference is in the direction of the bias coefficients. If the bias effect is consistent across the two approaches, the rho (probit) and lambda (Weibull) coefficients should have the same direction (Greene, 2000). But this difference is an artifact of our use of alternative numbering conventions for the selection dependent variable.[3] We also found differences in the level of statistical significance. While this effect is not the focus of our investigation, we conducted additional analyses to better understand the issue. First, we observed that a portion of the difference in statistical significance comes from a suppressing effect of historical time. Including an effect of historical time in the continuous-time approach leads to greater significance for lambda by controlling for, or suppressing, variance that is shared with lambda and not with the likelihood of innovation (Pedhazer, 1982).[4]

The difference in statistical significance also stems from the nature of estimation between the simultaneous and two-stage approaches. In subsequent analyses with the simultaneous probit, we found some sensitivity in selection bias from including the log of historical time as a predictor variable. But even after including a historical time effect, the selection bias did not approach statistical significance at conventional levels. However, we found statistical significance for lambda in two-stage discrete-time models (probit, logit and complementary log-log) after including the log of historical time. These results suggest that our finding of selection bias in the continuous-time approach is, in part, a function of the two-stage estimation process.

The moderating effect of organizational size

Model 3 provided the empirical evidence regarding Hypotheses 2. This hypothesis predicts that, as organizational size increases, organizations are more likely to employ temporal routines for generational product innovation. According to Hypothesis 2, we expect to find a negative effect for the interaction between organizational size and the square of time since previous innovation. We found support for Hypothesis 2 with both the probit model ($p<0.001$) and the Weibull model ($p<0.01$).

In examining the control variables, we found similar results compared to Model 2. As one distinction of note in Model 3, we observed that both approaches have a positive coefficient for OrgSize ($p<0.01$ on probit, not significant on Weibull), indicating a positive effect of OrgSize on generational product innovation at the means of TimeSinceInnov and OrgSize. In subsequent analyses, we determined that the difference in significance levels largely stems from the inclusion of a historical time effect in the Weibull model, reflecting a degree of shared variance between the organizational size and historical time variables.

Given the interactive nature of the effect of organizational size and time since previous innovation, we further examined this relationship (Aiken and West, 1991). First, we plotted the effect of time since previous innovation on generational product innovation for three levels of organizational size: $OrgSize_L$ (small organizations: one standard deviation below the mean), $OrgSize_M$ (medium-sized organizations: at the mean of organizational size), and $OrgSize_H$ (large organizations: one standard deviation above the mean). We prepared plots for both discrete-time (Figure 3) and continuous-time (Figure 4) approaches. The plots used coefficients from Model 3 in Tables 2 and 3, respectively. For the x-axis (TimeSinceInnov), the plot extends from the negative-end of the data range (TimeSinceInnov = -21.4) to +2 standard deviations (TimeSinceInnov = 38.6). Figures 3 and 4 report these plots.

For the discrete-time plot (Figure 3), along the y-axis is a Z-score, which is an unobservable variable common to probit models. To equate the Z-score with the probability of the occurrence of a generational product innovation event, consider a standard normal distribution curve. The probability of event occurrence is equal to the area under the curve from negative infinity to the Z-score. As reference, a -2.4 Z-score is equivalent to < 1% probability of event occurrence (single asterisk, Figure 3). A -1.25 Z-score is equivalent to 11% probability of event occurrence (double asterisk, Figure 3).

For the continuous-time plot (Figure 4), along the y-axis is the instantaneous rate of generational product innovation. Alternatively, we could present Figure 4 with the multiplier of the rate along the y-axis. The multiplier is the multiplicative effect of a variable on the rate. If a multiplier is greater than one, the rate increases; if it is less than one, the rate decreases. As points of reference, at TimeSinceInnov = -16, the multiplier for small organizations is 0.3 and that of large organizations is 0.1. At TimeSinceInnov = 8, the multipliers for small and large organizations are 1.0 and 1.5, respectively.

In comparing Figures 3 and 4, a notable distinction is the nature of the curvature in the relationship. In the Weibull model (Figure 4), the rate of innovation is an exponential function of the covariate effects. This approach restricts the rate of innovation to positive values and explains the curvature distinction between Figures 3 and 4. These figures help illustrate our differing findings for the effect of organizational size in Model 2. In Figure 3 (probit estimates), we observe a positive effect of organizational size on innovation for the large majority of the time since previous innovation range. This is consistent with the positive and significant effect of organizational size in Model 2, Table 2. In Figure 4 (Weibull estimates), we observe a negative effect of organizational size on innovation for a slight majority of the range of time since previous innovation. This is consistent with a negative and insignificant effect of organizational size in Model 2, Table 3. As discussed above, the difference in the organizational size effect reflects, in part, the inclusion of a historical time effect in the Weibull model.

From Figure 3, when organizational size was low, there was little curvature in the relationship between time since previous innovation and likelihood of generational product innovation. As organizational size increased, however, Figure 3 highlights an increasingly inverse-U shaped relationship. These visual observations are consistent with Hypothesis 2. Note that the peak of the curve corresponds with the most likely length of time until a generational product innovation event. One can calculate this length of time by using coefficient estimates from Model 3 (Table 2). For this calculation, we took the derivative of the estimated GenProdInnov function with respect to TimeSinceInnov and set it equal to zero. For medium-sized organizations, we found that the most likely length of time until a generational product innovation is 30 months.

Next we transitioned from visual observation to statistical analysis using a series of simple slope tests (Aiken and West, 1991). The simple slope tests use the discrete-time analysis. Here nine simple slopes examined the effect of time since previous innovation on generational product innovation. These tests were various combinations of organizational size ($OrgSize_L$, $OrgSize_M$, $OrgSize_H$) and time since previous innovation ($TimeSinceInnov_L$, $TimeSinceInnov_M$, $TimeSinceInnov_H$). The subscripts are as follows: L (one standard deviation below the mean), M (the mean), and H (one standard deviation above the mean). See Table 4 for the test results.

For small organizations, when time since previous innovation was low, there was a positive effect of time since previous innovation on generational product innovation ($p<0.05$); when time since previous innovation was high, its effect was negative and weakly significant ($p<0.10$). For medium-sized and large organizations, when the time since previous innovation was low, there was a positive effect on generational product innovation ($p<0.001$). Finally, when the time since previous innovation was high, there was a negative effect on generational product innovation ($p<0.01$).

Using the results from the simple slope tests, we also examined the effect of organizational size on generational product innovation at various levels of time since previous innovation. In this case, slope tests examined the effect of organizational size on generational product innovation at three levels of time since previous innovation: $TimeSinceInnov_L$, $TimeSinceInnov_M$, and $TimeSinceInnov_H$. Here we observed that when little time had elapsed since the previous innovation ($TimeSinceInnov_L$), there was only an insignificant negative effect of organizational size on the likelihood of generational product innovation. At the mean of time since previous innovation ($TimeSinceInnov_M$), there was a positive effect of organizational size on the probability of generational product innovation ($p<0.01$). Then, after much time has elapsed since the previous innovation ($TimeSinceInnov_H$), we found a weakly significant positive effect of organizational size on generational product innovation ($p<0.10$).

Sensitivity analyses

The standard analyses included a set of control variables to help account for alternative explanations of innovation activity. For this dataset, however, there are limitations associated with using control variables to rule out alternative arguments. One limitation is the availability of data and its cost of acquisition. A second limitation focuses on the power of the test. While this sample has a relatively large number of organization-month observations (2617), there are relatively-few generational product innovation events in the sample (72). While the first limitation is largely unavoidable, in part, we can address the second limitation by including a greater number of control variables in separate sets of sensitivity analyses.

Using discrete-time and continuous-time approaches, we conducted four sets of sensitivity analyses: (1) examining whether recent change in market size may be a determinant of innovation activity, beyond the recent level in market size, (2) examining whether recent change in organization size may be a determinant of innovation activity, beyond the recent level of organization size, (3) examining whether two additional lags of innovation by peer organizations may be a determinant of innovation activity (i.e., in total, the effect of the previous quarter of innovations by peers), and (4) examining whether temporal routines were the result of diminished competition, rather than organizational size. For the last examination, we included interactions between (a) MktConc and TimeSinceInnov and (b) MktConc and TimeSinceInnovSqr, rather than between (a) OrgSize and TimeSinceInnov and (b) OrgSize and TimeSinceInnovSqr. In all four cases, the additional variables for the sensitivity analyses were not significant. Further, they did not have any substantive impact on the results for our hypotheses.

We note that there were moderately-high correlations (0.40-0.50) between several of the control and/or explanatory variables. As a result, we ran three additional sets of discrete-time and continuous-time analyses after removing one of the correlated variables: (1) running one set of analyses without MktSize, given its correlation with WIN and OrgSize, (2) running one set without Age, given its correlation with TotPrevInnov, and (3) running one set of analyses without MktConc, given its correlation with TimeSinceInnov. In all three cases, there were no substantive changes in the hypotheses results.

Extension: External entrainment as an alternative explanation

As presented to this point, the results are consistent with the existence of temporal routines for generational product innovation. Our argument centers on pressure within the producing organization and pressure between the producing organization and its organizational customers. However, an alternative argument based on consistency in the delivery of technological or market opportunities could also align with the empirical evidence. This argument focuses on the idea of entrainment, which refers to "the adjustment of the pace or cycle of an activity to match or synchronize with that of another activity" (Ancona and Chong, 1996: 253). We demonstrate that, even after controlling for potentially-entraining technological and market opportunity events, we still find support for our hypotheses.

There are several candidates for exogenous entrainment in the context of microcomputer applications software. In this extended analysis, we consider two technological opportunity variables and one market opportunity variable as synchronous entraining factors. Synchronous entrainment refers to generational product innovation releases of application software that occur in the same month as the technological or market opportunity events (Bluedorn, 2002). As we discussed earlier, microcomputer applications software is part of a larger, complex technological system. In addition to applications software, two of the fundamental components in this system are the microprocessor and operating system software. Therefore, for the technological opportunity variables, we considered the release of generational product innovations in microprocessors and operating system software. For the market opportunity variable, we used the occurrence of major industry trade show events.

We turned to archival sources to collect data for the technological opportunity variables. We first considered microprocessors for IBM-compatible and Macintosh computers. Intel was the dominant supplier of microprocessors for the IBM-compatible in this time window. Using archival data from the Intel web site, we examined the organization's history of microprocessor innovations in the 1994-1998 timeframe. Two key dimensions of technological innovation in this industry are increases in the number of transistors and increases in the clockspeed. Significant increases in the number of transistors associate with the introduction of new classes of microprocessors (e.g., Pentium, Pentium II), while increases in clockspeed tend to be minor, more frequent innovations. For Intel, we operationalized technological performance in terms of significant increases in the number of transistors observing two generational product innovations within this time period.

For the Macintosh, Motorola was the dominant supplier of microprocessors in this time window. Using archival data from Apple-based web sites, supplemented with trade press, we examined the history of microprocessor innovations for the Macintosh in the 1994-1998 timeframe. In this case, detailed information was available for clockspeed but not for the number of transistors. However, significant increases in the top-end clockspeed for a microprocessor are typically associated with large increases in the number of transistors (i.e., the introduction of new classes of microprocessors). Therefore, we used significant increases in the top-end clockspeed as a proxy for generational product innovation among microprocessors for the Macintosh. We observed three generational product innovations for Macintosh microprocessors within this time period.

The microprocessor innovation variable (TechOppMP) is a binary variable. Zeros represent the absence of generational product innovation releases and ones represent the occurrence of generational product innovation releases.

We then considered operating system software. Microsoft was the dominant supplier of operating system software for the IBM-compatible microcomputer in this time window. Using archival data obtained from the Factiva informative database, we identified four generational product innovations in this time period. The first two innovations focused on both corporate and end customers (Windows 95, Windows 98), while the second two innovations focused on corporate customers (Windows NT 3.5, Windows NT 4.0). Microsoft did not release a generational product innovation for the DOS operating system in this timeframe. For the Macintosh operating system, using a combination of Apple-based web sites and the Factiva database, we identified three generational product innovations. The operating system variable (TechOppOS) is a binary variable, similar in format to the earlier-described TechOppMP variable.

In addition to entrainment deriving from technological opportunities, we also considered an entraining factor based on market opportunities in the form of major trade shows. The COMDEX/Fall trade show is recognized as the largest computer trade show in the world. Within the 1994-1998 time window, the COMDEX/Fall trade show occurred each year in mid-November in Las Vegas. For organizations competing on the IBM-compatible system, COMDEX/Fall represented the focal trade show event. For organizations competing on the

Macintosh system, the bi-annual Macworld Expo trade show event offered an alternative venue. Within the 1994-1998 time window, Macworld Expo shows were held each January in San Francisco and each August in Boston. The only exception was the occurrence of a July 1998 Macworld Expo in New York, rather than an August 1998 show in Boston.

The market opportunity variable (MktOpp) is a binary variable. Zeros represent the absence of major trade show events, and ones represent the occurrence of major trade show events. Guided by the trade press, for DOS and Windows organizations, we viewed COMDEX/Fall as the sole major trade show. For Macintosh organizations, we viewed both COMDEX/Fall and the Macworld Expos as major trade show events.

Table 5 presents the entrainment results. The models extend Model 3 from Tables 2 and 3. As such, they are labeled Models 4a and 4b. For both the probit and Weibull models, we found a positive effect of generational product innovation releases of microprocessors and operating system software ($p<0.05$). We also found a positive and weakly significant effect of major trade events ($p<0.10$). But, even after inclusion of the entraining variables, we retain empirical evidence in support of our hypotheses.

Limitations

There are several limitations associated with the empirical assessment. First, we studied generational product innovation in a single industry, which may limit the generalizability of the work. While generational product innovations are visible and relatively frequent in applications computer software, it is important to examine the generalizability of the concept. We consider both product and generational aspects. With respect to the emphasis on product innovation, approximately three-quarters of industrial R&D in the U.S. focuses on product innovation (Scherer and Ross, 1990). With respect to generational innovation, Scherer and Ross (1990: 642) note that "most industries experience a continuing stream of innovations over time, and in many cases, each completed new product or process sets an agenda focusing improvement work for the next technological generation." Similarly Schumpeter notes that "improvement in the quality of products is hence a practically universal feature of the development of individual concerns and industries" (1942: 92) and further that "a new type of machine is in general but a link in a chain of improvements" (1942: 98). While somewhat limiting, studying innovation in a single industry context offers the opportunity to develop an appropriate operationalization of the innovation concept. Cohen and Levin (1989: 1026) note that currently there is not a measure of innovation that "permits readily interpretable cross-industry comparisons."

Second, in addition to a cross-sectional limitation (i.e., a single industry), the data is limited longitudinally. Due to cost and data availability limitations, we could examine only a relatively-developed stage of the computer software industry. This necessarily limits our ability to study how these routines emerged in the earliest stages of the industry. Nonetheless, generational product innovation within more established markets is an important phenomenon.

Third, the number of generational product innovation events in the dataset is relatively small. The limited number of events posed a power concern, limiting our analytic technique options. In particular, we were unable to employ fixed-effects that could control for the likelihood of innovation by each organization. Fortunately, statisticians and econometricians demonstrate that this limitation is a minor one, resulting only in less efficient estimates (Maddala, 1987; Robinson, 1982). Therefore, while the theory allows organizations to differ in the length of time between generational product innovations, an assumption of commonality in time intervals across organizations limits the empirical test. Note that in order to examine a fixed organization effect for temporal routines, it may be necessary to include not only an effect for the likelihood of innovation by each organization but also a fixed effect for time since previous innovation by each organization. In this case, future empirical work in this area could require substantial length in data panels to study organization-specific temporal routines.

In summary, we found results that are consistent with temporal routines for generational product innovation. First, in a developed stage of the microcomputer applications software industry, organizations employed temporal routines for generational product innovation. Second, with increasing size, organizations had a greater tendency to employ these routines. Third, even after controlling for potentially-entraining exogenous factors (e.g., generational product innovation releases of microprocessors), we found empirical evidence of temporal routines for generational product innovation.

DISCUSSION AND CONCLUSION

Understanding the implications of time-based pacing of innovation has been an area of emerging interest in the organizations literature. Through inductive theory development, Brown and Eisenhardt (1997) and Gersick (1994) have made important contributions to this line of research. At the same time, though, we have limited understanding as to why organizations employ time-based patterns of innovation. Examining this research question is worthy of our attention, particularly as Brown and Eisenhardt (1997) posit a positive influence of time-based pacing on organizational performance. In this study, we draw from routines-based theory in our examination of time-based pacing of product innovation.

Our results lend support to a temporal routines-based perspective of generational product innovation in the computer software industry. We find that, on average, software organizations employ temporal routines for generational product innovation. In further analysis, we find stronger evidence of temporal routines in larger organizations. The results imply that there are scale-based conditions that precede the employment of temporal routines for generational product innovation. This implication sheds light on routines-based theory from two vantage points. First, from a rational investment perspective, it suggests that organizations undertake the costs of establishing routines for innovation in response to scale-based coordination needs. Second, from the perspective of constraints on change, the implication suggests that after establishing routines for innovation, organizations face significant pressures that inhibit their ability to break or change the established routines.

The results of this study also make contributions to the inertia perspective from organizational ecology. The seminal contribution in this area is the importation of inertia from physics into organizational ecology by Hannan and Freeman (1984). The Hannan and Freeman (1984) study draws from the 'body at rest' aspect of Newton's first law of motion. In an organizations context, the 'body at rest' aspect examines the effect of external forces on organizational change, given an organization in a particular (i.e., unchanging) state. Less work has examined the 'body in motion' aspect of Newton's first law of motion. This aspect has been termed the dynamics of inertia, and in an organizations context, it refers to the idea that a changing organization (i.e., body in motion) has a tendency to maintain its existing change behavior. Terry Amburgey and his colleagues have made important contributions to the dynamics of inertia in the form of repetitive momentum (Amburgey and Miner, 1992; Amburgey, et al., 1993). The repetitive momentum perspective focuses on a positive effect of the cumulative number of previous changes on the probability of repeating an organizational change of the same type. In reviewing the empirical work on organizational ecology, Baum (1999) found that repetitive momentum is unusual in that it has strong and consistent support across studies.

Nonetheless, the current view of the dynamics of inertia is incomplete. In addition to the effect of the cumulative number of previous changes, time since previous change influences the likelihood of change. The organizational ecology literature currently focuses on a negative effect of the time since previous change on the likelihood of change (Baum, 1999). The rationale is that organizations search locally in time for change solutions. Thus, organizations are more likely to repeat recently-enacted changes. But in this study, we find that due to the disruptive nature of change, organizations are more likely to change at consistent, periodic time intervals. Consistent with a dynamics of inertia perspective, this finding underscores the value of viewing individual changes as elements within larger, historical patterns of change in organizations.

Substantial future research opportunities surround routines-based theory. As Winter (1995) notes, routines-based theory in evolutionary economics initially arose as a descriptive theory. First, we can improve and extend this theory with greater attention to organization- and market-based factors that enable or constrain the employment of routines. For example, at the organization level, the following two factors may help to explain the employment of routines for innovation: (1) market expansion efforts by the organization, and (2) top management team beliefs and experiences. Second, we can expect market attributes to influence the employment of routines for innovation. Third, researchers are beginning to develop performance implications from routines-based theory in efforts to guide managerial decision-making (Knott and McKelvey, 1999).

This study also offers important implications for practice. Brown and Eisenhardt (1997) suggest performance advantages for organizations that employ time-based pacing of generational innovation. At the same time, though, recent attention to the implications of routines for innovation in the practitioner press suggests the importance of viewing routines for innovation within a given context or paradigm (*Economist*, 2003; *Red Herring*, 2003). In particular, this attention focuses on the adherence to Moore's Law in the semiconductor industry, despite declining consumer demand. In essence, this discussion highlights the implications of employing temporal routines for innovation when the assumption of consumer demand for repetitive innovation no longer holds. Commenting on breaks in the cycle of generational adoption by semiconductor customers, Marc Andreessen, cofounder of Netscape, notes "this is a fundamental, even revolutionary, change in the IT world ... it's going to be disastrous for a lot of big companies out there" (*Red Herring*, 2003: 30).

The importance of routinized innovation in stimulating technological change and economic performance is not new (Schumpeter, 1942). But our understanding of routines for innovation remains limited. In this study, we offer both theoretical and empirical contributions toward further development of a routines-based perspective of innovation.

ENDNOTES

[1] Another anecdote, though, offers an alternative view on the demand perspective on upgrades: "Once the driving force behind technological change, [customers] have instead become the protectors of the status quo... five years ago having the latest version of an application was an unquestioned necessity... but today, software upgrades and changes are driven more by the immediate needs of a project or by corporate dictum than by users eager to use only the newest version of a product" (*InfoWorld*, 1990).

[2] As described in the previous section, we aggregated multiple versions and formats into representative product families. Among the forty-six organizations competing in these market segments, there were three cases in which generational product innovation activity occurred for more than one version of the product (e.g., WordStar, WordStar 2000) within the market segment. In only one case, TurboCad on the Windows platform, did this issue extend into the time window of the dataset, although the other two cases are relevant for historical tracking of variables. By using the history of product development for the three products, we identified a dominant version of the product and used innovation activity for the dominant product version to represent the innovation activity for the organization.

[3] Following the Stata heckprob procedure, the selection dependent variable is operationalized with 1 as observed, or uncensored, observations and 0 as unobserved, or censored, observations. In the two-stage continuous-time model, we use the standard convention for the selection dependent variable, with 1 as an indication of organizational failure (i.e., the censoring event) and 0 otherwise. Therefore, between the two approaches, we found similar results with respect to direction of bias.

[4] While shared variance is present between historical time and lambda, recall that our estimation of the continuous-time selection model did not find significant improvement from including a historical time effect.

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