TEMPORAL ROUTINES FOR GENERATIONAL PRODUCT INNOVATION IN COMPUTER SOFTWARE

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ABSTRACT

This study examines time-based pacing of generational product innovation in the applications software industry. We argue that firms tend to develop temporal routines for introducing generational product innovations due to customer demands and internal operating procedures that value temporal consistency. The argument 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. The analysis suggests that software organizations, particularly larger organizations, employ temporal routines for generational product innovation. The results control for technological and market entrainment from the external environment, as well as several other common alternative explanations.

KEY WORDS

time-based pacing
routines-based theory
generational product innovation
computer software

Time-based pacing of innovation has drawn recent interest from both academics (Brown and Eisenhardt, 1997; Souza, *et al.*, 2004) and practitioners (*Economist*, 2003). Time-based pacing is especially important for generational product innovation. 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 eighteen months. Timing of generational product innovations is often central to firms' technological decision-making and has an important effect on business performance. 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). Despite the strategic importance, there are substantial conceptual and empirical limits to our understanding of time-based pacing of generational product innovation.

Time-based pacing is a theme within the general issue of how organizations deal with time. Ancona, *et al.* (2001) refer to time-based pacing as mapping activities to time. Within time-based pacing scholarship, there are two classes of mapping activities to time: single-activity and repeated-activity. To date, most research activity has focused on single-activity mapping, such as studies of the occurrence of mid-point transitions in task-completion activities (e.g., Gersick, 1989; Waller, *et al.*, 2002) and theory-building research on the pacing of key decisions during new venture start up (Gersick, 1994). Repeated-activity mapping, such as the release of generational product innovations, has received much less attention.

The small body of work that examines repeated-activity mapping includes Brown and Eisenhardt (1997, 1998) and Souza, *et al.* (2004). These studies focus on the performance consequences of using time-based pacing of generational product innovation. Brown and Eisenhardt (1997, 1998) inductively develop the argument that time-based pacing couples current and future product development efficiently, provides a rhythm for synchronizing development activities, and creates a recurring sense of urgency for innovation. Using analytic models, Souza, *et al.* (2004) find that time-based pacing of generational product innovation performs well, relative to a release policy that reacts to industry demand, production and inventory costs, and competitive pressure. Nonetheless, despite the arguments concerning the performance benefits, we have little understanding as to why time-based pacing of generational product innovation occurs and to what extent time-based pacing actually takes place.

Some scholars argue that time-based pacing results from synchronizing the pace or cycle of one activity with that of another activity. This notion is also referred to as entrainment (McGrath and Rotchford, 1983; Ancona and Chong, 1996). However, the entrainment argument simply shifts the question, in the sense that what causes time-based pacing of the entraining activity remains unanswered. We have limited conceptual understanding of the pressures that cause firms to employ time-based pacing of innovation, and how these pressures vary among different organizations. For instance, Brown and Eisenhardt (1998) contrast the case of Zeus, a top-performing business that employed time-based pacing of innovation, and Callisto, an organization that suffered from its absence. Yet the literature offers little guidance as to why one organization would employ time-based pacing while another would not.

Moreover, despite the interest in time-based pacing, few large scale empirical studies have investigated time-based pacing of innovation. Empirical analysis is necessary to learn the extent to which theoretical notions of time-based pacing explain innovation behavior within a population or sub-population of organizations. Further, research has not yet determined whether time-based pacing arises independently of other forces for product innovation, such as organizational experience, market structure, and entrainment to technological and marketing events in the environment.

This study develops our conceptual understanding of why organizations employ time-based pacing of generational product innovation and demonstrates its empirical existence. We use a routines-based theoretical lens (Nelson and Winter, 1982) to develop our argument. This lens views time-based pacing of innovation as a particular form of modification routine that arises due to internal and external pressure for temporal consistency.

Our argument devotes particular attention to how organizational size affects incentives for time-based pacing. While numerous studies examine the effect of organizational size on innovation (Cohen and Levin, 1989), little research examines its effect on the time-based pacing of innovation. Yet this topic offers important implications for competitive strategy. Hannan and Freeman (1984) suggest that inertia increases with organizational size. In turn, this may lead to seemingly counterintuitive routine behavior, in which larger organizations establish routines for innovation as a form of inertia of change. If so, this tendency can shed light on how different sizes of organizations compete via innovation, suggesting that large organizations tend to compete on the reliability of their innovation processes, while smaller rivals may be more likely to compete on the adaptability of their innovation processes.

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. In examining this industry, we develop a systematic methodology for identifying generational product innovations that is more general than the context-specific approaches in prior research. We undertake event history analysis, offering a comparison of results using discrete-time and continuous-time approaches. Consistent with our expectations, we find that organizations in the software industry maintain temporal consistency in their release of generational product innovations. Moreover, this pattern of temporal consistency is stronger in larger organizations. These results hold after controlling for multiple alternative explanations, including technological and marketing entrainment.

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 stem from firms' deliberate choices to maintain the routines.

Scholars often view routines in a hierarchy of operating and modification procedures. Operating routines are standard patterns of organization activity in a given context, while modification routines are patterns of activity that systematically change the operating routines of an organization (Nelson and Winter, 1982; Nelson, 1991). This study aligns with the tradition of examining routines in the form of self-sustaining operating and modification types. Nelson and Winter (1982) advance 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.

Routines-based research takes two approaches: (1) examining organizations as portfolios of routines and (2) examining specific routines within organizations (Cohen, *et al.*, 1996). The first approach studies the process by which organizations function according to a set of routines (Cyert and March, 1992; Karim and Mitchell, 2000). The second approach focuses on a particular routine, which may include sub-level routines (Pentland and Rueter, 1994; Feldman, 2000). This study takes the latter approach.

Our focal routine is the temporal routine for generational product innovation. 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 core ideas that shape our research and then turn to hypotheses.

Boundary conditions, assumptions, and concepts

Two boundary conditions define the scope within which our theoretical perspective addresses 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 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 or 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), the organization must make a corresponding series of changes (e.g., marketing, customer support training). Similarly, when an organizational customer changes an existing element of its production process (i.e., adopting a new product version), the change triggers disruptions within its set of operating routines. In a recent study, Mukherjee, *et al.* (2000) found that variation in a set of inputs results in disrupted performance of the routine.

Our argument makes two assumptions within these boundary conditions. First, we assume that producers and organizational customers have favorable perceptions about changing a product. Abernathy (1978) observed that firms make functional improvements that provide substantial value to customers in early stages of product life in the automobile industry. 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 (Pfeffer and Salancik, 1978; 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: degree of change in core design concepts and 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 innovation within the definition of generational product innovation. This allows greater focus in developing our conceptual argument. In our empirical context, architectural product innovations typically represent entry into new technological markets (i.e., from DOS to Windows operating systems). We treat these innovations as new market entries.

We note that generational innovation arises relative to the existing product. Therefore, generational product innovations may include the addition of features that are entirely new to a product market or features that are new only to a given product within the market. In the latter case, technical improvements may include the imitation of features from competing products.

To clarify the notion of generational product innovation, we consider 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. For instance, 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.

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.

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 (i.e., market-based orientation) and internal to the organization (i.e., bureaucratic orientation). Both dimensions arise in industrial organization economics and organizational ecology, but industrial organization economics places greater emphasis on the external dimension (Scherer and Ross, 1990), while organizational ecology places greater emphasis on the internal dimension (Baum, 1999). 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.

Hypotheses

Hypothesis 1 predicts temporal consistency in the release of generational product innovations. For this argument, we must address both demand for generational product innovation and 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). 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; 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 prime examples (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 routines for adopting innovations at customers and the preference for routines for developing innovations 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 routines within producers 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 routines for adoption leads customers to encourage temporal reliability in the release of generational product innovations (Amburgey and Miner, 1992). Thus, the routines for producers and 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. This convergence is consistent with emergence of a common market cycle for innovation. Often, though, the technical and adoption pressures will allow variety in cycles. For example, some customers may develop routines for adoption 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 the release of generational product innovations.

The alignment of routines helps explain why temporal routines for innovation exist in competitive markets, despite apparent 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 Nelson and Winter's (1982) sense of routine as truce.

> **Hypothesis 1.** The likelihood of generational product innovation will have a non-monotonic relationship with time since previous innovation, first increasing and then decreasing beyond a threshold.

Next, we address the moderating effect of organizational size on the relationship between time since previous innovation and generational product innovation. We base our argument on the premise that organizations function according to self-sustaining routines, and we direct our attention to a positive influence of organizational size on the employment of temporal routines for generational product innovation. Figure 1 illustrates the expected relationship, using an inverse-U function as an example of a non-monotonic form. [1]

In larger organizations, departing from a routine for innovation will impose greater costs. 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 complexity-based argument that focuses on the costs of coordinating change in an innovation routine. One can think of the complexity of an organization in terms of the number of its components, N, and the degree of interactions among its components, K (Simon, 1962; Rivkin, 2000). Both aspects of complexity tend to increase with size (Arthur, 1994). Thus, with increasing complexity from internal and external linkages, larger organizations face greater coordination costs when they disrupt an established 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 routine for innovation 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.

With greater numbers of agents, larger organizations face greater costs of coordinating change based on the number and interactions of department-level routines (Simon, 1962). Therefore, as organizations become larger, the coordination costs of disrupting established routines increase. In smaller organizations, coordination among agents is easier. In smaller organizations, there is less need to establish the routine in order to maintain coordination and, if established, the cost of disrupting the routine is smaller than in larger organizations.

Second, consider customer pressure. We previously argued that, to help them plan and coordinate, producers and their organizational customers establish routines that align with one another. Given the producer-customer linkage of routines, if producers change their established routines for developing innovations, their organizational customers face significant pressure to change their routines for adopting innovations.

If producers are sensitive to their impact on customer routines, they will attempt to communicate and/or negotiate changes in their 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), concerning both content (e.g., inter-generational compatibility) and timing (e.g., communications involving release schedules).

Since larger organizations typically 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.

> **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.

We argue that larger organizations will have greater temporal consistency in the release of generational product innovations. Alternatively, one might argue that smaller organizations release generational product innovations with greater consistency. The latter situation could occur when organizations find it difficult to achieve a routine state of behavior (Nelson and Winter, 1982). If generational product innovation represents this type of behavior, with a greater number of agents for coordination, larger organizations would face greater costs in establishing and maintaining a consistent pattern of generational product innovation.[2] While acknowledging this tension, we develop our hypotheses in accordance with the more dominant perspective of self-sustaining routines, which Nelson and Winter (1982: 112) argue are "more than half of the story and... a basic assumption of our evolutionary models".

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. The segments suit the boundary conditions and assumptions that we outlined earlier. Appendix A provides evidence from the software industry trade press regarding our use of applications software as the empirical context.

Data

PC Data (now NPD INTELECT), a market research firm that specializes in information technology markets, provided the starting point for the dataset. PC Data reports monthly product sales data in the four segments of the business productivity computer software from 1994-1998. The CAD, desktop publishing, spreadsheet, and word processing segments derive from 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.

The following is a brief overview that describes how we constructed the dataset. Using the initial categorization from PC Data, we created product market segments with products that are functional substitutes. First, we aggregated individual formats or versions (e.g., TurboCAD 5.0, Academic) into representative product families (e.g., TurboCAD), which represent the product offerings from their respective organizations. In many cases, the organizations in the study are business units within larger firms.

The second phase of construction identified products that perform similar functions. This step was necessary due to the listing of add-on products and products that are similar in content but different in functionality within the PC Data database. Our 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 (e.g., Factiva, *InfoWorld*) and company web pages to confirm product similarity.

The third phase of construction further segmented products into competitively-equivalent markets. We segmented the product markets by format and tier of market. First, in terms of format, the categorization focused on operating platform. We segmented the products into three 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.

We used these reports to identify product-market segments. 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). Few high-end CAD products are sold through the retail channel that PC Data tracks, however, so that this study analyzes only the low-end CAD segment. We identified two market segments for desktop publishing: high-end (approximately $500-$900 in list price) and low-end (approximately $100-$300). PC Data did not list a well-known low-end desktop publishing product, however, so that this study analyzes only the high-end segment. 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 generational innovation, this study analyzes only the high-end of the word processing market. We identified a single segment for spreadsheets, with list prices in the range of $100 to $600. Thus, we assess low-end CAD (<$1000), high-end desktop publishing ($500-$900), high-end word processing ($350-$700), and spreadsheets ($100-$600).

The final stage of archival research involved tracing the innovation history of each product family. These histories identified the cumulative number and timing of generational product innovation releases. The tracing process included reviewing every issue of the weekly industry trade publication *InfoWorld* from 1981-1990, as well as searching in online databases from their earliest available dates (typically the early 1980s) through the end of 1998. Our initial year, 1981, is an appropriate initial 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). In addition to archival searches with secondary data sources, the tracing process involved searching company web pages and, if necessary and available, contacting companies directly to help resolve any uncertainties.

Operational variables

There are three focal variables in the empirical model. The dependent variable is generational product innovation, while 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.

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).[3] Overall, there were 72 generational product innovation events among 46 organizations competing in four segments of microcomputer applications software from 1994 to 1998.[4] Within the 1994-1998 time frame, the number of generational product innovations per organization ranges from zero to six; for instance, the TurboCAD organization had four generational innovations on the Windows platform and two generational innovations on the Macintosh platform. For analysis purposes, we focus at the level of the organization-platform (e.g., FrameMaker on Macintosh).

Prior research offers limited conceptual and operational guidance for identifying generational product innovation. In part, this reflects alternative alignments of the term, generational, to types of innovation (Henderson, 1993; Lawless and Anderson, 1996). Researchers typically identify innovations as generational within particular industries (e.g., photolithography, microcomputers) and time periods, deriving historical knowledge from industry trade press, datasets, observers, and participants. However, this approach offers little guidance for identifying generational product innovation in alternative settings. Therefore, we needed to develop a methodology for this study, which in turn can help guide future research.

To identify 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 applications software innovation, we focused on three dimensions: (1) the number and magnitude of feature additions/enhancements, (2) the numbering convention for the product innovation release (i.e., Version 1.0, 1.01, 1.1, 2.0), and (3) 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. For the price dimension, for instance, 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 many of the product releases, multiple sources of data were available for 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 drew on the majority of evidence for the three dimensions.

To examine the reliability of our system for classifying innovation releases, following our classification guided by the three dimensions, we developed an explicit set of classification rules. We then reclassified each innovation release according to the rules. Comparing our initial classification against the classification using the explicit set of rules, we obtained a high degree of reliability. For the four markets, the following percentages represent identical release classifications between the two approaches: word-processing (94%), CAD (95%), spreadsheets (96%), and desktop publishing (100%). These classifications include any releases within our time window of data as well as prior releases identified in the trade press for the product families, since the latter is relevant for one of our control variables. Appendix B provides additional information for the classification-by-rule reliability assessment.

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 modeled the functional form of time since previous innovation as a quadratic relationship. The quadratic form provides a reasonable combination of approximating more complex nonmonotonic functional forms while also providing parsimony for the test of Hypothesis 2. In sensitivity analyses, we use an alternative piecewise approach that estimates the effect of time since previous innovation on the likelihood of generational product innovation at various spans of time since previous innovation (e.g., 11-15 months). The piecewise approach offers greater flexibility in estimation but consumes more statistical power.

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, we added one to the lag of organizational size prior to taking its logarithm in order to eliminate zero as a nuisance value. Because we study the interaction between the explanatory variables, we centered the organizational size and time since previous innovation variables to help with interpretation (Aiken and West, 1991).

Control variables. Guided primarily by the organizational ecology and industrial organization economics literatures, we controlled for a series of variables that may influence the likelihood of innovation. Two variables assessed firm experience. Age of the organizational unit (Age) is the number of months since the initial release of the product. Researchers have argued for alternative effects of age on organizational change (Hannan and Freeman, 1984; Singh and Lumsden, 1990) with the empirical evidence as mixed (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).

Two variables assessed market structure. We used a Hirschman-Herfindahl Index to measure market concentration (MktConc), using market share in terms of unit sales. The index is the sum of the squared values of products' market share (Curry and George, 1983). 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. A large body of work in industrial organization economics examines the effects of market concentration and market size on innovation (Porter, 1980; Cohen and Levin, 1989).

Drawing from institutional theory and the competitive rivalry literature (DiMaggio and Powell, 1983; Chen, 1996), we included market generational product innovation (MktInnov) as a binary variable that indicates whether any peer organizations released a generational product innovation in the previous time period. We employed a binary variable because there were few instances in which more than one peer organizations released innovations in the previous time period. Relative to this measure, innovation releases in the applications software industry involve significant levels of signaling and transparency. Thus, we expect that peer organizations have knowledge of upcoming innovation releases prior to the actual event. We discuss two extensions for this control variable in the sensitivity analysis section.

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, rather than the focal equation, to address potential survival bias in our discrete-time probit analyses. 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 (i.e., calendar 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. 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. 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 Heckman's (1979) original selection model. 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. For more information regarding sample selection bias, see Greene (2000) and Heckman (1979).

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. Nonetheless, statisticians and econometricians have found that ignoring the error correlations and using a standard probit model with pooled data yields consistent, albeit inefficient, estimates (Robinson, 1982; Maddala, 1987). 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). Given power concerns with the fixed effects logit and expected assumption violations with the Gauss-Quadrature and correlated random effects approaches, we selected the standard probit model with pooled data as the most appropriate discrete-time technique; we also incorporated selection into the model (van de Ven and van Praag, 1981; Maddala, 1987; Allison, 1995). 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 modeled 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. For our estimation of the selection model, we considered five different parametric models; the exponential distribution provided the best fit. Next, we calculated the following estimate of lambda (Lee, 1983):

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

with ϕ as the standard normal density and Φ as the standard normal distribution. We included the lambda estimate in the focal model (GenProdInnov) to control for survival bias. We omit the results of this model, which were materially equivalent to the probit selection equation.

We next 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. In a nested comparison of parametric models, 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.

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, the innovation rate follows a monotonically increasing pattern, consistent with the upper portion of an S-curve pattern.

Given similar findings of 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 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 of the discrete-time probit model. The focal equation has generational product innovation as the dependent variable. The table reports these results above the selection equation results. 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 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 did not 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 temporal consistency in the release pattern of generational product innovations. 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 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). The apparent difference, though, is an artifact of alternative numbering conventions for the selection dependent variable.[5] 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 (i.e., calendar 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).[6]

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 sensitivity in selection bias from including the log of historical time as a predictor variable. Including the log of historical time approximates the use of historical time as the time axis with a Weibull distribution in the continuous-time approach. Even after including a historical time effect in the simultaneous probit, though, 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 Hypothesis 2. This hypothesis predicts that, as organizational size increases, organizations are more likely to have temporal consistency in the release of generational product innovations. 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. 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 2) and continuous-time (Figure 3) approaches. The plots used coefficients from Model 3 in Tables 2 and 3, respectively. Figures 2 and 3 report these plots.

For the discrete-time plot (Figure 2), 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, while a -1.25 Z-score is equivalent to 11% probability of event occurrence.

For the continuous-time plot (Figure 3), along the y-axis is the instantaneous rate of generational product innovation. Alternatively, one could present Figure 3 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.

The curvature in the relationship is a notable distinction in Figures 2 and 3. In the Weibull model (Figure 3), 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 2 and 3. These figures help illustrate our differing findings for the effect of organizational size in Model 2. In Figure 2 (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. If we extend the plot in Figure 3 (Weibull estimates) throughout the entire range of time since previous innovation, we would observe a negative effect of organizational size on innovation for a slight majority of the range. 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 2, with low organizational size, there was little curvature in the relationship between time since previous innovation and likelihood of generational product innovation. As organizational size increased, however, Figure 2 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).

Table 4 presents 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).

Sensitivity analyses

We found materially equivalent results in three sets of sensitivity analyses. First, we added control variables to address alternative explanations of innovation. 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). This restricts our ability to include additional explanatory and control variables in the model. 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 five sets of sensitivity analyses relative to control variables. The first four analyses examine whether including the following variables helps explain innovation activity: (1) recent change in market size, beyond the recent level in market size, (2) recent change in organization size, beyond the recent level of organization size, (3) innovation by peer organizations in the current time period, beyond innovation by peer organizations in the most recent time period, and (4) two additional lags of innovation by peer organizations, beyond innovation by peer organizations in the most recent time period (i.e., in total, the effect of the previous quarter of innovations by peers). The fifth set examined whether temporal routines were the result of diminished competition, rather than organizational size. For this 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 five 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.

Second, we investigated the effect of correlation among the variables. There were moderately-high correlations (r = 0.40 to 0.50) between several of the independent 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.

Third, we ran a series of analyses using a piecewise approach for the time since previous innovation explanatory variable. While this approach consumes additional degrees of freedom, it allows greater flexibility in the relationship, relative to a quadratic effect. To enhance estimation power, we empirically determined the length of the time since previous innovation spans (i.e., pieces) by balancing the number of events within each span. With 13-17 innovation events per span, we divided the time since previous innovation spans at 0-10 months, 11-15 months, 16-20 months, 21-27 months, and >27 months. Using the piecewise approach, our post-estimation plots of the interactions compared favorably to Figure 2. Using the earlier conventions (i.e., +/-

1 standard deviation), for large and medium-sized organizations, we observed an inverse-U shaped relationship with a single peak on the 21-27 month span. For small organizations, we observed a relatively-flat curve with two small peaks occurring at 11-15 months and 21-27 months. While the piecewise approach indicates a slightly shorter cycle length (21-27 months) than the quadratic model (30 months), the results were similar.

Extension: External entrainment as an alternative explanation

So far, 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, the results still support the hypotheses.

Microcomputer applications software has several candidates for entrainment. 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). Microcomputer applications software is part of a complex technological system. In addition to applications software, two 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 used archival data for the technological and market opportunity variables.

First, we considered microprocessors for IBM-compatible and Macintosh computers. Intel was the dominant supplier of microprocessors for the IBM-compatible in this time window. From the Intel web site, we gathered archival data on its history of microprocessor innovations. 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 the 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 TechOppMP variable.

In addition to entrainment deriving from technological opportunities, we 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 a July 1998 Macworld Expo in New York, rather than an August 1998 show in Boston.

Guided by the trade press, we viewed COMDEX/Fall as the major trade show for DOS and Windows organizations. For Macintosh organizations, we viewed both COMDEX/Fall and the Macworld Expos as major trade show events. 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.

Table 5 presents the entrainment results. Models 4a and 4b extend Model 3 from Tables 2 and 3. 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 ($p<0.10$). Yet even after inclusion of the entraining variables, the results support our hypotheses.

Limitations

The analysis has several limitations. First, we studied generational product innovation in a single industry. While generational product innovations are visible and relatively frequent in software, it is important to consider the generalizability of the concept. 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." 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, the data is limited longitudinally. Due to cost and data availability, we could examine only a relatively-developed stage of the computer software industry. This 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 dataset has only a moderate number of generational product innovation events. The limited number of events constrained our analytic 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 (Robinson, 1982; Maddala, 1987). Without the use of fixed effects, we assume a commonality in the length of time between generational product innovations. This is consistent with the idea that most organizations adhere to a common market cycle (Ancona and Chong, 1996; Brown and Eisenhardt, 1997). While an empirical limitation, this assumption seems reasonable within a relatively-narrow window. Moreover, fixed effect estimates to address organization-specific differences would create other limitations. In order to examine a fixed organization effect for temporal routines, it would be necessary to include not only an effect for likelihood of innovation by each organization but also an effect for time since previous innovation by each organization. In this case, empirical work would require substantial length in data panels to study organization-specific temporal routines. In addition to the data requirements, a fixed effect approach would require the assumption that organizations do not change the length of time between generational product innovations throughout their life cycle.

In summary, we found results that are consistent with temporal routines for generational product innovation. First, organizations release generational product innovations in consistent temporal patterns. Second, larger organizations had a greater tendency to employ these routines. Third, we found evidence of temporal routines for generational product innovation even after controlling for exogenous entrainment.

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 and modeling, Brown and Eisenhardt (1997, 1998) and Souza, *et al.* (2004) 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 necessary, particularly as Brown and Eisenhardt (1997, 1998) 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 product innovation in the computer software industry. We find that software organizations tend to release generational product innovations at consistent time intervals. In further analysis, we find stronger evidence of temporal consistency 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 inertia arguments in organizational ecology. The seminal contribution in this area is the importation of inertia from physics into organizational ecology. 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" notion examines the effect of external forces on organizational change, given an organization in a steady 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 argument 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 the notion of dynamics of inertia, 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. 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, top management team beliefs and experiences may help to explain the employment of routines for innovation. Researchers are also beginning to develop performance implications from routines-based theory in efforts to guide managerial decision-making (Knott and McKelvey, 1999; Knott, 2001).

Further, this study contributes to our understanding of, and means of identifying, generational product innovation. In addition to specifying generational product innovation within the Henderson and Clark (1990) innovation typology, we offer a triangulation methodology for identifying generational product innovation that draws on technological and marketing dimensions. Despite the difficulties with inter-industry innovation research, these developments offer a step towards a classification system for product innovation that permits greater generalizability across industries and time periods. Despite the prevalence of generational product innovation (Scherer and Ross, 1990), the body of conceptual and empirical work is still in its infancy. We hope that these contributions help stimulate future intra- and inter-industry innovation research in this area.

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 business 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 for new semiconductors. 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] We use an inverse-U function as the primary functional form in our analyses. We discuss this choice, as well as an alternative piecewise approach, in the measurement and sensitivity analyses sections of the paper.

[2] We also consider a context-specific argument. Many scholars expect the presence of network effects in computer software applications (Brynjolfsson and Kemerer, 1996; Chacko and Mitchell, 1998), although some researchers question the extent of these effects (Liebowitz and Margolis, 1999). When network effects are present, the size of installed base influences product value. From this perspective, larger organizations have less customer pressure for temporal consistency in the release of generational product innovations. While the net effect of these pressures cannot be determined a priori, if we expect a similar level of internal pressure and a reduced level of customer pressure, applications software provides a conservative setting for testing our hypotheses.

[3] As the previous section noted, we aggregated multiple versions and formats into 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.

[4] Despite gathering the entire history of innovation releases for the 46 organizations, our analysis must be limited to the 1994-1998 empirical window for two reasons. First, several variables require the 1994-1998 sales data from PC Data. Second, including the pre-1994 data as observations would bias our findings since the early years of the dataset would include only those organizations that survived through 1994.

[5] Following the Stata heckprob procedure, the selection dependent variable is operationalized with 1 as uncensored cases and 0 as censored cases. 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.

[6] 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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Table 1. Variable Summary Statistics and Product-Moment Correlations (N = 2617 organization-months)

	Variable	Mean	StdDev	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	GenProdInnov	0.028	0.164	0.000	1.000	1.000														
2	OnMkt	0.990	0.097	0.000	1.000	0.017	1.000													
3	DOS	-0.138	0.748	-1.000	1.000	-0.038	-0.034	1.000												
4	WIN	0.063	0.881	-1.000	1.000	0.038	0.029	0.557	1.000											
5	MktDens	4.759	1.811	1.000	10.000	0.017	-0.022	0.052	0.253	1.000										
6	MktSize	3.605	0.723	0.778	5.010	0.055	0.039	-0.087	0.439	0.250	1.000									
7	MktConc	0.552	0.233	0.198	1.000	-0.069	-0.023	0.204	-0.266	-0.465	-0.265	1.000								
8	MktInnov	0.103	0.304	0.000	1.000	0.004	-0.005	-0.053	0.126	0.184	0.108	-0.209	1.000							
9	Age	113.354	45.721	2.000	201.000	-0.048	0.016	0.177	-0.048	-0.370	-0.135	0.394	-0.120	1.000						
10	TotPrevInnov	3.097	2.102	0.000	8.000	-0.052	0.033	0.251	-0.170	-0.256	-0.260	0.250	-0.125	0.495	1.000					
11	OrgSize	0.000	1.272	-2.292	2.558	0.075	0.151	-0.093	0.268	-0.064	0.416	-0.286	0.040	0.110	0.119	1.000				
12	TimeSinceInnov	0.000	19.296	-21.470	69.530	-0.023	-0.137	0.237	-0.241	-0.171	-0.377	0.504	-0.107	0.305	-0.044	-0.520	1.000			
13	TimeSinceInnovSqr	372.209	634.166	0.221	4834.474	-0.068	-0.139	0.202	-0.124	-0.127	-0.275	0.354	-0.074	0.169	-0.065	-0.389	0.720	1.000		
14	OrgSize*TimeSinceInnov	-12.767	27.440	-157.099	49.217	0.066	0.149	-0.183	0.062	0.133	0.098	-0.327	0.079	-0.267	-0.002	0.240	-0.593	-0.755	1.000	
15	OrgSize*TimeSinceInnovSq	-313.837	1281.872	-10766.020	1135.969	0.043	0.172	-0.151	0.167	0.092	0.293	-0.347	0.064	-0.139	0.076	0.562	-0.723	-0.883	0.766	1.000

1	GenProdInnov	Generational Product Innovation
2	OnMkt	On-Market Status of Organization
3	DOS	DOS Operating Platform
4	WIN	Windows Operating Platform
5	MktDens	Market Density
6	MktSize	Market Size
7	MktConc	Market Concentration
8	MktInnov	Innovation by Peer Organizations
9	Age	Organizational Age
10	TotPrevInnov	Cumulative Number of Previous Innovations by Organization
11	OrgSize	Organizational Size
12	TimeSinceInnov	Time Since Previous Innovation
13	TimeSinceInnovSqr	Square of Time Since Previous Innovation
14	OrgSize*TimeSinceInnov	Interaction between Organizational Size and Time Since Previous Innovation
15	OrgSize*TimeSinceInnovSq	Interaction between Organizational Size and Square of Time Since Previous Innovation

Table 2. Probit Estimates for Generational Product Innovation and On-Market Selection
(N = 2617 organization-months, 2592 on-market observations, 72 generational product innovation events)

		1			2			3		
DV	IVs	Coeff.	S. E.	t-statistic	Coeff.	S. E.	t-statistic	Coeff.	S. E.	t-statistic
GenProdInnov	Intercept	-1.557	0.316	-4.92***	-1.115	0.444	-2.51**	-1.108	0.433	-2.56**
	DOS	-0.259	0.127	-2.04*	-0.330	0.146	-2.26*	-0.313	0.141	-2.22*
	WIN	0.106	0.091	1.16	0.177	0.111	1.58#	0.164	0.109	1.51#
	MktSize	0.023	0.079	0.29	0.032	0.105	0.30	0.033	0.117	0.28
	MktConc	-0.384	0.202	-1.90*	-0.459	0.251	-1.83*	-0.534	0.254	-2.10*
	MktInnov	-0.094	0.177	-0.53	-0.087	0.184	-0.47	-0.084	0.188	-0.45
	Age	-0.002	0.001	-2.39**	-0.004	0.001	-3.22***	-0.004	0.001	-2.66**
	TotPrevInnov	-0.051	0.030	-1.69*	-0.024	0.041	-0.59	-0.028	0.041	-0.67
	OrgSize	0.127	0.057	2.22*	0.203	0.062	3.27***	0.314	0.111	2.84**
	TimeSinceInnov				0.024	0.005	4.59***	0.020	0.006	3.55***
	TimeSinceInnovSq (H1)				-0.001	0.000	-3.70***	-0.001	0.000	-3.82***
	OrgSize*TimeSinceInnov							0.009	0.004	2.06*
	OrgSize*TimeSinceInnovSq (H2)							-0.001	0.000	-3.53***
OnMkt	Intercept	2.578	0.517	4.99***	2.526	0.535	4.72***	2.532	0.533	4.75***
	DOS	-0.165	0.182	-0.90	-0.162	0.183	-0.89	-0.164	0.183	-0.90
	WIN	0.163	0.223	0.73	0.157	0.229	0.69	0.155	0.227	0.68
	MktDens	-0.055	0.060	-0.91	-0.052	0.063	-0.84	-0.054	0.062	-0.88
	MktSize	0.046	0.132	0.35	0.043	0.136	0.32	0.046	0.134	0.34
	MktConc	1.306	0.455	2.87**	1.342	0.452	2.97**	1.340	0.449	2.98**
	Age	0.002	0.002	1.00	0.003	0.002	1.24	0.003	0.002	1.12
	OrgSize	0.702	0.168	4.19***	0.711	0.168	4.24***	0.709	0.169	4.19***
	TimeSinceInnov	-0.017	0.005	-3.87***	-0.018	0.004	-4.15***	-0.018	0.005	-3.94***
	rho (residual correlation)	-0.761	0.218		-0.329	0.407		-0.633	0.568	
Model loglikelihood			-408.285			-389.630			-385.209	
Likelihood ratio test (d.f.)			43.14 (8)***			64.84 (10)***			78.90 (12)***	

*** p<0.001, ** p<0.01, * p<0.05, # p<0.10

Table 3. Continuous Time: Weibull Estimates for Rate of Generational Product Innovation
(N = 2617 organization-months, 2592 on-market observations, 72 generational product innovation events)

DV	IVs	1 Coeff.	S. E.	t-statistic	2 Coeff.	S. E.	t-statistic	3 Coeff.	S. E.	t-statistic
GenProdInnov	Intercept	-5.264	1.440	-3.66***	-6.979	1.865	-3.74***	-5.834	1.939	-3.01**
	DOS	-0.479	0.417	-1.15	-0.477	0.447	-1.07	-0.486	0.427	-1.14
	WIN	0.108	0.312	0.35	0.168	0.343	0.49	0.191	0.326	0.58
	MktSize	0.023	0.216	0.11	0.085	0.260	0.33	0.017	0.253	0.07
	MktConc	-1.389	0.572	-2.43**	-2.632	0.877	-3.00**	-2.432	0.841	-2.89**
	MktInnov	-0.261	0.404	-0.65	-0.281	0.396	-0.71	-0.308	0.406	-0.76
	Age	-0.004	0.001	-3.09**	-0.013	0.003	-4.40***	-0.011	0.003	-3.42***
	TotPrevInnov	-0.167	0.098	-1.70*	-0.091	0.120	-0.76	-0.102	0.115	-0.88
	OrgSize	0.118	0.171	0.69	-0.254	0.259	-0.98	0.105	0.314	0.33
	TimeSinceInnov				0.065	0.012	5.19***	0.052	0.014	3.76***
	TimeSinceInnovSq (H1)				-0.003	0.001	-3.09**	-0.003	0.001	-3.22***
	OrgSize*TimeSinceInnov							0.014	0.009	1.63#
	OrgSize*TimeSinceInnovSq (H2)							-0.001	0.001	-2.41**
	lambda	0.616	0.252	2.44**	1.522	0.453	3.36***	1.243	0.458	2.71**
	rho (time dependence)	1.340	0.191		1.621	0.251		1.507	0.258	
Model loglikelihood			-83.911			-62.892			-60.473	
Likelihood ratio test (d.f.)			62.90 (9)***			72.57 (11)***			90.64 (13)***	

*** p<0.001, ** p<0.01, * p<0.05, # p<0.10

Table 4. Simple Slope Tests for the Effect of Time Since Previous Innovation on Generational Product Innovation at Three Levels of Organizational Size (Based on Model 3, Table 2)

		1 $OrgSize_L$ (small)	2 $OrgSize_M$ (medium)	3 $OrgSize_H$ (large)
	estimate	0.029	0.072	0.116
$TimeSinceInnov_L$	standard error	0.013	0.016	0.024
	t-statistic	2.20*	4.42***	4.77***
	estimate	0.008	0.020	0.031
$TimeSinceInnov_M$	standard error	0.009	0.006	0.006
	t-statistic	0.85	3.55***	5.14***
	estimate	-0.013	-0.033	-0.053
$TimeSinceInnov_H$	standard error	0.010	0.013	0.022
	t-statistic	-1.34#	-2.50**	-2.42**

L subscript Low (one standard deviation below the mean)
M subscript Medium (at the mean)
H subscript High (one standard deviation above the mean)

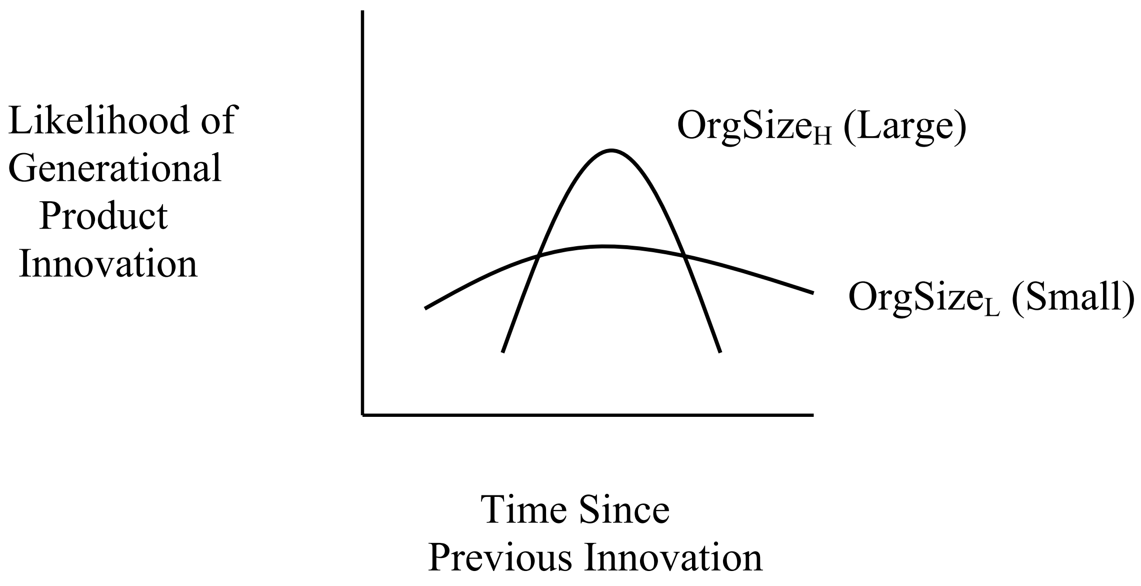
*** p<0.001, ** p<0.01, * p<0.05, # p<0.10

Table 5. Estimates for Generational Product Innovation (Entrainment Analyses)

DV	IVs	Discrete-time (probit) 4a Coeff.	S. E.	t-statistic	Continuous-time (Weibull) 4b Coeff.	S. E.	t-statistic
GenProdInnov	Intercept	-1.252	0.439	-2.85**	-5.896	1.890	-3.12***
	DOS	-0.289	0.145	-2.00*	-0.452	0.431	-1.05
	WIN	0.162	0.111	1.46#	0.204	0.326	0.63
	MktSize	0.057	0.121	0.47	0.079	0.248	0.32
	MktConc	-0.526	0.247	-2.13*	-2.202	0.831	-2.65**
	MktInnov	-0.019	0.198	-0.10	-0.173	0.419	-0.41
	Age	-0.004	0.001	-3.01**	-0.012	0.003	-3.42***
	TotPrevInnov	-0.023	0.042	-0.55	-0.089	0.115	-0.78
	OrgSize	0.292	0.124	2.37**	0.146	0.310	0.47
	TimeSinceInnov	0.021	0.006	3.59***	0.050	0.014	3.61***
	TimeSinceInnovSq	-0.001	0.000	-3.77***	-0.003	0.001	-3.20***
	OrgSize*TimeSinceInnov	0.008	0.005	1.46#	0.015	0.009	1.74*
	OrgSize*TimeSinceInnovSq	-0.001	0.000	-3.86***	-0.001	0.000	-2.54**
	TechOppMP	0.462	0.212	2.18*	0.848	0.436	1.95*
	TechOppOS	0.344	0.178	1.93*	0.789	0.381	2.07*
	MktOpp	0.240	0.176	1.37#	0.495	0.387	1.28
	lambda				1.147	0.450	2.55**
OnMkt	Intercept	2.550	0.536	4.76***			
	DOS	-0.153	0.184	-0.83			
	WIN	0.121	0.238	0.51			
	MktDens	-0.057	0.059	-0.97			
	MktSize	0.049	0.129	0.38			
	MktConc	1.329	0.457	2.91**			
	Age	0.002	0.003	0.84			
	OrgSize	0.700	0.172	4.08***			
	TimeSinceInnov	-0.018	0.005	-3.90***			
	rho (probit, residual correlation)	-0.831					
	rho (Weibull, time dependence)				1.440	0.254	
Model loglikelihood			-380.243			-55.768	
Likelihood ratio test (d.f.)			122.02 (15)***			125.13 (16)***	

*** p<0.001, ** p<0.01, * p<0.05, #p<0.10

Figure 1. Expected Relationship for Hypothesis 2



≅ This figure illustrates the prediction that as organizational size increases, the likelihood of generational product innovation (a) increases within a narrowing range of time since previous innovation and (b) decreases outside that range.

Figure 2. Effect of Time Since Previous Innovation on Generational Product Innovation
(Probit Estimates using Model 3, Table 2)

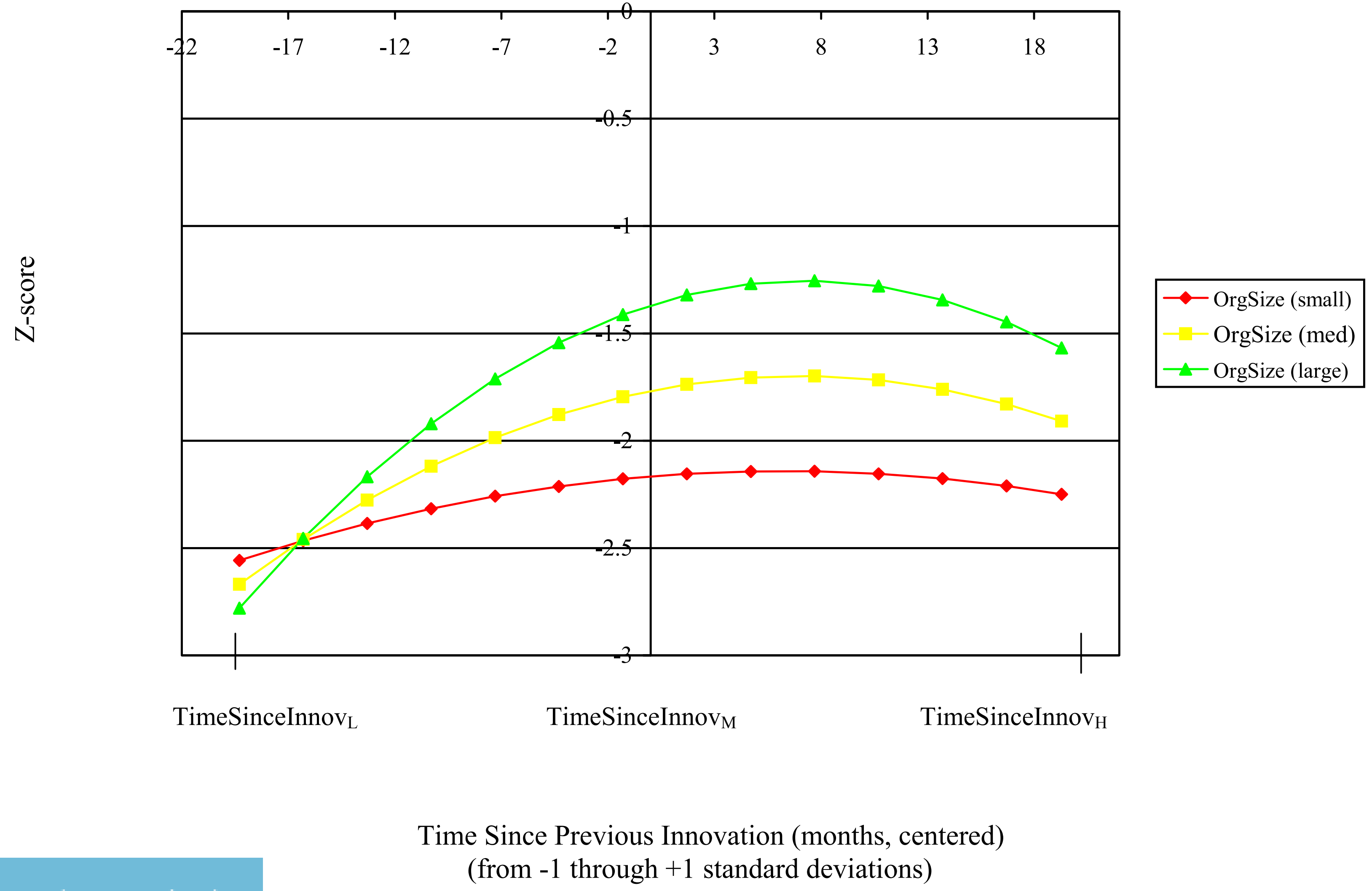
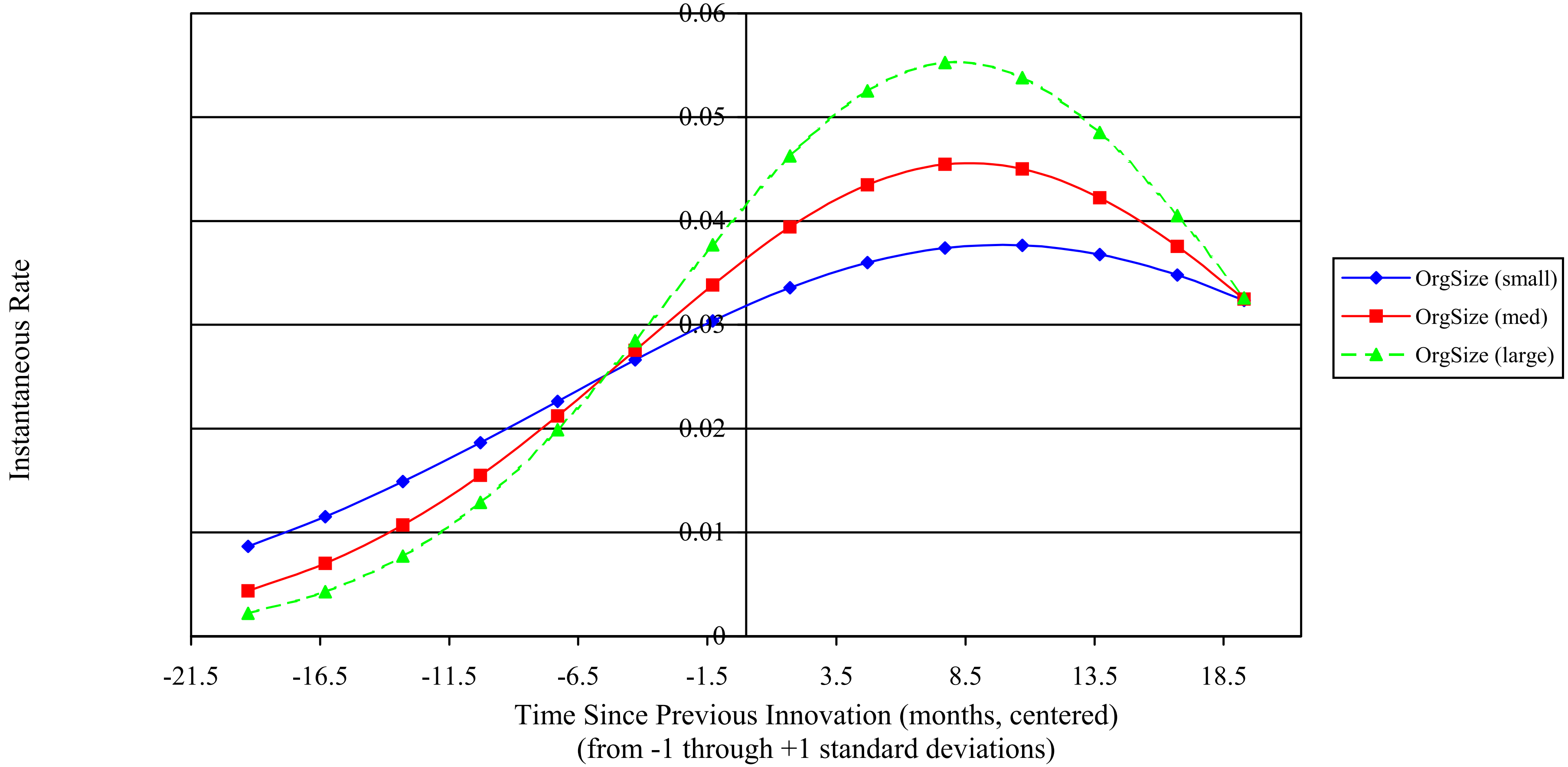


Figure 3. Effect of Time Since Previous Innovation on Rate of Generational Product Innovation
(Weibull Estimates using Model 3, Table 3)



Appendix A: Empirical Context

The first boundary condition limits the scope of the 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 (e.g., *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 its 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. John Walker, founder of Autodesk and co-author of AutoCAD, offers perhaps the strongest statement in support of this assumption: “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 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.

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[1] Another anecdote 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).

Appendix B: Reliability of the Generational Product Innovation Classification

To examine the reliability of our initial classification system, we developed a set of rules to classify each product release that our information search identified. The rules correspond to the three dimensions: (a) technical improvement relative to the prior release of the product on a platform, (b) the numbering/title convention for the release relative to the prior release, and (c) the pricing schedule for the release (upgrade list price relative to the full list price).

For technical improvement, the rule was to classify the release along this dimension as a generational release if the trade press described the release as containing any new features relative to the prior release. This rule is more likely than our initial classification approach to identify a release as a generational innovation. As such, its use as an explicit rule provides a conservative check for establishing the reliability of our classification system.

For the release numbering/title convention, the rules were as follows. (1) Classify an innovation as generational if one of the following conditions is true: (a) the release number is greater than or equal to 0.3, relative to the prior release (e.g., WordPerfect 3.0 versus WordPerfect 2.1), (b) the release title includes a year within the title and the prior release did not include a year (e.g., Word 95 versus Word 6.0), or if the release title includes a subsequent year from the prior release title (e.g., Word 97 versus Word 95), (c) the release title includes a operating system in the title and the prior release title did not include a operating system (e.g., AutoCAD LT for Windows 95 versus AutoCAD LT 2.0), or if the release title includes a operating system in the title and the prior release title included an earlier operating system (e.g., Drafix CAD for Windows 95 versus Drafix CAD for Windows 3.0), or (d) the release title is the same as the prior release but includes a "plus" designation (i.e., MiniCAD+ versus MiniCAD). (2) Do not classify an innovation release as generational if one of the following conditions is true: (a) the release title is the same as the prior release but adds a letter to the title number (e.g., WordPerfect 6.0a versus WordPerfect 6.0), or (b) the release title is the same as the prior release but adds a modification number (e.g., Displaywrite 5, Modification 1 versus Displaywrite 5).

For the pricing schedule, the rule was to classify a release as a generational release if the upgrade list price was more than 10% of the list price.

Using the above explicit rules, we classified each product release along the three dimensions as: (1) generational innovation, (2) not a generational innovation, or (3) missing information. The overall classification of the innovation release equaled the majority of non-missing information across the three dimensions.

Statistics: The explicit set of rules and the initial approach led to identical classifications to the following degree: CAD (95%), word-processing (94%), desktop-publishing (100%), spreadsheets (96%). Data was present for at least two of the three dimensions and the classification-by-rule results were consistent without the presence of any dissenting classification information to the following degree: CAD (65%), word-processing (65%), desktop-publishing (64%), spreadsheets (80%). Data were present for two of the three dimensions and the results of the classification-by-rule system were inconclusive (i.e., one dimension toward generational innovation, one dimension toward not generational innovation) to the following degree: CAD (0.9%), word-processing (2.9%), desktop-publishing (0), and spreadsheets (3.7%). The classification-by-rule approach differed from our initial release classification to the following degree: CAD (3.7%), word-processing (2.9%), desktop-publishing (0), spreadsheets (1.2%). These small differences reflect the more conservative judgment in our initial classification.