Responding to rivals and compliments:
How market concentration shapes generational product innovation strategy

Scott F. Turner
Moore School of Business, University of South Carolina
1705 College Street
Columbia, SC 29208
phone: 803-777-5973, fax: 803-777-6782
scott.turner@moore.sc.edu

Will Mitchell
Duke University, The Fuqua School of Business
Box 90120
Durham, NC 27708
phone: 919-660-7994, fax: 919-681-6244
will.mitchell@duke.edu

Richard A. Bettis
Kenan-Flagler Business School, University of North Carolina at Chapel Hill
Campus Box 3490, McColl Building
Chapel Hill, NC 27599-3490
phone: 919-962-3165, fax: 919-962-4266
r_bettis@unc.edu

Version: June 21, 2008
Responding to rivals and compliments:
How market concentration shapes generational product innovation strategy

Abstract

Generational product innovation (GPI) is an important but understudied element of innovation strategy. In the limited discussion to date, organizational strategy scholars have emphasized internally-driven strategies of generational product innovation, typically centered around temporal pacing. While such internally-driven strategies may predominate when firms face diffuse competition, the literature largely overlooks the point that firms need to be increasingly responsive to external events as market concentration increases. This study examines how competitive market conditions shape the responsiveness of firms’ GPI releases to the introduction of both competitor and complementary innovations. We argue that increasing industry concentration raises the stakes surrounding market positions and leads to greater interdependence of innovation strategies in an industry -- including interactions with competitors and with other players in a larger system of complementary products. The analysis, which examines firms competing in the U.S. packaged software industry in the 1990s, shows that market concentration strongly influences GPI strategies. As concentration increases, organizations are less driven by historical patterns of innovation and become increasingly responsive to both competitor and complementary innovations. In parallel, we find that innovation releases diverge temporally from competitor innovations in low concentration markets.
Generational product innovations are technical advances in the performance of products within technology regimes. This form of innovation, such as the introduction of motor vehicle model upgrades and successive generations of microprocessors, is common in many industries but is an under-studied element of innovation strategy (Lawless and Anderson 1996). The initial discussions of generational product innovation (GPI) in the organizational strategy literature have emphasized internal drivers (Brown and Eisenhardt 1997, 1998) with little attention to assessing external influences on GPI introduction. This study extends the emerging literature on GPI by examining how competitive and complementary technological events in the external environment influence the timing of generational product innovation introductions. We focus on how market concentration shapes the responsiveness of firms’ GPI releases to the release of competitor and complementary innovations.

The innovation studies literature suggests that, without impetus from particular external events, firms tend towards internally-driven product introduction strategies. This broad-based literature draws notably upon routines-based perspectives of organizations (Baum 1999, Brown and Eisenhardt 1995, Nelson and Winter 1982). In this stream of research, the time since the previous innovation is a central concept. Drawing on the idea of organizational momentum, scholars argue that the timing of innovation is a function of interdependencies between organizational routines and innovation. This argument reflects the idea that introducing innovations is disruptive for internal operating routines (Amburgey, et al. 1993, Barnett and Carroll 1995), yet routines for innovation are themselves subject to atrophy when too much time passes (Argote 1999, Greve 2007). Similarly, coordination-based arguments suggest that internally-driven product innovation strategy may arise from tendencies towards time-based pacing of innovation (Gersick 1994, Brown and Eisenhardt 1997, Sastry 1997) in which firms seek to release innovations based on consistency in the passage of calendar time. These temporal patterns (e.g., releasing GPIs every 24 months) reflect inertial forces associated with stable development and marketing routines, corresponding organizational efficiencies, and the organizational memory function of routines (Perrow 1970, Brown and Eisenhardt 1998, Nelson and Winter 1982).

Despite the incentives for internally-driven innovation timing, most firms operate in competitive
markets, in which external events in the competitive landscape intrude on internal rhythms (Bettis and Hitt 1995, Lee, Smith, Grimm and Schomburg 2000). These external events force firms to adapt to competitors’ actions and complementary technological opportunities rather than relying solely on internally-driven patterns of innovation. We refer to GPI introduction strategies that respond to external events as externally-driven GPI strategy. Prior research has not examined the conditions under which external events override incentives for internally-driven GPI strategy. This is an important element in the overall strategy for generational product innovation, because mistakes in this transition are likely to engender competitive problems. We argue that externally-driven GPI strategy becomes more significant as markets consolidate and strategies become more interdependent.

We investigate two external events that may trigger GPI, the introduction of generational product innovations by competitors and the introduction of innovations in technologies that complement a core set of products. These events address two important domains for innovation strategy: the pattern of interactions with competitors and the pattern of interactions with other players within larger systems of complementary products and firms. Competitor innovation has received some attention as a spur to a firm’s innovation strategy in the economics of innovation literature and in studies of competitive rivalry (Lee, Smith, Grimm and Schomburg 2000, Reinganum 1989). Complementary innovation, meanwhile, has received little attention to date; indeed, firms producing complementary products and their activities are underemphasized elements of industry dynamics (Brandenburger and Nalebuff 1997). We argue that the degree of concentration in the market influences the extent to which both of these types of external events spur the introduction of generational product innovations.

We study generational product innovation strategies in the packaged software industry during the 1990s, focusing on four software application markets (computer-aided design, desktop-publishing, spreadsheets, and word processing) and two operating system platforms (Windows and Macintosh). The results support our argument that increasing market concentration raises the stakes surrounding market positions and leads to greater competitive interdependence in an industry, forcing firms to undertake GPI strategies that respond to competitive and complementary external events. The findings extend our
understanding of market concentration and external coordination as important elements of firms’
innovation strategies and offer implications for the economics of innovation and competitive rivalry
literatures, as well as helping advance the emerging literature in dynamic capabilities.

CONCEPTUAL BACKGROUND

Generational product innovation

A generational product innovation represents an advance in the technical performance of an
existing product within a technology regime. Consider applications software. In January of 1994,
Microsoft introduced Version 5.0, a GPI for its Excel for Windows product line. The GPI release of
Excel provided new features for graphing and charting as well as retrieving and manipulating data. By
contrast, later that same year Microsoft introduced Version 5.0a of Excel. The release was not a
generational product innovation, because it did not advance the technology but instead served to correct
several automation and implementation problems that surfaced from the preceding version release.

GPI can range from refreshing a product line to substantial transformation of product scope. In
the auto industry, annual model changes (the most modest form of generational product innovation for
this industry) are often referred to as refreshing a model. In consumer electronics, meanwhile, recent
generational product innovations by Apple for the iPod have transformed this device from a mobile music
source to a broader multimedia package (e.g., photographs, movies, and TV episodes) and integrated it
with cellular phone technology (iPhone).

It is useful to position GPI within the innovation studies literature. Within the definitions of the
economics of innovation literature, generational innovations are non-drastic innovations. Where the
economics of innovation literature suggests that drastic innovations result in post-innovation monopolies
for the innovating firm, non-drastic innovations retain elements of the pre-innovation market structure
(Gilbert and Newbery 1982, Baldwin and Scott 1987). In this sense, generational product innovation is an
evolutionary form of innovation (Dougherty 1992) that occurs under what Kuhn (1962) refers to as
normal organizational and technological conditions. In the organizational concept of normality, GPI
represents homeostatic change, which Huff, Huff, and Thomas (1992) describe as an ongoing process of
innovation conducted within an existing organizational context. In the sense of normal technological conditions, generational product innovation occurs within technology regimes, which represent periods of continuous and cumulative advance along accepted technological trajectories (Dosi 1982, Nelson and Winter 1982).

While scholarly research directs most attention to drastic innovations, firms in many industries commonly expend as much or more effort on non-drastic changes such as generational product innovations (Brown and Eisenhardt 1997, Lawless and Anderson 1996). As Scherer and Ross (1990: 642) point out, "most industries experience a continuous 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". Yet few academic studies have focused on the GPI form of technological change. The primary reason for this disconnect is that GPI does not fit neatly within traditional innovation categories, such as the long-standing incremental-radical distinction or more complex schema such as Henderson and Clark’s (1990) radical-modular-architectural-incremental categories. Hence, while GPI reflects elements of broader conceptualizations (i.e., non-drastic, evolutionary), generational product innovation has traveled largely under the radar of academic research. We develop the arguments about GPI at the level of the product line, because the concept of generational product innovations relates to existing product lines; in turn, our research question focuses on competitive conditions in the product market.

**Strategies for innovation timing: Internally-driven and externally-driven**

The timing of innovation release is a critical element of product strategy (Reinganum 1989, Brown and Eisenhardt 1997). Firms have strong incentives towards internally-driven strategies for generational product innovation, and the time since previous innovation plays a central conceptual role in this strategy for innovation. Pacing the release of generational product innovations based on the passage of time between innovations enables organizations to balance the costs associated with the disruption of internal routines from innovation release with the costs of allowing a product to become stagnant in the marketplace. At the same time, the consistency of time-based pacing facilitates the development and
coordination of stable internal routines (Nelson and Winter 1982, Winter 1987), permitting efficient resource allocations within and between organizational units (March and Simon 1958, Brown and Eisenhardt 1997). However, the control and stability of an internally-driven innovation strategy may ignore or only partially account for the resolution of technological uncertainties in the industry. Seldom can a single firm dominate or even maintain pace within an industry exclusively through an internally-focused innovation strategy; instead, as the industry evolves, external factors eventually must play important roles for all competitors.

By contrast with internally-driven innovation strategies, externally-driven innovation represents a strategy in which firms release generational product innovations in response to events in the competitive marketplace. The innovation studies literature directs particular attention to competitor innovations as events that will be relevant for GPI strategy (Lee, Smith, Grimm, and Schomburg 2000, Reinganum 1989), and hints at a second type of relevant event in the form of complementary innovations (Klevorick, Levin, Nelson, and Winter 1995, Teece 1986). Competitor innovation events center on interdependence in the form of innovation rivalry among competing products (Beath, Katsoulacos, and Ulph 1995). By contrast, complementary innovations focus on the interdependence among technologies within larger systems (Dosi 1988, Brandenburger and Nalebuff 1997). Whereas competitor innovation represents a direct form of interdependence, complementary innovation represents an indirect form of interdependence in which firms compete to align themselves with supporting technologies (e.g., the alignment of packaged software with changes in operating systems, or vehicle design with advances in highway technology). The implications of both forms of interdependence for industry dynamics suggest that these events will often trigger generational product innovation responses.

**Market concentration**

Market concentration is a function of the number of products in a market and their respective shares of total sales. The more concentrated an industry, the larger the share of production that tends to consolidate in the hands of a smaller set of firms. The traditional industrial organization economics literature views market concentration as a key element of industry structure, arguing that concentration
strongly influences firm behavior (Curry and George 1983). In the Schumpeterian tradition of innovation research, meanwhile, market concentration is the dominant industry-level factor for explaining innovation, with extensive research focusing on the direct effect of concentration on firm innovation.

Economic arguments raise alternative views on concentration and innovation. Scholars in the Schumpeterian tradition argue that increasing concentration provides firms with greater opportunity to appropriate the returns of their investments in innovation, including greater price control, and posit that concentration facilitates innovation (Scherer 1992, Schumpeter 1950). In fact, Kamien and Schwartz (1982: 84) note that this idea represents "the heart of Schumpeterian theory." However, industrial organization economists also argue that as concentration increases, firms face less competitive pressure to stimulate innovation (Scherer and Ross 1990). Empirically, studies have found mixed relationships between concentration and innovation. Indeed, Cohen’s (1995) expansive review of this empirical research concluded that concentration has little direct effect on innovation.

Reflecting the mixed results in prior work, Cohen (1995) suggested that an understudied area for innovation research lies at the intersection of industry conditions and organization activities. Concentration may have a contingent effect, in which its major influences on innovation strategy arise in combination with other factors, such as external competitive and complementary events. This study examines the effect of market concentration on the responsiveness of innovation to these external events in the context of generational product innovation, which represents a promising arena in which to examine such contingencies.

HYPOTHESES

The need to understand external drivers of innovation strategy is important in many industries, as different as automobiles, consumer electronics, and software. Market concentration is likely to shape the impact of two types of external events – the release of competitor and complementary innovations – that reflect patterns of interactions with competitors and other players in larger market contexts.

We assume that firms have incentives to release generational product innovations, even in concentrated markets. As a point of reference, an oligopolistic theory of competition might suggest that
competitors would avoid innovation, attempting to jointly maximize profits by eliminating the costs associated with this form of innovation. Yet economics of innovation scholars argue that traditional oligopoly theory, with roots in pricing, faces challenges in explaining innovation behavior (Scherer and Ross 1990). These challenges lend support for our assumption of incentives to innovate for three reasons. First, in order to maximize joint profits, all players must restrict innovation, but such coordination is difficult to maintain given the threat that at least one player conceals its investment in innovation and, by cheating, overtakes the market (Baumol 2002). Second, innovation-avoidance strategies suit static markets in which innovations only affect the allocation of market shares. However, many generational innovations, such as new automotive models and software upgrades, stimulate market growth as firms compete for new customers (Scherer 1984). Third, even within relatively static markets, incumbents have incentives to introduce generational product innovations in order to dissuade new market entrants, analogous to limit pricing (Schumpeter 1950: 90).

We begin by considering the logic for internally-driven innovation strategy, with a baseline expectation of a curvilinear effect of time since previous innovation on the rate of generational product innovation. The curvilinear effect integrates two central elements of a routines-based perspective of innovation: one that innovation is disruptive for internal routines (Barnett and Carroll 1995, Nelson and Winter 1982, Hannan and Freeman 1989), and another that innovation is subject to organizational momentum (Amburgey, et al. 1993, Argote 1999, Baum 1999).

From the innovation as disruptive view, we expect that in the initial stages following an innovation release, organizations are less likely to introduce a generational product innovation. The delay occurs because there is little incentive to revisit the corresponding disruption of operating routines while the product innovation represents a recent introduction in the marketplace. As the time since previous innovation increases, though, the incentive for releasing a generational product innovation increases, as the product in the market becomes increasingly out of date.

Generational product innovation is also subject to forces of momentum, as organizations go through phases of innovation and phases of inertia (Kelly and Amburgey 1991, Miller and Friesen 1980).
Following behavioral theory, organizations search for solutions, such as product innovation, in the neighborhood of their most-recently enacted routines (Cyert and March 1963). It follows that as time since previous innovation increases beyond a threshold, the routines that are involved in generational product innovation increasingly atrophy through lack of use (Argote 1999, Greve 2007). Thus, the logic of internally-driven innovation strategy suggests an inverse-U shaped relationship between the time since previous innovation and the rate of generational product innovation.

The incentives for an internally-driven strategy for generational product innovation focus largely on minimizing the disruptions and coordination costs associated with developing and introducing innovations (Barnett and Carroll 1995, Brown and Eisenhardt 1997). As market concentration increases, however, there are heightened risks from releasing innovations according to historical patterns. Indeed in the face of strong competitors, adaptation becomes more important because the stakes associated with existing market positions increase (Somaya 2003). Specifically, there are greater potential losses in terms of market share for the product line, and there is greater profitability associated with the market share at risk (Bain 1951, Scherer and Ross 1990). As markets consolidate, organizations’ strategic choices will increasingly be driven by internal disruption of routines related to innovation (Greve 2007, Nelson and Winter 1982). Thus, we expect that as market concentration increases, the inverse-U shaped relationship between time since previous innovation and the rate of generational product innovation will diminish.

**Hypothesis 1.** The greater the market concentration, the weaker the inverse-U shaped relationship between time since previous innovation and the rate of generational product innovation.

Next, we consider the responsiveness of GPI to competitor innovation events. As a baseline, organizations have incentives to respond to generational product innovations by marketplace rivals. Otherwise, they may sacrifice profit opportunities, cede market share, and face heightened survival pressure (Lee, Smith, Grimm, and Schomburg 2000, Smith, Ferrier, and Ndofor 2001). While responses to rival innovations may take multiple forms, we focus on matching responses (i.e., responding to generational innovation with generational innovation). This approach is consistent with the game theory literature on innovation from economics (Reinganum 1989, Baldwin and Scott 1987) and the competitive
rivalry literature from strategic management (Smith, Grimm, Gannon, and Chen 1991).

We expect a positive relationship between market concentration and response to competitor GPI. While economic theories direct attention to pricing interdependencies in concentrated markets, less attention has been directed to the impact of concentration on innovation rivalry (Grabowski and Baxter 1973, Cohen 1995). As non-drastic innovations, generational product innovations do not result in post-innovation monopoly conditions; instead the market structure following the innovation release retains elements of the pre-innovation structure (Baldwin and Scott 1987, Gilbert and Newbery 1982). As such, we expect market concentration to increase the incentives to respond to other firms in the marketplace.

As market concentration increases, the stakes associated with existing market positions increase (Bain 1951, Kamien and Schwartz 1982, Somaya 2003). At high market concentration, greater market share is typically allocated across fewer products. Therefore, each product in the market faces a greater risk of losing market share in response to generational product innovation releases by competitors. Further, in concentrated markets, organizations have greater power for setting prices and realize greater profitability (Bain 1951, Scherer and Ross 1990). Therefore, as market concentration increases, firms stand to lose more in terms of product profitability. In sum, with greater streams of rents at stake, we expect greater responsiveness to generational product innovations by rival firms (Scherer 1984).

**Hypothesis 2.** The greater the market concentration, the greater the rate of generational product innovation in response to the release of a generational product innovation by a competitor.

Next, we consider responsiveness to complementary innovation events. The value of many products is influenced by their interdependence with complementary technologies (Stieglitz and Heine 2007, Teece 1986). Consider micro-computing systems, in which the value of applications software depends on complementary technologies such as operating systems and microprocessors. Such complement interdependencies exist within a variety of systems, including telecommunication networks (Davies 1996), industrial ecosystems (Desrochers 2002), and surgical units (Edmondson, Bohmer, and Pisano 2001).

As a baseline, organizations have incentives to release generational product innovations in
response to complementary innovations. The release of complementary innovations provides new technological opportunities, which increase the likelihood of successful innovation for any given amount invested in the search process (Breschi, Malerba, and Orsenigo 2000, Klevorick, Levin, Nelson, and Winter 1995). Expansion in the interstate highway in the United States during the 1950s, for example, increased incentives for generational vehicle innovations suited to longer distances and higher speeds. Similarly, advances in biomechanics science and the technology of anthropomorphic devices (i.e., crash test dummies), have increased incentives for automotive firms to invest in generational vehicle innovations related to passenger safety.

In turn, advances in technological opportunity stemming from complementary innovations affect competitive dynamics. The stability of incumbent market positions is partly a function of the distance between the technological potential for a product and the state of technological advance realized in incumbent products. Thus, complementary innovations reduce the stability of market positions (Kamien and Schwartz 1982) by providing new technological opportunities (i.e., increasing the distance between technological potential and realized product technology), which cause corresponding reductions in entry barriers and increased competitive threat to incumbents by potential market entrants (Utterback 1996, Hartman, Teece, Mitchell, and Jorde 1993). Therefore, incumbents have incentives to innovate in order to preempt or match challenges from potential entrants.

The next hypothesis predicts a positive relationship between market concentration and externally-driven innovation in response to complementary innovations. As market concentration increases, there is greater risk of loss of market share for incumbents, and the market share at risk tends to be more profitable than would be expected in more fragmented market conditions (Bain 1951, Kamien and Schwartz 1982). As market concentration increases, therefore, there is greater potential loss for incumbents, such that these firms have greater incentive to preempt or match challenges from potential entrants (Gilbert and Newbery 1982, Reinganum 1989). Thus, as concentration increases, organizations are more likely to respond to the challenges associated with complementary innovation releases.

**Hypothesis 3.** The greater the market concentration, the greater the rate of generational product
innovation in response to the release of a generational product innovation in a complementary technology.

In summary, as market concentration increases, we expect GPI to become less reflective of historical time-based patterns of innovation (i.e., a weaker inverted-U relationship) and increasingly responsive to external events. Within the external environment, we expect greater responsiveness to reflect both competitor innovation and complementary innovation as key influences on GPI strategy. Figure 1 summarizes the conceptual model for these arguments.

********** Figure 1 here **********

DATA AND METHODS

Data

Our analysis focuses on business productivity software products in the United States from 1994 to 1998. We considered organizations competing in four market segments: computer-aided design (CAD), desktop-publishing, spreadsheets and word-processing. Primary data sources included market research data and historical industry trade publications. PC Data, a market research firm that specialized in the computing industry, supplied us with monthly product sales data for the four market segments. Product data came from stand-alone product sales and did not include integrated software sales (bundled software sales were low during the study period). PC Data informed us that their data represent the following annual percentages of the U.S. retail software market in each year from 1994-1998: 33%, 60%, 70%, 80%, and 80%.

We used multiple secondary sources to gather baseline data, such as cumulative innovations in the industry, covering the life span of all the products in our dataset. Our historical starting point was 1981, the year in which IBM introduced its personal computer. We conducted extensive searches across multiple information databases and industry trade publications for the 1981 through 1998 period (e.g., Factiva, InfoWorld). We also searched company web pages, and at times, contacted companies directly to address areas of uncertainty.

We referenced product comparison reports in the trade press to segment products into
competitively-equivalent markets. We obtained data about four substantial segments, which the industry typically identifies by approximate list price ranges. The four segments include low-end CAD (<$1000), high-end desktop publishing ($500-$900), spreadsheets ($100-$600), and high-end word-processing ($350-$700). Representative products include TurboCAD, PageMaker, Excel, and WordPerfect.

Our examination considered products competing on the Macintosh and Windows operating platforms. Between 1994 and 1998, we identified 35 software business lines across the two platforms and four market segments. The large majority of the business lines were owned by different corporations, consistent with Campbell-Kelly's (2001: 110) historical account of the relatively low degree of diversification for most personal computer software firms, and did not experience ownership changes between 1994 and 1998. In some cases, though, acquisitions did occur and caused business lines to change corporate hands; for example, Adobe took over the Framemaker desktop publishing line when it acquired Frame Technology, the original developer of the product, in 1995.

**Variables**

Tables 1 and 2 present descriptive statistics for the variables.

********** Tables 1 and 2 here **********

**Dependent variable**

Our focal dependent variable, generational product innovation (GenProdInnov), is a binary event with values equaling one for the month in which an organization released a generational product innovation and zero otherwise. Between 1994 and 1998, 69 generational product innovation events occurred across the 35 software business lines. The range of generational product innovation releases per business line was 0 to 6 between 1994 and 1998. Our analysis focused at the product line level (e.g., Excel for Windows), which can be contrasted with the business line level (e.g., Excel) and the firm level (e.g., Microsoft). The product line level of analysis aligns with the central concepts in our arguments.

To identify generational product innovations, we determined whether an innovation release represented a significant advance in technical performance, relative to the existing product and within a technological regime. This required two related assessments. The first aspect was whether an innovation
advance crossed the threshold into a new technological regime. We based this assessment on the operating system. For the Macintosh platform, there was no new technological regime within our empirical window. Alternatively, when DOS-centric organizations released their first Windows product, we viewed the event as crossing technological regimes and operationalized the event as a new market entry. As such, we considered any innovation releases with significant technical advance within an operating system platform as generational product innovation releases.

The second aspect was to distinguish between generational innovations and minor “bug fix” releases. While technical performance may improve in both cases, based on trade press accounts, we assumed the significance of the advance to be more corrective in the case of minor releases. In addition, the trade press did not publish many of the release dates for the minor innovations. To distinguish generational product innovations from minor innovation releases, we focused on the significance of the technical advance through the archival trade press. To obtain reliable classifications, we employed a triangulating, multiple-indicator approach that focused on three dimensions: (a) the number of feature additions and enhancements, (b) the numbering convention for the product innovation release (i.e., Version 1.2, 1.21, 2.0), and (c) the pricing schedule for the product innovation release (i.e., the upgrade list price relative to the full list price). Through our historical review of the trade press, we observed that the latter two indicators typically reflect technical advances.

As a validity check, we discussed the concept and measurement of GPI with an industry expert with extensive relevant experience in software development, market research, and a leading software trade association. He confirmed that GPI is a relevant distinction from minor innovation bug fixes. In addition, he agreed that the three dimensions (new features, numbering convention, and pricing schedule) are meaningful indicators of GPI. Appendix A describes the reliability of the generational product innovation classification system.

**Focal explanatory variables**

For internally-driven innovation, we examined time since previous innovation to capture time-based influences on firm innovation. Our measure is the elapsed calendar time since the prior innovation
release for the product line. Prior release can be either the initial release of the product or the prior generational product innovation release. TimeSinceInnov starts at one for the first month following an innovation release. This monthly clock then increments by one for each month until a subsequent innovation release, its removal from the market, or the end of our data panel.

For the competitive aspects of externally-driven innovation, we identify the competition’s release of GPI (CompetitionInnov) with a binary variable indicating whether any competing organizations released a generational product innovation in the prior month. We employed the binary form because there were only three instances in which more than one competitor released a generational product innovation in the same market segment and month. These instances were limited to the word-processing and CAD segments for the Windows platform. We found materially equivalent results in sensitivity analyses that used the total number of competitor innovations in place of the binary indicator variable.

For the complementary elements of externally-driven innovation, we examined two technological opportunity event variables: microprocessor innovation (TechOppMP) and operating system innovation (TechOppOS). For microprocessor innovation, Intel and Motorola were the dominant suppliers for the IBM-compatible and Macintosh systems in the 1994-1998 time frame. To identify new classes of microprocessors, we focused on increases in the number of transistors and clockspeed. Between 1994 and 1998, we identified two new microprocessor classes for the IBM-compatible and three new classes for the Macintosh. For operating system innovations (TechOppOS), Apple supplied the operating system for its Macintosh, and Microsoft was the dominant supplier for the IBM-compatible computer. Based on trade press accounts, we identified three GPIs for the Macintosh operating system. For the IBM-compatible, we identified four GPIs: two focused on corporate and end-consumers (Windows 95, Windows 98) and two focused on corporate customers (Windows NT 3.5, Windows NT 4.0).

The market concentration (MktConc) measure uses a Hirschman-Herfindhal Index. This measure captures dispersion in unit market share among competing organizations. We calculated the index as the sum of the squared values of products’ market share (Curry and George 1983).
Control variables

The industrial organization economics and organizational ecology literatures suggest control variables at the level of the product line, business unit, and market that may influence the likelihood of innovation. At the product line level, we controlled for innovation experience and size. For innovation experience (TotPrevInnov), which may increase the tendency towards innovation (Amburgey, et al. 1993), we employed a count measure. This measure drew on our review of industry trade publications beginning in 1981, and started with the month in which the product line was released into the market. The innovation experience measure incremented by one after each release of a generational product innovation for the product line. We operationalized the size of the product organization (OrgSize), which may provide resources needed for innovation (Cohen 1995), based on unit sales volume, lagged and logged; lagging addressed the potential for simultaneity, while logging assumed that the effect declined as size increased. At the business unit level, we operationalized organizational age (OrgAge), which can either facilitate responsiveness or induce inertia (Baum 1999), as the log of the number of months since a firm first released the product in the market (irrespective of operating platform).

Our primary market-level variables addressed operating system platform, market segments, market size, and industry trade shows. Operating system platform captures the potential for differences in technological opportunity across platforms (Scherer, 1984). For operating system platform, we included a dummy variable (WIN) to capture the effect of the operating platforms (Windows and Macintosh). Market segments control for the potential for technological opportunity differences across segments (Cohen, 1995). We included three dummy variables (DesktopPublishing, Spreadsheets, WordProcessing) to represent the four market segments (computer-aided design, desktop publishing, spreadsheets, and word processing). The dummy variables were effect-coded, such that a negative effect for DesktopPublishing, Spreadsheets, or WordProcessing represents a lower respective likelihood of releasing a generational product innovation relative to the average likelihood across all four market segments. Market size may influence innovation incentives through differences in potential returns associated with the innovation investment (Schmookler 1966). Our market size (MktSize) variable
captured the total number of units sold in a given product market, lagged and logged. Industry trade shows are major industry events that concentrate stakeholder attention and may increase firm incentives to release innovations. The variable (MktTradeShow) is binary: ones represent the month of occurrence for trade shows and zeros represent the absence of trade shows. Based on the trade press, we identified COMDEX/Fall as the major trade show for Windows-based products. For Macintosh-based products, in addition to COMDEX, we included the Macworld Expo as a major trade show.

Our analyses also included two variables as part of our controlling for selection bias that might arise from market exits. To illustrate why we employed the selection correction, suppose our objective is to examine the direct effect of market concentration on the instantaneous rate of generational product innovation, and we assume that market concentration also influences the rate of market exit. By controlling for survival bias, our estimates can properly reflect the marginal effects that market concentration has on both market exit and generational product innovation, rather than over-attributing its effect on the rate of generational product innovation (see Greene 2000, Heckman 1979). In controlling for the potential selection bias, our first stage analysis included two additional variables that may affect survival but are less likely to affect the rate of innovation. Market density (MktDens) represents the total number of products operating in a market, lagged one time period and logged, drawing from density dependence research in organizational ecology (Hannan and Freeman 1989). Studies of industry evolution, meanwhile, suggest that calendar time (Months), which is also logged, often affects survival (Klepper and Simon 1997).

Models and Analysis

We used parametric event history analysis for the study, using calendar time as the time axis. We updated all time-dependent variables on a monthly basis. To minimize time aggregation bias (Peterson 1991), we set the selection and innovation events to the mid-point for their months of occurrence.

For our focal model, we clustered observations by business line. Utilizing both visual inspection and the AIC criterion, we determined that the most appropriate parametric distribution was the exponential distribution with annual dummy variables. We present the coefficient results in a hazard
format. In the hazard format, a positive coefficient reflects an increase in the instantaneous rate of generational product innovation.

To control for selection bias that might arise from market exits, we included a lambda estimate in the focal model based on Lee’s (1983) generalization of the Heckman (1979) two-stage estimator. We calculated lambda as: \( \lambda = \frac{\phi(\Phi^{-1}[1-S(t)])}{S(t)} \), where \( \phi \) is the standard normal density, \( \Phi^{-1} \) is the inverse of the standard normal distribution, and \( S(t) \) is the survivor function.

RESULTS

Table 3 presents the results of the first-stage selection model that produced the lambda variable for the second-stage analysis that tested the hypotheses. With thirteen selection events in our dataset, we included a moderate number of explanatory variables in the selection model. Market-level variables in the selection model included market density, market size, market concentration, and calendar time. Organizational age was included as a business level variable, and organizational size and time since previous innovation were variables at the product line level. The likelihood of failure declines with market size, market concentration, calendar time, and organizational size, while failure increased with market density and time since previous innovation.

********** Table 3 here **********

Table 4 reports the second-stage analysis, which tests the hypotheses. All models included random effects for the business lines. Model 1 included the controls. Models 2 to 5 added the explanatory variables independently, while Model 6 added the explanatory variables simultaneously. Given the directional predictions, we present the results based on one-tail significance tests.

********** Table 4 here **********

Model 1 included all control variables, including baseline effects for time since previous innovation (TimeSinceInnov, TimeSinceInnov\(^2\)), competitor innovation (CompetitionInnov), and complementary innovation (TechOppMP, TechOppOS). As expected, this model found statistical significance for a curvilinear, inverse-U baseline effect for the time since previous innovation and a positive effect for the occurrence of complementary microprocessor innovations.
Models 2 and 6 addressed Hypothesis 1, which predicts that the relationship between the historical pattern of innovation activity (i.e., time since previous innovation) and the rate of generational product innovation will diminish as market concentration increases. We tested this hypothesis by including interaction terms between market concentration and time since previous innovation (MktConc*TimeSinceInnov) and between market concentration and the square of time since previous innovation (MktConc*TimeSinceInnov^2). We expected a positive coefficient for MktConc*TimeSinceInnov^2, indicating a diminishing of the inverse-U shaped relationship between time since previous innovation and generational product innovation. As expected, Models 2 and 6 report significant interaction effects in the expected direction (p<0.10), supporting Hypothesis 1.

Models 3 and 6 examined Hypothesis 2, which predicts that GPI releases will be more responsive to competitors’ innovations as market concentration increases. The interaction term (MktConc*CompetitionInnov) tests the hypothesis. A positive coefficient for the interaction would indicate greater event responsiveness. Model 3 (separate introduction) and Model 6 (simultaneous introduction) report significant positive interaction terms (p<0.05), supporting Hypothesis 2.

Models 4, 5, and 6 addressed Hypothesis 3, which predicts that generational product innovation releases will be more responsive to the occurrence of complementary technological opportunity events as market concentration increases. We considered complementary innovations at two foundational levels in the technological system: the microprocessor and the operating system. For microprocessor innovations, we added an interaction term (MktConc*TechOppMP), but did not find a significant effect either separately (Model 4) or simultaneously (Model 6). For operating system innovations, we added the MktConc*TechOppOS interaction term, finding a significant positive coefficient for both Model 5 and Model 6 (p<0.05).

To more clearly understand the significance of our interaction results, we conducted a series of simple slope tests (Aiken and West 1991). The tests identify the direction and magnitude of the effects of time since previous innovation as well as innovations by competitors and in complementary technologies at specific levels of market concentration. We conducted external event tests for competitor innovations
and operating system innovations, as the two events that significantly interact with market concentration, at three referent levels of market concentration: its mean, one standard deviation above the mean (“high”), and one standard deviation below the mean (“low”).

The simple slope tests yield additional insight. For time since previous innovation (H1), as predicted, Figure 2 reports that the inverse-U shaped relationship with the rate of generational product innovation diminished as market concentration increased from low to high. Specifically, the coefficient estimates for the square of time since previous innovation diminished from the low level of market concentration (b=-0.005, s.e.=0.001, p<0.01) to the mean level (b=-0.004, s.e.=0.001, p<0.01) to the high level of market concentration (b=-0.002, s.e.=0.001, p<0.05). For responsiveness to competitor innovations (H2), as expected and shown in Figure 3, we find that firms are more likely to release generational product innovations in response to competitor innovations at a high level of market concentration (b=1.107, s.e. = 0.733, p<0.10). At the mean of market concentration, however, the competitor innovation effect was insignificant (b=0.203, s.e.=0.429), and at the low level of concentration, the results indicate that firms are actually significantly less likely to release an innovation in response to competitors (b=-0.701, s.e.=0.468, p<0.10). For responsiveness to complementary innovations (H3), we find that the release of an operating system innovation has a positive and significant effect at the high level of concentration (b=1.760, s.e.=0.670, p<0.01) and the mean level (b=0.779, s.e.=0.458, p<0.05), while the effect was insignificant at the low level of concentration (b=-0.201, s.e.0.685). Figure 2 presents the effects of time since previous innovation, while Figure 3 reports the corresponding event effects from the simple slope tests as multipliers on the base rate.

********** Figures 2 and 3 here **********

In sum, the results support most predictions. The analyses support Hypothesis 1. The results support Hypothesis 2, with an interesting caveat. As market concentration increases, firms are more likely to release generational product innovations in response to those of competitors. Yet at low levels of concentration, firms are significantly less likely to do so, suggesting that under these market conditions, firms react to competitor innovations with active avoidance. The results also support Hypothesis 3 for
operating system innovations, but do not find that market concentration influences responsiveness to microprocessor innovations. We address these differences in the discussion section.

**Sensitivity Analyses**

We undertook several exploratory extensions. First, we examined additional lags for generational product innovations by competitors and in complementary technologies, which were not statistically significant. Second, Scherer and Ross (1990) suggest that market concentration may have a curvilinear effect on innovation, but our results did not support such a relationship. Third, to provide a greater accounting for potential dependence among observations, we employed a conditional risk set approach by replacing the TotPrevInnov variable with a set of dummy variables representing the generational product innovation event that each product line was at risk for throughout the panel. In all cases, the sensitivity analyses provide materially equivalent results to those that Table 3 reports.

Fourth, Cohen (1995) concludes that, once firm size is accounted for, market concentration has little direct effect on innovation. Therefore, we employed additional models that examined the hypothesized interactions, while controlling for interactions between (a) organizational size and competitor innovation events, (b) organizational size and complementary innovation events, and (c) organizational size and time since previous innovation. In addition, we ran a probit model that simultaneously estimates the market exit and generational product innovation equations. In all cases, our sensitivity analyses provided equivalent results to the hypothesis tests in Table 3.

We also examined whether our results were sensitive to excluding the 1994 observations based on potential for inadequate representation of the product markets in 1994, given the moderate coverage of the market research data in that year (30%). After excluding the 1994 observations, our analyses yielded the same coefficient directions for the hypothesized interactions, although the interactions were not statistically significant. This reflects that there were a large number of GPI events in 1994, as Table 2 reports. We believe that including the 1994 data is appropriate for the analyses, based on our visual inspection of product market share trajectories spanning the 1994 and 1995-1998 data within our dataset, as well as comparisons of our data with similar data presented in Liebowitz and Margolis (1999).
Finally, we examined whether generational product innovation responsiveness to competitor innovations may differ by the market dominance of the products. We categorized products with greater than 50% share of the market as dominant and other products as non-dominant. Our sensitivity analyses indicated that for non-dominant products, higher concentration significantly increased the responsiveness to GPI releases by other non-dominant products. For GPI releases by dominant products, the interaction coefficient was in the expected direction, but it was not statistically significant; this likely reflects the modest number of GPI events by dominant products in our dataset. When examining GPI releases by dominant products, our analyses focused on the effect of competitive innovations by non-dominant products, as there were not corresponding innovations by dominant products; for these analyses, the market concentration interaction was not statistically significant. This finding may reflect that rising concentration has less effect on innovation responsiveness for dominant competing products, versus non-dominant products, or the fewer number of GPI events by dominant products.

**DISCUSSION**

Understanding how market conditions influence strategies for the timing of innovation is a central issue for scholarship on the organization and economics of innovation (Brown and Eisenhardt 1995, 1997, Cohen 1995, Reinganum 1989, Schumpeter 1950). The objective of this study was to investigate how market concentration, a central factor in Schumpeterian theories of innovation, shapes the extent to which generational product innovation strategies reflect innovation events in the external marketplace and historical patterns of innovation. The premise behind our arguments is that greater concentration increases the stakes surrounding market positions and leads to greater competitive interdependence, such that firms need to evolve their generational product innovation strategy in order to respond to competitor and complementary innovations. Our core findings support this argument. As market concentration increases, we found GPI strategies were less reflective of historical time-based patterns of innovation and increasing responsiveness both to innovations by competitors and to innovations in complementary technologies, although with two intriguing caveats that we discuss below.

The study has implications for three strands of innovation studies: economics of innovation,
competitive rivalry, and the emerging literature on dynamic capabilities. First, consider the economics of innovation literature. In examining the timing of generational product innovation, we draw from auction models of non-drastic innovation as the basis for incentives surrounding preemptive innovation.¹ For non-drastic innovations, which tend to be relatively high certainty R&D outcomes, pre-innovation market concentration shapes preemption incentives and, in turn, influences the timing of innovation (Gilbert and Newbery 1982, Reinganum 1989). While traditional auction models and related empirical analyses focus on the direct effect of market concentration on innovation, we extend the competitive threat rationale to examine the effect of concentration on the responsiveness of innovation.

This study relates closely to the game theoretic concept of competitive threats, which stresses that firms’ innovation incentives respond to potential losses associated with current market position (Beath, Katsoulacos, and Ulph 1995). However, this literature typically does not operationalize and test the models. Because the stakes surrounding market positions increase in concentrated markets, product innovation behavior tends to be less reflective of historical patterns of innovation and more responsive to competitor and complementary innovation events. Adapting to the release of innovations by competitors helps firms to retain valuable market position, a finding which is consistent with Grabowski and Baxter’s (1973) conclusion that R&D investment patterns are more similar in concentrated markets. For at least some forms of complementary innovations, greater responsiveness helps the firms preempt or at least match other firms. Thus, our study both clarifies concepts in economic models of innovation and empirically demonstrates how market concentration shapes the responsiveness of generational product innovation to innovations from competitors and in complementary technologies.

Second, our study offers implications for the competitive rivalry literature in strategic management. Competitive rivalry research draws substantially from Schumpeterian (1934) theories of

¹ Economic models of innovation timing encompass two basic frameworks: auction (deterministic) models and racing (stochastic) models (Reinganum 1989). Due to differences in conditions, particularly R&D certainty and innovation type, these models generate contradictory predictions for innovation preemption. Auction models of non-drastic innovation support preemptive innovation by incumbents, while racing models of drastic innovation indicate preemptive innovation by challengers. Reinganum (1989) argues that auction models are appropriate for development (product introduction) innovations and that racing models capture basic research (invention) innovations.
competitive dynamics and examines innovation introductions as central moves and countermoves (Lee, Smith, Grimm and Schomburg 2000, Young, Smith, and Grimm 1996). Extant research argues that as concentration increases, competitive rivalry decreases, based on the logic that greater concentration decreases the incentives to compete aggressively and, therefore, firms restrict investment in innovation to achieve higher profitability (Schomburg, Smith, and Grimm 1994, Smith, Ferrier, and Ndofor 2001).

By contrast, our findings indicate that with increases in market concentration, when competitors do introduce innovations, organizations become more responsive in their release of generational product innovations. Given the centrality of responsiveness to the concept of competitive rivalry, this represents an important implication. Moreover, the results offer insight into how firms react to competitor innovations. In current research on competitive rivalry, responding is implicitly equated with rapid imitative moves by rivals. In highly-concentrated markets, we do find evidence of this type of response, which one can refer to as 'temporal conformity'. In low concentration markets, by contrast, our results suggest an alternative type of reaction – one of 'temporal divergence' – in which firms actively avoid the temporal proximity of rival innovation releases. Although the temporal divergence implications are only suggestive, we conjecture that this behavior reflects firms seeking out uncontested times of market attention when competing in fragmented market conditions. When facing numerous competitors, firms may be selecting temporal position as one means of differentiating their generational product innovation releases relative to competing product innovations. It may also reflect, in part, the complexity of the information environment facing consumers in highly-fragmented markets, such that distancing GPI releases from competitor innovations increases the information-processing potential of consumers and as a result, impacts purchasing behavior (Jacoby 1984, Simon 1947).

The study also extends the rivalry literature by identifying complementary innovations as potential preemption points. In particular, our unexpected results help clarify the incentives and threats associated with the preemption surrounding complementary innovations. Recall that we found no influence of market concentration on one form of complementary external event, the introduction of microprocessors, in contrast with the significant interaction of concentration with new generations of
operating systems. At the same time, though, the main effect results indicate that microprocessor innovations do stimulate generational product innovation by application software firms.

This difference in the two forms of complementary innovation likely arises because changes in operating systems require greater redesign effort for applications software products than do microprocessor innovations, as applications software code needs fewer changes in response to microprocessor changes (e.g., increased processor speed). Generational product innovation in response to microprocessor innovations requires relatively low investment in redesign; by contrast, responding to operating system innovations requires substantial effort. This difference suggests that application software firms will be more sensitive to the surrounding competitive implications for investments in generational product innovation that are tied to operating system innovations.

This empirical difference has a general implication. Complements that involve high interdependence with the focal product require greater innovative responsiveness because they generate heightened implications for obtaining competitive advantage or maintaining competitive parity.

Third, the study contributes to our understanding of the dynamic capabilities that firms use to change their strategies for generational product innovation. The results show that the need to develop the capability to use externally-driven innovation strategy depends on the level of market concentration. Inductive innovation research suggests that firms tend to follow internally-driven strategies (Brown and Eisenhardt 1997). Our results indicate, however, that as concentration increases, firms increasingly turn to externally-driven generational product innovation strategy. Moreover, the events that will have the greatest effect on GPI strategies are the ones that involve the possibility for shifts in competitive advantage in the face of strategic interdependence.

Firms that learn to use both internally- and externally-driven innovation strategies under the appropriate business conditions will be best able to renew themselves in the face of GPI-embodied technological competition. The argument concerning dynamic capabilities suggests that the ability to use externally-driven innovation strategies becomes increasingly important as competition becomes more interdependent. Internally-driven forms of innovation strategy are common in traditional atomistic
markets, because firm success depends largely on own-firm efficiency rather than on technological 
competition with rivals (Dosi 1988). Small-scale fruit orchardists, for example, traditionally grafted new 
varieties of apples annually, with little attention to the choices that other farmers were undertaking. 
Similarly, prior to banking deregulation in the U.S., firms in the historically-fragmented banking industry 
tended to follow their own pace in introducing new banking services.

Primary reliance on internally-driven strategy is less viable in more competitively interdependent 
markets, because firms face greater risk of losing market opportunities if they do not respond to the 
actions of direct rivals or of complementary firms. As apple farming has become a global industry, for 
instance, North American orchardists need to respond to varietal innovations by competitors in locations 
such as Chile and New Zealand. Similarly, in the now much more concentrated U.S. banking industry, 
banks need to respond quickly to rival competitive moves and to complementary innovations such as 
Internet-based channels for services. In the presence of strong rivalry, an internally-driven strategy 
realizes its coordination efficiencies at the expense of opportunity costs from forgoing adaptation in 
response to competitors’ actions and other external events. This gives rise to the need for greater 
externally-driven pacing.

The need to select among internally-driven and externally-driven strategies involves particularly 
intriguing forms of dynamic capabilities because the choices reflect what some scholars have referred to 
as shaping and adapting strategies (Courtney, Kirkland, and Viguierie 1997, Courtney 2001). Internally-
driven innovation timing is a form of a shaping strategy. Shaping strategies aim to influence industry 
structure and conduct through changes that improve the competitive standing of the company. 
Companies adopting internally-driven innovation strategies seek to systematically improve the 
competitive standing of their products through independent innovation, rather than innovate in response to 
external events. By contrast, externally-driven innovation is an example of an adapting strategy. 
Adapting strategies take industry structure and competitive conduct as given and respond – often rapidly 
– rather than seeking to shape aspects of the industry. Adapting strategies attempt to respond 
appropriately as external events in the marketplace occur. As shaping and adapting strategies, internally-
and externally-driven innovation strategies stand in strong contrast to traditional positioning strategies that take the market as exogenous or, at best, forecastable.

One potential limitation of our study is the treatment of market structure as exogenous. While we believe it is appropriate to treat market structure as exogenous in the short-term, an interesting avenue for future research lies in examining how generational product innovation strategy might subsequently shape industry structure and dynamics. In turn, from the perspective of competitive rivalry, the literature can be advanced by examining how the responsiveness of GPI to competitive innovations, whether conforming or diverging in timing, and complementary innovations of varying degrees of interdependence affect firm performance. Another potential limitation for the generalizability of our findings is the single-industry empirical setting. While generational innovation is pervasive within industries (Scherer and Ross 1990), it is not clear under what conditions strategies for generational innovation are pursued by businesses. Further, our understanding of GPI strategy could usefully examine longer periods of time and greater spans of the industry life cycle. Future research may also examine how industry structure affects the impact of generational product innovation on performance, relative to more extensive innovation strategies.

Additional research could examine other industry settings, both to determine generalizability and to explore boundary conditions. We would expect the results to hold in established sectors such as autos and consumer electronics in which ongoing innovation provides substantial competitive advantage. It is possible that the results would be weaker in more cost-driven sectors, such as commodity chemicals.

Scholars recognize generational product innovations as an important and understudied element of innovation strategy (Brown and Eisenhardt 1997, 1998, Tushman and Anderson 1996). In examining how market concentration shapes the responsiveness of generational production innovation strategy to both competitor and complementary innovation, this research extends our understanding of the role of competitive conditions, complementing inductive research that has focused on internal conditions. More broadly, this research provides insight into how market conditions influence the internal and external drivers of innovation strategy.
REFERENCES


APPENDIX A: 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).

*Technical improvement rule:* The technical improvement rule classified the release as a GPI 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 product innovation. As such, its use as an explicit rule provides a conservative check for establishing the reliability of our classification system.

*Release numbering rule:* The release numbering/title rule was 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 an 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).

*Pricing rule:* 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.

*Classification scheme:* 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.
Table 1. Variable Summary Statistics and Product-Moment Correlations (N = 2,041 organization-months)

| Variable | Mean | StdDev | Min | Max | 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 |
|----------|------|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| GenProdInnov | 0.03 | 0.18  | 0.00 | 1.00 | 1.00 | 1.00 |
| MktFailure  | 0.01 | 0.16  | 0.00 | 1.00 | 1.00 | 1.00 |
| Months      | 1.39 | 0.28  | 1.00 | 1.00 | 1.00 | 1.00 |
| Year_1995   | 0.21 | 0.35  | 0.00 | 1.00 | 1.00 | 1.00 |
| Year_1996   | 0.20 | 0.18  | 0.00 | 1.00 | 1.00 | 1.00 |
| Year_1997   | 0.20 | 0.38  | 0.00 | 1.00 | 1.00 | 1.00 |
| Year_1998   | 0.20 | 0.30  | 0.00 | 1.00 | 1.00 | 1.00 |
| WIN         | 0.54 | 0.50  | 0.00 | 1.00 | 1.00 | 1.00 |
| DesktopPublishing | -0.16 | 0.35 | -0.16 | 1.00 | 1.00 | 1.00 |
| Spreadsheets | -0.18 | 0.35 | -0.09 | 1.00 | 1.00 | 1.00 |
| WordProcessing | -0.15 | 0.30 | -0.09 | 1.00 | 1.00 | 1.00 |
| MktDensity  | 0.09 | 0.50  | 0.00 | 1.00 | 1.00 | 1.00 |
| MktSize     | 3.76 | 0.45  | 2.00 | 5.00 | 1.00 | 1.00 |
| MktTradeShow| 0.25 | 0.30  | 0.00 | 1.00 | 1.00 | 1.00 |
| Age         | 2.02 | 0.30  | 0.00 | 1.00 | 1.00 | 1.00 |
| OrgSize     | 2.50 | 0.21  | 0.00 | 4.00 | 1.00 | 1.00 |
| TimeSinceInnov| 17.80 | 15.46 | 8.00 | 175.40 | 1.00 | 1.00 |
| MktConc     | 0.50 | 0.21  | 0.00 | 1.00 | 1.00 | 1.00 |
| CompetitionInnov | 0.13 | 0.30 | 0.00 | 1.00 | 1.00 | 1.00 |
| TechOppMP   | 0.30 | 0.15  | 0.00 | 1.00 | 1.00 | 1.00 |
| TechOppOS   | 0.04 | 0.20  | 0.00 | 1.00 | 1.00 | 1.00 |
| MktConc*TimeSinceInnov | 0.05 | 0.15 | 0.00 | 1.00 | 1.00 | 1.00 |
| MktConc*TimeSinceInnov 2 | 0.03 | 0.13 | 0.00 | 1.00 | 1.00 | 1.00 |

Variable Description

1 GenProdInnov: Generational Product Innovation (1 if generational product innovation release occurs during month, 0 otherwise)
2 MktFailure: Market Failure (1 if product exits from the market, 0 otherwise)
3 Months: Calendar Time in Months (logged)
4 Year_1995: Calendar Year 1995 (1 if observations are during 1995, 0 otherwise)
5 Year_1996: Calendar Year 1996 (1 if observations are during 1996, 0 otherwise)
6 Year_1997: Calendar Year 1997 (1 if observations are during 1997, 0 otherwise)
7 Year_1998: Calendar Year 1998 (1 if observations are during 1998, 0 otherwise)
8 WIN: Windows Operating Platform (1 if observations are Windows platform, 0 otherwise)
9 DesktopPublishing: Desktop Publishing Market Segment (Effect-coded dummy variable)
10 Spreadsheets: Spreadsheets Market Segment (Effect-coded dummy variable)
11 WordProcessing: Word Processing Market Segment (Effect-coded dummy variable)
12 MktDensity: Market Density (Total number of firms on the market; lagged one time period and logged)
13 MktSize: Market Size (Total number of product units sold in the market; lagged one time period and logged)
14 MktTradeShow: Market Opportunity Event (1 if major industry trade show occurs during month, 0 otherwise)
15 Age: Organizational Age (Number of months since firm first released the product in the market; logged)
16 TotPrevInnov: Cumulative Number of Previous Innovations by Organization (Count variable that increments by one after each innovation release)
17 OrgSize: Organizational Size (Total number of product units sold by the organization; lagged one time period and logged)
18 TimeSinceInnov: Time Since Previous Innovation (Elapsed time in months since initial product release or most recent generational product innovation)
19 TimeSinceInnov 2: Square of Time Since Previous Innovation
20 MktConc: Market Concentration (Hirschman-Herfindahl index)
21 CompetitionInnov: Competition Innovation (1 if competing organizations released a generational product innovation, 0 otherwise; lagged one time period)
22 TechOppMP: Technological Opportunity Event: Microprocessor (1 if new class of microprocessor is released in month, 0 otherwise)
23 TechOppOS: Technological Opportunity Event: Operating System Software (1 if major operating system innovation is released during month, 0 otherwise)
24 MktConc*TimeSinceInnov: Interaction between Market Concentration and Time Since Previous Innovation
25 MktConc*TechOppMP: Interaction between Market Concentration and Square of Time Since Previous Innovation
26 MktConc*TechOppOS: Interaction between Market Concentration and Technological Opportunity Event: Microprocessor
27 MktConc*TechOppMP 2: Interaction between Market Concentration and Square of Time Since Previous Innovation
28 MktConc*TechOppOS 2: Interaction between Market Concentration and Square of Time Since Previous Innovation

31
Table 2. Generational product innovations by Market Segment and Operating Platform

| Table 2. Generational product innovations by Market Segment and Operating Platform |
|----------------------------------|------------------|------------------|------------------|------------------|
| **CAD**                          | **Spreadsheets**  |                  |                  |                  |
| Aggregate (Windows, Macintosh)   |                  |                  |                  |                  |
| Number of product lines on-market (in January) | 11 | 13 | 12 | 14 | 14 | Number of product lines on-market (in January) | 9 | 9 | 5 | 6 | 6 |
| Number of product line entrants (during year) | 3 | 2 | 2 | 1 | 2 | Number of product line entrants (during year) | 0 | 0 | 1 | 0 | 0 |
| Number of product line exits (during year) | 2 | 2 | 0 | 1 | 2 | Number of product line exits (during year) | 0 | 4 | 0 | 0 | 0 |
| Number of GPI events (during year) | 6 | 5 | 7 | 8 | 4 | Number of GPI events (during year) | 3 | 1 | 2 | 3 | 2 |
| Windows                         |                  |                  |                  |                  |
| Number of product lines on-market (in January) | 5 | 8 | 6 | 8 | 8 | Number of product lines on-market (in January) | 4 | 4 | 3 | 3 | 3 |
| Number of product line entrants (during year) | 2 | 1 | 2 | 0 | 2 | Number of product line entrants (during year) | 0 | 0 | 0 | 0 | 0 |
| Number of product line exits (over year) | 0 | 2 | 0 | 0 | 1 | Number of product line exits (over year) | 0 | 1 | 0 | 0 | 0 |
| Number of GPI events (during year) | 3 | 3 | 4 | 7 | 3 | Number of GPI events (during year) | 2 | 1 | 2 | 2 | 1 |
| Macintosh                        |                  |                  |                  |                  |
| Number of product lines on-market (in January) | 6 | 5 | 6 | 6 | 6 | Number of product lines on-market (in January) | 5 | 5 | 2 | 3 | 3 |
| Number of product line entrants (during year) | 1 | 1 | 0 | 1 | 0 | Number of product line entrants (during year) | 0 | 0 | 1 | 0 | 0 |
| Number of product line exits (over year) | 2 | 0 | 0 | 1 | 1 | Number of product line exits (over year) | 0 | 3 | 0 | 0 | 0 |
| Number of GPI events (during year) | 3 | 2 | 3 | 1 | 1 | Number of GPI events (during year) | 1 | 0 | 0 | 1 | 1 |
| Desktop Publishing              |                  |                  |                  |                  |
| Aggregate (Windows, Macintosh)   |                  |                  |                  |                  |
| Number of product lines on-market (in January) | 8 | 8 | 8 | 7 | 7 | Number of product lines on-market (in January) | 7 | 7 | 8 | 7 | 7 |
| Number of product line entrants (during year) | 0 | 0 | 0 | 0 | 0 | Number of product line entrants (during year) | 0 | 1 | 0 | 0 | 0 |
| Number of product line exits (during year) | 0 | 0 | 1 | 0 | 0 | Number of product line exits (during year) | 0 | 0 | 1 | 0 | 0 |
| Number of GPI events (during year) | 3 | 4 | 2 | 5 | 1 | Number of GPI events (during year) | 5 | 3 | 1 | 4 | 0 |
| Windows                         |                  |                  |                  |                  |
| Number of product lines on-market (in January) | 4 | 4 | 4 | 4 | 4 | Number of product lines on-market (in January) | 4 | 4 | 4 | 4 | 4 |
| Number of product line entrants (during year) | 0 | 0 | 0 | 0 | 0 | Number of product line entrants (during year) | 0 | 0 | 0 | 0 | 0 |
| Number of product line exits (over year) | 0 | 0 | 0 | 0 | 0 | Number of product line exits (over year) | 0 | 0 | 0 | 0 | 0 |
| Number of GPI events (during year) | 2 | 2 | 2 | 1 | 1 | Number of GPI events (during year) | 2 | 2 | 1 | 2 | 0 |
| Macintosh                        |                  |                  |                  |                  |
| Number of product lines on-market (in January) | 4 | 4 | 4 | 3 | 3 | Number of product lines on-market (in January) | 3 | 3 | 4 | 3 | 3 |
| Number of product line entrants (during year) | 0 | 0 | 0 | 0 | 0 | Number of product line entrants (during year) | 0 | 1 | 0 | 0 | 0 |
| Number of product line exits (over year) | 0 | 0 | 1 | 0 | 0 | Number of product line exits (over year) | 0 | 0 | 1 | 0 | 0 |
| Number of GPI events (during year) | 1 | 2 | 0 | 3 | 0 | Number of GPI events (during year) | 3 | 1 | 0 | 2 | 0 |

~ The product line entered in January 1995
Table 3. Estimates for Market Exit  
N = 2041 organization-months, 2028 on-market observations, 13 market exit events  
Exponential distribution for calendar time; coefficients in hazard format (positive coefficient indicates greater rate of market exit)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Coeff.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Controls</td>
<td></td>
</tr>
<tr>
<td>MktSize</td>
<td>-0.792*</td>
</tr>
<tr>
<td>MktConc</td>
<td>-1.942*</td>
</tr>
<tr>
<td>MktDensity</td>
<td>5.308*</td>
</tr>
<tr>
<td>Months</td>
<td>-1.062*</td>
</tr>
<tr>
<td>Age</td>
<td>0.699</td>
</tr>
<tr>
<td>OrgSize</td>
<td>-2.002**</td>
</tr>
<tr>
<td>TimeSinceInnov</td>
<td>0.033*</td>
</tr>
<tr>
<td>Intercept</td>
<td>-3.613</td>
</tr>
<tr>
<td>Model loglikelihood</td>
<td>-13.294**</td>
</tr>
</tbody>
</table>

** p<0.01, * p<0.05, # p<0.10 (one-tail tests)
Table 4. Estimates for Generational Product Innovation
N = 2041 organization-months, 1972 on-market observations, 69 generational product innovation events
Piecewise-exponential distribution for calendar time (annual dummies); coefficients in hazard format (positive coefficient indicates greater rate of release)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year_1995</td>
<td>-0.495</td>
<td>-0.518*</td>
<td>-0.502*</td>
<td>-0.526*</td>
<td>-0.483</td>
<td>-0.521*</td>
</tr>
<tr>
<td>Year_1996</td>
<td>-0.412</td>
<td>-0.379</td>
<td>-0.402</td>
<td>-0.419</td>
<td>-0.390</td>
<td>-0.336</td>
</tr>
<tr>
<td>Year_1997</td>
<td>0.393</td>
<td>0.463</td>
<td>0.389</td>
<td>0.389</td>
<td>0.385</td>
<td>0.465</td>
</tr>
<tr>
<td>Year_1998</td>
<td>-0.661*</td>
<td>-0.649</td>
<td>-0.624</td>
<td>-0.662*</td>
<td>-0.692*</td>
<td>-0.617</td>
</tr>
<tr>
<td>WIN</td>
<td>0.306</td>
<td>0.325</td>
<td>0.320</td>
<td>0.294</td>
<td>0.349</td>
<td>0.374</td>
</tr>
<tr>
<td>DesktopPublishing</td>
<td>-0.162</td>
<td>-0.153</td>
<td>-0.179</td>
<td>-0.149</td>
<td>-0.137</td>
<td>-0.136</td>
</tr>
<tr>
<td>Spreadsheets</td>
<td>0.099</td>
<td>0.063</td>
<td>0.117</td>
<td>0.118</td>
<td>0.092</td>
<td>0.088</td>
</tr>
<tr>
<td>WordProcessing</td>
<td>-0.072</td>
<td>-0.046</td>
<td>-0.080</td>
<td>-0.058</td>
<td>-0.034</td>
<td>-0.009</td>
</tr>
<tr>
<td>MktSize</td>
<td>0.099</td>
<td>0.109</td>
<td>0.092</td>
<td>0.080</td>
<td>0.067</td>
<td>0.061</td>
</tr>
<tr>
<td>MktTradeShow</td>
<td>0.568*</td>
<td>0.576*</td>
<td>0.604*</td>
<td>0.562*</td>
<td>0.583*</td>
<td>0.628*</td>
</tr>
<tr>
<td>Age</td>
<td>-1.554**</td>
<td>-1.613**</td>
<td>-1.562**</td>
<td>-1.576**</td>
<td>-1.567**</td>
<td>-1.650**</td>
</tr>
<tr>
<td>TotPrevInnov</td>
<td>-0.011</td>
<td>-0.009</td>
<td>-0.010</td>
<td>-0.013</td>
<td>-0.010</td>
<td>-0.010</td>
</tr>
<tr>
<td>OrgSize</td>
<td>0.206</td>
<td>0.209</td>
<td>0.211</td>
<td>0.204</td>
<td>0.197</td>
<td>0.201</td>
</tr>
<tr>
<td>TimeSinceInnov</td>
<td>0.214*</td>
<td>0.318**</td>
<td>0.214**</td>
<td>0.213**</td>
<td>0.212**</td>
<td>0.323**</td>
</tr>
<tr>
<td>TimeSinceInnov^2</td>
<td>-0.004**</td>
<td>-0.006**</td>
<td>-0.004**</td>
<td>-0.004**</td>
<td>-0.004**</td>
<td>-0.006**</td>
</tr>
<tr>
<td>MktConc</td>
<td>-1.516</td>
<td>-0.202</td>
<td>-1.919^</td>
<td>-1.366</td>
<td>-2.035^</td>
<td>-0.910</td>
</tr>
<tr>
<td>CompetitionInnov</td>
<td>-0.356</td>
<td>-0.369</td>
<td>-1.828*</td>
<td>-0.323</td>
<td>-0.353</td>
<td>-1.941*</td>
</tr>
<tr>
<td>TechOppMP</td>
<td>0.661*</td>
<td>0.647^</td>
<td>0.653^</td>
<td>1.930*</td>
<td>0.659^</td>
<td>1.430</td>
</tr>
<tr>
<td>TechOppOS</td>
<td>0.552</td>
<td>0.556</td>
<td>0.569^</td>
<td>0.548</td>
<td>-1.411</td>
<td>-1.546</td>
</tr>
<tr>
<td>MktConc*TimeSinceInnov</td>
<td>-0.191</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.207</td>
</tr>
<tr>
<td>MktConc*TimeSinceInnov^2</td>
<td>0.005^</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.005^</td>
</tr>
<tr>
<td>MktConc*CompetitionInnov</td>
<td>3.550*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3.881*</td>
</tr>
<tr>
<td>MktConc*TechOppMP</td>
<td>-3.092</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-2.023</td>
</tr>
<tr>
<td>MktConc*TechOppOS</td>
<td>3.860*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4.209*</td>
</tr>
<tr>
<td>Lambda</td>
<td>-4.019*</td>
<td>-4.219*</td>
<td>-4.007*</td>
<td>-4.072*</td>
<td>-4.116*</td>
<td>-4.389*</td>
</tr>
<tr>
<td>Theta</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

** p<0.01, * p<0.05, # p<0.10 (one-tail tests)
Figure 1. Conceptual model of generational product innovation release.

- Time Since Previous Innovation
- Market Concentration
- Innovation Events: Competitor Innovations, Complementary Innovations
- Likelihood of GPI Release

H1, H2, H3
Figure 2. Effect of Time Since Previous Innovation on Innovation Likelihood at Three Levels of Market Concentration
Figure 3. Slope Test Results for Response to Competitor and Operating System Innovations at Three Levels of Concentration

3a. Multiplier Effect of Competitor Innovation Release on the Rate of Generational Product Innovation

3b. Multiplier Effect of Operating System Release on the Rate of Generational Product Innovation