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Effects of Entry Mode and Incumbency Status on the Rates of Firm Product Innovation in the Worldwide Optical Disk Drive Industry, 1983-1999*

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Abstract

Firms entering an industry *de novo* (start-up) and firms entering *de alio* (diversification away from another industry) differ in the initial entry conditions. In this paper I propose that the differences in resource endowment, previous experience, and structural flexibility between *de novo* and *de alio* firms at the time of entry have long-lasting imprinting effects on their innovation behavior. In particular, I predict that *de novo* firms exert greater efforts and achieve greater technological outcomes in product innovation than *de alio* firms. Furthermore, I argue that firm entry mode explains additional variance in firm innovative behavior, which is not explained by entrant-incumbent status alone. I find strong empirical support for these predictions when analyzing product innovation of all firms that ever participated in the worldwide optical disk drive industry, 1983-1999. I discuss the implications of my findings for the entrant-incumbent research in the literature of the management of innovation.

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Introduction

Students of innovation have long recognized that incumbents and entrants differ in their innovative abilities (e.g., Anderson & Tushman 1990; Henderson & Clark 1990; Tripsas 1997). Most scholars agree that entrants are more capable than incumbents at introducing and developing major (e.g., radical, competence-destroying, architectural, etc.) innovations (Tushman & Anderson 1986; Henderson & Clark 1990; Henderson 1993). However, recent empirical research suggests the opposite: incumbents can outperform entrants at major innovations (Methe, et. al. 1996; Christensen & Bower 1996; Klepper & Simons 2000).

One possible explanation for this conflicting evidence is unobserved heterogeneity within the two types of firms. In other words, not all entrants are the same and not all incumbents are the same with respect to technological change. There is systematic variation in innovative behavior within populations of entrants and incumbents. I suggest that a firm's entry mode into an industry as either *de novo* (i.e., as a start-up entrant) or *de alio* (i.e., diversifying from another industry) can be an important source of this variation that has not been fully considered.

Another possible explanation for the divergent findings in the literature regarding innovative behavior of incumbents and entrants is the reliance on the concepts of major vs. incremental innovation (i.e., radical vs. incremental, competence-destroying vs. competence-enhancing, architectural vs. modular). These concepts can be misleading. Innovation that is major for one incumbent in an industry can be incremental for another, since they could come into the focal market from industries more or less related to the innovation in question (Levinthal 1998; Klepper & Simons 2000), have different complementary assets (Tripsas 1997), or develop different absorptive capacities (Cohen & Levinthal 1990). Furthermore, innovation is defined as either major or incremental *ex-post* by the subjective judgment of experts (e.g., Anderson &

Tushman, 1990; Henderson & Clark, 1990) making it difficult, if not impossible, to make cross-study and cross-industry comparisons.

This problem is exacerbated by the fact that scholars apply different measures of innovation success. As a measure of innovation success scholars use market leadership (Henderson & Clark 1990; Christensen & Rosenbloom 1995; Christensen & Bower 1996), market share (Henderson 1993; Banbury & Mitchell 1995; Tripsas 1997), early adoption of new technology (Tushman & Anderson 1986; Anderson & Tushman 1990; Methe et al. 1996; Carroll & Teo 1996), technical performance (Anderson & Tushman 1990; Lerner 1997; Tripsas 1997), entry into a new technological niche (Tushman & Anderson 1986; Mitchell 1989), survival (Carroll & Teo 1996; Banbury & Mitchell 1995), and the rate of patenting (Sorensen & Stuart 2000).

In sum, I suggest that the three described issues – heterogeneity of both incumbents and entrants, the arbitrary nature of defining an innovation as either major or incremental, and inconsistent measures of innovation success – can drive conflicting evidence about what type of organization is more adept at innovation. I address the first two issues by studying product innovation in the worldwide optical disk drive industry, 1983-1999. I begin to approach the problem of unobserved heterogeneity between incumbents and entrants by exploring how a firm's entry into an industry *de novo* vs. *de alio* affects the rate of a firm's product innovation and whether a firm's entry mode explains additional amount of variance in firm product innovation that is not explained by entrant-incumbent status alone. I focus on realized innovation, in particular, on the rate of market introduction of the products with improved technical performance. I avoid defining innovation dichotomously as either major or incremental. Instead, I measure the extent of an innovation's advancement by the distance of a firm's new product performance parameters from the technological frontier.

The rest of the paper proceeds as follows. First, I review research done in the literatures of the management of innovation and organizational ecology that may provide insight to understanding innovative activities of firms with different entry modes. Second, I develop my theoretical arguments and hypotheses regarding differences in innovative behavior between *de novo* and *de alio* firms. Then I describe the research setting of all firms in the worldwide optical disk drive industry from 1983 through 1999, outline methodology and test my hypotheses. Finally, I summarize results of the analyses and state major conclusions.

BACKGROUND

To understand whether and why the differences in innovative behavior between *de novo* and *de alio* firms exist, I rely on the literatures of management of innovation and organizational ecology.[1]

The management of innovation literature mainly focuses on differences in innovative behavior between entrants and incumbents, but not on those between *de novo* and *de alio* firms.[2] Yet it offers some insights for understanding the innovative dynamics of firms with different entry modes. In particular, the management of innovation literature implies that there are two key components of a firm's success at innovation. First, well-developed organizational routines are important for a firm's ability to succeed at incremental innovation (i.e., innovation that is based on existing knowledge), and are a key reason for incumbents' advantage at this type of

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[1] The arguments developed in this paper concern only firms' product innovation and may not generalize to process innovation.

[2] No direct parallels between entrants and *de novo* firms and incumbents and *de alio* firms can be drawn. Entrants can be both *de novo* and *de alio* firms. In fact, a number of innovation studies have shown that many entrants, that outperformed incumbents at major innovation, were *de alio* firms (e.g., Henderson & Clark 1990; Christensen & Rosenbloom 1995).

innovation (Tushman & Anderson 1986; Henderson 1993; Tripsas 1997). Second, flexibility in internal structures and relations with external actors is crucial for a firm's ability to undertake and succeed at major innovation (i.e., innovation that is not based on existing knowledge), and is a key reason for entrants' advantage at this type of innovation (Anderson & Tushman 1990; Henderson & Clark 1990; Henderson 1993; Christensen & Rosenbloom 1995).[3]

Although the management of innovation literature concludes that incumbents tend to have better-developed organizational routines, whereas entrants tend to have a higher level of structural flexibility, recent research shows that the opposite is also possible. Some incumbents possess a higher level of structural flexibility, and as a result, can succeed at major technological change (e.g., Christensen & Bower 1996; Methe, Swaminathan & Mitchell 1996). This literature, however, does not explain why this heterogeneity in structural flexibility and, consequently, in innovative abilities among incumbents is sometimes observed. As I stated in the introduction, entry mode can be one factor that drives this heterogeneity. Therefore, understanding whether and how *de novo* and *de alio* firms differ in their innovative behavior may help to clarify the debate regarding whether entrants or incumbents are better at major technological change.

As the management of innovation literature suggests, to understand what type of firm is likely to be more innovative, it is necessary to establish what type of firm has better-developed

[3] Major technological change by incumbents is difficult and error-prone for various reasons related to a lack of structural flexibility. New organizational routines have to be developed quickly. Yet their path-dependent nature makes the change difficult and slow (Nelson & Winter 1982). Commitment to old technologies may block implementation of new production principles (Henderson & Clark 1990). Attachment to outdated practices resulting from competency traps and myopia of learning makes it difficult to handle innovations demanding completely different approaches (Levitt & March 1988; March 1991; Levinthal & March 1993). Complementary assets can be difficult or even impossible to redeploy (Teece 1986; Tripsas 1997). Attachment and loyalty to existing networks of customers result in the lack of attention to emerging markets and demands (Christensen & Rosenbloom 1995). Finally, internal political resistance created by changes in a firm's reward and status systems may bring the innovation process to a halt (Pfeffer & Salancik 1978; Pfeffer 1981).

organizational routines and a higher level of structural flexibility. However, this literature has developed the theory and collected evidence only with respect to differences in organizational routines and structural flexibility between incumbents and entrants, and therefore, can offer only limited help to understanding such differences between *de novo* and *de alio* firms.

Similar to the management of innovation literature, organizational ecology proposes that organizational routines and structural flexibility are key to a firm's ability to undertake organizational change, of which innovation is one kind (Hannan & Freeman 1984; Barnett & Carroll 1995; Carroll & Teo 1996; Sorensen & Stuart 2000). However, in contrast to the management of innovation literature, organizational ecology offers very generalizable theories of imprinting and structural inertia that explain first, what organizations and why are likely to be more structurally flexible and possess better developed organizational routines, and second, how and why these differences in structural flexibility and routines come into existence, persist or change over time (Hannan & Freeman 1984; Carroll & Hannan 2000; Hannan, Polos & Carroll 2002).

According to organizational ecology, the ability of a firm to undertake change (including technological innovation) is shaped by the interplay between its organizational competence and structural flexibility. Organizational competence (also called capabilities) refers to an organization's ability to execute routines and solve problems and includes a firm's ability to coordinate organizational structures of employment and production and the relationships with external actors (Nelson & Winter 1982; Carroll & Hannan 2000; Sorensen & Stuart 2000). Organizations develop and refine their organizational competence in the process of learning as they age and acquire more experience (Nelson & Winter 1982). Firms with a high level of organizational competence can provide reliable and accountable performance (Hannan &

Freeman 1984). However, whether organizational competence brings innovative advantages to a firm depends on the extent to which this competence (a set of routines) can be adjusted to the current state of the technological environment, that is, on this firm's structural flexibility (Hannan & Freeman 1977; Carroll & Hannan 2000; Sorensen & Stuart 2000).

The processes of imprinting and structural inertia shape organizations' abilities to adjust to the current state of the environment (Hannan & Freeman 1977; Carroll & Hannan 2000). Imprinting is a process, in which events that an organization experiences at certain key developmental stages have persisting, possibly lifelong, consequences for the organization's development and life chances (Stinchcombe 1965; Carroll & Hannan 2000). Most influential and long-lasting imprinting happens at the time of an organization's founding. As Stinchcombe (1965) suggested, in attempting to accumulate financial and human capital, entrepreneurs expose their proposals to scrutiny of resource-holding agents. These proposals are more likely to be approved when they match taken-for-granted assumptions about organizational structural forms and employment relationships. Since taken-for-granted assumptions change over time, the kinds of organizations that emerge reflect the social structure of the founding period. Structural inertia, which is a persistent organizational resistance to change in organizational structure and culture, ensures the preservation of founding imprints over organizational life cycle (Hannan & Freeman 1984; Baron, Hannan & Burton 1999; Baron, Burton & Hannan 1996; 1999; Hannan, Polos & Carroll 2002).

The strength of inertial pressures varies across organizational types. Structural inertia is stronger for complex and opaque organizations than for simple and transparent ones, because complexity and opacity limit foresight of disruptive effects of organizational change and in this way make the implementation of organizational change hazardous (Hannan, Polos & Carroll

2002). Accordingly, empirical research in organizational ecology showed that small and young organizations are more likely to undertake significant organizational change than large and old organizations (Hannan & Freeman 1984; Delacroix & Swaminathan 1991; Kelly & Amburgey 1991; Amburgey, Kelly & Barnett 1993; Halliday, Powell & Granfors 1993; Wade 1996; Greve 1998).

The ecological theories of imprinting and structural inertia imply that *de alio* firms tend to have better-developed organizational competence, but *de novo* firms tend to be more structurally flexible (Carroll et al. 1996). However, empirical research has never tested the relationship between entry mode and structural flexibility directly. Instead it has focused on the relationships between entry mode and survival. The general idea underlying this research is that initial resource endowments and previous experience provide survival advantages to *de alio* firms as compared to *de novo* firms. However, *de novo* firms are more flexible and, over time, this flexibility can shift the advantages to *de novo* firms if the environment changes fast enough (Carroll et al 1996). Accordingly, in the U.S. automobile industry and the U.S. medical sector, it was found that *de novo* producers had higher initial mortality rates than *de alio* firms, but as these firms aged, their mortality rates converged (Carroll et al 1996; Mitchell 1994).

Although the described empirical studies shown that entry mode may affect firm mortality, it is not clear whether structural flexibility and organizational competence are driving this effect. A direct test of the relationship between entry mode and structural flexibility has yet to be done. By demonstrating the effect of entry mode on firm innovation, I hope to provide this kind of test.

THEORETICAL ARGUMENTS and HYPOTHESES

I advance my arguments about differences in product innovation between *de novo* and *de alio* firms in three steps. First, I consider whether *de novo* and *de alio* firms differ in their product innovation rates and if so, what the direction of these differences is. Second, I explore whether the differences in product innovation rates between *de novo* and *de alio* firms change over the life history of these firms in the focal industry. Finally, I examine whether entry mode explains additional variance in firm product innovation beyond the variance that is explained solely by incumbency status.

Firm entry into an industry *de novo* or *de alio* involves a different balance between organizational competence and structural flexibility. At the time of entry, *de alio* firms are likely to have a fairly well developed organizational competence, because they transfer many routines from their parent companies along with financial, technical, human, and social capital. These routines may range from a form of employment relationships (Baron et al. 1996; Baron et al. 1999) to positions in the social structure, such as status and reputation (Podolny 1993; Barnett 1997). Routines are not perfectly transferable (Nelson & Winter 1982) but to the extent they are, *de alio* firms are likely to have an advantage over *de novo* firms that have to start their business life from scratch. This advantage should be most pronounced around the time of entry into an industry. Over time *de novo* firms develop organizational competence in the process of learning. Therefore, this initial advantage of *de alio* firms is likely to decrease with time.

Since imprinting and inertia processes shape organizational abilities to undertake structural changes, *de novo* firms should have an advantage over *de alio* firms in terms of structural flexibility. At the time of entry, *de novo* firms' organizational competence is not well developed. Therefore, these firms have significant freedom over what capabilities they may choose to cultivate. Additionally, *de novo* firms are created specifically and solely for operating in a focal industry. Since a *de novo* firm's entry into an industry coincides with its founding, it is reasonable to expect that *de novo* firms' structural forms and employment relationships fit the environmental demands at the time of entry into a focal industry and need little adjustment (Stinchcombe 1965). In contrast, at the time of entry into the focal industry, *de alio* firms have already been participating in other industries and have more or less well-developed organizational competence. These firms were created to fit environmental demands of the industries in which they were founded and carry the imprints from their industries of origin. Even if at the time of entry into the focal industry, managers try to modify their firms' organizational competence to fit the environment of the focal industry, inertial pressures are likely to make this structural change difficult, hazardous, and limited (Barnett & Carroll 1995). Thus, it is reasonable to assume that at the time of entry into a focal industry, *de novo* firms' structural forms and employment relationships have a better fit with the focal environment than those of *de alio* firms. Additionally, *de novo* firms are more capable of structural changes to adjust to the shifting environment than *de alio* firms.

What are the implications of the processes of organizational competence and structural flexibility for firm innovation? Firms with better-developed capabilities and greater resources are more likely to "routinize" their innovative activity (Nelson & Winter 1982; Cohen & Levinthal 1990; Sorensen & Stuart 2000). Since, at the time of entry, *de alio* firms tend to be those with more developed capabilities and resources, it is reasonable to expect that many of them have routines for innovation, such as in-house R&D, that allow them to undertake innovation regularly and on a large scale (Mowery 1995). However, the same factors that make it possible for *de alio* firms to innovate regularly and on a large scale may hamper their involvement into and success at a state-of-the-art innovation, if these factors do not allow firms to adjust to shifting technological demands of the environment. For example, well-developed organizational competence constrains the information search of *de alio* firms forcing it to be "local" and "exploitative" (Cyert & March 1963; Nelson & Winter 1982; Henderson & Clark 1990; March 1991; Levinthal & March 1993). Established positional advantages, such as customer value networks, may prevent *de alio* firms from engaging in promising but uncertain innovations (Christensen & Rosenbloom; 1995; Christensen & Bower 1996). Other positional advantages, such as status or market leadership, may retard *de alio* firms' learning and result in poor innovation as well (Barnett & Hansen 1996; Lerner 1997; Barnett & McKendrick 2001). In sum, whereas organizational competence of *de alio* firms may allow them to innovate regularly, poorer structural flexibility causes their innovations to be detached from environmental demands.

The situation is different for *de novo* firms. A lack of well-developed capabilities, resources and positional advantages prevent *de novo* firms from innovating on a large scale. However, underdeveloped organizational competence and a high level of structural flexibility allow these firms to build capabilities that match the current state of a focal technological environment (Stinchcombe 1965; Hannan & Freeman 1977; Carroll et al. 1996; Sorensen & Stuart 2000). Therefore, *de novo* firms should be more alert to innovative opportunities and more pro-active in undertaking risky technological change than *de alio* firms. Based on this discussion, I predict that *de novo* firms produce significant product innovations at a higher rate than *de alio* firms.[4]

> **Proposition 1:** *De novo* firms undertake significant product innovation at a higher rate than *de alio* firms.

[4] However, technological success does not necessarily translate into commercial success (Teece 1986). Greater organizational competence of *de alio* firms should allow them to produce more reliable products that may enjoy greater market success, although they may not be state-of-the-art. Chapter 3 of my dissertation "Product Dynamics of *De Novo* and *De Alio* Firms in the Worldwide Optical Disk Drive Industry, 1983-1999" explores this issue.

Do differences in innovative behavior between *de novo* and *de alio* firms change as firms' tenure in the industry increases? Organizational ecology asserts that structural differences between organizational types at the time of industry entry may decrease over time but never completely disappear because of imprinting effects and inertial pressures (Hannan & Freeman 1984; Carroll & Hannan 2000).

As I discussed earlier, at the time of entry into a focal industry, imprinting and inertial processes make *de novo* firms' structural forms more flexible than those of *de alio* firms'. This difference between *de novo* and *de alio* firms in structural flexibility is likely to persist over time. As *de novo* firms age, they become subject to inertial pressures and become less and less structurally flexible. However, since *de novo* firms tend to be structurally simpler and more transparent than *de alio* firms that entered at the same time, inertial pressure is likely to be weaker for *de novo* firms than for *de alio* firms (Hannan, et al. 2002). Due to weaker inertial pressures, *de novo* firms are likely to maintain an advantage in structural flexibility over *de alio* firms and, therefore remain capable of introducing more significant organizational changes (including innovation) than *de alio* firms that entered at the same time.

As *de novo* firms age, their organizational competence is likely to improve, since firms develop better internal routines and relationships with the external environment (Nelson & Winter 1982; Hannan & Freeman 1984). Improved organizational competence coupled with greater structural flexibility should confer more innovative advantages onto *de novo* firms than onto *de alio* firms. Thus, innovation rates of *de novo* firms should increase with increasing organizational competence. However, at some point inertial pressure should overcome gains from improving organizational competence and innovation rates of *de novo* firms should decrease but probably never converge with those of *de alio* firms that entered at the same time.

This theoretical discussion makes it possible to suggest that the differences in innovation rates between *de novo* and *de alio* firms persist over time but the magnitude of these differences is likely to change. The difference in product innovation rates between the two types of firms is likely first to increase with increasing firms' tenure in the industry, as *de novo* firms develop organizational competence in the process of learning. However, after a certain point, the difference in product innovation rates between the two types of firms should decrease with firms' increasing tenure, as *de novo* firms' structural flexibility starts to decline.

> **Proposition 2**: The difference between *de novo* and *de alio* firms' product innovation rates is non-monotonic: *de novo* firms first have increasingly higher innovation rates, then decreasingly higher innovation rates than *de alio* firms, as firms' tenure in the industry increases.

Thus, I predict entry mode to have a strong effect on firm product innovation. If this relationship is true then I expect that entry mode explains additional variance in firm innovative behavior besides the variance explained by entrant-incumbent status.

> **Proposition 3**: Firm entry mode explains additional variance in firm product innovation that is not explained by firm incumbency status alone.

In the next section I convert my propositions into testable hypotheses.

Hypotheses Development

There are many different ways to measure technological innovation. In this study I focus on realized product innovation, which refers to innovations that made it to the market in the form of a product with improved technical performance. The difference in product innovation rates between *de novo* and *de alio* firms can be observed at two different levels. At the firm level, a firm successfully innovates every time it introduces to the market a product with technical performance better than that of its previous best product. At the industry level, a firm successfully innovates every time it introduces to the market a product with technical performance close to the technological frontier. The first process describes a firm's <u>absolute</u>

innovation rate: it reflects the firm's innovative efforts. The second process describes a firm's innovation rate relative to that of other firms in the industry. This process indicates whether the innovative efforts of a firm were successful at the industry level, that is, whether the firm's innovative efforts resulted in a product with performance that is among the best in the industry. Since the two processes do not always coincide, I consider how *de novo* and *de alio* firms differ with respect to both absolute and relative innovation rates.

The first set of my hypotheses predicts the differences between *de novo* and *de alio* firms in their absolute innovation rates, which I defined as firms' rates of market introduction of products with technical performance better than that of these firms' previous best products. Based on my theoretical discussion concluding that *de novo* firms tend to be more structurally flexible and more prone to organizational change than *de alio* firms, I predict that *de novo* firms undertake product innovation by improving the technical performance of their best products more often than do *de alio* firms:

> **Hypothesis 1.1:** *De novo* firms introduce products with performance parameters better than those of their previous best product at a higher rate than *de alio* firms.

Given that as *de novo* firms age, they develop organizational competence (e.g., refine their innovation routines), I expect their rates of introducing products with performance better than their previous best products to increase over time. However, after a certain point increasing inertial pressures should cause *de novo* firms' rates of product improvement to decrease. I believe, however, that the rates of product innovative improvement of the two types of entrants will never converge, because even as *de novo* firms age, they keep their advantage in structural flexibility over *de alio* firms because of weaker inertial pressures, and, therefore, should always have relatively higher product innovation rates. Therefore, I predict:

> **Hypothesis 1.2**: The difference between *de novo* and *de alio* firms' rates of introduction of products with performance parameters better than those of their previous best product is non-monotonic: *de novo* firms first have increasingly higher innovation rates, then decreasingly higher innovation rates than *de alio* firms, as firms' tenure in the industry increases.

Finally, I predict that entry mode explains additional variance in the firms' rates of introduction of products with performance better than that of these firms' previous best products, beyond the variance explained by incumbency status alone.

> **Hypothesis 1.3**: Firm entry mode explains significant amount of variance not explained solely by firm incumbency status in the rates of firms' introduction of products with performance parameters better than those of their previous best products.

I propose a matching set of hypotheses regarding the firms' innovation rates <u>relative</u> to other firms in the industry, which I measure as the rates of market introduction of products with performance close to the technological frontier. In particular, the previous theoretical discussion about entry mode and structural flexibility suggests that product innovations introduced by *de novo* firms are likely to be more significant in terms of their proximity to the technological frontier than product innovations introduced by *de alio* firms.

> **Hypothesis 2.1:** *De novo* firms introduce products with performance parameters close to the technological frontier at a higher rate than *de alio* firms.

Following my theoretical discussion about firm aging, I suggest that both *de novo* and *de alio* firms' rates of introducing products near the technological frontier change as their tenure in the industry increases. As firms acquire experience in a focal industry, their innovation rates first rise. However, as firms spend more time in the industry they become more and more inert as the environment shifts and their innovation rates decline. Since inertial pressures are much stronger for *de alio* than for *de novo* firms, I expect to observe that the ability of *de novo* firms to introduce products near the technological frontier starts deteriorating later and slower than that of *de alio* firms. In other words, I believe that, first, *de novo* firms' rates of innovation near the technological frontier are always higher than those of *de alio* firms; second, as *de novo* firms develop better organizational competence, their innovation rates first increase, and then as inertial pressures get stronger, *de novo* firms' innovation rates decrease. Therefore, I predict:

> **Hypothesis 2.2**: The difference between *de novo* and *de alio* firms' rates of introduction of products with performance parameters close to the technological frontier is non-monotonic: *de novo* firms first have increasingly higher innovation rates, then decreasingly higher innovation rates than *de alio* firms, as firms' tenure in the industry increases.

Finally, I expect entry mode to explain additional variance in firms' rates of introducing products with performance parameters close to the technological frontier beyond the variance explained solely by incumbency status.

> **Hypothesis 2.3**: Firm entry mode explains significant amount of variance not explained solely by firm incumbency status in the rates of firms' introduction of products close to the technological frontier.

METHODOLOGY

Data Sources for Optical Disk Drive Firms and Products

I test my hypotheses on the population of all optical disk drive producers that operated in the worldwide market from the beginning of the industry in 1983 through 1999, which is the last year of full coverage in the most comprehensive data source available.

The original data come from Disk/Trend, Inc., a market research company located in Mountain View, California. Disk/Trend publishes annual reports on different data storage devices, including optical disk drives. The first Disk/Trend report on optical disk drives was published in 1985. The reports publish technical specification on each product shipped by each producer of optical disk drives. There is also firm-level data on revenues and unit shipment for the largest firms in the industry.

Background on Optical Disk Drives

Technology. The key product of the optical disk drive industry is the optical disk drive, which is one of the main devices (among hard drives, floppies, tapes, disk arrays, etc.) used for the storage and retrieval of information. The optical method for data storage is based on the recording and retrieval of information with the help of a laser. Optical disk systems are composed of two main components: a disk for storage and a drive for recording, retrieval, and output (Purcell 2000).

An optical disk consists of four layers: a polycarbonate substrate layer, a reflective layer, a protective layer, and the label. Optical storage media use the intensity of reflected laser light as an information source. In the polycarbonate substrate layer, a laser beam encounters holes that correspond to the coded data, which are called *pits*. The areas between these pits are called *lands*. The substrate layer is covered with a thin reflective layer. The laser beam is focused on the reflective layer from the substrate layer. The reflected beam has a strong intensity at the lands and a weak intensity at the pits.

The process of optical recording and the retrieval of information can be described as follows. Information is stored on a polycarbonate disk in the form of pits. During recording, pits are generated by a laser beam. The stored digital information can later be retrieved by an optical disk drive. The drive's optical pickup creates a laser beam directed at the spinning disk. Logic timing circuits can register the difference between distance the light travels when it strikes lands and distance the light travels when it strikes pits. The pattern composed of pits and lands corresponds to the coding of 1s and 0s. The reflected signals are directed to a processor that reads the reflection and converts it into a stream of digital pulses, which in turn are converted into text, pictures, or sounds. The entire system is controlled via a microprocessor-based central processing unit.

Brief History of the Optical Data Storage Technology. In 1972, Philips Corporation announced a method of optical storage of audio content based on analog modulation techniques. The analog modulation approach was soon abandoned in favor of more promising digital signal encoding methods. During the same period, Sony Corporation was engaged in research to perfect error-correction methods that could be applied to digitally encoded audio. Collaboration between Sony and Philips resulted in the merging of Philips's signal format with Sony's error-correction method, and in June of 1980, the two companies introduced their proposal for the Compact Disc Digital Audio system. The proposed standard was adopted by 25 manufacturers and efforts shifted toward retooling the industry to support manufacturing products incorporating the new standard.

Adoption of the optical method for audio storage was paralleled by efforts of Philips, Sony, NEC, and other companies to develop techniques for storing data on disk. The result of these efforts was the CD-ROM (Compact Disk – Read Only Memory) format, tagged Yellow Book, which was introduced in 1985. Initially the costs and dismal performance of the first optical disk drives discouraged many potential users. However, further development drove costs down and improved performance. In 1986, a number of industry representatives agreed upon a common file system structure that became known as the High Sierra format. Following increasing adoption rates of High Sierra format, this format was formalized as ISO 9660 standard in 1988. ISO 9660 standard had a noticeable stimulating effect on the development of CD-ROM technology (Disk/Trend Report 1999; Purcell 2000).

The success of the audio CD and eventual acceptance of CD-ROM stimulated manufacturers to introduce and promote numerous types of digital storage products, some of which failed on the market but some of which still exist in various forms (see Figure 1).

[Figure 1 about here]

The next-generation device, which was introduced in the mid-1980s, provided a flexible write-once, read-many (WORM) capability. This enabled end-users to record and playback computer data from the same drive. The third generation optical disks, which are today's rewritable systems, were introduced in 1988. They offer record, playback, and erase capabilities.

Two different digital videodisk formats emerged in January 1995. One camp, led by Toshiba, introduced the Super Density format. Sony and Philips devised their own approach – the Multi Media Compact Disc. In December 1995, the charter for the DVD Consortium was drawn up and dissension among the industry leaders diminished as the standard for the Digital Versatile Disk (DVD) was formalized. The first DVD players were shipped in 1996.

The industry has been always characterized by format wars. The firms that instigated format wars were mostly large *de alio* producers fighting to increase their market share. The Optical Storage Technology Association (OSTA) was established in 1992 with a goal to end format wars by promoting industry standards that would allow compatibility across different types of drives and manufacturers. In 1997, OSTA developed MultiRead specification that enables all classes of CD disks to be read on current and future CD and DVD devices. The efforts of OSTA to promote the common standard succeeded in 2000, when 17 CD drive manufacturers, representing over 90 percent of all CD optical drive shipments worldwide, have achieved compliance with MultiRead specification.

Demographics of the Industry. Two types of firms have populated the optical disk drive industry. In the history of the industry, 83 diversifiers entered the market and 47 exited, while 24 start-ups entered and 18 exited. Eighty out of 83 diversifiers came into the optical disk drive industry from related industries: computers and computer peripherals, consumer electronics, electronic and electrical components, and optics. Figure 2 shows density of *de novo* and *de alio* firms over the history of the industry development. The fact that *de alio* firms have always dominated this industry and established all major technological formats makes this industry a conservative setting for testing my hypotheses about the innovative advantage of *de novo* firms.

[Figure 2 about here]

Operationalization of Variables

Starting events of production. I defined a firm's entry into the optical disk drive industry as occurring when the firm shipped its first optical disk drive product to the customer market. The Disk/Trend report provides information on the first customer shipment in varying degrees of precision. Disk/Trend gives some dates with precision to the month, others with precision to the quarter, and still others with precision to the year. To make the analysis tractable, all the information about timing was converted to decimal years. Dates given to the month were coded as occurring at the beginning of the month. Following Petersen's (1991) recommendations for dealing with time aggregation, dates given to only the quarter were coded as occurring at the midpoint of the quarter. Dates given to only the year were coded as occurring at the midpoint of the year.

Ending events of production. I defined a firm's exit from the optical disk drive industry as occurring when the firm stopped shipping its optical disk drive products. The Disk/Trend report does not provide exact information on the last customer shipment of the product. The report comes out in the third quarter of each year. It covers revenues and unit shipment for the previous calendar year, but it covers firms and products for the current year. Based on this information I assumed that the last shipment of the product happens in the third quarter of the year the product was last mentioned in a Disk/Trend report and coded a firm's exit as occurring at the midpoint of the third quarter of the last year the firm shipped its last product.

From 1983 to 1999, 107 firms entered the worldwide optical disk drive industry, and 65 exited. The data include 651 firm-year observations. These firms shipped 1,358 products on the worldwide optical disk drive market, of which 1,053 products exited the market. The data include 3,078 product-firm-year observations.

Dependent Variables. There are several dependent variables in this study designed to measure rates of firm product innovation. Rates of firm product innovation are operationalized as the rates at which a firm introduces to the market products with advanced level of technical performance.

I use a product's data access time as a performance parameter to construct the dependent variables. *Data access time* is the physical operation associated with positioning the read/write head of a storage device in the proper location to read or write a particular piece of data. Technically, data access time is the sum of the average positioning time plus the rotational latency (the inherent delay experienced by the laser read head when locating specified data). Data access time is an appropriate technical parameter for constructing measures of firm product innovation, because it is one of few important indicators of optical disk drive performance (Disk/Trend Report 1999; Purcell 2000). Time performance of optical disk drives greatly affects their competitiveness with other types of drives and their attractiveness to users (Disk/Trend Report 1999).[5]

Data access time is measured in milliseconds. Smaller (i.e., faster) data access time signifies better optical disk drive performance. As the industry has evolved, the industry's average data access time has decreased. To make the effects of product data access time across different years easy to interpret, I standardized its measure by dividing a product's data access time in each year by the industry's mean data access time in the year.

To test Hypotheses 1.1-1.3, I focus on the rate at which a firm introduces to the market a product with performance parameters better than those of this firm's best product made in the previous year. I created the variable *firm's rate of product improvement* that takes the value of one if in year *t* a firm introduced a product with data access time faster than data access time of its best product made in year *t-1*, and the value of zero otherwise. Both nominal and standardized measures of data access time are used to create two versions of this dependent variable.

To test Hypotheses 2.1-2.3, I created a set of dependent variables representing the rates of firms' introduction of products with data access time of different proximity to the technological frontier. I look at how firms differ in the rate of introduction of all products, technologically advanced products, technologically non-advanced products, and products with technical performance in the top 15%, 20% and 25% of the industry's performance distribution in a given year.

[5] Technically, market attractiveness of an optical disk drive is defined not only by its time performance but also by its recording capacity. Historically, however, time performance parameters have turned out to be much more decisive than recording capacity in defining the attractiveness of optical disk drives to users and in shaping their chances to compete with other types of drives, e.g., hard drives (Disk/Trend Report 1999; Merrill Lynch & Co. and McKinsey & Company Report 2001).

There are different ways to define the technological frontier. I constructed an endogenous measure of the technological frontier using a product with the best data access time in the industry in a given year as a point of reference for this year. Figure 3 shows the technological frontier defined by the product with the best (fastest) data access time in the industry in a given year. Figure 3 also shows that at the beginning of the industry, *de novo* firms moved the technological frontier, but *de alio* firms took the lead later.

[Figures 3 about here]

A product is defined as a *product with technical performance in the top 15%* of the industry's performance if its data access time is among the lowest (fastest) 15% data access time across all products in the industry in a given year. The same method is used to define whether a *product is in the top 20% and 25%* of the industry's performance. A product is defined as a *technologically advanced product* if its data access time is faster than industry mean data access time in a given year. A product is defined as a *technologically non-advanced product* if its data access time is equal to or slower than the industry mean data access time in a given year.

Independent Variables. There are two sets of independent variables in this study. The first variable measures firm entry mode, the second set of variables measures firm incumbency status. Unless otherwise noted, all the variables are updated annually.

De novo Firm Dummy. *De novo firm dummy* takes the value of one if a firm entered the worldwide optical disk drive industry as a start-up, and the value of zero if a firm diversified into this industry from another market. This variable is time-invariant.

Incumbent-Entrant Status Measures. Although the comparison of industry incumbents and entrants is a primary focus of the management of innovation literature, there is no uniform agreement about how to measure the incumbent-entrant construct. It is generally assumed that an incumbent is a firm that has been in the industry for a while, and an entrant is firm that has come into the industry more recently. However, what constitutes a temporal breakpoint separating incumbents from entrants is a serious definitional and measurement problem in this literature. I used four different measures of entrant-incumbent status that correspond to the most common constructs of incumbency status in the literature. I created and used all four measures in order to demonstrate that independently of how incumbency status is measured, entry mode explains additional variance in firm product innovation rates not explained by incumbency status alone.

The most popular approach in the innovation literature to the operationalization of an incumbent-entrant construct is to use a date of a major technological event as a breakpoint dividing the history of an industry into the "incumbent" and "entrant" periods. Firms that entered the industry before the technological event are defined as incumbents; firms that entered the industry after the technological event are defined as entrants. Technological discontinuity and the emergence of the dominant design are two technological events commonly used in the innovation literature for constructing incumbent-entrant measures.

Following the innovation literature, my first measure of incumbency status indicates whether a firm entered the industry before or after a technological discontinuity (Anderson & Tushman 1990; Henderson & Clark 1990; Christensen & Bower 1996; Tripsas 1997). Scholars who use this operationalization of incumbency assume that entrants are more likely to succeed at innovation than incumbents if a discontinuity is competence-destroying, the reverse is predicted for competence-enhancing discontinuities (Tushman & Anderson 1986; Henderson & Clark 1990). The most likely candidate for a technological discontinuity in the history of optical disk drive industry is the emergence of DVD technology in 1995. I coded *DVD incumbent* as a dummy variable that takes the value of one if a firm entered the industry anytime between 1983 and 1995, and the value of zero if a firm entered after 1995. This variable is time-invariant.

Using an event of technological discontinuity as a breakpoint separating incumbents and entrants is problematic for several reasons. First, it is unlikely to predict *ex-ante* what technological change introduces a discontinuity. Second, it is not clear what date should be chosen as the date of a technological discontinuity: the date of the invention that created a discontinuity, the date when the new technology became a focus of attention or some other date? Finally, as I mentioned earlier, it is not very meaningful to define a technological discontinuity as either competence-enhancing or competence-destroying, since what is destroying for some incumbents can be enhancing for others (Cohen & Levinthal 1990; Levinthal 1998; Klepper & Simons 2000).

The second measure of incumbency status, which is based on the breakpoint of a major technological event, indicates whether a firm entered the industry before or after the emergence of the dominant design. It was found that firms that entered the industry before the establishment of the dominant design, defined as a major standard, had a time advantage in the developing of complementary assets, and therefore, better opportunities to reap benefits from a new institutionalized technology than firms that entered after the dominant design emerged (Suarez & Utterback 1995; Baum, Korn & Kotha 1995). The issue with this measure is the choice of a breakpoint. What date should be chosen as the date of the emergence of the dominant design: the date when a standard was officially accepted or the date when a format that became a base for this standard was first adopted?

The most likely candidate for a dominant design in the history of the optical disk drive industry is the only official standard ISO 9660. This standard formalized a CD-file data structure format that made compatibility across different optical disk drives possible. ISO standard 9660 was adopted in 1988. *CD incumbent/ ISO 9660* is a dummy variable that takes the value of one if a firm entered the industry anytime in 1983-1988, and the value of zero if a firm entered after 1988. To test for sensitivity of this measure to the chosen date, an alternative measure based on the date of the acceptance of High Sierra format (1986) that became a base for ISO 9660, is constructed. *CD incumbent/ High Sierra Format* is a dummy variable that takes the value of one if a firm entered the industry anytime in 1983-1986, and the value of zero if a firm entered after 1986. Both variables are time-invariant.

The second major approach to the operationalization of incumbency status assumes that incumbency is a function of time a firm has been operating in the industry. Both categorical and continuous measures can be used. The innovation literature tends to use a categorical construct, which is based on the temporal breakpoint dividing a firm's life in the industry into the "entrant" and "incumbent" periods. This literature assumes that entrants are more innovative than incumbents, because they have greater structural flexibility.

I specified this measure as follows. *Entrant dummy with 4-year window* is a time-variant dummy variable that for each year of a given firm's existence in the industry takes the value of one if this firm entered the industry 4 years ago or less, and takes the value of zero if this firm entered the industry more than 4 years ago. *Entrant dummy with 5-year window* is constructed in the equivalent way to test for sensitivity of results to a breakpoint dividing a firm's life into "entrant" and "incumbent" periods. The problem with this measure is the arbitrary nature of a breakpoint choice.

A continuous measure of incumbency avoids the problem of choosing an arbitrary breakpoint dividing a firm's life into the entrant and incumbent periods. It is assumed that the longer the firm has been in the industry, the less it is perceived as an entrant and the more it is perceived as an incumbent. Unfortunately, to my knowledge, this measure of incumbency is only rarely used in the innovation literature (but see Sorensen & Stuart 2000). Given a continuous measure of incumbency, it is possible to predict a curvilinear relationship between innovation rates and increasing incumbency status. In particular, as a new entrant ages in the industry, it acquires experience and resources that help it innovate at a higher rate. However, continuous aging (increasing incumbency) results in increasing structural rigidity and inflexibility and is likely to decrease the firm's innovation rates (Hannan & Freeman 1984; Carroll at el. 1996; Sorensen & Stuart 2000.)

I specified the continuous measure of incumbency as *firm's tenure,* which is a variable corresponding to the number of years a firm has been in the industry. Interaction between firm tenure and the *de novo* dummy captures the effect of *de novo* firm aging on innovation rates. Firm tenure captures the effect of *de alio* firm aging on innovation rates. In models with categorical measures of incumbency status, firm tenure is used as an organizational control.

Organizational Controls. Organizational characteristics other than entry mode and incumbency status may affect a firm's ability to innovate. Several organizational controls are used to account for these influences. Unless otherwise noted, all controls are updated annually.

Prior theoretical and empirical research in the organizational ecology and innovation literatures suggests that aging has an inverted-U shape relationship with the organizational propensity and ability to innovate. On the one hand, as new entrants age, they acquire experience and resources that allow them to innovate at a higher rate. On the other hand, as firms continue aging they become more inert and inflexible and their innovation rates are likely to decrease (Hannan & Freeman 1984; Sorensen & Stuart 2000). *Firm tenure* measured as the number of years a firm has operated in the optical disk drive industry, and its square term are controlled to account for a curvilinear effect of firms' aging on their innovation rates.

Larger firms have more resources that they can devote to innovation efforts than smaller organizations (Cohen 1995; Freeman & Soete 1999). To account for these differences organizational size is controlled. I constructed a measure of the *firm's size* as scale of operations, specifically, as a firm's annual revenue in millions of US dollars from its sale of optical disk drives. Disk/Trend provides precise firm-specific revenue data only for the major producers in the market: the top 10 to 20 optical disk drive manufacturers, such as Sony, NEC, and Philips, which collectively represent approximately 90% of all annual industry revenue. For non-major producers, Disk/Trend does not publish firm-specific revenue figures. However, Disk/Trend records the annual aggregate revenue of these non-major, smaller producers based on their geographic location: companies based in the United States and those not in the United States. I imputed the annual revenue for each smaller producer in non-US and US categories by dividing the total revenue of non-major producers in a category by the number of non-major producers in that category. The measure is logged to reduce skewness, and one-year lagged.

Firms that have large market shares have more resources to innovate than other firms (Schumpeter 1950; Freeman & Soete 1999). On the other hand, a dominant position on the market may retard learning of these firms that may suppress their innovation efforts (Barnett & Hansen 1996). *Dominant firm* dummy takes the value of one if a firm is among ten firms with the greatest market share in a given year and zero otherwise to control for these influences. The data on market share is available for 1988-1999. This measure is one-year lagged.

Japanese headquarters dummy takes the value of one if a firm has headquarters in Japan and zero if otherwise and is controlled to account for the innovative distinctiveness attributed to Japanese manufacturers (Gerlach & Lincoln 2000; West 2002).

Firms with products near the technological frontier may have a low rate of product performance improvement, not because of fewer innovation efforts, but because their current products' performance is already near the frontier and it is very difficult to improve further. To control for this influence, I constructed two measures. The first variable *firm's best product data access time* is the data access time of a firm's fastest product in a given year. The larger the size of this variable is, the slower the product performance, and therefore, the larger the room for product performance improvement. Thus, I expect this variable to have a positive effect on firms' rate of product performance improvement. The other variable *firm cumulative number of products within top 15% of industry performance* is a firm's cumulative number of products with data access time in the top 15% of industry performance. This variable is also used as a control for a possible disincentive for firms that introduced "best products" in the past to innovate again (Barnett & Hansen 1996; Lerner 1997). Its expected effect is negative. Both variables are one-year lagged.

When firms have large number of products on the market, the probability that they have at least one product with performance closer to the technological frontier can be higher than for firms with very few products on the market. To control for this possibility, I construct the variable *firm's total number of products on the market*, which is the total number of products a firm has on the market in a given year. This variable is one-year lagged.

Environmental Controls. Several variables are used to control for industry processes. Unless otherwise noted, all variables are updated annually. I include *worldwide industry* *revenues*, which is measured in millions of U.S. dollars, to control for the effect of environmental munificence.

The number of other product models in the market may affect the probability that a firm will introduce a new product. More product models in the market indicate more intense competition, which is likely to stimulate a focal firm to introduce a new product in an attempt to gain or regain competitive advantage (Barnett & Hansen 1996; Barnett & McKendrick 2001). *Industry product density* measured as the number of products on the market in a given year is controlled to account for this effect. This measure is one-year lagged.

As Figure 1 shows, different formats were introduced in almost every year of industry existence. Some of these were influential; others had hardly any significant impact. Only the High Sierra format became a widely adopted industry format that was formalized as the ISO 9660 standard in 1988. Thus, the variable s*tandard ISO 9660 period dummy*, which takes the value of one for years 1988-1999 and zero otherwise, is created to control for the effects of this standard on firm product introduction rates. The effects of other formats are captured by the variable *industry age,* which is a time trend in the worldwide optical disk drive industry. The industry age variable is also meant to control for other unobserved and observed temporal changes that may affect product chances to disappear from the market.

Identification Issue. Sample selection bias may result when factors that affect the rates of product introduction also cause firms to be selected out of the industry. Descriptive analysis shows that firms that exit the optical disk drive industry in a given year are two times less likely to introduce products with performance close to the technological frontier than firms that do not exit in the given year. In cases where exiting firms do introduce products at the technological frontier, they introduce three times fewer products than non-exiting firms. Thus, exiting and non-exiting firms have a significantly different dynamic of introducing technologically advanced products to the market. I have to control for this difference to avoid a sample selection bias.

I created a *sample selection term* to control for any effect that exiting the industry firms have on their probability to introduce innovative products. I used the technique described by Lee (1983) and implemented by Barnett (1994). This technique is a generalization of Heckman's (1979) two-stage sample selection estimation procedure.[6] I followed Barnett's (1994) technique of calculating F(t), the cumulative hazard function, which was then used to calculate $\lambda = [\phi(\Phi^{-1}[F(t)/[1\text{-}F(t)]$, where ϕ and Φ are the standard normal density and distribution functions respectively. F(t) was calculated based on a selection hazard rate model. This model was specified based on usual ecological guidelines for building models of organizational mortality rates (Carroll & Hannan 2000) and includes lagged organizational density, organizational density at founding, firm size, firm tenure, firm number of products on the market, *de novo* status dummy, and worldwide industry revenues. This model is given in Table A1 in the Appendix. I included λ, the sample selection term, as a control in the analyses.

Model Specification

To test Hypotheses 1.1-1.3 that make predictions about rates at which a firm introduces to the market a product with performance parameters better than those of this firm's best product in the previous year, I use continuous-time event-history analysis. I treat a firm as the unit at risk, and the "dependent variable" is the probability of a firm's introduction of a product with data access time better than that of its previous best product, i.e., the probability that the firm will experience a product improvement event defined as:

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[6] "In Heckman's model it is assumed that F(t) is normally distributed. This allows λ to be estimated by the inverse mills ratio from a probit model (see Maddala 1983). However, Goldberger (1983) shows that this approach is sensitive to violations of the normality assumption. Lee's approach, used here, requires no such restriction on the distribution of F(t)." (Barnett 1994:354)

$$r(t) = \lim_{\Delta t \to 0} \frac{\text{Prob}[t < T < t + \Delta t \mid T < t]}{\Delta t} ,$$

where *T* is a random variable for the time of the event of interest, *t* is the time elapsed since the last time a firm experienced a product improvement event, and *P(.)* is the probability of the firm's product improvement event over the interval *[t, t+Δt]* given that the improvement did not happen at time *t*. Since some firms experience more than one product improvement event over the course of their tenure in the industry, a focal firm's duration clock is set back to zero after each event of product improvement. I use a *piecewise exponential* function to represent variation in the timing of a firm's rate of improved product introduction to allow a flexible specification of duration-dependence. A *piecewise exponential* model represents a widely used strategy that splits the time-axis into time pieces determined by an analyst (Carroll & Hannan, 2000: 136-38). After examining life tables and exploring estimates of a variety of choices of the breakpoints, I decided to break the duration scale in years in two time pieces: 0-1 and 1 and greater.

To test Hypotheses 2.1-2.3 about the firms' rates of introduction of products with performance parameters close to the technological frontier, I have to take into account that many firms introduce more than one product in a given year and that introductions can happen at any time during the year. Since a larger part of the data source is precise only to the year, it is not possible to determine the waiting time between all events of product introduction. It is common to analyze data of this form using event-count analysis (Carroll & Hannan 2000: 129-31; 146-49). Firms' product introduction rates are assumed to be events governed by stochastic processes. The transition rate of event occurrence (i.e., the rate at which a firm undertakes its next product introduction) is defined as

$$h_n(t) = \lim_{\Delta t \to 0} \frac{\text{Prob}[Y(t+\Delta t)-Y(t) = 1 \mid Y(t) = n]}{\Delta t} ,$$

where $Y(t)$ is a random variable denoting the cumulative number of products introduced by a firm by time t. The stochastic process of interest, the product introduction process, is $[Y(t)| t\leq 0]$ with state space equal to $[0,1,2,\ldots]$. The fundamental parameter of such a process is a firm's product introduction rate, the rate of arriving at state $n+1$ at time t. The analysis focuses on year-to-year variations in counts.

The two common estimation models used in event-count analysis are Poisson regression model and negative binomial regression model. The later is used if the data is overdispersed that happens when an assumption of Poisson that the variance in counts is equal to the mean is violated. Overdispersion in this data arises from the years when firms do not introduce any products, i.e., from the years with zero events of product introduction. I used a zero-inflated Poisson model designed to deal with excess zeros in the data (Greene 1997: 943-945). The model for Y_{it}, the number of products introduced by a firm in a given year, is given by two equations: $Y_i=0$ with probability q_i and $Y_i \sim$ Poisson (λ_i) with probability $1-q_i$. This implies that prob ($Y_i = 0$) = $q_i +[(1-q_i) R_i(0)]$, and prob($Y_i = j > 0$) = $(1-q_i) R_i (j)$, where $R_i (y) = \exp(-\lambda_i) \lambda_i / y_i!$, the Poisson probability, and the rate of events $\lambda_t = \exp(\beta' X_i)$. The state probability q_i is specified as $q_i \sim$ logistic (v_i), where $v_i = \gamma' Z_i$ (Carroll & Swaminathan 2000).

In the zero-inflated Poisson model, X_i is a vector of variables that affects the occurrence of non-zero counts, years when a firm introduces one or more products to the market, and Z_i is a vector of variables that affects zero counts, years when a firm introduces no products. In this study I expect that the likelihood of zero product introduction increases with industry age, as a result of the shift from product innovation to process innovation (Abernathy & Utterback 1978, Gort & Klepper 1982; Klepper 1997), and include this variable into the part of the model that predicts the occurrence of zero events, i.e., into a so-called inflated model. Vuong test (Greene

1997: 944-945) shown that a zero-inflated Poisson framework is favored over either negative binomial or zero-inflated negative binomial models, i.e., event counts are not overdispersed in the zero-inflated Poisson framework.

A general form of the models I estimate specifies the rate of product introduction in year *t* as a log-linear function of whether a firm is *de novo* or *de alio*, whether a firm is an incumbent or an entrant, interaction term between a firm's entry mode and incumbency status and a vector of organizational and environmental controls *X(t):*

$$\ln(\text{rate of product introduction}(t)) = \beta 1(\text{denovo}) + \beta 2(\text{incumbent}) + \beta 3(\text{denovo}*\text{incumbent}) + \gamma X(t)$$

In testing the hypotheses, I estimated piecewise exponential and zero-inflated Poisson models using the method of maximum likelihood as implemented with user-defined routines in STATA. To estimate rate models with time-varying covariates, I constructed split-spell data breaking observed durations in year-long periods with values of covariates updated every year.

FINDINGS

Table 1 provides descriptive statistics for the variables used in the analyses. It shows that, on average, firms introduce two products to the market in a given year. However, on average, firms introduce only about one product with technical performance close to the technological frontier in a given year. While some firms introduce no products to the market at all, some firms introduce as many as 22 products in a given year. The average tenure of firms in the industry is about 3.6 years (3.6 standard deviation). *De alio* firms stay in the industry, on average, for 3.9 years (3.6 standard deviation), whereas *de novo* firms stay for 2.1 years (2.7 standard deviation).

Tables 2 and 3 are *piecewise exponential* hazard rate models designed to test Hypotheses 1.1-1.3 predicting that *de novo* firms introduce products with performance (measured as <u>nominal</u>

data access time) better than that of their previous best product at a higher rate than *de alio* firms.[7]

In Table 2, Model 2.1 provides a baseline for the key covariates that influence firms' rate of introducing products with data access time faster than that of their previous best product. In this model, coefficients on duration dependence show that the more time has elapsed since the last "product improvement" event, the more likely a firm undertakes an innovative improvement in its best product. Organizational tenure in the industry has a strong negative effect on firm product improvement rates: the longer the firm has been in the industry, the lower the rate at which this firm introduces a product with data access time faster than that of its previous best product. The effect of the quadratic term of firm tenure is not significant and, therefore, not included into the model. Organizational size has a predicted positive effect on firm product improvement rates, indicating that firms with more resources exert more innovative efforts. Firms with the largest market share have lower product improvement rates than the other firms, but this effect is not significant. Japanese multinationals do not significantly differ in product improvement rates from firms with headquarters in other geographic regions.

Firms whose best products are relatively slow in terms of time performance have a higher rate of improving their product performance relative to firms whose products are already fast (as shown by the significant positive effect of the variable a *firm's best product data access time*). Firms with extensive cumulative experience of introducing products close to the technological frontier (defined as the top 15% of industry performance) show nearly significant lower rate of product improvement, indicating that it is very difficult to innovate in products already near the

[7] The same models were run to test whether *de novo* firms introduce products with standardized data access time better than those of their previous best product at a higher rate than *de alio* firms. The results were virtually identical to those based on the product performance measure of nominal data access time.

technological frontier. Firms with a high risk of exit from the industry (as indicated by sample selection term) have insignificantly lower product improvement rates than firms with a lower risk of exit. Neither of environmental controls has a significant effect on a firm's rate of introducing products with data access time faster than that of their previous best products.

In Model 2.2, I add a key explanatory variable – *de novo* firm dummy. This variable has a predicted significant positive effect on firm product improvement rate. In addition, Model 2.2 significantly improves over Model 2.1 statistical fit (likelihood ratio test of 8.6, 1 d.f., p<.003). This effect indicates that *de novo* firms introduce to the market products with data access time faster than that of their previous best product at a significantly higher rate than *de alio* firms. In other words, *de novo* firms have higher absolute product innovation rates than *de alio* firms. Thus, Hypothesis 1.1 is supported.

In Model 2.3, I add the interaction term between *de novo* dummy and firm tenure. Although its effect in the predicted positive direction, it is highly insignificant. This result indicates that the difference between *de novo* and *de alio* firms in product improvement rates persists but the magnitude of this difference does not change as firm tenure in the industry increases. Thus, Hypothesis 1.2 about non-monotonic difference between *de novo* and *de alio* firms in absolute innovation rates (measured as product improvement rates) is rejected.

Table 3 is a summary of twenty different models that are designed to test whether entry mode explains additional variance in firm product performance improvement rates not explained by incumbency status alone. Model 2.1 is used as the baseline for all twenty models. There are five sets of models that correspond to five different measures of entrant-incumbent status found in the literature. Each set includes four different models. Within each set of four models, the first model includes only the *de novo* dummy, the second model includes only the incumbent measure, the third model includes both the *de novo* dummy and the incumbent measure, and the last model includes the *de novo* dummy, the incumbent measure and the interaction term between them. The columns of Table 3 display coefficients for the *de novo* dummy, the incumbent measure and their interaction, and model log likelihood statistics. Each row of Table 3 indicates which measure of incumbency is used in each set of four models: the DVD Incumbent dummy, the CD Incumbent/ High Sierra dummy, the CD Incumbent/ ISO9660 dummy, the entrant with 4-year window, or the entrant with 5-year window.

Table 3 shows that only the CD Incumbent/ High Sierra variable among five incumbency measures shows a significant effect on firm product improvement rates (See Models 3.22-3.24). This effect indicates that firms that entered the industry before or during the emergence of High Sierra format in 1986 (that became a dominant design for CD drives two years later) have significantly higher product improvement rates than firms that entered after the establishment of this format. This effect is consistent with the literature that implies that firms that entered before the emergence of the dominant design (incumbents) have a time advantage allowing them to develop complementary assets and reap benefits from the newly institutionalized technology over latecomers (entrants) (Suarez & Utterback 1995; Baum, Korn & Kotha 1995). Model 3.34 shows a significant interaction effect between *de novo* dummy and the CD Incumbent/ ISO9660 indicating that *de novo* firms that entered before or during the emergence of Standard ISO 9660 in 1988 experience lower product improvement rates than those that entered later.

Most importantly, Table 3 consistently shows that the significant effect of entry mode on firm product performance improvement rates holds when either of five different measures of incumbency is included into the same model. Thus, Hypothesis 3.1 is supported.

Tables 4-6 are zero-inflated Poisson models that are designed to test Hypotheses 2.1-2.3 predicting that *de novo* firms introduce to the market products with performance parameters close to the technological frontier at a higher rate than *de alio* firms.

In Table 4, Model 4.1 provides a baseline for the key covariates that influence firms' rate of introducing products with data access time in the top 15% of industry performance. In this model, organizational tenure has the predicted curvilinear effect on introduction rates of top 15% products with a turning point of about six years. A firm's rate of innovative product introduction increases with increasing firm tenure in the industry until the firm reaches about six years old and then the rate decreases. Organizational size has the predicted positive effect: the larger the firm, the higher its introduction rates of products with top 15% performance. The Japan HQ dummy has a positive but not significant effect. Firms with largest market share do not make a difference either. A firm's total number of products on the market has a positive significant effect on firm probability to introduce a product with performance close to the technological frontier. The large significant negative effect of the sample selection term on innovative product introduction rates indicates that the more likely a firm is to exit the market, the lower its rate of introduction of products with top 15% data access time. Among environmental controls, industry product density has a predicted positive effect showing that increasing competition makes firms innovate by introducing technologically advanced products at a higher rate. Worldwide revenues have a significant negative effect: the more sales are generated from existing products, the less likely firms are to introduce new advanced products. The period effect of standard ISO 9660 has a positive effect but it is not significant.

In Model 4.2, I add a key explanatory variable – *de novo* firm dummy. This variable has a predicted significant positive effect on firm introduction rate of products with top 15%

technical performance. In addition, Model 4.2 significantly improves over Model 4.1 statistical fit (likelihood ratio test of 5.5, 1 d.f., $p < .02$). This effect indicates that *de novo* firms introduce to the market products with data access time in the top 15% of industry performance at a significantly higher rate than *de alio* firms. In other words, *de novo* firms introduce more significant product innovations (i.e., innovations close to the technological frontier) than *de alio* firms. Thus, Hypothesis 2.1 is supported.

In Model 4.3, I interact *de novo* firm dummy and firm tenure (continuous specification of incumbency)[8]. In Model 4.3, the effect of *de novo* firm dummy becomes insignificant, but the interaction term shows a significant positive effect on firm introduction rates of top 15% products. The effect of firm tenure is still an inverted U-shape and significant. As Figure 4 visually demonstrates, together the main and interaction effects show that there is no difference between *de novo* and *de alio* firms in the introduction rates of top 15% products at the time of industry entry, when firms' tenure is equal to zero. However, as *de novo* firms' tenure in the industry increases, their rates of introducing products with top 15% data access time become significantly and increasingly greater than those of *de alio* firms. In contrast, as *de alio* firms' tenure in the industry increases, their rates of introducing products with top 15% data access time first increase then decrease when firms' tenure reaches about six years old. Thus, although there is no significant difference between *de novo* and *de alio* firms at the time of entry, their innovation rates become significantly different as their incumbency status increases. It appears that the observation window in this study is too short (15 years for *de alio* firms and 12 years for *de novo* firms) to see the prediction of the second part of Hypothesis 2.2 regarding the decreasing

[8] I also interacted *de novo* dummy with the quadratic term of firm tenure but this effect was highly insignificant and I did not include it into Model 4.3.

difference in the rates of advanced product introduction between *de novo* and *de alio* firms. Thus, Hypothesis 2.2 is only partially supported.

[Figure 4 about here]

Table 5 is a summary of twenty different models that are designed to test whether entry mode explains additional variance in firm introduction rates of products with top 15% technical performance that is not explained by incumbency status alone. Model 4.1 is used as the baseline for all twenty models. Table 5 is constructed in the same manner as Table 3. Table 5 shows a significant effect on firm advanced product introduction rates of only one incumbency measure: CD incumbent/ISO 9660. In other words, firms that entered the optical disk drive industry before or during the establishment of the dominant design of ISO 9660 in 1988 (incumbents) have higher rates of top 15% product introduction than those entered after the standard was formalized (entrants). Again, this effect is consistent with the literature on the dominant design (Suarez & Utterback 1995; Baum, Korn & Kotha 1995). Surprisingly, the effect of DVD incumbent measure (that indicates whether firms entered the industry before and after technological discontinuity of DVD technology) is not significant either statistically or in magnitude. However, it is possible that the insignificance of this variable is driven by a short "post-discontinuity" observation window, which is only 3 years (1996-1999).

Most importantly, Table 5 demonstrates that *de novo* firms have significantly higher rates of introduction of top 15% products than *de alio* firms even when different incumbency measures are included into the same models. This consistent effect of *de novo* dummy indicates that entry mode explains additional variance in firm product innovation (measured as a rate of introduction of products close to the technological frontier) that is not explained by incumbency status alone. Thus, Hypothesis 2.3 is supported.

Finally, Table 6 compares the effects of entry mode on the rates of market introduction of all products, products with performance faster than the industry mean, products with performance slower or equal to the industry mean, and products with performance of different proximity to the technological frontier: 15%, 20%, and 25%. The goal of this table is to test for sensitivity of my findings to different operationalizations of proximity to the technological frontier. This table shows that there is no difference between *de novo* and *de alio* firms in the rate of introduction to the market of all products and products with performance equal or slower than the industry mean. However, *de novo* firms introduce products with data access time faster than the industry mean, and products with data access time in the top 15%, 20% and 25% of industry performance distribution at a significantly higher rate than *de alio* firms.

CONCLUSION

The results demonstrate that entry mode explains additional variance in firms' innovation rates that is not explained by incumbency status alone. I have three key findings. First, I found that *de novo* firms introduce products with performance parameters that improve over those of these firms' previous best products at a significantly higher rate than *de alio* firms. These results hold when different measures of incumbency status are considered. Second, I found that *de novo* firms introduce products within 15%, 20% and 25% of the top industry performance at a significantly higher rate than *de alio* firms. These results hold even when different measures of incumbency status are controlled.

Finally, I found that as firms' tenure in the industry increases, *de novo* firms introduce products within the top 15% of industry performance at an increasingly higher rate than *de alio* firms. If one assumes that incumbency is a function of time that a firm spends in the industry, then this finding suggests that among incumbents (i.e., firms with long tenure in the industry), those that entered the industry as *de novo* firms are more likely to introduce innovation at the technological frontier than those that entered the industry as *de alio* firms. Thus, firm entry mode can be one reason the management of innovation literature reports conflicting findings regarding incumbents' abilities to undertake major innovations.

In sum, the findings of consistent significant effects of entry mode on firms' product innovation suggest that entry mode is an important predictor of firm innovative behavior and it deserves further attention.

Figure 1. Historical Summary of Optical Data Storage Technology

1972 Philips announces optical storage method for audio

1978 Sony and Philips collaborate on signal format and disk material

1980 Compact Disc Digital Audio (CD-DA) system standard developed by Sony and Philips is adopted

1983 Compact Disc is introduced in the United States

1984 CD-ROM (Compact Disk–Read Only Memory) format is introduced

1986 High Sierra format is established

1986 CD-I (Compact Disk-Interactive) standard developed by Philips is released

1988 The standard (ISO 9660) for file structure of CD-ROM for information interchange is adopted

1988 The first rewritable optical format is introduced

1992 Optical Storage Technology Association (OSTA) is established to help the creation of optical standards

1993 CD-R (Compact Disk – Write Once) format is introduced by Philips

1994 Video-CD format is introduced

1995 DVD Consortium (DVD Forum since 1997) is established to define DVD standards

1996 DVD (Digital Versatile Disk) format is agreed upon

1996 CD-RW (Compact Disk–Rewritable) format emerges as a result of collaboration between Hewlett-Packard, Mitsubishi Chemical Corporation, Philips, Ricoh, and Sony

1997 DVD-ROM (read only) drives become available

1997 OSTA develops MultiRead specifications and test plans for compatibility among CD-DA, CD-ROM, CD-R, CD-R/RW & DVD-ROM devices

1997 DVD-R (write once) format appears

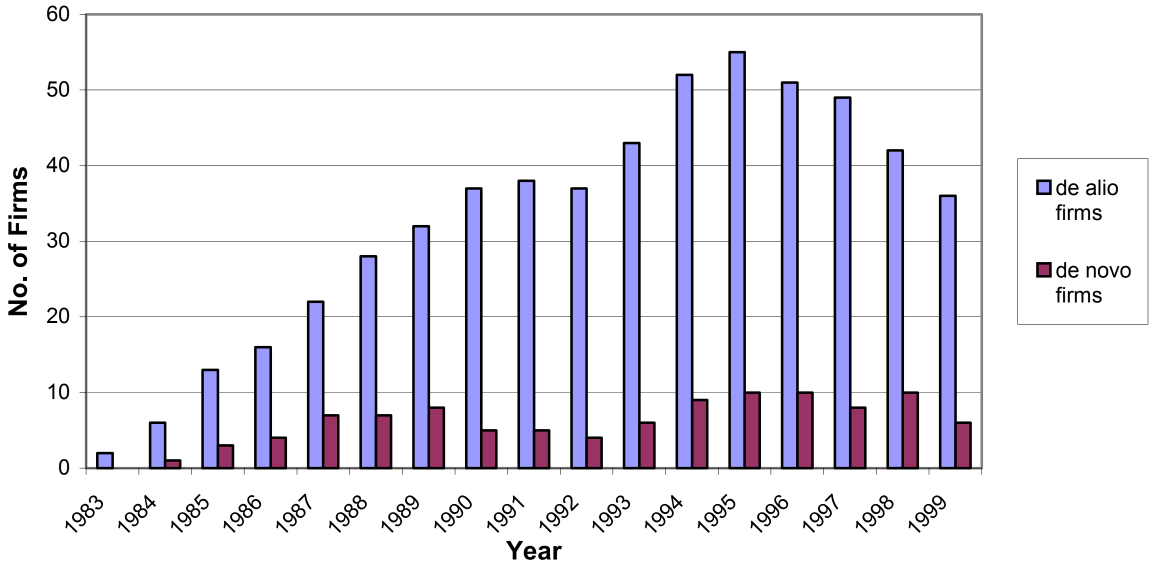
1997 DVD-RAM (rewritable) format is released by Hitachi, Matsushita Electric and Toshiba

1997 DVD+RW (rewritable) format is released by Sony, Philips & Hewlett-Packard

1999 OSTA develops MultiRead2 specifications and test plans for compatibility among CD-ROM, CD-R, CD-R/RW, DVD-Video, DVD-Audio, DVD-ROM and DVD-RAM drives

2000 17 CD drive manufacturers, representing well over 90 percent of all CD optical drive shipments worldwide, achieve compliance with MultiRead specification developed by OSTA

Figure 2. Density of Firms by Entry Mode



Figire 3. Technological Frontier Defined by the Fastest (Minimum) Data Access Time by Entry Mode

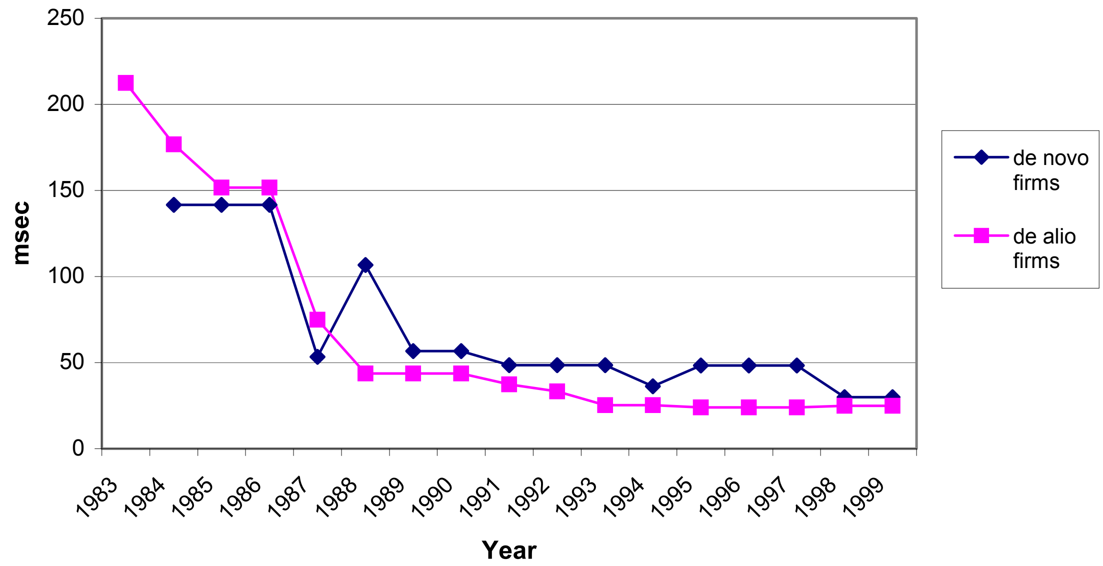


Figure 4. Joint Effect of Firm Entry Mode and Firm Tenure on the Organizational Rates of Introduction of Products with Top 15% Data Access Time

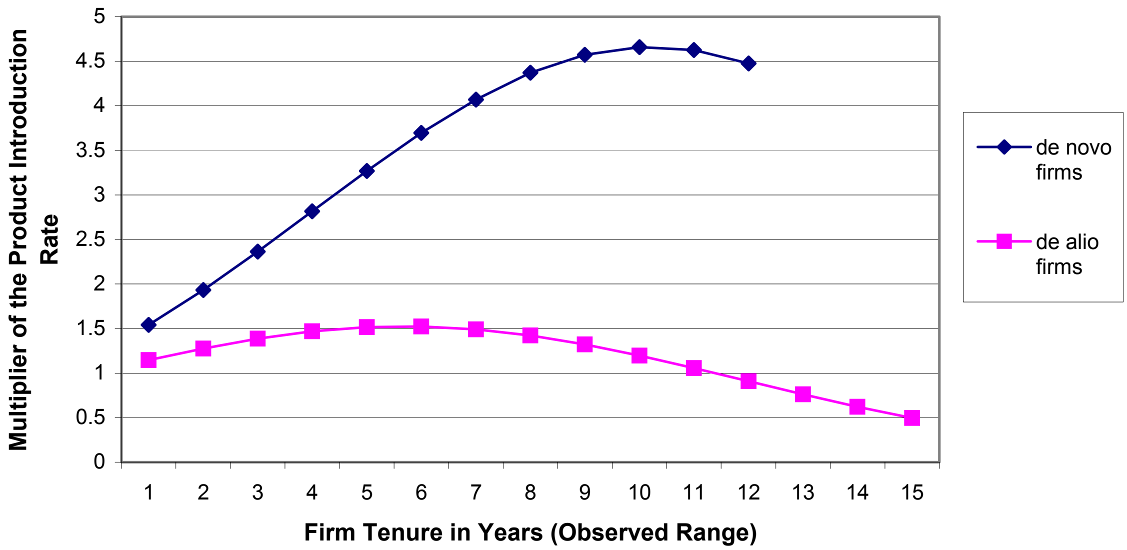


Table 1. Descriptive Statistics for Optical Disk Drives Producers: Split-Spell File

	Mean	St.Dev	Min	Max
Firm introduced a product with nominal data access time that improves over its best previous product (t)	.263	.440	0	1
Firm introduced a product with standardized data access time that improves over its best previous product (t)	.272	.445	0	1
Firm's number of new products (t)	2.09	2.80	0	22
Firm's number of new products with data access time faster than industry mean (t)	1.10	1.77	0	12
Firm 's number of new products with top 15% data access time (t)	1.18	2.01	0	19
Firm's number of new products with top 20% data access time (t)	1.46	2.32	0	20
Firm's number of new products with top 25% data access time (t)	1.59	2.42	0	21
Firm's number of new products with data access time equal or slower than industry mean (t)	.737	1.32	0	9
De novo Firm dummy=1	.157	.364	0	1
DVD Incumbent dummy [entry in 1983-1995=1]	.920	.271	0	1
CD Incumbent dummy/ IS09660 [entry in 1983-1988=1]	.547	.498	0	1
CD Incumbent dummy/ High Sierra [entry in 1983-1986=1]	.343	.475	0	1
Entrant dummy [4-year window] (t)	.535	.499	0	1
Entrant dummy [5 year window] (t)	.625	.484	0	1
Firm Tenure in the Industry [in years] (t)	3.61	3.55	0	15.13
De alio firm tenure	3.88	3.62	0	15.13
De novo firm tenure	2.14	2.69	0	12.5
Firm Size: revenue in the optical disk drive industry	64.8	151.94	.28	1079.9
[not logged, logged] (t-1)	2.59	1.78	-1.27	6.98
Firm's Number of Products on the Market (t-1)	4.83	5.91	0	43
Dominant firm =1 [10 firms with the largest market share] (t-1)	.199	.399	0	1
Japan HQ Firm dummy =1	.458	.499	0	1
Firm's Best Product Data Access Time (t-1)	169.34	149.68	24	1005
Firm's Cumulative Number of Products with Data Access Time in the top 15 % of industry performance (t-1)	4.79	8.34	0	72
Industry Product Density (t-1)	215.49	115.29	2	375
Worldwide Industry Revenues (t-1) \[in millions of US dollars]	2922.6	2633.3	2	8293.1
Industry Age/ Time Trend (t)	10.02	4.00	0	16
Period Effect of ISO9660 (1988-1999) =1	.888	.316	0	1
λ all firms	-1.59e-09	1	-.689	9.18
de novo firms	.547	1.65	-.675	9.18
de alio firms	-.102	.786	-.689	4.74

N of firms 107 (*de alio*=83, *de novo* =24); N of exits 65 (*de alio*=47, *de novo* =18); N of firm-years 651 (*de alio*=549, *de novo*=102)
N of products 1,358 (*de alio*=1,219; *de novo* =139); N of product-years 3,078 (*de alio*=2,805; *de novo* =273)

Table 2. Piecewise Exponential Models of **Entry Mode** Effect on the Rate of a Firm's Introduction of a Product with Nominal Data Access Time Better than that of this Firm's Previous Best Product.
(Standard errors shown in parentheses)

	Model (2.1)	Model (2.2)	Model (2.3)
Duration Dependence: 0-1 Years since last "improvement" event	-5.23*** (.739)	-5.70*** (.764)	-5.70*** (.764)
Duration Dependence: 1+ Years since last "improvement" event	-2.58*** (.679)	-2.96*** (.697)	-2.96*** (.698)
Firm Size (logged): revenue in the optical disk drive industry [in millions of US dollars] (t-1)	.438*** (.112)	.484*** (.113)	.484*** (.113)
Dominant firm dummy =1 [10 firms with the largest market share] (t-1)	-.531 (.343)	-.586 (.346)	-.587 (.347)
Japan HQ Firm dummy =1	-.005 (.180)	.125 (.190)	.126 (.192)
Firm's Best Product Data Access Time (t-1)	.002** (.0005)	.002*** (.0005)	.002*** (.0005)
Firm cumulative # products within top 15% industry performance (t-1)	-.028 (.016)	-.036* (.016)	-.036* (.016)
Industry Product Density (t-1)	.009 (.006)	.008 (.006)	.008 (.006)
Worldwide Industry Revenues (t-1) [in millions of US dollars]	-.000 (.000)	-.000 (.000)	-.000 (.000)
Period Effect of ISO9660 dummy (1988-1999) =1	.726 (.643)	.703 (.640)	.703 (.640)
Industry Age/Time Trend (t)	-.138 (.171)	-.115 (.172)	-.115 (.172)
λ [Sample Selection Term] (t)	-.083 (.107)	-.133 (.108)	-.135 (.117)
Firm Tenure in the Industry [in years] (t)	-.104** (.033)	-.089** (.034)	-.090* (.035)
De novo Firm dummy =1		.764** (.249)	.756* (.313)
De novo Firm Dummy * Firm Tenure			.004 (.100)
Number of Observations	736	736	736
No. of Subjects	245	245	245
No. of Events of Product Improvement	171	171	171
Chi-square	203.21	211.81	211.82
Log-likelihood	-152.47	-148.17	-148.17
(d.f.)	(12)	(13)	(14)

p* < .05; p** < .01; p*** < .001

Table 3. Piecewise Exponential Models of **Entry Mode** and **Incumbency Status** Effects on the Rate of a Firm's Introduction of a Product with Nominal Data Access Time Better than that of this Firm's Previous Best Product.
(Standard errors shown in parentheses)*

Type of Incumbency Measure \ Variable		***De novo* Dummy**	**Incumbent Measure**	***De novo* * Incumbent**	**Log likelihood (d.f.)**
DVD Incumbent [incumbent enters in 1983-95]	Model (3.11)	.764** (.249)			-148.17 (13)
	Model (3.12)		-.056 (.384)		-152.46 (13)
	Model (3.13)	.788** (.255)	.172 (.387)		-148.07 (14)
	Model (3.14)	1.13* (.540)	.352 (.475)	-.427 (.600)	-147.82 (15)
CD Incumbent/ High Sierra [incumbent enters in 1983-86]	Model (3.21)	.764** (.249)			-148.17 (13)
	Model (3.22)		.960** (.300)		-147.21 (13)
	Model (3.23)	.644** (.251)	.841** (.301)		-144.16 (14)
	Model (3.24)	.686** (.262)	.872** (.307)	-.292 (.593)	-144.04 (15)
CD Incumbent/ ISO 9660 [incumbent enters in 1983-88]	Model (3.31)	.764** (.249)			-148.17 (13)
	Model (3.32)		.176 (.297)		-152.29 (13)
	Model (3.33)	.755** (.250)	.096 (.306)		-148.12 (14)
	Model (3.34)	1.09*** (.268)	.114 (.302)	-1.42* (.602)	-144.78 (15)
Entrant [4-year window]	Model (3.41)	.764** (.249)			-148.17 (13)
	Model (3.42)		-.042 (.274)		-152.46 (13)
	Model (3.43)	.764** (.249)	-.047 (.277)		-148.15 (14)
	Model (3.44)	.138 (.572)	-.134 (.285)	.770 (.609)	-147.26 (15)
Entrant [5-year window]	Model (3.51)	.764** (.249)			-148.17 (13)
	Model (3.52)		.078 (.298)		-152.43 (13)
	Model (3.53)	.770** (.249)	.125 (.301)		-148.08 (14)
	Model (3.54)	.266 (.661)	.069 (.309)	.576 (.685)	-147.69 (15)

p* < .05; p** < .01; p*** < .001

*Table 3 is a summary of different models that are designed to test whether entry mode explains additional variance in firm product performance improvement rates not explained by incumbency status alone. Model 2.1 is used as the baseline for all twenty models.

There are five sets of models that correspond to five different measures of incumbent status found in the literature. Each set includes four different models. Within each set of four models, the first model includes only the *de novo* dummy, the second model includes only the incumbent measure, the third model includes both the *de novo* dummy and the incumbent measure, and the last model includes the *de novo* dummy and the incumbent measure and interaction term between them. The columns of Table 3 display coefficients for the *de novo* dummy, the incumbent measure and their interaction and model log likelihood statistics. Each row of Table 3 indicates which measure of incumbency is used in each set of four models.

Table 4. Zero-inflated Poisson Models of **Entry Mode** Effect on the Rate of a Firm's Introduction of Products with Top 15% Data Access Time
(Robust standard errors shown in parentheses)

	Model (4.1)	Model (4.2)	Model (4.3)
Main Model			
Constant	-2.45***	-2.61***	-2.61***
	(.383)	(.388)	(.393)
Firm Size (logged): revenue in the optical disk drive industry [in millions of US dollars] (t-1)	.245**	.240**	.246**
	(.073)	(.073)	(.074)
Dominant firm dummy =1 [10 firms with the largest market share] (t-1)	.047	.070	.053
	(.189)	(.193)	(.192)
Japan HQ Firm dummy =1	.119	.168	.187
	(.148)	(.154)	(.156)
Firm's Total Number of Products on the Market (t-1)	.014*	.012*	.011
	(.006)	(.006)	(.006)
Industry Product Density (t-1)	.009***	.009***	.010***
	(.002)	(.002)	(.003)
Worldwide Industry Revenues (t-1) [in millions of US dollars]	-.000*	-.000*	-.000*
	(.000)	(.000)	(.000)
Period Effect of ISO9660 dummy (1988-1999) =1	.085	.055	.041
	(.458)	(.457)	(.458)
λ [Sample Selection Term] (t)	-.440***	-.503***	-.555***
	(.100)	(.098)	(.102)
Firm Tenure in the Industry [in years] (t)	.132*	.163**	.148*
	(.056)	(.058)	(.059)
Firm Tenure in the Industry Squared [in years] (t)	-.012**	-.014***	-.013**
	(.004)	(.004)	(.004)
De novo Firm dummy =1		.413*	.179
		(.163)	(.185)
De novo Firm Dummy * Firm Tenure			.118*
			(.055)
Inflated Model			
Industry Age/ Time Trend (t)	.009	.003	-.004
	(.063)	(066)	(.066)
Constant	-1.15	-1.12	-1.04
	(.841)	(.876)	(.873)
Number of Observations	544	544	544
No. of None-zero Observations	246	246	246
No. of Zero Observations	298	298	298
Wald Statistics	331.76	345.60	356.88
Log-likelihood	-701.95	-699.20	-697.59
(d.f.)	(10)	(11)	(12)

p* < .05; p** < .01; p*** < .001

Table 5. Zero-inflated Poisson Models of **Entry Mode** and **Incumbency Status** Effects on the Rate of Firms' Introduction of Products with Data Access Time in Top 15% of Industry Performance
(Robust standard errors shown in parentheses)*

Variable / Type of Incumbency Measure		***De novo* Dummy**	**Incumbent Measure**	***De novo* * Incumbent**	**Log likelihood (d.f.)**
DVD Incumbent [incumbent enters in 1983-95]	Model (5.11)	.413* (.164)			-699.20 (11)
	Model (5.12)		-.026 (.201)		-701.94 (11)
	Model (5.13)	.436* (.178)	.103 (.226)		-699.08 (12)
	Model (5.14)	.098 (.266)	-.064 (.265)	.464 (.320)	-698.34 (13)
CD Incumbent/ High Sierra [incumbent enters in 1983-86]	Model (5.21)	.413* (.164)			-699.20 (11)
	Model (5.22)		.340 (.204)		-699.66 (11)
	Model (5.23)	.365* (.165)	.291 (.204)		-697.54 (12)
	Model (5.24)	.309 (.171)	.275 (.203)	.388 (.418)	-697.11 (13)
CD Incumbent/ ISO 9660 [incumbent enters in 1983-88]	Model (5.31)	.413* (.164)			-699.20 (11)
	Model (5.32)		.583** (.212)		-696.64 (11)
	Model (5.33)	.346* (.164)	.539* (.216)		-694.73 (12)
	Model (5.34)	.349* (.165)	.540* (.216)	-.014 (.442)	-694.73 (13)
Entrant [4-year window]	Model (5.41)	.413* (.164)			-699.20 (11)
	Model (5.42)		.322 (.251)		-700.74 (11)
	Model (5.43)	.408* (.160)	.316 (.256)		-698.04 (12)
	Model (5.44)	.516 (.420)	.330 (.263)	-.131 (.432)	-697.98 (13)
Entrant [5-year window]	Model (5.51)	.413* (.164)			-699.20 (11)
	Model (5.52)		.420 (.253)		-699.61 (11)
	Model (5.53)	.434** (.166)	.447 (.260)		-696.56 (12)
	Model (5.54)	.868 (.564)	.464 (.263)	-.479 (.570)	-696.07 (13)

p* < .05; p** < .01; p*** < .001

*Table 5 is a summary of different models that are designed to test whether entry mode explains additional variance in firm rates of introduction of products with top 15% technical performance not explained by incumbency status alone. Model 4.1 is used as the baseline for all twenty models.

There are five sets of models that correspond to five different measures of incumbent status found in the literature. Each set includes four different models. Within each set of four models, the first model includes only the *de novo* dummy, the second model includes only the incumbent measure, the third model includes both the *de novo* dummy and the incumbent measure, and the last model includes the *de novo* dummy and the incumbent measure and interaction term between them. The columns of Table 5 display coefficients for the *de novo* dummy, the incumbent measure and their interaction and model log likelihood statistics. Each row of Table 5 indicates which measure of incumbency is used in each set of four models.

Table 6. Zero-inflated Poisson Models **Entry Mode** Effect on the Rates of Firm Introduction of Products of Different Proximity to the Technological Frontier (Robust standard errors shown in parentheses)

	Model (6.1)	Model (6.2)	Model (6.3)	Model (6.4)	Model (6.5)	Model (6.6)
			Dependent Variables:			
	Firm all new products	Firm new products faster industry mean	Firm new products in top 15%	Firm new products in top 20%	Firm new products in top 25%	Firm new products slower industry mean
Main Model						
Constant	-.906**	-2.61***	-2.61***	-2.63***	-2.61***	-.636
	(.280)	(.370)	(.388)	(.373)	(.393)	(.383)
Firm Size (logged): revenue in the optical disk drive industry [in millions of US dollars] (t-1)	.278***	.300***	.240**	.303***	.323***	.140
	(.060)	(.070)	(.073)	(.066)	(.071)	(.105)
Dominant firm dummy =1 (t-1) [10 firms with the largest market share]	-.351*	-.039	.070	-.157	-.246	-.452
	(.151)	(.191)	(.193)	(.176)	(.177)	(.246)
Japan HQ Firm dummy =1	.216	.086	.168	.292*	.302*	.373
	(.112)	(.152)	(.154)	(.139)	(.128)	(.203)
Firm's Total Number of Products on the Market (t-1)	.022***	.004	.012*	.014*	.010	.025**
	(.006)	(.006)	(.006)	(.006)	(.007)	(.007)
Industry Product Density (t-1)	.004*	.008**	.009***	010***	.009***	.003
	(.002)	(.002)	(.002)	(.002)	(.002)	(.003)
Worldwide Industry Revenues (t-1) [in millions of US dollars]	-.000	-.000*	-.000*	-.000**	-.000**	-.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Period Effect of ISO9660 dummy (1988-1999) =1	-.208	.224	.055	.108	.327	-.346
	(.316)	(.420)	(.457)	(.415)	(.413)	(.498)
λ [Sample Selection Term] (t)	-.477***	-.590***	-.503***	-.463***	-.468***	-.396**
	(.078)	(.114)	(.098)	(.093)	(.088)	(.134)
Firm Tenure in the Industry [in years] (t)	.123**	.191**	.163**	.125*	.139**	.071
	(.045)	(.055)	(.058)	(.052)	(049)	(.078)
Firm Tenure in the Industry Squared [years] (t)	-.011***	-.015***	-.014***	-.011**	-.012**	-.008
	(.003)	(.004)	(.004)	(.004)	(.003)	(.006)
De novo Firm dummy =1	.207	.429*	.413*	.416**	.382**	-.075
	(.131)	(.171)	(.164)	(.148)	(.147)	(.338)
Inflated Model						
Industry Age/ Year	-.215***	.026	.003	-.043	-.081	-.158**
	(.050)	(068)	(.066)	(.075)	(.082)	(.048)
Constant	.548	-1.45	-1.12	-1.09	-.792	1.48**
	(.501)	(.913)	(.876)	(.977)	(1.05)	(.538)
Number of Observations	544	544	544	544	544	544
No. of None-zero Observations	344	240	246	282	296	191
No. of Zero Observations	200	304	298	262	248	353
Wald Statistics	382.36	334.10	345.60	403.05	21.99	76.20
Log-likelihood	-923.95	-669.56	-699.20	-771.73	-806.40	-597.34
(d.f.)	(11)	(11)	(11)	(11)	(11)	(11)

p* < .05; p** < .01; p*** < .001

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Appendix

Table A1. Sample Selection Model
(Hazard Rate Weibull Model of Firm Exit from the Optical Disk Drive Industry)

Firm Density (t-1)	.043*
	(.020)
Firm Density delay (u_0)	.039*
	(.019)
WW Revenues (t)	.000
	(.000)
De novo Firm Dummy	.654*
	(.313)
Firm's Number of Products (t)	-.331***
	(.087)
Ln Firm Size (t)	-.385
	(.205)
Firm Tenure/Duration	.650*
	(.306)
Constant	-5.02***
	(1.07)
/ln_p	.499**
	(.186)
p	1.65
1/p	.607
No. of observations	544
No. of subjects	97
No. of exits	56
Chi-square	85.33
Log likelihood (d.f.)	-66.75 (6)

p* < .05; p** < .01; p*** < .001