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Vicarious Learning in New Product Introductions in the Early Years of a Converging Market

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Technological developments combine previously distinct technologies that result in converging markets. In converging markets, firms from different industries compete against each other, often for the first time. We propose that firms introducing new products in converging markets will learn vicariously from other firms in the market. Further, we propose that this learning will vary across the dual-technology frontier (DTF), where the high-technology frontier (HTF) and low-technology frontier (LTF) map onto innovative activities driven by technological opportunity and user needs. We propose that at the HTF, local search will dominate and firms will be influenced by HTF product introductions of similarly sized, successful firms. At the LTF, learning will occur across the DTF, vary by origin industry of the firm, and be affected by complementarities in routines and capabilities and market competition among firms. We test the proposed model of vicarious learning using panel data on new product introductions of 67 firms in the U.S. digital camera market in the 1990s. Findings generally support our proposed model of vicarious learning in this market. They show heterogeneity in vicarious learning across the technology frontier and firm characteristics—including the origin industry of target firms. Our results show that vicarious learning in new product introductions in converging markets—which includes both mimetic and nonmimetic learning—is similar in some ways, but different from more traditional markets. We conclude with a discussion of the implications of our findings for theories of organizational learning, new product development, and converging markets.

Key words: vicarious learning; new product introductions; converging markets; technology frontier; count models; Bayesian estimation
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Organization theorists contend that firms learn vicariously, imitating or avoiding actions of other firms (Levitt and March 1988, Huber 1991, March 1991). There is robust evidence of such vicarious learning across several contexts including acquisitions (Haunschild 1993, Haunschild and Miner 1997, Beckman and Haunschild 2002), market entry (Haveman 1993; Greve 1996, 1998; Greve and Taylor 2000; McKendrick 2001), chain units' location (Baum et al. 2000), entrepreneurial decisions (Lant and Mezias 1990), and airline performance (Haunschild and Sullivan 2002). In this paper, we examine vicarious learning in new product introductions of firms in the early years of a converging market.

Developments across diverse industries are combining previously distinct technologies into new products, resulting in converging markets (Yoffie 1997, *Economist* 2000). Some examples of converging markets include the markets for digital cameras, personal digital assistants, Internet multimedia players, and video-on-demand. Firms in converging markets face challenges as they master new technologies to develop new products, while simultaneously competing in markets beyond their traditional spheres of competence (Greenstein and Khanna 1997).

The limited empirical research on converging markets has focused on the dynamics of market structure (e.g., Gambardella and Torrisi 1998), and few insights exist on firms' strategic behaviors (for an exception, see Tripsas and Gavetti 2000). As Malerba (2002, p. 259) notes "more work is necessary when the transformation of sectors involves . . . the emergence of new clusters that span over several sectors . . . . The analysis of sectoral systems has to consider the fusion of previously separated knowledge and technologies and . . . the new relations and overall dynamics between the different types of users, consumers, and firms with different specializations and competencies."

Under conditions of high uncertainty, firms learn from the actions of other firms (e.g., Mezias and Lant 1994, Haunschild and Miner 1997, Mezias and Eisner 1997). Thus, early converging markets, characterized by high uncertainty, provide a good setting in which to explore vicarious learning. Studying vicarious learning in this context (new product introductions in converging markets) can contribute to the organizational learning literature. First, as previously noted, there is evidence that vicarious learning affects many important strategic decisions. Yet we know little about vicarious learning with respect to new product development (NPD), an important strategic context for firms. The actions of other firms are likely to affect these decisions as well, as suggested by Greve and Taylor's (2000) finding that radio stations change formats based on other stations' format changes. Indeed, past research suggests the potential value of the external environment on NPD at the team level (e.g., Ancona and Caldwell 1992). However, few insights exist on the specific nature of organizational vicarious learning processes in NPD processes.

Second, past research on vicarious learning has primarily examined intra-industry learning (for an exception, see Kim and Miner 2000) focusing on industries that have been in existence for some time. In a converging market, entrants from different industries compete for the first time. According to evolutionary theory, firms in a given industry possess similar resources and routines (Nelson and Winter 1982). This insight raises the possibility that vicarious learning in a converging market, where entrants from different industries compete, may vary systematically across firms' origin industries. Our understanding of inter- and intra-industry learning can be enhanced by exploring vicarious learning in the converging-market context.

Finally, many markets are characterized by a *dual-technology frontier* (DTF), where the high-technology frontier (HTF) represents innovations arising from technological opportunities, and the low-technology frontier (LTF) represents innovations driven by user needs (Schmookler 1962, Rothwell 1994). In this paper, we incorporate this notion of the DTF to theorize differences in vicarious learning across the frontier.

Thus, extending developments in organizational learning (e.g., Baum and Mezias 1992, Baum and Haveman 1997, Haunschild and Miner 1997) and technology strategy (Schmookler 1962, Rothwell 1994), we propose a model of vicarious learning for new product introductions, in which learning varies across firm characteristics, origin industries, and the DTF. We test this model using a panel data of 429 new product introductions of 67 firms in the early years of the converging U.S. digital camera market between 1991 and 1999.

Theory

New Product Introductions as an Indicator of Vicarious Learning

Innovation is a central mechanism by which organizations adapt and transform themselves (Eisenhardt and Tabrizi 1995). For example, by changing its products, Hewlett-Packard transformed itself from an instruments company to a computer company. Likewise, by offering new products Intel changed from a memory company to a microprocessor company (Burgelman 1991). More generally, organizational adaptation changes organizational processes and routines (Nelson and Winter 1982). Thus, new product introductions—a key manifestation of innovation—is an important adaptation mechanism that can dramatically change both the nature of internal (e.g., relationships between marketing and research functions) and external (e.g., relationships with suppliers, distributors, and customers) organizational routines.

A key tenet in organizational learning theory is that changes in organizational routines reflect learning (Argote et al. 1990, Huber 1991, March 1991, Mezias and Lant 1994, Haunschild and Miner 1997). Thus, new product introductions—accompanied by significant changes in organizational routines—reflect organizational learning. Indeed, the theme of "innovation as organizational learning" has long been examined in both theoretical (e.g., Van de Ven and Angle 1989, Mezias and Glynn 1993) and empirical (e.g., Cohen and Levinthal 1990, Henderson and Clark 1990, Mezias and Eisner 1997) research. Note that this view does not imply that such learning is necessarily efficient, because past research documents both problems and biases in learning (e.g., Levitt and March 1988).

We focus on vicarious learning in new product introductions in converging markets. Vicarious learning is likely to occur under conditions of uncertainty, when managers look outside their own organizations for guidance (e.g., Mezias and Lant 1994, pp. 187–188; Haunschild and Miner 1997; Mezias and Eisner 1997). Converging markets are characterized by high uncertainty about technologies and products. Accordingly, we expect vicarious learning to generally affect firms' strategic behaviors in converging markets, and specifically affect their new product introductions.[1]

Consistent with past research (Baum and Haveman 1997, Haunschild and Miner 1997, Lant and Hewlin 2002), we define vicarious learning as occurring when

[1] Note that other types of organizational learning (e.g., experiential learning) are also likely to be reflected in new product introductions. We control for these other types of learning in the proposed model. Additionally, as we subsequently discuss, the proposed estimation procedure also accounts for unobserved firm heterogeneity.

firms alter their behaviors in response to the behaviors of other firms. Thus, changes in the rates of firms' new product introductions arising from changes in new product introductions of other firms reflect vicarious learning. Past empirical research supports three types of vicarious learning: frequency-based, trait-based, and outcome-based learning (Haunschild and Miner 1997). With frequency-based learning, firms learn from the prevalence of practices in a population of organizations; with trait-based learning, firms learn from the practices of other firms with certain traits (e.g., similarly sized firms, successful firms); and with outcome-based learning, firms learn from the outcomes associated with other firms' practices. In the early years of the digital camera market, information on performance outcomes (e.g., sales, market shares) was not available. Hence, our ex-ante representation of vicarious learning includes frequency-based and trait-based learning and excludes outcome-based vicarious learning. In a departure from past research that has modeled frequency-based and trait-based vicarious learning separately (e.g., Haunschild and Miner 1997, Baum et al. 2000), we combine frequency and trait-based vicarious learning, to develop an integrated measure of vicarious learning; i.e., the number of new product introductions (frequency-based learning) of target firms with certain traits (i.e., similar size, success, origin industry).

The DTF

The role of technological opportunity versus market demand on innovative activity has been the subject of ongoing debate in the innovation literature. Some (Schumpeter 1934, Geroski 1990) argue that NPD is driven by technological opportunity, while others (Schmookler 1962, Kamien and Schwartz 1979) suggest that consumer needs and preferences fuel innovative activity. Our review of the converging digital camera market suggests that both technological opportunity and user needs simultaneously influenced innovative activity, producing the DTF.

Specifically, products at the HTF represent "technology push" efforts driven by the technical possibilities of industry research and development (R&D) (Rothwell 1994). Thus, HTF products represent leading-edge technology developments, are risky, require substantial "lumpy" R&D investments, and tend to be aimed at small, niche markets with low growth rates. Products at the LTF, in contrast, represent "market pull" efforts and are driven by the fusion of user needs and technical possibilities (Rothwell 1994). Thus, LTF products typically require lower R&D investments relative to HTF products, are aimed at the large mass market, and have strong anticipated growth rates.

Given the distinctive nature of the DTF, we propose different vicarious learning processes for HTF and LTF product introductions. We propose that vicarious learning will vary depending on (1) whether the focal firm's learning is embodied in its HTF or LTF products and (2) whether the learning target is at the HTF or LTF. In the following sections, we discuss vicarious learning from other firms' product introductions as reflected in the focal firm's HTF product introductions, followed by vicarious learning from other firms' product introductions as reflected in the focal firm's LTF product introductions.

Product Introductions at the HTF

Because HTF products are at the leading edge of technology developments, firms likely experience a high degree of uncertainty about both their technical feasibility and their market acceptance. Under conditions of high uncertainty, local and limited search (Cyert and March 1963) tends to dominate widespread search (Fleming 2001). Thus, we propose selective vicarious learning at the HTF, with organizational search limited to the HTF products of a select group of firms, rather than of all firms (Haveman 1993, Haunschild and Miner 1997, Tripsas and Gavetti 2000).

Specifically, we propose that local search for HTF product introductions will be restricted to the HTF product introductions of similarly sized firms and successful firms. Because HTF products are driven by technology push and *not* by market pull, we do not anticipate vicarious learning for new HTF products from the LTF products of other firms. However, we control for such effects in the estimated model.

HTF Product Introductions of Similarly Sized Firms. Organizations of similar size generally rely on the same resources, and face similar constraints. For example, in most organizational populations, larger organizations have different structures and strategies than medium and small organizations (Haveman 1993). Organizations compete most aggressively with others of similar form or size, which typically operate in similar market niches (Hannan et al. 1990, Baum and Mezias 1992). This match of size and strategy profiles suggests the appropriateness of size peers as good learning targets (Haunschild and Miner 1997). Indeed, there is robust evidence for such size-localized vicarious learning in market entry of banks (Haveman 1993), survival of hotels (Baum and Mezias 1992), and hiring of investment bankers (Haunschild and Miner 1997).

Thus, we propose that, for HTF product introductions—which are characterized by high uncertainty—organizations will pay selective attention to the HTF product introductions of their size peers. The HTF product introductions of their size peers will contain diagnostic information on the technical feasibility of HTF products, and reinforce for the focal firm that they too have the capabilities to produce these products, spurring their introduction. Therefore, we expect the rate of new HTF product introductions of firms to be positively related to the HTF product introductions of other similarly sized firms. Hence,

Hypothesis 1. *The greater the number of HTF products introduced by similarly sized firms, the higher the rate of new HTF product introductions by the focal firm.*

HTF Product Introductions of Successful Firms. In addition to local search of similarly sized organizations under conditions of high uncertainty, firms pay attention to others perceived to be successful (DiMaggio and Powell 1983). However, the empirical evidence on learning from the actions of successful others is mixed. Some studies find a mimetic response (e.g., Burns and Wholey 1993, Haveman 1993), others find no response (e.g., Rogers 1995), and yet other studies find a nonmimetic response (e.g., Greve and Taylor 2000). We propose that, under high uncertainty, firms will pay attention to the HTF product introductions of other successful firms, but they will use the information more selectively than they do information pertaining to their size peers. This selective attention occurs because organizations believe that successful organizations are doing "X" as a proxy for "X's" technical results (i.e., as a proxy for the practice's success). But under high uncertainty, the relationship between the practice's success and organization's success is ambiguous (Haunschild and Miner 1997). This unclear contingency is especially likely in converging markets, where data on products' performance are not available.

In addition, HTF product introductions represent technological experimentation. Given the rapid pace of HTF technological developments, the HTF is characterized by technological turbulence (Yoffie 1997). Further, the market for HTF products is a small, evolving niche market with limited commercial potential. Thus, in addition to the unclear contingency between the practice's success and the firm's success, an increasing number of HTF product introductions by successful firms suggests increased competitive activity in this small, turbulent niche for HTF products. This, in turn, is likely to decrease the attractiveness of HTF to the focal firm (Miller and Chen 1986, Chamley and Gale 1994). Hence, given the HTF introductions of other successful firms, focal firms may perceive reduced innovation rents for their HTF products aimed at the small, niche market and reduce their HTF product introductions.

Hypothesis 2. *The greater the number of HTF products introduced by successful firms, the lower the rate of new HTF product introductions by the focal firm.*

Product Introductions at the LTF

We expect a different representation of vicarious learning for firms' LTF product introductions. First, because LTF product introductions involve less technological uncertainty than HTF products, and are aimed at the much larger mass market, we expect vicarious learning to be less dominated by local search and more affected by complementarities in routines between the focal firm and the learning targets. These complementarities likely vary across origin industry. As noted earlier, firms in a given industry tend to possess similar resources and routines (Nelson and Winter 1982). This raises the possibility that vicarious learning in a converging market, where entrants from different industries are competing, may vary systematically across origin industries. These origin industries include firms from traditional film-based analog photography, consumer electronics, and the computer industries. Further, because LTF products involve a fusion of both user needs and technical knowledge, they are characterized by more market knowledge (relative to HTF products). Market knowledge is also likely to vary across origin industries, with firms in a given industry possessing similar market knowledge. Accordingly, we expect that the demand-side characteristics of target firms (i.e., origin industry, reflecting market knowledge) will affect vicarious learning in LTF products of focal firms, while supply-side characteristics of target firms (i.e., size and success) may be less important. We next discuss vicarious learning from the HTF product introductions of target firms, followed by vicarious learning from the LTF product introductions of target firms.

HTF Product Introductions of Firms from the Same Origin Industry and from Outside the Origin Industry. How are the LTF product introductions of focal firms affected by the HTF product introductions of others? Because LTF product introductions are based on the fusion of technology developments and user needs (Schmookler 1962, Rothwell 1994), the HTF product introductions of other firms contain information about the possibilities of various technologies underlying the emerging products. Indeed, some technical features of HTF products are, over time, frequently incorporated into LTF products. Thus, we expect the HTF product introductions of other firms to spur the LTF product introductions of focal firms. We propose that this likely occurs with respect to learning from both the HTF products of firms within the same origin industry as the focal firm, as well as those outside their origin industry. The shared knowledge base of firms from within a given origin industry is likely to create greater absorptive capacity (Cohen and Levinthal 1990) for vicarious learning. Further, firms from the same origin industry are likely to have similar industry networks (e.g., membership in industry bodies, trade conferences, etc.), which may facilitate the transfer and assimilation of HTF technical knowledge into the focal firm's LTF product introductions (Abrahamson and Rosenkopf 1997). As a result, the HTF product introductions of firms from the same origin industry may increase the rate of LTF product introductions of focal firms.

In contrast, the HTF product introductions of firms from outside the origin industry generate information about technology developments outside their origin industry's knowledge domains. This knowledge will be different, but still complementary, because LTF products are still targeted toward the anticipated mass market. Complementary knowledge from the actions of other firms tends to increase the impact of those actions on the focal firm (Haunschild and Beckman 1998). Integrating the above arguments, we expect that the HTF products of other firms, whether from the same origin industry or from outside the origin industry, will increase the rate of LTF product introductions of the focal firm. Thus,

Hypothesis 3A. *The greater the number of HTF products introduced by firms from the same origin industry as the focal firm, the higher the rate of new LTF product introductions by the focal firm.*

Hypothesis 3B. *The greater the number of HTF products introduced by firms outside the origin industry of the focal firm, the higher the rate of new LTF product introductions by the focal firm.*

LTF Product Introductions of Firms from the Same Origin Industry and from Outside the Origin Industry. At first glance, the shared knowledge base of firms competing in the LTF and mimetic pressures to respond to competitors' product introductions might be assumed to increase a focal firm's LTF product introductions in response to the LTF product introductions of other firms from the same origin industry. However, as we discuss below, there is also likely to be intense rivalry among firms competing for the potentially large mass-market, regardless of whether the firms are from the same origin or outside their origin industry, which results in a nonmimetic response to the LTF product introductions of other firms.

Firms from the same origin industry directly compete for resources (e.g., finance, labor, customers) in the converging market. Indeed, when the focal and target firms are from the same origin industry and the source of learning is the target firm's LTF product introductions, the threatening, competitive aspects of these new LTF product introductions are likely to be more salient than their informational value (Ocasio 1997, Lant and Hewlin 2002). In addition, as the number of LTF products by firms from the same origin industry increases, the focal firm is likely to obtain from these products the necessary information about consumer preferences at the LTF. As a result, the focal firm may focus its effort on leveraging the innovation rents in its existing product portfolio, lowering its LTF product introduction rate.

Likewise, we expect that the LTF product introductions of target firms from outside the focal firm's origin industry to increase the perceived competition for LTF products, lowering the focal firm's rate of LTF product introductions. When firms observe increased LTF product introductions by firms outside their origin industry in these converging markets where product forms, revenue models, and market feasibility are uncertain and still emerging, they may infer that the resources and competencies of firms from their origin industry are not adequate to compete effectively. Thus, the focal firm may perceive a threat to the performance and survival of firms from their origin industry in the converging market. Such threat-rigidity perceptions (Staw et al. 1981) may prompt the focal firm to conserve resources, in this case by further decreasing its LTF product introductions. Thus,

Hypothesis 4A. *The greater the number of LTF products introduced by firms from the same origin industry as the focal firm, the lower the rate of new LTF product introductions by the focal firm.*

Hypothesis 4B. *The greater the number of LTF products introduced by firms outside the origin industry of the focal firm, the lower the rate of new LTF product introductions by the focal firm.*

Method

Context: The Early Years of the U.S. Digital Camera Market

The advent of digital imaging technology in 1991 shook up the traditional photography industry as charge-coupled devices (CCD) technology (converts light images to binary data) replaced traditional film-based photography (Tripsas and Gavetti 2000, Benner 2002). The creation of the digital camera involved the integration of diverse technologies covering microelectronics, integrated circuit design, image processing, software design, CAD/CAM design, and fiber optics. In the early years of the digital camera market, there was uncertainty about form factor (e.g., the digital camera as a computer or a consumer durable) and revenue models (e.g., hardware or consumables). The converging digital camera market witnessed the entry of firms from different industries (e.g., photography, consumer electronics, computing) competing against each other for the first time.

Our discussions with digital imaging industry experts and review of trade reports (e.g., the *Future*

Image Report) indicated the existence of a DTF in the digital camera market. The HTF corresponds to the segment aimed at photography professionals, and the LTF is aimed at the mass market. The uncertainty, diverse origin industries of firms, and the DTF in the digital camera market thus provide a rich context to address vicarious learning.

Data

We tracked the evolution of the digital camera starting in 1991, when the first digital camera was launched. Information on camera product introductions was obtained from the *Future Image Report*, an industry newsletter published 10 times each year. Firms entered the data set the year in which they introduced their first digital camera and were observed untill 1999; unless they went out of business. The data set includes 67 firms with 429 product introductions between 1991 and 1999, resulting in 296 firm-year observations.

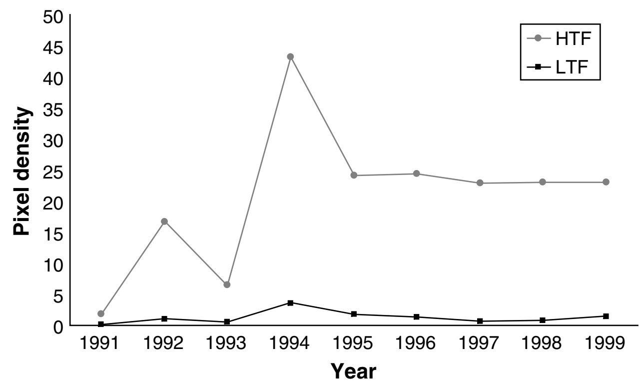
Measures

Like other complex, technology-intensive products, early digital cameras differed on several attributes including pixel density, memory format and size, lens features, storage device options, and prices (*Future Image Report* 1993). In this paper, we focus on pixel density to identify the DTF, because discussions with industry experts indicated that pixel density was the key attribute that differentiated early digital cameras. Indeed, consistent with the importance of pixel density, comprehensive data on other product attributes are not available for the early years.

For each year in the data set, we conducted independent latent class cluster analysis using the pixel density of the digital cameras introduced each year to empirically identify HTF and LTF products. Latent class cluster analysis offers several advantages over traditional cluster analysis to identify the DTF (for details, see Wedel and Kamakura 2000).[2] We used the consistent Akaike's information criterion (CAIC) to determine whether the two-cluster solution was better than a single-cluster solution. In every year, the two-cluster solution was superior—supporting the existence of a DTF. We had 76 (varying from 1 to 27 per year) HTF products and 353 (varying from 3 to 89 per year) LTF products.

The mean pixel densities for the DTF for each year are shown in Figure 1. Figure 1 shows a clear demarcation between the HTF and LTF for all years, with HTF higher than LTF in each year. Validating the

Figure 1 **Evolution of the Dual-Technology Frontier**



Note. HTF: High-technology frontier; LTF: Low-technology frontier.

empirical operationalization of the DTF, we note that the mean pixel density at the HTF in every year is significantly higher than that at the LTF (t-tests are significant at $p < 0.05$ for each year).

From Figure 1, we see that the mean pixel density for both the LTF and HTF decreases in some years. This observed discontinuity in product performance pattern is consistent with the technology evolution literature (Utterback 1994) which suggests that in the early stages of an emerging market, technological developments create a rivalry between alternative designs, resulting in a period of design variation or ferment. At some point, one product design—i.e., the future dominant design—is favored by the market over other designs. A dominant design may not necessarily embody superior technical performance; sometimes, it is a satisficing design in terms of technical possibilities (Tushman and Rosenkopf 1992).

Discussions with photoimaging industry experts confirmed that extensive technological experimentation resulted in high variability in the specifications of early digital cameras. Products with very high pixel densities were introduced in these early years, causing the observed spikes followed by the dips. For example, the spike observed in 1992 and 1994 for HTF products resulted from the product introductions of three firms—HP Marketing Inc. (1992), Dicomed Inc. (1994), and Phase One Inc. (1994). Indeed, supporting this idea of technological experimentation, these three products were withdrawn within a year of their introduction.

Also, from a customer perspective, consumers were satisficing, in the sense that higher levels of pixel density were not valuable to them because "megapixels permit bigger enlargements and more room to crop, but do not affect photo quality" (Pogue 2005). As noted in professional photography circles, "To the eye, the difference is not nearly so great. So, for 35-mm images, effective pixel count is typically on the order of 4.5 megapixels for color images" (Merklinger

[2] A technical appendix that details the latent class cluster analysis is available on request from the authors. Due to the small number of new products introduced in 1991 and 1992, we could not estimate the latent class model for these early years. Instead, we used K-means to determine cluster membership.

2005). Indeed, consumer ratings suggest that "For most digital camera purchasers, a three-megapixel digital camera will provide an excellent balance of features and exposure options without breaking the bank" (Creech 2005). Corroborating these ideas, the mean level of the pixel density of the HTF declined over time, indicating that the product design in the digital camera market was being optimized at a lower level of pixel density.[3]

We measured *new product introductions*, the dependent variable, as the number of HTF and LTF product introductions by a firm in a given year.

Independent Variables. We measure size by firm sales lagged one year (Cohen 1995). For publicly traded firms, we obtained sales information from the COMPUSTAT and WORLDSCOPE databases. We created a quartile split and coded size as ranging from 1 to 4. To create the size-similarity variables, we used the number of HTF and LTF product introductions of those firms with the same size code as the focal firm in the previous year.

Several criteria have been used to evaluate the success of firms including reputation, efficiency, profitability, and growth. In the corporate sector, highly profitable organizations are naturally viewed as more successful than less profitable organizations (Burns and Wholey 1993). We thus use the firm's profitability, measured as return on assets (ROA) as the indicator of its success. To create the product introductions variables of successful firms, we used the previous year's number of HTF and LTF product introductions by highly profitable firms (in the top quartile of firms).

We measured the *origin industry* of a firm based on whether it entered the digital camera market from one of the following three industries: (1) photography, (2) consumer electronics, or (3) computing. Accordingly, we used the number of new product introductions in the previous year by all firms from the focal firm's origin industry and outside the focal firm's origin industry at the LTF (and HTF) as an indicator of vicarious learning from firms in the same origin industry and from firms from outside the origin industry at the LTF (and HTF), respectively.

Control Variables. We also controlled for several variables that may affect the rate or type of new product introductions. First, we controlled for the cumulative number of previous product introductions by that firm to capture any effects of experiential learning (Argote et al. 1990). We also include the squared term of a firm's cumulative prior introductions as the positive effects of prior experience may increase at a decreasing rate (Argote 1999). Second, as the availability of resources to fund product introductions may affect the dependent variable, we included both firm size and free cash flow (both lagged one year) as proxies for resource availability.[4] Third, we control for the firm's technical expertise, which may also affect product introductions, by measuring the total number of patents granted to a firm in the previous year in the 12 patent classes pertinent to digital cameras.[5] We obtained patent data from the U.S. Patent and Trademark Office (http://www.uspto.gov). Fourth, we controlled for the firm's age (logarithm of age in years) because firms' search and learning strategies, as well as their ability to generate new products, may vary with age (Gavetti and Rivkin 2005). Finally, we controlled for the use of alliances as another source of interorganizational learning—by counting the number of firm alliances in the previous year. Alliance data was obtained from Thompson Financial Mergers and Alliances database. Table 1 contains the descriptive statistics and correlation matrix of the variables.

Model Specification

As the two dependent measures are count variables, we use the Poisson distribution to model the mean of the distribution (i.e., at the HTF and LTF) as a function of the explanatory variables using the log link function (e.g., Cameron and Trivedi 1998). To relax the assumption of the Poisson distribution that the mean equals the variance, and to incorporate unobserved firm heterogeneity we introduce a firm-specific intercept term. Specifically:

$$\begin{aligned}\log(\lambda_{H(ft)}) &= \beta_H X_{(ft)} + \kappa_{Hf}\\ \log(\lambda_{L(ft)}) &= \beta_L X_{(ft)} + \kappa_{Lf},\end{aligned} \tag{1}$$

where f subscripts the firms and t subscripts time; β_H and β_L are the parameter estimates for the effect

[3] We thank the two reviewers, the associate editor, and the editor for their inputs on the refinement of the measure of the dual-technology frontier.

[4] Because some firms in our data set are not publicly listed, we were not able to obtain this data for all the firms in the data set. However, we used data imputation techniques built into SPSS using EM algorithm to obtain the missing values. The correlation between free cash flows and the other variables, before and after imputation, show that it did not change significantly, testifying to the validity of the imputation process. We also ran a subanalysis on only those public firms in the data—the ones for which we had free cash flow data. We found similar patterns of results to the imputation. The directionality and statistical significance of the parameter estimates were unchanged.

[5] The 12 patent classes include: radiant energy (patent class = 250); computer graphics processing, operator interface processing, and selective visual display systems (345); television (348); photocopying (355); optics: measure and testing (356); optics: systems (including communication and elements) (359); dynamic magnetic information storage or retrieval (360); image analysis (382); television signal processing for dynamic recording or reproducing (386); photography (396); stock material or miscellaneous articles (428); and radiation imagery chemistry: process, composition or product thereof (Benner 2002).

Table 1 Descriptive Statistics and Correlation Matrix

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. HTF product introductions	1.00															
2. LTF product introductions	0.025	1.00														
3. HTF product introductions of similarly sized firms	0.15	−0.06	1.00													
4. LTF product introductions of similarly sized firms	0.064	0.17	−0.09	1.00												
5. HTF product introductions of successful firms	0.01	0.03	0.29	0.35	1.00											
6. LTF product introductions of successful firms	−0.02	−0.06	0.13	0.39	0.78	1.00										
7. HTF product introductions of firms from the same origin industry	0.15	0.07	0.41	0.02	0.36	0.17	1.00									
8. LTF product introductions of firms from the same origin industry	0.14	−0.01	0.23	0.09	0.46	0.52	0.67	1.00								
9. HTF product introductions of firms firms from outside the origin industry	−0.11	0.03	0.15	0.22	0.38	0.20	−0.36	−0.39	1.00							
10. LTF product introductions of firms from outside the origin industry	−0.10	−0.02	0.09	0.41	0.68	0.71	−0.19	−0.17	0.67	1.00						
11. Firm size	−0.05	0.17	−0.01	0.33	0.01	−0.05	−0.22	−0.27	0.23	0.18	1.00					
12. Firm age	−0.07	0.25	−0.10	0.29	0.05	0.06	−0.03	0.02	0.09	0.06	0.35	1.00				
13. Free cash flows	−0.14	0.16	−0.04	0.08	−0.00	−0.02	0.13	0.10	0.20	0.17	0.15	0.12	1.00			
14. Number of patents	−0.03	0.54	−0.10	0.19	−0.13	−0.20	−0.07	−0.15	−0.02	−0.09	0.55	0.36	0.15	1.00		
15. Number of alliances	−0.01	0.37	−0.11	0.14	0.01	−0.04	−0.11	−0.16	0.16	0.12	0.14	0.21	−0.06	0.34	1.00	
16. Cumulative product introductions	0.26	0.69	−0.07	0.19	0.03	0.06	0.06	0.19	−0.15	−0.07	0.11	0.12	0.31	0.49	0.30	1.00
Mean	0.24	1.17	2.03	17.83	1.03	29.46	5.96	26.07	4.32	32.11	7,704.60	39.31	5,309.01	134.08	0.32	4.55
Standard deviation	0.99	1.76	1.77	14.42	0.88	13.90	7.84	17.40	7.29	21.65	13,214.16	36.28	14,251.99	230.75	0.64	6.12

Note. Correlations above 0.10 significant at $p < 0.10$, correlations above 0.14 significant at $p < 0.05$, and correlations above 0.18 significant at $p < 0.01$.

of the various explanatory variables ($X_{(ft)}$) at the HTF and LTF, respectively; and κ_{Hf} and κ_{Lf} represent the firm-specific term for incorporating unobserved heterogeneity.

Assuming that κ_{Hf} and κ_{Lf} are normally distributed and correlated with each other gives us the Bivariate-Poisson-Normal model (BPN) (Cameron and Trivedi 1998). The BPN distribution offers two advantages over other models: (1) The firm-specific terms (one each at HTF and LTF) account for unobserved firm heterogeneity, which may explain additional differences in the HTF and LTF new product introductions of firms (e.g., organizational culture, quality of R&D personnel, brand equity) and account for overdispersion—fairly common in Poisson count models (Cameron and Trivedi 1998). (2) It allows for the correlation of the firm-specific terms in Equation (1) so that we can account for any dependencies between the HTF and LTF product introductions of a given firm.

Model Estimation

We estimate the BPN model specified in Equation (1) using Markov Chain Monte Carlo methods (Gilks et al. 1998). For the purpose, we use conjugate and noninformative priors. Specifically, we specify the two parameter vectors (i.e., β_H and β_L) to be distributed multivariate normal with a diagonal Wishart distribution for the precision matrix. We assumed hierarchical shrinkage specification for the individual firm-specific intercept term such that the firm-specific effects shrunk to an aggregate effect, which in turn shrunk to a mean of zero and low precision (i.e., high variance). We simulated four chains for the model and ensured convergence by inspecting the Gelman-Rubin statistics (Gelman and Rubin 1992). For model comparison purposes, we estimated two additional models: (1) a model with only the control variables as explanatory variables but excluded the vicarious learning variables and (where the errors are correlated) to examine the explanatory power of the vicarious learning variables, and (2) a model where the errors were uncorrelated, but included all the vicarious learning variables and the control variables, to examine whether the HTF and the LTF product introductions of firms are independent of each other. We used the deviance information criterion (DIC) to compare the models, in which lower values signify better fit (Spiegelhalter et al. 2002).

Results

Based on DIC, the hypothesized model with all the proposed vicarious learning variables (DIC = 988.913) outperformed the model with only the control variables (DIC = 1,044.020). It also outperformed the model in which we specify the two equations for HTF and LTF products to be uncorrelated (DIC = 1,000.070). The correlation coefficient between the firm-specific effects for products introduced at HTF and LTF was −0.883 ($p < 0.01$),[6] indicating a model

[6] This negative correlation ($\rho = -0.883$) is the correlation between unobserved firm effects at the HTF and LTF (not the correlation

Table 2 Vicarious Learning in New Product Introductions

Explanatory variable	Model 1 HTF product introductions	Model 2 LTF product introductions
Intercept	−267.60 (155.61)	26.22 (18.57)
Firm size	1.85 (2.28)	−0.72 (0.69)
Free cash flow	1.01 (1.77)	−0.35 (0.66)
Firm age	1.28 (1.20)	0.80 (0.39)**
Number of patents	−3.06 (1.63)	0.94 (0.44)**
Number of alliances	−0.45 (0.99)	0.22 (0.25)
Cumulative number of new products	8.71 (3.16)***	7.50 (1.01)***
Cumulative number of new products^2	−5.63 (3.22)	−5.57 (1.06)***
HTF introductions of similarly sized firms	5.32 (1.59)*** (H1)	−0.24 (0.68)
LTF introductions of similarly sized firms	2.27 (1.92)	−0.05 (0.33)
HTF introductions of successful firms	−3.55 (0.98)*** (H2)	−0.71 (4.38)
LTF introductions of successful firms	−3.88 (2.41)	−1.51 (1.43)
HTF introductions of firms from the same origin industry	0.20 (1.21)	1.22 (0.47)*** (H3A)
LTF introductions of firms from the same origin industry	1.27 (1.37)	−0.32 (0.41) (H4A)
HTF introductions of firms from outside the origin industry	−4.12 (2.37)	0.99 (0.44)** (H3B)
LTF introductions of firms from outside the origin industry	101.40 (81.72)	−0.34 (0.16)** (H4B)

Note. The density plots for the parameter of interest were all normal. Thus, we report the mean and standard deviation as sufficient statistics.
$^{**}p < 0.05$ and $^{***}p < 0.01$.

that allows for correlation between the firm specific effects of a firm's HTF and LTF product introductions fit the data best—which suggests the need to account for unobserved heterogeneity in modeling this process. We present the results for the BPN model at the HTF and LTF in Table 2.[7]

Because the correlation matrix (Table 1) shows some fairly high correlations among independent variables, we checked whether multicollinearity may be affecting the validity of the results. First, we examined the variance inflation factors, all of which were below five, which suggests that multicollinearity is not a threat to the validity of the study's findings. Second, we ran models entering one variable at a time and inspected the estimated parameters (e.g., sign change) to judge whether multicollinearity was affecting our results. There did not appear to be any harmful effects due to multicollinearity in any model. Therefore, we report models with all variables included. For model completeness, we also include all terms of the explanatory variables in the two models for HTF and LTF product introductions (e.g., learning in HTF product introductions from the LTF product introductions of similarly sized and successful firms) even though we had not hypothesized these effects.

Results for the control variables show that neither firm size nor free cash flow affected product introductions. Cumulative product introductions have the expected positive effect, and the negative coefficient on the squared term indicates decreasing returns to experience.[8]

In Hypothesis 1, we predicted that firms will learn vicariously from the HTF product introductions of similarly sized firms. Table 2, Model 1 shows an increase in the rate of the focal firm's HTF product introductions as a function of the HTF product introductions of similarly sized firms ($b = 5.32$, $p < 0.01$). Thus, Hypothesis 1 is supported. In Hypothesis 2, we predicted that competition concerns will create a nonmimetic response such that firms will decrease their rate of HTF product introductions as a function of the HTF product introductions of successful firms. We find support for this hypothesis as well ($b = -3.55$, $p < 0.01$). As expected, we do not find any support for the unhypothesized effects of LTF product introductions of similarly sized and successful firms. Thus, the results confirm that vicarious learning at the HTF is frontier specific and does not extend to learning from LTF products.

We next turn to product introductions at the LTF. Table 2, Model 2 presents these results. Results for the control variables show that firm age and number of patents positively affect LTF product introductions, while the number of alliances has no effect. In Hypothesis 3A, we had predicted that firms will introduce more LTF products in response to the HTF product introductions of firms from the same origin industry. As shown in Table 2, Hypothesis 3A is supported ($b = 1.22$, $p < 0.01$). We also find support for Hypothesis 3B, that firms will introduce more LTF products in response to HTF product introductions of firms from outside their origin industry ($b = 0.99$, $p < 0.05$). These results confirm that vicarious learning in LTF product introductions from the HTF products of other firms is mimetic in nature and not origin-industry specific. Thus, at the LTF, both the shared knowledge of firms from the same origin industry and the complementary knowledge of firms from outside the origin industry appears to influence the vicarious learning from HTF products.

However, we do not find support for Hypothesis 4A, where we had hypothesized that firms will

between HTF and LTF product introductions, which we observe from Table 1 of the descriptive statistics is 0.025). This negative correlation between unobserved firm effects at the two technology frontiers suggests that some unobserved firm characteristics have opposing effects on the product introductions at the two technology frontiers.

[7] To normalize the scale of the independent variables for efficiency in estimation, we took z-scores for all independent variables for model estimation. Thus, the results reported in Table 2 show these z-scores.

[8] The density plots for the parameter of interest are normal. Thus, we report the mean and standard deviation as sufficient statistics.

reduce their LTF product introductions in response to the LTF product introductions of firms from their origin industry. Although the coefficient is negative as expected, it is not statistically significant ($b = -0.32$, ns). This lack of support for Hypothesis 4A is surprising, and we discuss this result in detail in the discussion section. On the other hand, there is support for Hypothesis 4B, where we had predicted that firms would decrease their LTF product introductions in response to the LTF product introductions of firms from outside their origin industry ($b = -0.34$, $p < 0.05$). Finally, as expected, we also do not find any support for the unhypothesized vicarious learning from HTF products (i.e., from similarly sized firms, successful firms) on LTF product introductions.

To summarize, we find support for the expected effects for HTF product introductions. They are affected positively by HTF products of similarly sized firms and negatively by HTF products of successful firms. We also find that LTF products are affected by HTF products of other firms, irrespective of origin industry. However, LTF product introductions are affected only by the LTF products of firms from different origin industries, not of firms from the same origin industry.

Discussion

Our findings generate insights on vicarious learning in NPD in converging markets. We find support for heterogeneity of vicarious learning in the converging digital camera market. The heterogeneity occurs across two dimensions—the DTF and origin industry. We conclude by discussing the paper's contributions to theory and then identifying the study's limitations and directions for future research.

Theoretical Contributions

Organizational Learning. Our research makes four contributions to the organizational learning literature. First, while there is extensive support for vicarious learning in other strategic contexts, we know little about the nature of vicarious learning in NPD, a strategic organizational adaptation mechanism. By finding strong support for vicarious learning in new product introductions, we take a first step in this direction.

Consistent with past research on trait-based learning (Haveman 1993, Haunschild and Miner 1997), firms in converging markets are influenced by similarly sized and successful firms. Some of this learning is mimetic. For example, HTF product introductions of similarly sized firms positively affected the rate of HTF product introductions by the focal firm. Another contribution of our study, however, lies in showing that some learning is nonmimetic (cf, Baum and Haveman 1997, Greve and Taylor 2000). For example, firms introduce fewer HTF product introductions in response to more HTF product introductions of successful firms. Indeed, our discussions with industry experts anecdotally support this logic. After the introduction of high-end cameras by Sony in 1994 (a very successful firm in the digital camera market in the 1990s), other firms in the digital camera market interpreted this action as a signal that the market for high-end digital cameras was too competitive, and lowered the rate of their HTF product introductions. The support for bi-directional vicarious learning processes (both mimetic and nonmimetic) supports the contingent nature of vicarious learning in converging markets, based on the characteristics of other firms.

Second, in a departure from much past research on vicarious learning—primarily focused on intra-industry learning in stable markets—we focus on a young industry in which firms originating from different industries competed against each other for the first time. We hypothesized differences in vicarious learning based on the origin industry of the target firm. Again, we find evidence of both mimetic (from HTF products of firms outside the origin industry for LTF product introductions) and nonmimetic vicarious learning (from LTF products of firms outside the origin industry for LTF product introductions). This finding extends past research (Baum and Haveman 1997, Greve and Taylor 2000), which has reported nonmimetic vicarious learning from firms in nearby markets. Our findings suggest that this nonmimetic effect is supported at the LTF for firms similar in some ways (e.g., facing the same competitive conditions) but distinctive in others (i.e., from different origin industries and with different routines and practices). Somewhat surprisingly, we found no support for Hypothesis 4A, in which we had hypothesized that nonmimetic learning from the LTF product introductions of target firms from the same origin industry will lower the LTF product introductions of focal firms. We conjecture that the hypothesized nonmimetic effects are perhaps offset by mimetic vicarious learning because of shared, complementary knowledge bases of firms from the same origin industry—which produce the observed null effect.

Third, this paper's findings extend past organizational search literature, which has—for the most part—adopted an inward-focused approach to search (Pisano 1990, Tripsas and Gavetti 2000). For example, while Pisano (1990) outlined "learning by doing" and "experimentation" as alternative search systems, he did not consider vicarious learning. While our findings support the idea that in high uncertainty situations (e.g., with HTF products), local search will dominate (e.g., Cyert and March 1963), the empirical evidence supports extensive external organizational search, not only of firms within a given technology frontier but also of firms in the other technology frontier, and of firms from both inside and outside their origin industry. The findings reiterate the role of vicarious learning and the importance of including it in a comprehensive model of organizational search.

Finally, in a departure from past research that has modeled frequency-based and trait-based vicarious learning separately, we use an integrated measure combining frequency-based learning (i.e., number of new product introductions) and trait-based learning (i.e., size, success, and origin industry of target firms). Our findings indicate that this integrated measure is an ecologically valid representation of vicarious learning and suggest that firms use multiple rules for learning, combining frequency and trait-based learning modes. Researchers can use this measure and other integrated representations of vicarious learning to explore rules by which firms integrate information on outcomes, frequency, and traits of target firms.

NPD. Although the potential value of the external environment has been raised in the context of NPD teams, empirical NPD research has primarily focused on the role of firm characteristics on firm-level NPD outcomes (e.g., Moorman 1995). This paper's findings suggest that the external environment—consisting of the actions of firms from various origin industries and across the DTF—has significant mimetic and nonmimetic effects on new product introductions of firms in converging markets. Thus, the finding that the firms' external environment has an important, *strategic* role on innovation outputs (i.e., increasing or decreasing new product introductions), importantly extends past empirical NPD research primarily focused on organizational characteristics.

In addition, most past NPD research has examined product innovation as developments along a single-technology frontier. In this study, we conceptualize and find support for a DTF, in which product innovation simultaneously proceeds across the HTF and LTF. At the same time, note the interconnectedness of the dual frontiers as evidenced by vicarious learning from HTF product introductions on the LTF product introductions of focal firms. We view the DTF as a useful research tool to reexamine extant NPD research in a new light.

Converging Markets. Developments across diverse industries are combining previously distinct technologies into new products resulting in converging markets. Despite the dramatic effects of converging markets on firms' strategies and the growing economic significance of these markets, there are few insights on strategic processes of firms in such markets. We take a first step by examining vicarious learning in new product introductions, a key strategic behavior of firms.

Specifically, vicarious learning processes in new product introductions in converging markets vary by the technology frontier and the origin industry of firms. For HTF product introductions, we conjectured that technology supply-side considerations play an important role. In support of this idea, we find that the origin industry of target firms does not affect vicarious learning processes (i.e. the unhypothesized null effects of origin industry), but supply-side characteristics (firm size and success) do. In contrast, for LTF product introductions aimed at the mass market, we conjectured that demand-side considerations are important. In support of this idea, supply-side characteristics (e.g., firm size and success) of target firms do not affect vicarious learning (i.e., the unhypothesized null effects of size and success), but demand-side characteristics (technology frontier and origin industry) do. Further, the lack of support for Hypothesis 4A (no learning from the LTF products of firms from their origin industry) combined with the support for Hypothesis 4B (learning from the LTF products of firms from outside their origin industry) suggests that the extreme uncertainty about key success factors in converging markets makes very salient the competitive threats from firms from other origin industries.

Limitations and Future Research

The study has some limitations that suggest areas for further research. We focus on new product introductions, an important strategic activity for firms. However, new product introductions are not the only way that firms innovate. For example, firms may innovate on other aspects of their products (e.g., price) and marketing mix (e.g., advertising). A promising area for future research would be the integration of product attributes and marketing mix to investigate vicarious learning in an organizational marketing context.

In this study of the early years of the converging digital camera market, we do not consider outcome-based vicarious learning because such information (e.g., sales data) was not available. However, outcome-based vicarious learning is an important source of learning in mature industries (cf. Haunschild and Miner 1997). During the early stages of market development, learning from successful firms may have substituted for outcome-based learning. Future studies to investigate the interplay between trait-based and outcome-based vicarious learning, using the integrated representation of vicarious learning discussed earlier, would be valuable.

Finally, we investigated the early years of the digital camera market, characterized by high uncertainty—which is very conducive to vicarious learning. While the findings suggest significant differences in vicarious learning of firms in converging markets, further research on whether the findings extend to other converging markets and persist as markets evolve would be informative.

Conclusion

In sum, we view this study as an important initial step to investigate vicarious learning in an innovation context in converging markets. Beyond digital cameras, our research points to the importance of investigating vicarious learning processes in other innovation contexts. The proposed model of vicarious learning may also apply to other product markets where products are developed simultaneously at the HTF and LTF. For example, the pharmaceutical industry, which includes therapeutic products (e.g., treatment for diseases, infections) and diagnostic products (e.g., imaging, testing) in which the HTF is aimed at hospitals and the LTF is aimed at physicians' offices, respectively, may be one such important context to extend the ideas proposed in this study. We hope the insights offered by this research will stimulate further work in the area.

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References

Abrahamson, E., L. Rosenkopf. 1997. Social network effects on the extent of innovation diffusion: A computer simulation. *Organ. Sci.* **8** 289–309.

Ancona, D. G., D. Caldwell. 1992. Bridging the boundary: External activity and performance in organizational teams. *Admin. Sci. Quart.* **37** 634–665.

Argote, L. 1999. *Organizational Learning: Creating, Retaining, and Transferring Knowledge*. Kluwer Academic, Boston, MA.

Argote, L., S. L. Beckman, D. Epple. 1990. Persistence and transfer of learning in industrial settings. *Management Sci.* **36**(2) 140–154.

Baum, J., S. Mezias. 1992. Localized competition and the dynamics of the Manhattan hotel industry. *Admin. Sci. Quart.* **37** 580–604.

Baum, J. A. C., H. A. Haveman. 1997. Love thy neighbor? Differentiation and agglomeration in the Manhattan hotel industry: 1898–1990. *Admin. Sci. Quart.* **42** 304–338.

Baum, J. A. C., S. X. Li, J. M. Usher. 2000. Making the next move: How experiential and vicarious learning shape the locations of a chain's acquisitions. *Admin. Sci. Quart.* **45** 766–801.

Beckman, C. M., P. R. Haunschild. 2002. Network learning: The effects of partners' heterogeneity of experience on corporate acquisitions. *Admin. Sci. Quart.* **47** 92–124.

Benner, M. J. 2002. Process management and technological innovation: A longitudinal study of the photography and paint industries. *Admin. Sci. Quart.* **47**(December) 676–706.

Burgelman, R. A. 1991. Intraorganizational ecology of strategy making and organizational adaptation: Theory and field research. *Organ. Sci.* **2** 239–262.

Burns, L. R., D. R. Wholey. 1993. Adoption and abandonment of matrix management programs: Effects of organizational characteristics and interorganizational networks. *Acad. Management J.* **36** 106–138.

Cameron, C. A., P. K. Trivedi. 1998. *Regression Analysis of Count Data*. Cambridge University Press, New York.

Chamley, C., D. Gale. 1994. Information revelation and strategic delay in a model of investment. *Econometrica* **62**(5) 1065–1085.

Cohen, W. M. 1995. Empirical studies of innovative activity. P. Stoneman, ed. *Handbook of the Economics of Innovation and Technological Change*. Basil Blackwell, Oxford, UK.

Cohen, W. M., D. A. Levinthal. 1990. Absorptive capacity: A new perspective on learning and innovation. *Admin. Sci. Quart.* **35**(September) 128–152.

Creech, H. 2005. Digital camera buyer's guide. *Epinions.com* (December 8), http://www.epinions.com/buyers_guide/Digital_Cameras_buyers_guide_p1.html.

Cyert, R. M., J. G. March. 1963. *A Behavioral Theory of the Firm*. Prentice-Hall, Englewood Cliffs, NJ.

DiMaggio, P. J., W. W. Powell. 1983. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *Amer. Sociol. Rev.* **48** 147–160.

Economist, The. 2000. The great convergence gamble. **357**(82) 67–68.

Eisenhardt, K. M., B. N. Tabrizi. 1995. Accelerating adaptive processes: Product innovation in the global computer industry. *Admin. Sci. Quart.* **40**(1) 84–10.

Fleming, L. 2001. Recombinant uncertainty in technological search. *Management Sci.* **47**(1) 17–132.

Future Image Report. 1993. Published by Future Image Inc., San Francisco, CA.

Gamberdella, A., S. Torrisi. 1998. Does technological convergence imply convergence in markets? *Res. Policy* **20** 465–483.

Gavetti, G., J. W. Rivkin. 2005. How strategists really think: Tapping the power of analogy. *Harvard Bus. Rev.* **83**(4) 54–65.

Gelman, A., D. B. Rubin. 1992. Inference from iterative simulation using multiple sequences. *Statist. Sci.* **7** 457–511.

Geroski, P. A. 1990. Innovation, technological opportunity and market structure. *J. Indust. Econom.* **38** 586–602.

Gilks, W. R., S. Richardson, D. J. Spiegelhalter. 1998. *Markov Chain Monte Carlo in Practice*. Chapman & Hall, New York.

Greenstein, S., T. Khanna. 1997. What does industry convergence mean? D. Yoffie, ed. *Competing in the Age of Digital Convergence*. Harvard Business School Press, Boston, MA.

Greve, H. R. 1996. Patterns of competition: The diffusion of a market position in radio broadcasting. *Admin. Sci. Quart.* **41** 29–60.

Greve, H. R. 1998. Managerial cognition and the mimetic adoption of market positions: What you see is what you do. *Strategic Management J.* **19**(October) 967–988.

Greve, H. R., A. Taylor. 2000. Innovations as catalysts for organizational change: Shifts in organizational cognition and search. *Admin. Sci. Quart.* **45** 54–80.

Hannan, M. T., J. R. Ranger-Moore, J. Banaszak-Holl. 1990. Competition and the evolution of organizational size distributions. J. V. Singh, ed. *Organizational Evolution*. Sage, Newbury Park, CA, 248–256.

Haunschild, P. R. 1993. Interorganizational imitation: The impact of interlocks on corporate acquisition activity. *Admin. Sci. Quart.* **38** 564–592.

Haunschild, P. R., C. M. Beckman. 1998. When do interlocks matter? Alternate sources of information and interlock influence. *Admin. Sci. Quart.* **43** 815–844.

Haunschild, P. R., A. S. Miner. 1997. Modes of interorganizational imitation: The effects of outcome salience and uncertainty. *Admin. Sci. Quart.* **41** 472–500.

Haunschild, P. R., B. N. Sullivan. 2002. Learning from complexity: Effects of prior accidents and incidents on airlines' learning. *Admin. Sci. Quart.* **47** 609–643.

Haveman, H. A. 1993. Follow the leader: Mimetic isomorphism and entry into new markets. *Admin. Sci. Quart.* **38** 593–627.

Henderson, R., K. B. Clark. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Admin. Sci. Quart.* **35**(March) 9–30.

Huber, G. 1991. Organizational learning: The contributing processes and the literatures. *Organ. Sci.* **2**(1) 88–113.

Kamien, M. I., N. Schwartz. 1979. Optimal capital accumulation and durable good production. *Zeitschrift für National Ökonomie* **37** 25–43.

Kim, J., A. S. Miner. 2000. Crash test without dummies: A longitudinal study of interorganizational learning from failure experience in the U.S. commercial banking industry, 1984–1998. *Best Paper Proc.* Academy of Management Annual Meetings, Toronto, Ontario.

Lant, T. K., P. F. Hewlin. 2002. Information cues and decision making: The effects of learning, momentum and social comparison in competing teams. *Group Organ. Management* **27**(3) 374–407.

Lant, T. K., S. J. Mezias. 1990. Managing discontinuous change: A simulation study of organizational learning and entrepreneurial strategies. *Strategic Management J.* **11** 147–179.

Levitt, B., J. G. March. 1988. Organizational learning. W. R. Scott, J. Blake, eds. *Annual Review of Sociology*. Annual Reviews, Palo Alto, CA, 319–340.

Malerba, F. 2002. Sectoral systems of innovation and production. *Res. Policy* **31**(2) 247–264.

March, J. G. 1991. Exploration and exploitation in organizational learning. *Organ. Sci.* **2** 71–86.

McKendrick, D. G. 2001. Global strategy and population level learning: The case of hard disk drives. *Strategic Management J.* **22** 307–334.

Merklinger, H. M. 2005. The *Luminous Landscape* discussion forum. (December 8), http://www.luminous-landscape.com/reviews/merklinger.shtml.

Mezias, S. J., B. Eisner. 1997. Competition, imitation and innovation: An organizational learning approach. *Adv. Strategic Management* **14** 261–294.

Mezias, S. J., M. A. Glynn. 1993. The three faces of corporate renewal: Institution, revolution, and evolution. *Strategic Management J.* **14** 77–101.

Mezias, S. J., T. K. Lant. 1994. Mimetic learning and the evolution of organizational populations. J. Baum, J. Singh, eds. *Evolutionary Dynamics of Organizations*. Oxford University Press, New York, 179–193.

Miller, D., J. Chen. 1996. Nonconformity in competitive repertoires: A sociological view of markets. *Soc. Forces* **74**(June) 1209–1234.

Miner, A. S., S. J. Mezias. 1996. Ugly duckling no more: Past and future of organizational learning research. *Organ. Sci.* **7**(1) 88–99.

Montgomery, C., B. Wernerfelt. 1992. Risk reduction and umbrella branding. *J. Bus.* **65**(1) 31–50.

Moorman, C. 1995. Organizational market information processes: Cultural antecedents and new product outcomes. *J. Marketing Res.* **32**(August) 318–335.

Nelson, R., S. G. Winter. 1982. *An Evolutionary Theory of the Firm.* Harvard University Press, Cambridge, MA.

Ocasio, W. 1997. Towards an attention-based view of the firm. *Strategic Management J.* **18**(6, Summer Special Issue) 187–196.

Pisano, G. P. 1990. The R&D boundaries of the firm: An empirical analysis. *Admin. Sci. Quart.* **35** 153–176.

Pogue, D. 2005. Digital photos even a miser can enjoy. *The New York Times* (Dec. 15) C1, 1.

Porac, J. F., H. Thomas. 1990. Taxonomic mental models in competitor definition. *Acad. Management Rev.* **15** 224–240.

Rogers, E. 1995. *Diffusion of Innovations*, 4th ed. The Free Press, New York.

Rothwell, R. 1994. Industrial innovation: Success, strategy, trends. M. Dodgson, R. Rothwell, ed. *The Handbook of Industrial Innovation*. Edward Elgar Publishing, Cheltenham, UK, 33–53.

Schmookler, J. 1962. Economic sources of inventive activity. *J. Econom. Hist.* **22**(March) 1–20.

Schumpeter, J. A. 1934. *The Theory of Economic Development*. Harvard University Press, Cambridge, MA.

Spiegelhalter, D. J., N. G. Best, B. P. Carlin, A. van der Linde. 2002. Bayesian measure of model complexity and fit. *J. Roy. Statist. Soc., Ser. B* **64**(4) 583–639.

Staw, B. M., L. E. Sandelands, J. E. Dutton. 1981. Threat-rigidity effects in organizational behavior: A multilevel analysis. *Admin. Sci. Quart.* **26** 501–524.

Tripsas, M., G. Gavetti. 2000. Capabilities cognition and inertia: Evidence from digital imaging. *Strategic Management J.* **21** 1147–1161.

Tushman, M. L., L. Rosenkopf. 1992. Organizational determinants of technological change: Toward a sociology of technological evolution. *Res. Organ. Behav.* **14** 311–347.

Utterback, J. M. 1994. *Mastering the Dynamics of Innovation: How Companies Can Seize Opportunities in the Face of Technological Change*. Harvard University Press, Boston, MA.

Van de Ven, A. H., H. L. Angle. 1989. The Minnesota Innovation Research Program. A. H. Van de Ven, H. L. Angle, M. S. Poole, eds. *Research on the Management of Innovation: The Minnesota Studies*. Harper & Row, Ballinger Division, New York, 3–30.

Wedel, M., W. A. Kamakura. 2000. *Market Segmentation: Conceptual and Methodological Foundations*. Kluwer Academic Publishers, Boston, MA.

Yoffie, D. B. 1997. *Competing in the Age of Digital Convergence*. Harvard Business School Press, Boston, MA.