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Manufacturer Product Line Decisions In Growing Consumer Technology Markets:

A Case of Digital Cameras

by

Kyryl Lakishyk

A dissertation presented to the
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ABSTRACT

The objective of this dissertation is to deepen our understanding of competitive and demand drivers of manufacturer new product introductions in consumer technology markets.

Researchers in economics and marketing commonly view differentiated products as combinations of "attributes" that are located in multi-attribute space. In first study presented in Chapter 2 of this dissertation, I conform to this common view of products as multi-attribute bundles and, therefore, carefully construct both a multi-attribute product space, as well as, and even more importantly, product clusters within this multi-attribute product space. I focus on the early stages of US Digital Cameras category (1998-2000). Operationalizing and classifying all existing products in the category, as well as each new product introduction (when it occurs), on a common space of objective product attributes allows us to (1) explicitly understand whether a given introduction is an incremental innovation or a radical innovation, and (2) whether it is an introduction in to a cluster where the firm already has a strong presence or not etc. Further, it allows us to understand whether the new product introduction decisions of a firm are influenced by relative cluster characteristics which, in turn, are influenced by competitors' new product introductions in the different clusters etc. In the Chapter 2 of this dissertation I focus on two specific new product introduction decisions of digital camera manufacturers: timing and positioning. Additional insights are obtained from empirically estimating a pricing model using the same product cluster conceptual framework.

In Chapter 3, I study new product preannouncements, which have become commonplace in manufacturers product strategy in consumer technology markets. Here I undertake a detailed empirical analysis of the demand effects of product preannouncements within the digital cameras category. I estimate a new product adoption model using monthly data on product-level availability, sales and prices across hundreds of digital cameras that were introduced over a period of 4 years. I study the effects of the incidence and timing of a product preannouncement on demand for the preannounced product (i.e., digital camera model), as well as demand for its

competitors. In doing this, I implicitly accommodate the impact of product preannouncements for individual products on *category-level* demand growth. Using a detailed model-based accounting of preannouncement effects, I separate the effects of a preannouncement on (1) innovation and word-of-mouth components underlying demand for the preannounced product, and (2) consumer preferences for preannounced product attributes. I demonstrate the managerial implications of the estimated preannouncement effects using a numerical experiment.

ACKNOWLEDGEMENTS

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CHAPTER 1: **INTRODUCTION**

High technology, as defined by the Merriam-Webster dictionary, is "a scientific technology involving the production or use of advanced or sophisticated devices especially in the fields of electronics and computers". In the last decade 'high technology markets' have quickly become synonymous with a vast range of consumer electronics, including DVD players, portable MP3 music devices, digital cameras, and personal computers. The increasing prevalence of technology-based products and high financial rewards to successful companies in these categories explain the heightened interest from managers. However, these products differ from other durable and consumer packaged categories in that they depend and move through the technology life cycle. Creating and competing with technology-based products successfully has higher uncertainty, especially in the early stages of category development.

There are several key distinguishing traits of consumer technology products that make them an interesting subject for marketing practitioners and academics. Most of these markets are relatively new categories going through growth stage of their life cycle. Many technical components, such as memory chips and image sensors used in manufacturing of such products are supplied by third parties, effectively reducing barriers to entry in such markets. However, within a few years of most technology-based consumer markets have a set of a few dominant players. In digital cameras category top five manufacturers together account for over 80 percent of category sales (see Table 1) during my study period (1998-2001). These companies commercialize an impressive

variety of products that caters to heterogeneity of consumer tastes. For instance, in September 2001 Sony was offering 29 individual models of digital cameras.

[Insert Table 1 here]

What allows the manufacturers achieve such differentiation is the salience of several key technological attributes (both software- and hardware-based) to create and commercialize a variety of new products. For example, manufacturing a portable digital music player with an additional 32 GB of storage compared to its already existing model, a company effectively markets an entirely new product unit. Further, adding gaming software to the same digital music player the same brand can add another variant to its product line in the category, making new product introductions a strategic competitive tool. On one hand, broad product lines have been shown to serve as a credible entry-deterring strategy to protect an achieved market position (Bhatt 1987; Gilbert and Matutes 1993). On the other hand, new product introduction may be used in reaction to a competitive product that directly threatens firm's advantage.

The objective of this dissertation is to improve our understanding of strategic firms' new product introduction decision. Using digital cameras as a focal market I investigate new product introductions to and generalize the main competitive drivers behind firms' new product activities.

To provide answers to the questions raised in the present research, I use monthly data on sales, prices, and product attributes from the US digital camera market during the period of January 1998 to September 2001. I propose a clustering procedure for products along objective, time-invariant attributes, and then estimate the drivers of the manufacturer's chosen decisions of product introduction and positioning. I develop and

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empirically estimate firm-centric model of the on new product introductions as a two-step process: (1) whether to introduce a new product and (2) the conditional choice of positioning in the product cluster space, firm-specific strategic and structural covariates as explanatory variables. I obtain additional insights by estimating a pricing model of digital camera prices using product attributes, and product cluster covariates. In the Chapter 2 of this dissertation I focus on two specific new product introduction decisions of digital camera manufacturers: strategic *timing* and *positioning*.

My study contributes both conceptually as well as methodologically to the product line literature. Conceptually, my study recognizes that in addition to category-wide factors, product line decisions of a high tech manufacturer are also influenced by local competitive drivers pertinent to a specific product cluster. Methodologically, my study suggests the use of cluster analysis to operationalize product clusters and estimate the impact of competitive drivers on product line decisions. Substantively, I investigate the drivers behind manufacturers' product line decisions in the digital camera market.

In my first study I find support to category-driven pacing of new product introduction. The overall pattern of the product location of the products by the top digital cameras manufacturers is as follows: (1) firms choose to position their new products in larger product segments, while avoiding cannibalization of their current successful products by positioning; (2) the new products positioning is more likely to follow new product activity by competing firms in to brand's less established and new clusters (as measured by measures of relative special dispersion in product space); I find support for likelihood of speedy reactions to competitive product activity that threatens position of the focal firms where they have relatively strong commercial success; Finally, innovation

in products is more likely based on new product development experience of firms and rewards such innovation with price premium in contrast to downward price pressures characteristic to high-technology markets.

In Chapter 3 of this dissertation I develop a study of new product preannouncements the setting of digital cameras market. I make an important contribution to the marketing literature on preannouncements by estimating the demand effects – at both the category-level, as well as the product-level -- of product preannouncements both prior to, as well as after, actual product launch. For this purpose, I use monthly demand data for 303 products over 3 ½ years from the digital cameras category and track their product preannouncements through a variety of industry and public sources. I find that preannouncement timing has a non-monotonic impact in terms of influencing both their baseline adoption rates, as well as the estimated impacts of product characteristics on consumer utility for the preannounced product. Confirm that new product preannouncements play an advertising role in that they increase category adoption rates. In contrast, I also uncover evidence in favor of consumers postponing their purchase of existing digital cameras, as surmised in the existing literature, to wait for preannounced products. This latter finding has competing implications for manufacturers: on the one hand, product preannouncements can pre-empt purchases of competing manufacturers' existing products ("demand stealing"); on the other hand, product preannouncements can pre-empt purchases of the manufacturers' own existing products (self-cannibalization").

CHAPTER 2: **PRODUCT LINE COMPETITION IN HIGH-TECHNOLOGY CONSUMER MARKETS**

2.1   INTRODUCTION

Background

A key aspect of a firm's product strategy in a high-technology market is *product line management*, specifically pertaining to the sequential introduction of new products over time. The effect of competition is to render these new product introduction decisions to be inter-related across competing firms. From the perspective of each individual firm in such a high-technology market, a new product introduction decision typically involves two constituent strategic dimensions – (1) the *timing* of the new product introduction, and (2) the *position* – in terms of objective product features -- that is chosen by the firm for the new product relative to the firm's, as well as its competitors', existing products. The purpose of this research is to empirically study these two constituent strategic dimensions of firms' new product introduction decisions.

Over the years, beginning with the pioneering work of Hotelling (1929), there has emerged a rich body of analytical / game-theoretic research on competing firms' product positioning decisions (for a classic paper, see D'Aspremont, Gabszewicz and Thisse 1979). The marketing literature on this subject casts firms and consumers on a common perceptual map to analyze firms' optimal marketing decisions (Choi, Desarbo and Harker 1990; Hauser 1988; Hauser and Shugan 1983; Moorthy 1988). In this literature, there are two competing strategic forces that drive firms' new product positioning decisions. On

the one hand, a firm could specialize in one or more specific clusters on the perceptual map by introducing most of their new products in those clusters and, therefore, effectively "crowding out" competitors from those segments (Eaton and Lipsey 1979; Schmalensee 1978). On the other hand, a firm may choose to spread its new product introductions across a large number of clusters on the perceptual map, which gives the firm greater market reach while also reducing the effects of cannibalization among the firm's various products (Brander and Eaton 1984; Spence 1976). In fact, the latter strategy could also serve to deter the entry of new firms in to the product category as a whole (Bonanno 1987).

Related to the above discussion is the firm's decision of whether to employ an incremental innovation strategy (introduce variations of existing products) or a radical innovation strategy (introduce products that are radically different from existing products) over time. For example, if the firm wants to build the reputation of the brand as a pre-eminent brand in the product category, it may be worthwhile to frequently introduce incremental innovations. A wide product assortment increases the perceived product quality and, therefore, the equity of the brand (Agarwal and Bayus 2002). In his comments on developments in digital imaging markets, the President and CEO of Eastman Kodak Company, Daniel Carp declared: "The power of Kodak is the breadth [of product offerings]. At the end of the day, it is my relationship with the consumers that will drive their choice." (*Photo Marketing* 2003).

As far as the timing of a new product introduction is concerned, as a monopolist, a firm may wish to sustain the stream of revenues from its existing products, as implied by their product life cycles, for as long as possible and, therefore, delay the introduction

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of the next generation of products in order to minimize the cannibalization of its existing products (Cohen, Eliashberg and Ho 1996). However, competitive pressures, especially during the growth stage of the product category, may motivate companies to speed up their new product introductions in order to gain and maintain their advantage over their rivals (Bayus, Jain and Rao 1997). Being first to market benefits the firm by creating switching costs for consumers, pre-empting competitors etc. However, being the first mover also leads to increased R&D costs for the firm, especially since the firm's competitors can "free ride" on the firm's pioneering R&D efforts (Narasimhan and Zhang 2000). First-mover advantages typically weaken in multi-product (i.e., multiple firms competing in multiple product clusters) settings.

Another important driver of the timing of new product introductions is the speed of change in the industry's processes, supplier relationships, distribution chain design decisions etc., or, in other words, the industry's "internal clock-speed" (Mendelson and Pillai 1999; Souza, Bayus and Wagner 2004). Whether a firm is in a fast clock-speed industry (e.g., personal computers, semi-conductors, digital cameras) or a slow clock-speed industry (e.g., soft drinks) influences the temporal pace of the firm's new product introductions. A rapid pace of introductions is vital for the survival, as well as the maintenance of competitive advantage, of firms in high technology industries since they tend to be high clock-speed (Hauser, Tellis and Griffin 2006). Using a normative model, Souza et al. (2004) find that a firm's optimal rate of product innovation is *primarily* determined by the industry's clock-speed conditions, with a strategy of frequent incremental (versus radical) improvements being the optimal strategy for a firm in a high clock-speed industry.

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A competitor's new product that directly threatens a firm's positional advantage in an industry may accelerate the firm's introduction of a new product in order to neutralize the competitive threat. For example, in 2000, AMD threatened Intel's technological dominance by being first to break the 1GHz barrier with a version of its Athlon chip. Within days, Intel began marketing a limited-release Pentium III 1 GHz processor, and within little more than a year Intel became the first to introduce a 2 GHz chip (Thornhill, Lee and Shannon 2001).

Focus of this Research

Researchers in economics and marketing commonly view differentiated products as combinations of "attributes" that are located in multi-attribute space (Lancaster 1990). Competing products occupy alternative positions on a common multi-dimensional space of attributes. Products that are close to each other on this multi-attribute space share similar product features and, therefore, address similar consumer needs. Products that are far away from each other on this multi-attribute space represent different product features and, therefore, address different consumer needs. In this research, I conform to this common view of products as multi-attribute bundles and, therefore, carefully construct both a multi-attribute product space, as well as, and even more importantly, product clusters within this multi-attribute product space. I focus on the digital cameras category. In order to achieve the above-mentioned multi-attribute operationalization of competing products, I use the *objective* attributes of the products, i.e., technical characteristics of digital cameras, such as optical zoom, sensor resolution etc. Operationalizing and classifying all existing products in the category, as well as each new product introduction

(when it occurs), on a common space of objective product attributes allows us to explicitly understand whether a given introduction is an incremental innovation or a radical innovation, whether it is an introduction in to a cluster where the firm already has a strong presence or not etc. Further, it allows us to understand whether the new product introduction decisions of a firm are influenced by relative cluster characteristics which, in turn, are influenced by competitors' new product introductions in the different clusters etc. (Day 1997). I focus on two specific new product introduction decisions of digital camera manufacturers: timing and positioning. I discuss some key drivers of these two decisions below.

The firm's decision on whether to introduce a new product had been empirically studied in the framework of product line extensions, which in a given time period is driven by market opportunity – *growth of the market* demand and lack of *competitive new product activity* (Putsis and Bayus 2001; Stavins 1995). Several empirical studies on strategic drivers of competitive reactions proposed past competitor activity in explaining the likelihood of firm's current period actions (Chen, Smith and Grimm 1992; Leeflang and Wittink 2001; Shankar 2006). Specifically, Shankar (2006) explicitly studies and finds that in a printer market firms are more likely to engage in product actions when its competitors changed their product lines in the past.

In order to address the research questions in my study, I treat the new product introduction by each manufacturer as a two-stage decision process. First, the manufacturer decides on whether to expand current product offering. Second, the he decides on which product cluster(s) to enter. Such approach is similar in spirit to Putsis and Bayus (2001), who model proliferation strategy as a two-step process – direction of

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product line change, and magnitude of the change. By including the inclusive value of the second step of the decision allows us to capture net effect of strategic competitive variables on the product cluster entry level, which I discuss below.

Using the suggested product cluster framework which I describe in detail in Section 2.3.1., I compute several variables to capture the impact of timing and opportunity of new product introduction action suggested in the studies above - *category sales change*, *number of competitive products introduced* in the previous period, as well as *time since brand's own product activity in the category*. I describe specifics of operationalization of the variables in Section 2.3.2 and provide a summary in Table 4.

Leeflang and Wittink (2001) conclude that firms are more likely to react to past competitor moves and less to their own actions. The speed of a competitor's reaction a new product is related to the *market share* of the respondent firm (Bowman and Gatignon 1995). Chen, Smith and Grimm (1992) use *lag response of time* from the initial competitor action and find that strategic response (in contrast to tactical actions in marketing mix) has a significant delay. Their study of competitive moves among airlines concludes that companies *with high stake in the markets* under attack tend to react slowly. Therefore, it is important to develop a set of measure to capture key strategic dimensions of a new product positioning relative to firm's own products and those of the competitors.

Cross industry empirical studies of strategic impact of breadth of product line (Kekre and Srinivasan 1990), product proliferation (Bayus and Putsis 1999; Putsis and Bayus 2001) and model entry (Stavins 1995) employ various measures to capture the phenomena of product spread in a given product category - length of the product line

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(number of products in a given period) and measures of quality dispersion based on the hedonic regression estimates.

In my framework the product positioning choices made by the manufacturers are classified into product clusters based on the technical attributes. In order to capture *positioning* and *timing* strategic drivers of product competition in the market digital cameras I develop several measures of relative dispersion in the product space of the category market, as well as within individual product segments (clusters):

1) *Relative dispersion of the firm's products in a cluster* (measures dominance of one manufacturer);

2) *Relative dispersion of brands products in a category, relative to the overall category dispersion* (measures category-level proliferation by a brand);

3) *Relative dispersion of brand's products in a given cluster relative to the overall product category dispersion* (captures category dominance of a given cluster and a brands' products therein);

4) *Share of revenues derived by a brand from a specific cluster* (captures strategic importance of the cluster for brand's performance on the market).

5) *Lags of time since competitive product introductions* in a cluster.

Details of variable computations are provided in Section 2.3.2 and summary statistics in Tables 4 and 5.

Finally, radical product innovation is a major commitment by a company in high-technology market. The success of innovative products (pioneers) had been linked to firms' product development efficiencies and market estimates (Bayus et al. 1997). Therefore I extend the measures of *firm age* and *technology age* used by Putsis and

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Bayus (2001) to *relative product line age* (a sales weighted age of firm's products relative to the same measure of the category). If a new product performs well, the pioneer is likely to see a larger market share than the followers who enter the market later (Biggadike 1979; Bond and Lean 1977). In order to examine strategic possible preemption by firm, use the dispersion measure (2) above as a covariate of pioneering in a product space.

I discuss the details of my product clustering approach in Section 2.3.1. Using the suggested product cluster framework, I consider several strategic variables that prior studies have found to affect manufacturer's decisions related to product line. In general these covariates represent strategic industry, competitive, and firm factors that impact the firm's likelihood of responding to market opportunities or overcoming barriers. The details of the econometric model used for new product introductions are developed in Section 2.3.2.

To enhance our understanding of the product competition in high-technology markets in the setting of digital cameras market I develop and estimate a pricing model that accounts for invariant product attributes, as well as time varying competitive effects. The details of this model are provided in the Section 2.3.3.

Before I proceed to the details of my Econometric approach, I briefly describe US digital cameras market, which serves as the institutional setting of my study.

2.2 STUDY SETTING: DIGITAL CAMERAS

The first commercially available digital camera was "Dycam Model 1" introduced in 1990 by Logitech (*MacWeek* 1990). For the next few years the new product

introductions would remain few and appeal to a limited audience of institutional and professional users[1]. The introduction of Kodak's DC40 in 1995, "the first consumer-priced model from Kodak" marks the inception of the digital cameras as a consumer market. In the years following the introduction of these first consumer-level digital cameras, the market experienced explosive growth. In 1998 the US market sales totaled $605 million and by the end of 2000 the annual sales were a staggering $1,874 million. Over 7 million new households purchased a digital camera by the end of 2000, and the first nine months of 2001 had resulted in an additional 3.5 million new camera sales. The customer base had quickly broadened beyond the early adopter and high-end professionals, to include a much wider range of consumers (and, as a result, lead to greater heterogeneity of consumer preferences). As early as 1998 camera manufactures and retailers saw acceptance of the digital camera technology among mass consumer segments (*Discount Store News* 1998; *Mass Market Retailers* 2000). Such growth has been attributed to several factors, such as increased image quality, reduced prices and friendly interface, and a surge in consumers' Internet activity.

A relevant question that arises in this market is whether digital cameras are a distinct product category, and different from conventional film-based products. Although intended to perform a basic function similar to conventional film photography, digital cameras cater to a different set of consumer needs. Instant playback, ability to share images electronically, digital manipulation are just a few capabilities that establish digital

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[1] Leading up to the 1990 launch, the digital imaging technology had been evolving due to the efforts and innovations by several manufacturers of electronic and traditional photo-equipment, such as Casio, Kodak, and Nikon. The potential for takeoff of the technology as a consumer product category remained uncertain for several years after the Logitech launch. Despite technological and quality advancements, the products' price tag, albeit matched by the quality level, kept digital cameras out of mainstream-consumer's reach.

cameras a product category in its own right. Sony, the major player in this market does not even have a conventional film counterpart. Finally, studies on digital camera ownership and usage indicate that only 12 percent of digital cameras were purchased as replacements for film cameras. Most households indicated that they purchased a digital camera to use in addition to their film camera (*PMA Digital Imaging Survey* 2002).

Traditionally, in high technology markets with wide product lines each major manufacturer has several R&D projects in place. The decision to ship to the retailer one or several new products based on these projects often becomes that of a strategic nature. Digital cameras market, as mentioned above, has five major brands, yet no single firm plays the role of leader in innovation. This is partly due to the fact that the basic technology used in digital cameras is available to all the manufacturers in the market. Other than the sensor technology (CCD or CMOS[2]), the components inside the digital cameras are much like those in other consumer devices – microprocessor, DRAM, A/D converter, and flash memory (*Electronic Buyers' News,* 1998) Different manufacturers often use the same component suppliers such as Intel, Sierra Imaging, Sanyo Electric, and Motorola (Lagabeer. and Stoughton. 2001). Moreover, Kodak chose to openly offer their CCD image sensors by entering the market of the sensor merchants (*Electronic Engineering Times* 2000). A number of similar agreements in technology sharing that were implemented throughout the early years of digital camera category, allowing us to assume that none of the major manufacturers is significantly constrained in its technological capability. In addition to basic capabilities, manufacturers may offer some

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[2] CCD, or charge-coupled device, is the predominant image sensor used in digital cameras. A less capable but cost-effective sensor CMOS (complementary metal oxide semiconductor) was often used in lower end "toy" and PC cameras during the study period.

proprietary features in their cameras, such as Kodak's "Easy Share" technology and Sony's "Night Shot". These specialized features potentially contribute to differentiation among the competing product lines. In this research, however, I focus on the main product attributes such as resolution, digital and optical zooms, etc. which define product space common to all of the products in the category.

It is important to discuss the most salient product attributes in this category. I will use them in the empirical analyses in the following sections. The image sensor is the "heart" of the digital camera system. It is a device which actually captures "the picture". Originally developed for video applications, image sensors have progressed in resolution and color accuracy to a stage where multi-megapixel resolution cameras are common. Indeed, nearly 70% of all the digital cameras on the market between January 1996 and September 2001 had a resolution of more than one million pixels. Moreover, by the fourth quarter of 1999, one fifth of all the cameras made by top five manufacturers on the market had a resolution of two million pixels or above. Although seemingly a technical attribute, sensor resolution ultimately defines the use of a camera from the consumer point of view. Lower resolution cameras are usually fit only for taking pictures for web use and screen viewing. Higher resolution cameras allow printing of standard size (4x6 inches) prints, and cameras with 2 mega pixels resolution and above are capable of taking images that could be printed in size 8x10 inches and larger.

In addition to sensor resolution, other product attributes considered by consumers[3] include optical zoom and digital zoom. Optical zoom is the ability of a digital camera to

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[3] Trade magazines (PC World, Photo Marketing Association Reports), digital camera buyers' guides (Digital Photography Review) and experts in professional photo labs and retail stores (personal interviews) helped me define the focal product attributes in this category: resolution, optical zoom and digital zoom.

enlarge a certain portion of the scenery using only its lenses. In those cameras with optical zoom capability, magnification varies from two-fold to ten-fold. This attribute is almost entirely defined by the optical lens system of the camera and often serves as the proxy for photographic quality of the digital camera. Digital zoom performs a similar function – enlarging a portion of the image taken. It is achieved by multiplying the number of pixels of that portion. Unlike optical zoom, digital zoom is based entirely on the software used in the digital camera. This camera capability often serves as a proxy for general "digital" complexity of the camera system.

Several other digital camera attributes have become fairly standard in the category and vary only slightly from camera to camera. Most models feature liquid crystal display, which is used as a view finder and settings menu of the camera. Over the course of several years manufactures achieved some standardization in the issue of storage. As a result, users of different camera brands are bound to using one of the most common storage types – Compact Flash, Secure Digital, etc. There is, however, little differentiation on this attribute besides the type. Most of the models use Universal Serial Bus (USB) connectivity to transfer image from the camera's system onto a hard drive of a personal computer.

2.3   **THE ECONOMETRIC APPROACH**

2.3.1   **Product Clusters and Pioneering Introductions**

In defining "product space" in the category of Digital Cameras, as substantiated in the previous discussion, I focus on the top three product attributes, namely image sensor Resolution, Optical Zoom, and Digital Zoom. For each month in my study period I use these three attributes as input variables for product space classification. My classification approach involves three steps:

STEP 1: For each month I perform cluster analysis to classify all products that exist in the category at the beginning of the month. I employ two stages in this analysis. First, an iterative relocation method is used to determine the most likely cluster membership for each of the products, given a fixed number of clusters. In this stage each product represents a data point with three product attributes as location coordinates in the category product space. I use log-likelihood as a measure of distance between clusters. The composition of the clusters is finalized when the corresponding likelihood function is maximized. The procedure is repeated assuming a different number of hypothetical clusters. In the second stage of cluster analysis, all cluster solutions (with corresponding number of clusters) are compared using Akaike Information Criterion (AIC) to determine the most likely number of product clusters for the category (Chiu, Fang, Chen, Wang and Jeris 2001). To ease computation burden, I use Two-Step Cluster Analysis procedure in SPSS Statistical Software to perform this classification step.

STEP 2: Taking the cluster structure obtained in Step 1 as exogenous, I proceed to determine cluster membership of new products, if any were introduced during the current

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month. Based on the three product attributes as in Step 1, and using existing products as a training sample, I compute a set of discriminant functions that provide the best discrimination between the clusters. Functions are then applied to product attributes of new products to classify them into one product clusters. I use SPSS Statistical Software to compute discriminant functions and classify new products.

Given the nature of product innovation, the new product may be significantly different from any of product clusters that I've identified in Step 1. To explicitly allow for such 'pioneer' product introductions I perform an additional step in my classification analysis, which is detailed below.

STEP 3: As the final step of product classification performed for each month in the dataset, I investigate the degree of product differentiation of the cameras introduced during that month. Specifically, my goal is to identify product introductions that were radically different from incumbent digital cameras during that month. In the framework of product attribute space used in classification above, I can think of this as a question whether a newly introduced product does not belong to any of the existing product clusters. Furthermore, it should be classified as a "cluster of its own".

Identifying "pioneer" product introductions raises an interesting methodological issue of distance in product attribute space. Traditional measures of Euclidian distance have limitations in the presence of unequally sized and shaped product clusters. I also have to consider that the notion of innovation is always relative to the entire set of current products and their locations. If the distribution of the current products is non-spherical during that month (for instance ellipsoidal), identifying a "pioneer" product introduction should then consider not only the distance from the new product, but also the direction of

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the differentiation move, relative to the product category. A new product differentiated

along the long axis of the product space, would need to be further away from the center

before I should label it as "pioneer". In the direction where the ellipsoid has a short axis,

smaller degree of differentiation would be relatively important.

To address this issue I use Mahalanobis (1948) distance in this step of my

classification. Let $\bar{x}_m{}' = (\bar{x}_{1m}, \bar{x}_{2m}, ..., \bar{x}_{nm})'$ denote the vector of mean values for the

products in m^{th} cluster and C denote the pooled covariance matrix for n product

characteristics. Mahalanobis distance from observation $x' = (x_1, x_2, ..., x_n)'$ to the center

of cluster m is calculated as:

$$D_{mj} = \sqrt{(x - \bar{x}_m)'C^{-1}(x - \bar{x}_m)}$$

I used SPSS statistical software to compute and analyze squared Mahalanobis

distances. New products with extreme values of D_m^2 (2 standard deviations above the

average value for all products in the market that period) were classified as "pioneer"

introductions.

An example of a resulting product classification described in this section is

depicted in Figure 5. In February 2000 there were 52 incumbent digital camera products.

During this month Olympus launched two new cameras (D460Z and D360L, labeled

respectively as products '1' and '2' in Figure 5) and Nikon introduced CoolPix 990

(labeled '3').

[Insert Figure 5 here]

Based on the product cluster structure established through classification procedure described in this section, I generate a set of time variant brand-specific and cluster-specific variables that characterize each product introduction (detailed below). I use them as predictors in the new product introduction model developed in the next section.

2.3.2 New Product Introduction Model

During each period t, manufacturer k may introduce new products on the market. Following my discussion in the previous sections, I aim to capture the influence of several category level and product cluster-level drivers on this introduction. I model each new product introduction as a two-stage process, where manufacturer decides whether to introduce new products during period t, followed by decision to enter a specific product cluster. Let M_t denote the number of product clusters in the category at time period t. The probability associated with the introduction of a new product by manufacturer (brand) k in product cluster m_t can be expressed as:

$$\Pr_k(\, Intro_t, m_t) = \Pr_k(Intro_t) * \Pr_k(m_t \mid Intro_t) \tag{1.1}$$

Let V_{tkm_t} stand for strategic attractiveness for brand k of introducing a new product in cluster m_t and is given by:

$$V_{tkm_t} = Q_{tkm_t}\varphi, \tag{1.2}$$

where Q_{tkm_t} denotes a row-vector of brand specific characteristics of product cluster m evaluated at time t, and φ stands for the corresponding column-vector of parameters. The conditional probability on the right hand side in equation (1.1) can be expressed as

$$\Pr{}_k(m_t \mid Intro_t) = \frac{\exp(V_{tkm_t})}{1 + \exp(V_{tkm_t})} \tag{1.3}$$

Two clarifying remarks are in order here. First, brand can introduce more than one product each period. I simplify my model treating each introduction as independent of the rest, which effectively results in independent binary logit across product clusters. The second remark is regarding pioneer introductions discussed in the previous section. I model each as a "pioneer cluster", $\hat{m}_t$ and their attractiveness for brank k in period t is expressed as $V_{tk\hat{m}_t} = \hat{Q}_{tk\hat{m}_t}\hat{\varphi}$, where $\hat{Q}_{tk\hat{m}_t}$ denotes a row-vector of brand specific characteristics evaluated at time t, and $\hat{\varphi}$ stands for the corresponding column-vector of parameters. I discuss vectors Q_{tkm_t} and $\hat{Q}_{tk\hat{m}_t}$ in greater detail below.

The first component on the right hand side in (1.1) is the brand's marginal probability of introducing a new product. The option of introducing a new product in period t is evaluated as

$$\Pr{}_k(Intro_t) = \frac{\exp\left(Y_{kt}\gamma + \tau\bar{V}_{tkM_t}\right)}{1 + \exp\left(Y_{kt}\gamma + \tau\bar{V}_{tkM_t}\right)}, \tag{1.4}$$

where Y_{kt} stands for a time-variant row-vector of category characteristics for brand k, and $\bar{V}_{tkM_t}$ stands for "cumulative attractiveness" of all product clusters in the market at time t for brand k and is given by:

$$\bar{V}_{ktM_t} = \ln \sum_{m_t \in M_t} \exp(Q_{ktm_t}\varphi) \tag{1.5}$$

Let I_{tkm_t}, be an indicator variable that takes a value 1 if in period t manufacturer k introduces a new model in product cluster m_t, $m_t = 1, ..., M_t$. The impact of category and product cluster drivers on the introduction decision are expressed as:

$$L(\gamma, \tau, \varphi) = \prod_{t=1}^{T} \prod_{k=1}^{5} \left[\left(\frac{\exp\left((Y_{kt}\gamma + \tau\overline{V}_{tkM_t})\overline{I}_{tk}\right)}{1 + \exp(Y_{kt}\gamma + \tau\overline{V}_{tkM_t})} \right) * \frac{\exp\left(\sum_{m_t=1}^{M_t} V_{tkm_t} I_{km_t}\right) * r_{kt}}{\prod_{m_t \in M_t} \left(1 + \exp(V_{tkm_t})\right)} \right], \qquad (1.6)$$

where $\overline{I}_{tk} = \max\{I_{k1}, ... I_{kM_t}\}$ and $r_{kt} = \left(1 - \prod_{m_t \in M_t} \left(1 + \exp(V_{tkm_t})\right)^{-1}\right)^{-1}$.

Note that when all I_{tkm_t} take the value of 0, $\max\{I_{k1}, ... I_{kM_t}\} = 0$, which is equivalent to brand k's no-introduction decision on the category level. Equation (1.6) explains the decision to introduce a product line extension via a set of category variables Y_{kt} and further, describes the drivers behind positioning of the new addition(s) in a specific cluster (or group of clusters) by Q_{tkm_t} or $\widehat{Q}_{tk\widehat{m}_t}$ covariates.

New Product Introduction: Category level

I include the following category characteristics within the time-variant vector Y_{kt}:

1. $\Delta Category\$SalesLag_t$ (Category revenue change from t-2 to t-1);

2. $NumberCompetIntros_{k(t-1)}$ (Number of new digital cameras introduced in $(t$-1$)$ by competitors of brand k);

3. $TimeOwnCatIntro_{kt}$ (Time since own product introduction on the category level. Operationalized as the number of months elapsed since last own introduction in

the digital camera category by brand k, i.e., the age of k's newest model on the

market by brand k at the beginning of period t);

4. $TimeOwnCatIntro^{2}_{kt}$;

The category level of product introduction decision model also includes a set of brand

indicators and vector $\bar{V}_{ktM_t}$. The former allows us to estimate brand specific intercepts for

category introduction incidence. The latter, as discussed above captures overall strategic

utility of all product cluster choices on the lower level of the model.

Product Location Choice: Cluster level

I compute and include the following brand-specific cluster characteristics within the

time-variant vector Q_{tkm_t}:

1. *NumberModels*$_{tm_t}$ (Number of current products in product cluster m_t at the

beginning of period t);

2. *BrandClust|CatShare*$_{tkm_t}$ (Share of revenues derived by brand k in period *t-1*

from all products located in cluster m_t at the beginning of period t, relative to the

total category revenues of brand k obtained in period *t-1*.);

3. *RELATIVE.Brand-in-ClustDisp*$_{tkm_t}$ (Dispersion of brand k's products in cluster

m_t relative to dispersion of all cameras in cluster m_t in period t. Operationalized

as average squared Euclidian distance from brand's models j_k in a cluster m_t to

brand's centroid, relative to the same measure averaged across all of the products

in cluster m_t to the cluster centroid. Consider a case of classification based on

three product attributes - x, y, and z. Then brand k's centroid for m_t is denoted

by $\{\bar{x}_{km_t}, \bar{y}_{km_t}, \bar{z}_{km_t}\}$, and in contrast to the cluster centroid denoted by $\{\bar{x}_{m_t}, \bar{y}_{m_t}, \bar{z}_{m_t}\}$.

$$RELATIVE.Brand\text{-}in\text{-}ClustDisp_{tkm_t} = \frac{(Brand\text{-}in\text{-}ClustDisp_{tkm_t})}{(ClustDisp_{tm_t})},$$

where

$$Brand\text{-}in\text{-}ClustDisp_{tkm_t} = \frac{1}{N_{J_{km_t}}} \sum_{j=1}^{J_{km_t}} [(x_{jkm_t} - \bar{x}_{km_t})^2 + (y_{jkm_t} - \bar{y}_{km_t})^2 + (z_{jkm_t} - \bar{z}_{km_t})^2],$$

$$ClustDisp_{tm_t} = \frac{1}{N_{J_{m_t}}} \sum_{j=1}^{J_{m_t}} [(x_{jm_t} - \bar{x}_{m_t})^2 + (y_{jm_t} - \bar{y}_{m_t})^2 + (z_{jm_t} - \bar{z}_{m_t})^2]$$

4. $TimeCompClustIntro_{tkm_t}$ (Time since competitor introduction in cluster m_t, operationalized as the age of the newest digital camera model in cluster m_t at the beginning of period t, excluding brand k's own products);

5. $TimeCompClustIntro_{tkm_t}^2$;

6. $TimeOwnClustIntro_{tkm_t}$ (Time since brand k's own product introduction in cluster m_t, operationalized as age of brand k's newest camera model in product cluster m_t at the beginning of period t);

7. $TimeOwnClustIntro_{tkm_t}^2$;

I also include the following products the following interaction effects at the level of product cluster choice:

1. $RELATIVE.Brand\text{-}in\text{-}ClustDisp_{tkm_t} * BrandClust|CatShare_{tkm_t}$ (interaction between dispersion of brand k's products in a given cluster with the importance of the cluster for brand k's revenues);

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2. *RELATIVE.Brand-in-ClustDisp$_{tkm_t}$*TimeCompClustIntro$_{tkm_t}$ (interaction between dispersion of brand k's products in a given cluster and time since the last competitive introduction in that cluster);

3. *RELATIVE.Brand-in-ClustDisp$_{tkm_t}$*TimeCompClustIntro$_{tkm_t}^2$;

<u>Pioneer introduction: Cluster level</u>

I compute and include the following brand-specific category characteristics within the time-variant vector $\hat{Q}_{tk\tilde{m}_t}$:

1. $\Delta Brand|CatShare_{kt}$ (Change in brand k's share of category revenues from *t-2* to *t-1*);

2. *RELATIVE.AgeBrandPLine$_{kt}$* (Relative age of brand *k*'s product line at the beginning of period t. I operationalize it as average age of *k's* products at *t-1* weighted by their respective sales, divided by sales-weighted age of all camera products in the category in period *t-1*);

3. *RELATIVE.Brand*-in-*CatDisp$_{kt}$* (Dispersion of brand *k's* products in the category in period t relative to the overall dispersion in the category. I operationalize this as average squared Euclidian distance from all of brand *k*'s products in period *t* to their centroid, relative the same measure for all the products in the category to the category centroid). Let's consider again the case with three product attributes (x, y and z). Then brand *k*'s centroid for is denoted by $\{\bar{x}_{kt}, \bar{y}_{kt}, \bar{z}_{kt}\}$, and is different from category centroid $\{\bar{x}_t, \bar{y}_t, \bar{z}_t\}$. Then

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Then $RELATIVE.Brand\text{-}in\text{-}CatDisp_{kt} = \dfrac{(Brand\text{-}in\text{-}CatDisp_{kt})}{(CatDisp_t)}$,

where

$$Brand\text{-}in\text{-}CatDisp_{kt} = \frac{1}{N_{J_{kt}}} \sum_{j=1}^{J_{kt}} [(x_{jkt} - \overline{x}_{kt})^2 + (y_{jkt} - \overline{y}_{kt})^2 + (z_{jkt} - \overline{z}_{kt})^2],$$

$$CatDisp_t = \frac{1}{N_{J_t}} \sum_{j=1}^{J_t} [(x_{jt} - \overline{x}_t)^2 + (y_{jt} - \overline{y}_t)^2 + (z_{jt} - \overline{z}_t)^2]$$

Table 4 provides summary statistics for category characteristics Y_{kt} in category-level introduction decision. It also presents summary for key characteristics within the time-variant vector $\hat{Q}_{tk\hat{m}_t}$ for pioneer introductions, which are also category-level in my framework. Table 5 summarizes cluster characteristics within the time-variant vector Q_{tkm_t} used to model non-pioneer introductions.

[Insert Tables 4 and 5 here]

In order to estimate model parameters, the logarithm of the sample likelihood function (1.6) was maximized using gradient-based routines in GAUSS.

2.3.3 **Pricing**

Let $p_{j_k t}$ denote price of the product $j_k \in J_t$ in period t, X_{j_k} denote a row vector of time invariant product characteristics. Let $Z_{j_k t}$ for simplicity denote a row vector of time variant characteristics pertaining to pricing of product j_k (detailed below). λ_2 and λ_2 stand for column-vectors of the corresponding parameters. I assume normal distribution for the error term:

$$p_{j_k t} = X_{j_k} \lambda_1 + Z_{j_k t} \lambda_2 + \xi_{jt} \tag{1.7}$$

where ξ_t is an iid error term across brands and time. The likelihood function for the observed price data can then be written as follows:

$$L(\lambda_1, \lambda_2, \sigma^2) = \prod_{t=1}^{T} \prod_{j_k=1}^{J_t} (2\pi\sigma^2)^{-1/2} \exp\frac{(p_{j_k t} - X_{j_k}\lambda_1 - Z_{j_k t}\lambda_2)^2}{-2\sigma^2}. \qquad (1.8)$$

In pricing equation (1.7) I include the following product attributes in vector X_{j_k} :

1. *Brand intercepts* (Indicator variables for Brands);

2. *Sensor Resolution* (Megapixels)

3. *Optical Zoom* (Maximum Optical Zoom, Multiples of X)

4. *Digital Zoom* (Maximum Digital Zoom, Multiples of X)

5. *LCD Display Size* (inches)'

6. *USB Connectivity* (Indicator that takes the value 1 if USB Connectivity is available and 0 otherwise);

7. *Number of Software Titles* (Number of software titles listed as shipping with the camera model);

I include the following category product-level characteristics within the time-variant vector $Z_{j_k t}$:

1. *NewModel*$_{j_k t}$ (Indicator variable that takes value 1 for the launch month of product j_k that was not classified as "pioneer" and 0 for the remaining products/months).

2. *PioneerModel*$_{j_k t}$ (Indicator variable that takes value 1 for the launch month of product j_k that was classified as "pioneer" entry and 0 for the remaining products/months).

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3. $ModelAge_{j_k t}$ (Number of months elapsed since introduction of product j_k).

4. $TimeTrend_t$ (Time counter from the beginning of my study period, in months).

5. $Seasonality_t$ (Indicator variable for month of December).

6. $NoClusterCompetition_{j_k t}$ (Indicator variable that takes value 1 if in period t there are no competitive products in cluster $m_t^{j_k}$ where j_k resides).

7. $\Delta CompetitorPriceLag_{jm_t^{jk}}$ (Sales-weighted average price change of from t-2 to t-1 across all products competing with j in period t in its residence cluster, $m_t^{j_k}$,).

8. $\Delta CompetitorPriceLag_{jm_t^{jk}}^2$;

9. $RELATIVE.BrandClust$-in-$CatDisp_{j_k tm_t^{jk}}$ (for product j_k's residence cluster m_t^{jk} at time in period t, a measure of dispersion of all brand k's models in that cluster relative to dispersion of all products in the category. I operationalize it as the average squared Euclidian distance from brand k's models in cluster m_t^{jk} to brand's cluster centroid, relative to the same measure for all the models in the category to category centroid. In the case of three product attributes (x, y and z), brand k's cluster centroid for m_t^{jk} is given by $\{\bar{x}_{km_t^{jk}}, \bar{y}_{km_t^{jk}}, \bar{z}_{km_t^{jk}}\}$, and category centroid $\{\bar{x}_t, \bar{y}_t, \bar{z}_t\}$.

$$RELATIVE.BrandClust\text{-in-}CatyDisp_{j_k tm_t^{jk}} = \frac{(Brand\text{-in-}ClusteDisp_{km_t^{jk}})}{(CatDisp_t)},$$

where

$$Brand\text{-}in\text{-}ClustDisp_{km_t^{jk}} = \frac{1}{N_{J_k m_t^{jk}}} \sum_{j=1}^{J_{km_t^{jk}}} [(x_{j_k m_t^{jk}} - \bar{x}_{km_t^{jk}})^2 + (y_{j_k m_t^{jk}} - \bar{y}_{km_t^{jk}})^2 + (z_{j_k m_t^{jk}} - \bar{z}_{km_t^{jk}})^2],$$

$$CatDisp_t = \frac{1}{N_{J_t}} \sum_{j=1}^{J_t} [(x_{jt} - \bar{x}_t)^2 + (y_{jt} - \bar{y}_t)^2 + (z_{jt} - \bar{z}_t)^2]$$

10. $\Delta Brand|ClustShare_{j_k m_{t-1}^{jk}}$ (change in brand's share of total cluster sales from *t-2* to

t-1, for product j_k's residence cluster m_{t-1}^{jk});

Tables 6 and 7 present the summary statistics for variables included in vector X_{j_k} and

product-level characteristics within the time-variant vector $Z_{j_k t}$ respectively.

[Insert Tables 6 and 7 here]

In order to estimate model parameters, the logarithm of sample likelihood function (1.8)

was maximized using gradient-based routines in GAUSS.

2.4   EMPIRICAL RESULTS

NEW PRODUCT INTRODUCTION AND POSITIONING MODEL

The results of the new product introduction and cluster positioning model are presented in Table 8.

[Insert Table 8 here]

Category Level Introduction Parameters

Estimated brand specific intercepts are associated with the top 5 brands used in this study (Canon's intercept is suppressed). They can be interpreted as each brand's *new product activity propensity* since they capture average brand specific incidence of new product introductions after controlling for effects of brand-specific (i) category variables and the (ii) strategic utility of all product clusters. All but Nikon's are positive and significant. The value of these parameters suggests that Olympus (1.626), Sony (1.338) and Kodak (1.276) all had relatively similar propensity for new product introductions Canon.

The estimated linear effect of time since own introduction in the category is significant (-0.531), and the quadratic effect is positive (0.046) suggesting the U-shape relationship with previous product introductions. The average time between introductions is 4 months during my study period (see Table 4) with previous introduction time of its own model. Note that all else equal, in 2-6 moths range, the lower values of this covariate mean higher likelihood of another new product introduction. In the 6-13 months range the longer elapsed time is associated with higher likelihood a new product. These results appear to indicate that on aggregate, within my study period top 5 manufacturers of digital cameras paced introduction of their new

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products in the following pattern: introducing successive models within a span of several months, following approximately annual cycle between such roll-outs[4].

The estimated parameter on inclusive value term specified in equation (1.5) capture net effect of strategic competitive variables included at the product cluster entry level. It is positive and significant (2.001), validating the two-step decision approach modeled in my study. I also find that the lag of competitive activity (measured by number of competitive introductions in the previous period) is although negative (-0.019) as expected is not significant. The effect of the lag of category revenue change is also insignificant, however is positive (0.155) as expected. This would suggest that at the monthly level the measure of previous competitor activity and category growth are not effectively able to capture "category level opportunity" from the firm's perspective (as deliberated in section 2.1).

Product Cluster Entry Parameters

The estimate of the population size of product clusters is positive and significant (0.032), suggesting that in my study firms tend to locate their new products into larger product clusters. The effect of share of a given cluster (in brand's overall category revenues) is negative and significant (-1.807). This should be interpreted as firms less likely to locate their new products in segments where they already have a strong presence. Put differently, this is a sign of positioning that avoids cannibalization.

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[4] This conclusion is consistent with a tradition of various annual Consumer Electronics and Digital Photography trade shows and events spread-out throughout the year. Digital camera brands may use these events as an opportunity to launch their new product. Although I do not explicitly control for this in my study, the manufacturer' strategic choice to time the new launch then becomes the choice of the specific trade show, which doesn't change the conclusion above.

Incidentally, it is also consistent with the argument in Leeflang and Wittink (2001) that intra-firm competition should have lower intensity, if any.

The effect of relative dispersion of the brand in a cluster is also negative and significant (-0.879). This is further evidence that in their product locations firms are more likely to introduce in product segments where they are less dispersed, relative to the overall dimension of that product cluster. The estimated interaction effect between (i) relative brand dispersion in a cluster and (ii) category share derived from this cluster is positive (0.617) but not significant. I include this effect in order to estimate a possible strategic effect driving firm's new product activity into their dominant (high dispersion) and significant (high share of brand's revenues) product clusters. Although insignificant, I would conjecture that the positive sign reflects the small effect of new product introductions that serve as *replacement* of existing models in such a "cash-cow" product cluster.

I find no evidence of strategic impact of elapsed time since own product activity on firm's choice of cluster entry (in contrast to the category-level pacing I discussed earlier). Both linear (-0.048) and quadratic effects (0.001) of time since own introduction are insignificant.

The effects of time since competitive introductions are both significant, linear effect is negative (-0.985) and quadratic effect is positive (0.034). This is a baseline effect of competitor product introduction timing. Negative sign on the liner effect has straightforward interpretation. In my study, firms were more likely to enter product clusters with a more recent competitor product introduction than those with less recent activity by competition. The significance of the quadratic term implies curvilinear

relationship in this variable. I interpret this result as follows. From Table 5 I can note that although the range of this variable is from 0 to 25 months, the average time since competitive product across all clusters was 2.37 (St. Dev. 4.12). The value of these coefficients suggest that any competitive activity 14 months resulted in increasing likelihood of new product introduction by the focal firm.

My model yields significant interaction effects of time since competitive product introduction with (i) Relative brand dispersion in a cluster (1.98) and (ii) share of revenues from the cluster by the focal firm (-0.713). Both can be interpreted incorporating baseline estimates of the respective covariates. As discussed earlier, in their cluster entry locations avoided cannibalizing own sales (negative sign on $BrandClust|CatShare_{tkm_t}$ parameter estimate) and favored clusters with lower own dispersion (negative sing on $RELATIVE.Brand\text{-}in\text{-}ClustDisp_{tkm_t}$ parameter estimate). Positive sign on the interaction coefficient (i) suggests that either less recent timing of competitive product activity in a cluster, or lower levels of own dispersion in the same cluster 'softens' the strategic incentives of the focal firm to introduce in such cluster. In contrast the negative coefficient of interaction effect (ii) is interpreted as a reversal of the "no cannibalization" tendency. While the direction of the time since competitor activity suggests that clusters more recent introductions are more likely to be entered by the focal firm, increasing strategic importance of a cluster (higher share of focal brand's revenues) is compounding the speed of the retaliation.

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Pioneer Introduction Parameters

The effect of the brand category sales dynamics (lagged increase in brand's share in category sales) is positive, as expected (0.192) but not significant. I also find that firms stronger position product due to proliferation for the product space does not lead to higher propensity to innovate (as demonstrated by insignificant and negative coefficient (-0.355) on the effect of relative dispersion of brand's products relative to overall dispersion of the product category. However, I find support that innovation is likely to be driven by relative age of brand's product line. Since the age of models (on both brand and category level) are weighted by their respective sales, lower values of this measure imply that the focal firm is deriving more of its revenues from a 'younger' set of products. Such conditions are conducive to innovation and new product development efficiencies. Negative and significant estimate of this effect (-0.859) demonstrates that during my study period, when digital camera's firms had relatively higher dependency on aging products, they were less likely to innovate in my study.

PRICING MODEL ESTIMATION RESULTS

The results of the product pricing model are presented in Table 9. All effects are non-standardized expressed in units of the dependent variable price, $US..

[Insert Table 9 here]

Brand Intercepts

Estimated brand specific intercepts in the pricing model are associated with the top 5 brands used in my study (with Canon brand residing on the model level intercept, 448.14

significant). The other brand intercepts, have two possible interpretations: (i) they can be interpreted unobserved quality, such as *brand equity* of the individual firm, relative to Cannon, since they capture the residual price effect of digital cameras after controlling for differences among their time-invariant product characteristics and a set of competition and trend parameters discussed below; (ii) Since the product attributes in this estimation capture costs of production and consumer utility, the alternative interpretations of the brand intercepts could be "ability to price over cost". In this light, only Kodak (-48.69) and Sony (27.46) intercepts are significant and reveal that during the study period Sony enjoyed pricing premium, while Kodak products lacked such equity despite the company's roots in the analog photography market.

Product Attribute Parameters

Among the product attributes the most valuable product features were Sensor resolution (262.84, std.coeff 0.938), and Optical Zoom (42.19, std.coeff. 0.43). The effect of increasing performance of products on Digital Zoom attribute appears to lower the value of the camera model (-38.36, std.coeff -0.17). The rest of the significant attributes had marginally low impact in pricing ability– LCD Display Size (21.66, std.coeff 0.036) and Number of Software Titles (-0.068, std.coeff. -0.00). The effect of the USB connectivity attribute is positive (21.99, std.coeff 0.037), but not significant.

Competition and Trend Parameters

In my study of the digital cameras market manufacturers are decreasing prices over time. There are two distinct effects of such price decay – one on the level of the individual

products, and the other, on the product category level, all significant. The linear effect of individual product price decay is (-11.19) and positive in quadratic effect (0.202). The category-level linear decay is (-6.67) with negative quadratic term (-0.129).

The price decay process over the span of my study is depicted in Figure 6.

[Insert Figure 6 here]

The pressure to lower prices is twice as steep on the individual model level, compared to the category level pressures. Furthermore, newly launched product had a price penalty upon launch. After controlling for the product attributes and time trends, the estimated effect of such penalty is relatively large (-67.99) and statistically significant. In contrast, radical improvements (pioneering product launches) had a significant estimated premium (193.55) upon launch. Seasonality effect is positive but insignificant (19.84), and the estimated effects of lagged competitive prices are positive but insignificant.

The estimated effect of relative dispersion of a focal brand's products in a given cluster relative to the overall category dispersion is large, positive and significant (102.33). It captures the pricing power derived from relatively dominant position achieved through dispersion in the mainstream product cluster. The effect of being a local monopolist in a product cluster appears to create negative price effect (likely in the form of price discounts). The estimate of such effect from my model is -111.223 across all products, when their parent brands located in product clusters with no competitive products. However, fluctuations in brands' share of a given cluster do not appear to be affecting that brands pricing power. The effect of such changes is positive but insignificant (79.242).

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2.5   CONCLUSIONS

The study developed in this chapter focused on the strategic drivers of product competition in the setting of high-technology markets. I approached this by recognizing the interrelated nature of the new product introduction decisions across competing firms. From the perspective of each individual firm in the technology-based consumer markets, such as digital cameras, a new product introduction decision typically involves two constituent strategic dimensions – (1) the *timing* of the new product introduction, and (2) the *position* – in terms of objective product features -- that is chosen by the firm for the new product relative to the firm's, as well as its competitors', existing products.

In in the marketing and economics literature, there are two competing strategic forces that drive firms' new product positioning decisions. On one hand, a firm could specialize in one or more locations on the perceptual map by introducing most of their new products in those clusters and, therefore, effectively "crowding out" competitors from those segments (Eaton and Lipsey 1979; Schmalensee 1978). (2) On the other hand, a firm may choose to spread its new product introductions across a large number of clusters on the perceptual map, which allows them to reach broader market while also reducing the effects of cannibalization of the firm's own products (Brander and Eaton 1984; Spence 1976). In fact, the latter strategy could also serve to deter the entry of new firms in to the product category as a whole (Bonanno 1987).

To study these issues I focused on the digital cameras category, where I find that category-level diversification dominates behavior of new product introductions by the top

manufacturers. Their product positioning follows into large product clusters with least dispersion of own products, as well as avoidance of the clusters with currently high levels of revenues. I find that the timing of the decisions is likely to follow product cluster locations with recent product activity by competitors. Despite genera avoidance of cannibalizing sales of products clusters of high strategic importance (with relatively high levels of brands' category sales associated with it), firms have used speedy new product introduction to respond to the competitor entry. Finally, firms are more likely to pioneer radical product positioning in the attribute space when high levels of their product line comes from new products (relative to category level age). Such finding is consistent with firms enhanced product development efficiencies and improved market estimates (Bayus et al. 1997). Finally, I find that innovating in high technology setting of the digital camera market supports higher price premium benefit to the innovating firm(s), in contrast to downward price pressures characteristic to high-technology markets.

CHAPTER 3: **DEMAND EFFECS OF PRODUCT PREANNOUNCEMENTS.**

3.1   INTRODUCTION

Formal, deliberate communications, commonly referred to as *product preannouncements*, are often made by firms before introducing new products to the marketplace. Such preannouncements are typically directed at consumers, competitors, distributors and shareholders (see Figures 7 and 8 for examples of preannouncement releases for two of Sony's digital cameras). The benefits of preannouncing a new product are as follows: (1) It helps the firm develop initial levels of opinion leader support and favorable word of mouth needed to accelerate the diffusion of the new product, especially when there are strong demand-side economies of scale (Farrell and Saloner 1986); (2) It provides consumers with an early opportunity to learn about the new product, reducing the uncertainty associated with its purchase, as well as reducing switching costs (Kohli 1999; Schatzel, Droge and Calantone 2003); (3) It allows firms to influence consumers' expectations about price, that have been shown to impact acceptance of new products and speed of their subsequent price decline (Narasimhan 1989); (4) It gives the firm access to efficient distribution systems for the new product (Eliashberg and Robertson 1988); (5) It creates barriers to entry for competing firms by pre-emptively positioning the new product for the chosen target segments and improving the competitive equity of the preannouncing firm (Jung 2011; Schatzel and Calantone 2006). However, there are some costs associated with preannouncing a new product as well (Eliashberg and Robertson 1988): (1) It cues competitors to react more quickly by either introducing their competing version of the firm's new product or issuing their own preannouncement as a counter-

signal (Heil and Walters 1993; Robertson, Eliashberg and Rymon 1995);[5] (2) It leads consumers to postpone buying in the product category, thus cannibalizing the firm's current product line (Kohli 1999);[6] (3) It can damage the firm's reputation if the firm cannot deliver the preannounced product as promised (Hoxmeier 2000); such a failure to deliver can wreak further damage if the firm faces the scrutiny of judicial and governmental regulatory agencies in evidence of predatory business practices (Bayus, Jain and Rao 2001; Calantone and Schatzel 2000; Heil and Langvardt 1994). The benefits of preannouncements may outweigh the costs in some categories, such as automobiles and motion pictures, pharmaceutical prescription drugs, where patent protection and firm specialization are observed. In other categories, such as consumer packaged goods, the costs outweigh the benefits and preannouncements, therefore, are rarely observed.

[Insert Figures 7 and 8 here]

Beyond the benefits listed above, an additional motivation that has been provided for preannouncements is that they serve as a positive signal to corporate shareholders (Chaney, Devinney and Winer 1991; Devinney 1992; Eddy and Saunders 1980). Based on an analysis of product preannouncements made by publicly traded firms between 1980 to 1989, Koku, Jagpal and Viswanath (1997) find that preannouncements increase stock value of the firm. Using preannouncement data for computer hardware and software products, Sorescu, Shankar and Kushwaha (2007) show that the financial returns to shareholders are significantly positive in the long run.

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[5] Lilly and Walters (2000) study the viability of retaliatory preannouncements using a lab experiment.

[6] Kohli (1999) also argues, as do Greenleaf and Lehmann (1995), that a manufacturer may use a preannouncement to encourage their potential customers to postpone purchases of *competing* products, in which case the postponement may benefit the manufacturer.

Farquhar and Pratkanis (1993) study the effects of preannounced products, which they refer to as "phantom alternatives," on a consumer's choice process among available alternatives. Using a decision-theoretic framework, they argue that accounting for preannounced products in the decision-making process can lead to biases and suboptimal choice decisions for consumers. However, no explicit empirical testing is carried out to study how, in fact, consumers actually respond to preannouncements either in the lab or in the field.

The primary goal in this chapter is to study, for the first time in the literature on product preannouncements, the actual demand effects of preannouncements both prior to, as well as after, actual product launch. In doing this, I am able to study the effects of a preannouncement on demand for not only the preannounced product, but also the competing products (some of which may belong the same firm), at the time of the preannouncement and beyond. This allows us to study the competitive demand stealing benefits versus the within-firm cannibalization costs of preannouncements, a tension that has been extensively discussed but never estimated using actual data, in the existing literature on preannouncements. Additionally, I am able to decompose the demand effects of preannouncements between the category-level and product-level. For example, I can estimate whether category adoption, beyond market shares of the preannounced brand vis-à-vis its competitors, is influenced by product preannouncements. This is an issue that has not been discussed in the existing literature on product preannouncements, although recent findings in the new product diffusion literature show that new product introductions within a product category increase overall category adoption rates (see, for example, Krishnan, Seetharaman and Vakratsas 2012).

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Preannouncement times are commonly observed in practice to vary from only a few days to even a couple of years prior to product launch (Rabino and Moore 1989). Kohli (1999) argues that the lead time between preannouncement and actual product launch influences the success of the product launch, and shows, using survey data from senior marketing managers in the computer hardware and software industries, that the timing of preannouncements depends on factors related to the product (purchase cycle length, learning requirements, switching costs), design-related factors (forecast horizon), and industry-related factors (perceived competitive elasticity). Su and Rao (2011) develop a game-theoretic model to study the timing of new product preannouncement and launch under competition. They find that a firm should not preannounce early unless the preannouncement is effective in creating pent-up demand for the product. Beyond the fact that there is a paucity of additional analytical research on this important strategic question of how long prior to product launch to preannounce the product (if at all), the absence of empirical research on documenting the effects of the lead time between product preannouncement and actual product launch is even more striking.

The secondary goal in this chapter, therefore, is to study, also for the first time in the literature on product preannouncements, the impact of the lead time between product preannouncement and actual product launch on the estimated demand effects of the preannouncement (as discussed earlier under the first objective). In doing this, I investigate whether the impact of the lead time between product preannouncement and actual product launch on each component of demand could be non-monotonic, i.e., increasing (decreasing) with lead time until it peaks and then starts decreasing (increasing) with further lead time.

3.2 INSTITUTIONAL SETTING: DIGITAL CAMERAS

I use a database obtained from ARS Inc., a competitive market intelligence company (that was subsequently bought by the NPD group), coupled with an exhaustive manual analysis, using the Lexis-Nexis database, of all company announcements made by all digital camera manufacturers over a five year period, to construct a usable dataset for analysis. My dataset spans a 3 ½ - year period, from January 1998 to September 2001, and tracks the following information on each digital camera that was introduced in the US:

1. Description of product attributes: (i) sensor resolution, (ii) maximum optical zoom, (iii) maximum digital zoom, (iv) LCD display size, (v) internal storage capacity, (vi) external storage availability, (vii) photo flash availability, (viii) self-timer availability, (ix) connectivity transfer rate, (x) USB connectivity availability,

2. Preannouncement information: (i) whether or not the camera was preannounced, (ii) date of preannouncement (if any), (iii) listing of product attributes that were preannounced (if any),

3. Introductory launch information: (i) date of introductory launch, (ii) introductory launch price,

4. Time-varying information (over 45 months): (i) Monthly sales, (ii) Monthly prices.

My dataset includes a total of 303 digital cameras, 187 of which were introduced during my study period, while 116 pre-existed the beginning of my study period.[7] Given in Table 10 are some descriptive statistics pertaining to my dataset. The seven major digital camera manufacturers (among a total of 32 manufacturers) obtain 86% of the cumulative unit sales in the product category (which amounts to 9,935,051 units during my study period). In terms of cumulative market share during my study period, Sony comes first at 29%, while Olympus and Kodak are second and third at 18% and 12%, respectively. One can observe that a majority (259 out of 303) of digital cameras were preannounced.[8] As a percentage of models introduced by a manufacturer, Polaroid has the lowest (56.25%, or 9 out of 16), while Nikon (16 out of 16) and Canon (18 out of 18) have the highest (100%), rate of preannouncements, among the seven major manufacturers. Nikon's models are priced the highest ($850), while Polaroid's models are priced the lowest ($120), on average, among the seven major manufacturers.

[Insert Table 10 here]

In Figure 1, I plot monthly product category sales for digital cameras over the 45 months of study. One can discern an increasing temporal trend in product category sales, which suggests that the digital cameras are experiencing the growth stage of the product life cycle (PLC) during my period of study. One can also notice a strong sales spike during the Christmas season of each year. In Figure 2, I plot the monthly market shares of the seven major digital camera manufacturers over the 45 months of study. One can

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[7] For these 116 cameras, I have access to their preannouncement information even though I do not observe their sales and prices prior to the beginning of my study period.

[8] Out of the 250 preannouncements, 35 involved announcements just prior to introduction (during the same month). We treat these announcements as preannouncements in my empirical analysis.

observe that Canon and HP both steadily increase their market shares, while the market shares of the three dominant manufacturers – Sony, Olympus and Kodak – hold relatively steady, during the study period. Interestingly, one can also notice that during the Christmas shopping season, the market shares of all seven major manufacturers decrease to benefit the smaller manufacturers (represented collectively as "Others"). This suggests that during the holiday season, when many consumers "flood" the digital cameras market (as evidenced by the seasonality sales spikes in Figure 1), they tend to pick up smaller "value" brands disproportionately more than the larger brands.

[Insert Figures 1 and 2 here]

In Figures 9 and 10, I plot monthly unit sales and prices, respectively, for the 9 largest models (in terms of cumulative sales) of digital cameras over the 45 months of study. One can see that unit sales show additional spikes beyond those reflecting the Christmas season. One can also see that the price plot for at least one model – Sony MVCFD83 – shows a fair amount of spikiness as well. Taken collectively, this suggests that unit sales of each digital camera are influenced by both the presence of other digital cameras that are contemporaneously available in the market, as well as their relative prices.

[Insert Figures 9 and 10 here]

In order to deliver on the two stated objectives discussed in the introduction section, as well as be faithful to the features of the institutional context of digital cameras as outlined above, I next develop a demand model to explain the temporal evolution of each product's sales, while also explicitly accommodating the impact of preannouncements on the demand function.

3.3   ECONOMETRIC MODEL OF DEMAND FOR DIGITAL CAMERAS

Below I present an econometric model of demand for digital cameras that accommodates

the effects on the current demand for each digital camera of the following variables for

all digital cameras: (1) product-level baseline diffusion rates, (2) time-invariant product

characteristics, (3) time-varying product prices, (4) incidence and timing of all product

preannouncements.

The proposed demand model is utility-theoretic. Let us first consider a product

category with a single product only (without competitors). Consider a consumer with the

following indirect utility for the product during month t.

$$U_t = \ln\left[\ln\left(\frac{1 - F_{t-1}}{1 - F_t} \right) \right] + \varepsilon_t, \tag{2.1}$$

where F_t stands for the cumulative distribution function, evaluated at time t,

characterizing the baseline hazard process of consumers' product adoption times for the

product. Suppose the consumer's indirect utility for the outside good is as shown below.

$$U_{0t} = 0, \tag{2.2}$$

If I assume that the error term ε_t is distributed *iid* Gumbel with location 0 and scale 1, the

following probabilistic model for consumer purchase for product at time t is obtained.

$$P_t = \frac{F_t - F_{t-1}}{1 - F_{t-1}}, \tag{2.3}$$

which is the discrete-time hazard that is associated with a continuous-time distribution

function F_t (Seetharaman and Chintagunta 2003). Assuming F_t to be as follows,

$$F_t = \frac{1 - e^{-(p+q)t}}{1 + \dfrac{q}{p} e^{-(p+q)t}}, \tag{2.4}$$

I obtain the well-known Bass (1969) model.

For my estimation, I refine the above-mentioned utility-theoretic product adoption model in three important ways:

1. I assume the consumer's indirect utility for the outside good to be as shown below.

$$U_{0t} = \varepsilon_{0t}, \tag{2.5}$$

where ε_{0t} is distributed *iid* Gumbel with location 0 and scale 1. This would yield, in the above-mentioned single-product case, the logistic probability model, which has rich precedence in marketing, instead of the Gumbel probability model, of product adoption.

2. I allow for *J* products, instead of 1 product, with the consumer's indirect utility for product *j* during month *t* as shown below.

$$U_{jt} = \ln\left[\ln\left(\frac{1 - F_{jt-1}}{1 - F_{jt}} \right) \right] + \varepsilon_{jt}, \tag{2.6}$$

which yields the *multinomial* logistic model, a natural extension of the logistic adoption model derived in step 1 to the *J* product case.

3. I incorporate other time-varying covariates, such as those pertaining to product preannouncements etc. in the utility function (2.6).

The assumptions above yield the econometric model that I use in this study. The sales of product *j* at time *t* are given by:

$$Sales_{jt} = \left[M - CS(t)\right] * \frac{e^{V_{jt}}}{e^{V_{ot}} + \sum_{k=1}^{J_t} e^{V_{kt}}}, \quad (2.7)$$

where *M* stands for the market potential (i.e., total unit sales in the product category over its lifetime), *CS(t)* stands for the cumulative product category sales prior to time *t*, V_{jt} stands for the product attractiveness of product *j* at time *t* and is given by

$$V_{jt} = \alpha_j + Season * \lambda + \ln\left[\ln\left(\frac{1 - F_{jt-1}}{1 - F_{jt}}\right)\right] + \beta_{1jt} * Price_{jt} + X_j * \beta_{2jt} + Z_{jt} * \beta_3, \quad (2.8)$$

where α_j stands for a product-specific intercept for product *j* (*j* = 1,…,303), where I restrict α_j = 0 for any *j* that is not in the twenty top-selling products in the category, *Season* is an indicator variable that take the value 1 during high season, i.e., Christmas, and 0 otherwise, and γ captures the effect of seasonality on product demand, F_{jt} stands for the cumulative distribution function, evaluated at time *t*, characterizing the baseline hazard process of consumers' product adoption times for product *j* (assumed to be the Bass Model, with time-varying parameters p_{jt} and q_{jt}), which depends on the time elapsed since the actual time of launch of product *j*, $Price_{jt}$, stands for the time-varying price of product *j* at time *t*, β_{1jt} stands for the corresponding time-varying (as will be explained later) price parameter, X_j stands for a time-invariant row vector of product characteristics pertaining to product *j*, β_{2jt} stands for the corresponding time-varying (as will be explained later) column-vector of parameters pertaining to product *j*, Z_{jt} stands for a time-variant row vector of product characteristics pertaining to product *j* at time *t*, and β_3 stands for the corresponding column-vector of parameters.

I include the following product characteristics within the time-invariant vector X_j:

1. Luxury Model (Indicator Variable that takes the value 1 for a luxury digital camera and 0 otherwise),

2. Sensor Resolution (Megapixels),

3. Optical Zoom Availability (Indicator Variable that takes the value 1 if optical zoom is available and 0 otherwise),

4. Maximum Optical Zoom (Multiples of X),

5. LCD Display Availability (Indicator Variable that takes the value 1 if LCD Display is available and 0 otherwise),

6. LCD Display Size (inches),

7. Internal Storage Availability (Indicator Variable that takes the value 1 if Internal Storage is available and 0 otherwise),

8. Internal Storage Capacity (MB),

9. External Storage Shipped (Indicator Variable that takes the value 1 if External Storage was Shipped with the Digital Camera and 0 otherwise),

10. External Storage Available Not Shipped (Indicator Variable that takes the value 1 if External Storage is Available but Not Shipped with the Digital Camera and 0 otherwise),

11. External Storage Capacity (MB),

12. Photo Flash Availability (Indicator Variable that takes the value 1 if Photo Flash is available and 0 otherwise),

13. Self-Timer Availability (Indicator Variable that takes the value 1 if Self-Timer is available and 0 otherwise),

14. USB Connectivity Availability (Indicator Variable that takes the value 1 if USB Connectivity is available and 0 otherwise),

I include the following product characteristics within the time-variant vector Z_{jt}:

1. More than 15 Weeks since Launch (Indicator Variable that takes the value 1 if more than 15 weeks has elapsed since the product was launched and 0 otherwise),

2. Own Preannouncement Stock (Already Preannounced Products from the Same Manufacturer that are going to be Launched Soon),

3. Cross Preannouncement Stock (Already Preannounced Products by Competing Manufacturers that are going to be Launched Soon),

I operationalize Own Preannouncement Stock for Manufacturer m as follows:

$$\text{OwnPreannouncementStock}_{mt} = \sum_{q=1}^{Q_m} \left(1 - \frac{TimeLeftToLaunch_q}{LeadTime_q} \right), \tag{2.9}$$

where Q_m stands for the existing number of already preannounced products by manufacturer m that are yet to be launched, *Time Left to Launch* $_q$ stands for the number of months left until the date of actual launch of product q, *Lead Time* $_q$ stands for the number of months between preannouncement and actual launch date of product q. As far as product q's contribution to the above stock variable is concerned, it will increase from 0 (at the time of preannouncement of product q) to 1 (at the time of actual launch of product q). This variable is meant to capture the increasing pressure on a consumer to postpone purchase of an existing product the closer it is to the actual date of launch of a

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preannounced product by the same manufacturer, i.e., the self-cannibalization effect discussed in the literature.

I operationalize Cross Preannouncement Stock for Manufacturer m as follows:

$$\text{CrossPreannouncementStock}_{mt} = \sum_{m'=1,m'\neq m}^{M} \sum_{q=1}^{Q_{m'}} \left(1 - \frac{TimeLeftToLaunch_q}{LeadTime_q} \right), \qquad (2.10)$$

where $Q_{m'}$ stands for the existing number of already preannounced products by competing manufacturer m' that are yet to be launched. As far as product q's contribution to the above stock variable is concerned, it will increase from 0 (at the time of preannouncement of product q) to 1 (at the time of actual launch of product q). This variable is meant to capture the increasing pressure on a consumer to postpone purchase of an existing product the closer it is to the actual date of launch of a preannounced product by a competing manufacturer, i.e., the demand-stealing effect discussed in the literature.

In equation (2.7), V_{0t} stands for the product category attractiveness at time t and is given by

$$V_{0t} = \alpha - \ln\left[\ln\left(\frac{1-F_{t-1}}{1-F_t} \right) \right] + W_t \gamma, \qquad (2.11)$$

where α stands for a category-specific intercept, F_t stands for the cumulative distribution function, evaluated at time t, characterizing the baseline hazard process of consumers' category adoption times (assumed to be the Bass Model, with time-invariant parameters p

and q), W_t stands for a time-variant row-vector of category characteristics at time t, and γ stands for the corresponding column-vector of parameters.

I include the following product characteristics within the time-variant vector W_t:

1. Category Preannouncement Stock (Preannouncements of all Manufacturers in the Near Past).

I operationalize Category Preannouncement Stock as follows:

$$CategoryPreannouncementStock_t = \sum_{q=1}^{Q} 0.9^{TimeSincePreannouncement_q}, \quad (2.12)$$

where Q stands for the existing number of already preannounced products in the category that are yet to be launched, *Time Since Preannouncement* $_q$ stands for the number of months since preannouncement of product q, and 0.9 represents a "smoothing" coefficient to represent greater impact of more recent preannouncements. As far as product q's contribution to the above stock variable is concerned, it will decrease from 1 (at the time of preannouncement of product q) towards 0 (as time elapses since product preannouncement). This variable is meant to capture the "advertising" role of recent preannouncements in making the product category more attractive, which may increase category adoption rates. Such an effect of product preannouncements has not been discussed, far less estimated, in the literature.

I operationalize the time-varying aspect of the parameter vector β_{2jt} (which is a 14-dimensional vector as explained earlier[9]) as follows.

$$
\begin{aligned}
\beta_{2jt} = \beta_{20} &+ \text{PREANNOUNCEMENT}_{jt} \ .* \ \beta_{21} \\
&+ \text{PREANNOUNCEMENT}_{jt} \ .* \ LEADTIME_{jt}.* \ \beta_{22} \\
&+ \text{PREANNOUNCEMENT}_{jt} \ .* \ LEADTIME_{jt}^{2}.* \ \beta_{23},
\end{aligned}
\tag{2.13}
$$

where .* stands for element-by-element multiplication of two column vectors, β_{20} stands for the consumer's baseline sensitivities for product characteristics, $PREANNOUNCEMENT_{jt}$ is a vector of indicator variables whose r^{th} element (r = 1,...,14) takes the value 1 if the rth product characteristic has already been preannounced for product j prior to time t and 0 otherwise, β_{21} captures the effect of preannouncements on the consumer's sensitivities to product characteristics, $LEADTIME_{jt}$ is a vector of variables whose r^{th} element (r = 1,...,14) represents the time elapsed since the rth product characteristic for product j was preannounced (if at all), β_{22} captures the linear effect of the lead time of preannouncements on the consumer's sensitivities to product characteristics, and β_{23} captures the quadratic effect of the lead time of preannouncements on the consumer's sensitivities to product characteristics. In other words, this operationalization allows us to estimate the effect of the *incidence* of product preannouncements, as reflected in the vector β_{21}, as well as the effects of the timing of product preannouncements, as reflected in the vectors β_{22} and β_{23}, on consumers' sensitivities for product characteristics in terms of influencing demand for various products.

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[9] In the empirical analysis, I allow only 8 out of the 14 coefficients to show this time-varying relationship, restricting the remaining 6 coefficients to be time-invariant (see Tables 4-6).

Additionally, I operationalize the time-varying aspect of the price parameter β_{1jt} as follows.

$$\beta_{1jt} = \beta_{10} + \text{Preannouncement}_{jt} * \beta_{11} + \text{Preannouncement}_{jt} * LeadTime_{jt} * \beta_{12} +$$
$$\text{Preannouncement}_{jt} * LeadTime_{jt}^{2} * \beta_{13}, \tag{2.14}$$

where β_{10} stands for the consumer's baseline price sensitivity, $Preannouncement_{jt}$ is an indicator variable that takes the value 1 if product j has already been preannounced prior to time t and 0 otherwise, β_{11} captures the effect of the preannouncement on the consumer's price sensitivity, $LeadTime_{jt}$ represents the time elapsed since product j was preannounced (if at all), β_{12} captures the linear effect of the lead time of the preannouncement on the consumer's price sensitivity, and β_{13} captures the quadratic effect of the lead time of the preannouncement on the consumer's price sensitivity.

Last, I operationalize the time-varying aspect of the Bass diffusion baseline hazard parameters p and q as follows.

$$p_{jt} = \exp\left(\begin{array}{l} p_0 + \sum_{m=1}^{M} \lambda_{pm} * I_{jm} + \text{Preannouncement}_{jt} \; .* \; p_1 + \text{Preannouncement}_{jt} \; .* \; LeadTime_{jt} .* \; p_2 + \\ \text{Preannouncement}_{jt} \; .* \; LeadTime_{jt}^{2} .* \; p_3 \end{array} \right),$$

$$q_{jt} = \exp\left(\begin{array}{l} q_0 + \sum_{m=1}^{M} \lambda_{qm} * I_{jm} + \text{Preannouncement}_{jt} \; .* \; q_1 + \text{Preannouncement}_{jt} \; .* \; LeadTime_{jt} .* \; q_2 + \\ \text{Preannouncement}_{jt} \; .* \; LeadTime_{jt}^{2} .* \; q_3 \end{array} \right),$$

$$\tag{2.15}$$

where p_0 and q_0 stand for the baseline innovation and imitation intercepts, I_{jm} is an indicator variable that takes the value 1 if product j belongs to manufacturer m and 0 otherwise, λ_{pm} and λ_{qm} stand for the respective increases in p and q parameters (relative to

the "Other" brand) that are associated with products belonging to manufacturer m, p_1 and

q_1 capture the effects of the *incidence* of product preannouncements on p and q

respectively, p_2 and q_2 capture the linear effects of the *lead time* of product

preannouncements on p and q respectively, p_3 and q_3 capture the quadratic effects of the

lead time of product preannouncements on p and q respectively.

To summarize, my model allows us to flexibly estimate the effects of not only

baseline adoption rates and product characteristics on consumer demand for digital

cameras over time (explicitly disentangling a category-level diffusion pattern from

product-level diffusion patterns), but also, and even more importantly the effects of

product preannouncements – in terms of both their incidence, as well as timing

(accounting for a linear and quadratic impact) -- on these effects. This allows us to fully

characterize and understand the impact of product preannouncements on stimulating

and/or depressing demand for not only various products within the category, but also the

category adoption itself.

In order to estimate model parameters, the logarithm of the following sample

likelihood function is maximized using gradient-based routines in Matlab.

$$L = \prod_{t=1}^{45} \left[\left(\frac{e^{V_{0t}}}{e^{V_{0t}} + \sum_{j=1}^{J_t} e^{V_{jt}}} \right)^{M - \sum_{u=1}^{t-1} \sum_{j=1}^{J_t} S_{jt}} \prod_{j=1}^{J_t} \left(\frac{e^{V_{jt}}}{e^{V_{0t}} + \sum_{j=1}^{J_t} e^{V_{jt}}} \right)^{S_{jt}} \right], \qquad (2.16)$$

where S_{jt} is the observed sales for product j during month t.

3.4   EMPIRICAL RESULTS

Estimated Baseline Diffusion Hazard Parameters

Table 11 presents the estimates of the baseline diffusion hazard parameters. As far as the effect of the preannouncement timing on the estimated values of p and q are concerned, I find that the lead time between product preannouncement and actual product launch has a *non-monotonic* impact on both parameters. However, while the innovation parameter (p) first increases (linear effect of lead time is 0.260), and then decreases (quadratic effects of lead time is -0.356), the imitation parameter (q) first decreases (linear effect of lead time is -1.090), and then increases (quadratic effect of lead time is 0.097), with lead time. In other words, p shows an inverted U-shape, while q shows a U-shape, when plotted versus lead time (see Figures 11 and 12).

[Insert Table 11 here]

Figure 11 represents the impact of preannouncement timing on the estimated Bass innovation parameter (p). One can see that the peak value of the innovation parameter for all brands corresponds to a lead time of around 0.4 months. This means that the initial adoption rate of the product due to innovators is fastest if the product preannouncement happens about 12 days prior to actual product launch. Sony has the largest innovation parameter (while Olympus has the second largest), being around 0.9 or less, and Polaroid has the smallest innovation parameter (while Kodak has the second smallest), being around 0.004 or less, among the seven major brands. It is interesting to note that Kodak's innovation parameter is so low despite Kodak being the brand with the third largest cumulative sales (after Sony and Olympus) in the dataset.

[Insert Figure 11 here]

Figure 12 represents the impact of preannouncement timing on the estimated Bass imitation parameter (q). One can see that the trough of the imitation parameter for all brands corresponds to a lead time of around 5.6 months (which is much larger than the lead times that are typically observed in the digital cameras category). Figure 12 suggests that the eventual adoption rate of the product due to the effects of social contagion is fastest if the product preannouncement happens as close to product launch as possible. Sony has the largest imitation parameter (with Olympus having the second largest), being around 1.1 or less. Coupled with the finding in Figure 11, this suggests that Sony enjoys faster baseline adoption rates for its digital cameras on account of not only higher innovation-driven initial adoptions, but also higher social contagion-driven eventual adoptions, compared to its six competitors. HP has the smallest imitation parameter (with Canon having the second smallest), being around 0.15 or less, which suggests that HP does not enjoy as much social contagion-driven adoptions as the other brands.

[Insert Figure 12 here]

While both figures represent the effects of preannouncement timing separately on p and q, the larger question pertains to the impact of preannouncement timing on adoption timing. Figure 13 plots the implied baseline adoption densities (based on parameters p and q) for Sony Mavica FD73 under various preannouncement lead times. The fastest implied peak time of adoption[10] of 0.2 months is found to correspond to a preannouncement lead time of 3 months, while the peak time of adoption steadily increases as preannouncement lead times increase any higher.

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[10] For the Bass Model, the peak time of adoption is given by the formula [ln (q/p)] / (p + q).

Estimated Product Intercepts

Table 12 presents the product intercepts associated with the 25 cumulatively top-selling digital cameras in my dataset (α_j in equation (2.8)). These can be interpreted as *brand equities* of the digital camera models since they capture the residual demand of digital cameras after controlling for differences among their product characteristics, prices, preannouncement times, launch times etc. All 25 product intercepts are positive and significant, which suggests that the twenty top-selling models have higher brand equities than the remaining 283 digital camera models in the category. Among the twenty, Polaroid PDC640 has the highest value of the product intercept (4.497), while Sony DSCS50 has the lowest value (0.247).

Estimated Main Effects of Product Characteristics

Tables 13-15 report the remaining utility parameters (β's in equation (2.8)). The coefficient associated with luxury brands is negative (-0.774), which means that luxury digital cameras confer lower baseline utility to consumers, on average, than non-luxury digital cameras. This may reflect the fact that luxury digital cameras appeal to a smaller niche group of consumers (leading to lower unit sales, on average), while non-luxury digital cameras appeal to a broader swath of the digital cameras marketplace. The coefficient of price is negative (-0.064), as expected, which implies that demand for a digital camera decreases as its price increases.

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The coefficients of optical zoom availability (0.387) and maximum optimal zoom (0.048) are both positive. This suggests that while the availability of the optical zoom increases demand for the digital camera, a higher value of the maximum optimal zoom increases demand even further, both of which findings make intuitive sense. The coefficients associated with photo flash availability (0.393) and USB connectivity availability (0.715) are both positive, as expected.

The effect of LCD display availability on consumer utility for the product is positive (1.105), as expected. However, the effect of LCD display size is negative (-0.937), which could be capturing the fact that consumers value compactness (which is likely to be inversely related to the LCD display size) when purchasing a digital camera.

The effect of internal storage availability on consumer utility for the product is negative (-0.181), but the effect of internal storage capacity is positive (0.013). In other words, the availability of internal storage decreases consumer utility for the digital camera, which could perhaps be capturing the fact that consumers value compactness (which may be inversely related to the presence of a memory card slot within the digital camera). However, conditional on the availability of internal storage (which eliminates the possible adverse impact of decreased compactness of the camera, to the extent that increasing the internal storage capacity does not, by itself, further increase the size of the digital camera), increasing the storage capacity of the internal memory increases consumer utility for the digital camera, as expected.

The effect of external storage that is shipped with the retail package of the digital camera on consumer utility for the product is negative, in terms of both incidence (-0.042), as well as the external storage capacity (-0.025). This appears to be surprising.

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One reason for this could be a psychological bias on the part of consumers who (wrongly) assume that the price of the external storage device that is shipped must be reflected in the form of a higher retail price of the digital camera, which makes them more wary of purchasing the product.[11] On the other hand, the effect of external storage availability (i.e., plug-in capability) in the digital camera, without the external storage device itself being shipped with the camera, on consumer utility for the product is positive (0.231). Since there is no actual external storage device in this case, there is no psychological bias in terms of how consumers view the camera's price. In such a case, they view the plug-in capability of a camera to be a plus.

The effects of sensor resolution (-0.038) and self-timer availability (-0.008) on consumer utility for the product are both found to be negative, which appear to be counter-intuitive. [12]

[Insert Tables 13-15 here]

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[11] We acknowledge the speculative nature of my argument. There is no empirical evidence directly supporting it.

[12] Maximum Likelihood estimation, that treats each sold unit in my dataset as a unit of observation, while tremendously increasing the power of the statistical model, may dramatically deflate standard errors of the estimated parameters. Therefore, it is possible that these two coefficients are not truly significantly different from zero, especially since the economic magnitudes of these two coefficients are quite small compared to the others.

Estimated Impact of the Incidence of Preannouncements on Estimated Effects of Product Characteristics, i.e., Estimated Interaction Effects between Product Characteristics and Incidence of Preannouncements

The estimated interaction effects between (i) sensor resolution and its preannouncement (0.404), and (ii) LCD display size and its preannouncement (0.285), are both positive as expected. The estimated interaction effect between price and its preannouncement is insignificant.

The estimated interaction effects between (i) maximum optical zoom and its preannouncement (-0.327), (ii) internal storage capacity and its preannouncement (-0.013), (iii) external storage capacity and its preannouncement (-0.039), (iv) photo flash availability and its preannouncement (-0.819), (v) self-timer availability and its preannouncement (-0.09), (vi) USB connectivity availability and its preannouncement (-0.381) are all negative.

Estimated Impact of the Timing of Preannouncements on Estimated Effects of Product Characteristics, i.e., Estimated Interaction Effects between Product Characteristics and Timing of Preannouncements

The effect of the lead time between the preannouncement of the product characteristic and the time of actual launch of the digital camera is inverted U-shaped, i.e., first increasing, and then decreasing, for (i) price (linear effect of 0.142 and quadratic effect of -0.046), (ii) maximum optical zoom (linear effect of 0.434 and quadratic effect of -0.154), (iii) internal storage capacity (linear effect of 0.062 and quadratic effect of -0.032), (iv) external storage capacity (linear effect of 0.103 and quadratic effect of -

0.036), and (v) photo flash availability (linear effect of 0.466 and quadratic effect of -0.245). The implied optimal lead times for the preannouncement (from the standpoint of maximally increasing consumer utility for the product by preannouncing these characteristics) for these 5 product characteristics are, therefore, 1.5 months, 1.4 months, 1 month, 1.4 months and 1 month, respectively. From the standpoint of the managerial usability of my empirical findings, it is heartening to see that the implied optimal times for all these five product characteristics are close to each other (since these characteristics can all be preannounced simultaneously within a single preannouncement for the digital camera).

The effect of the lead time between the preannouncement of the product characteristic and the time of actual launch of the digital camera is U-shaped, i.e., first decreasing, and then increasing, for (i) sensor resolution (linear effect of -0.765 and quadratic effect of 0.304), and (ii) LCD display size (linear effect of -0.463 and quadratic effect of 0.219). From the standpoint of maximally increasing consumer utility for the product by preannouncing these characteristics, it is optimal to preannounce these two characteristics just prior to product launch.

The effect of the lead time between the preannouncement of the product characteristic and the time of actual launch of the digital camera is increasing in a convex manner for (i) self-timer availability (linear effect of 0.05 and quadratic effect of 0.206), and (ii) USB connectivity availability (linear effect of 0.086 and quadratic effect of 0.018). From the standpoint of maximally increasing consumer utility for the product by preannouncing these characteristics, it is optimal to preannounce these two characteristics as early as possible prior to product launch.

Estimated Impact on Demand for a Digital Camera of the Manufacturer's Own Preannouncement Stocks versus the Manufacturer's Competitors' Preannouncement Stocks

As far as the preannouncement stocks of the focal manufacturer (i.e., manufacturer of the digital camera in question) and competing manufacturers are concerned, I find that they both decrease consumers' current utilities for available products. My finding about the negative effect of cross preannouncement stock (-0.027) supports the existing claims favoring product preannouncements in the literature that consumers may delay purchasing available alternatives if they were informed about upcoming new products, which would effectively lead the preannounced product to steal current sales of competing products, by moving them to the future. In fact, this incentive to postpone the purchase of a product to wait for the launch of a new (previously preannounced) product from a competing manufacturer increases as the consumer gets closer to the actual launch date of the preannounced product (since the stock variable increases as one gets closer to the launch date of a preannounced product).

That said, my finding about the negative effect of own preannouncement stock (−0.056) also supports the existing claims arguing against product preannouncements in the literature that self-cannibalization of the firm's products' sales can also occur when a new product is preannounced. In fact, this incentive to postpone the purchase of a product to wait for the launch of a new (previously preannounced) product from the same manufacturer also increases as the consumer gets closer to the actual launch date of the preannounced product. How the two effects, i.e., demand-stealing from competitors'

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current products, versus self-cannibalizing one's own existing products, play out against each other is a matter that I take up in a numerical simulation in the next section.

Last, I also find that the impact of category-level preannouncement stock (which increases in the presence of recent product preannouncements and decreases in their absence) on consumer utility for the no-purchase option is negative (-0.016). This suggests, consistent with my earlier conjecture, that there is an "advertising" role that is associated with product preannouncements. When several products are preannounced in the category, the "buzz" that is created by these preannouncements effectively serve as advertising for the category as a whole, which increases the category adoption rate (by lowering the attractiveness of the outside good). This effect then decays over time as time elapses since product preannouncement (unless, of course, new product preannouncements happen in the future).

Other Estimated Utility Parameters

As expected, the coefficient associated with the high season (i.e., Christmas month), is positive (1.655) and significant, which means that more digital cameras sell during the winter holiday season than during the remaining months of the year. The coefficient associated with a variable that tracks whether or not a digital camera during a given month is "out of date," which is operationalized on the basis of whether the digital camera was launched more than 15 weeks ago, is negative (-1.826), which makes intuitive sense. The estimated intercept associated with the outside good (i.e., no purchase option) is 8.353, while the Bass diffusion parameters, p and q, estimated at the category-level (beyond the baseline adoption curves that are estimated for each product, as

discussed earlier) are estimated to be 1.199 and 0.732. Next I discuss some managerial takeaways associated with my key findings.

Substantive implications

In order to understand the substantive implications of my estimated demand parameters for manufacturers, I perform the following numerical simulation: Taking one manufacturer at a time, I compute the net impact (in terms of total revenues across all of its products, as well as across each of its competitors' products) of retracting preannouncements on all its products. In other words, I answer the question, "What would have been the revenue implications to a manufacturer, as well as its competitors, of not engaging in any product preannouncements during the study period?" As far as the top 3 manufacturers are concerned, I find that the total revenues would have increased from $18,703,182 to $19,263,518 (+3%) for Sony, decreased from $9,632,889 to $9,330,762 (-3%) for Olympus, and decreased from $5,354,502 to $4,173,969 (-22%) for Kodak, if product preannouncements had been absent during the study period. In other words, for two of the three largest manufacturers in the category, product preannouncements have represented a net plus during the study period.

Next, I perform the following second numerical simulation: Taking one manufacturer at a time, I compute the net impact (in terms of total demand across all of its products, as well as across each of its competitors' products) of alternative lead times – specifically, 0, 1, 2, 3, 4, 6 or 8 months ahead of product launch -- on their preannounced products. In other words, I answer the question, "What would have been the demand implications to a manufacturer, as well as its competitors, of engaging in

alternative lead times on their product preannouncements during the study period?" As far as the top 3 manufacturers are concerned, I find that not preannouncing is the demand-maximizing strategy for Sony (improving total unit sales across all its models by 15%), while preannouncing their products exactly at the time of product launch is the demand-maximizing strategy for Olympus and Kodak (improving total unit sales for Olympus and Kodak by 13.5% and 15%, respectively). In other words, for two of the three largest manufacturers in the category, product preannouncements exactly at the time of product launch appear to be the demand-maximizing strategy. Interestingly, the demand-maximizing strategy for Nikon involves a lead time of 3 months, i.e., pre-announcing their products 3 months prior to actual launch, which improves total unit sales for Nikon by 37%.

3.5 **CONCLUSIONS**

I make an important contribution to the marketing literature on preannouncements by estimating the demand effects – at both the category-level, as well as the product-level -- of product preannouncements. For this purpose, I use monthly demand data for 303 products over 3 ½ years from the digital cameras category. I find that preannouncement timing has a non-monotonic impact in terms of influencing both their baseline adoption rates, as well as the estimated impacts of product characteristics on consumer utility for the preannounced product. I uncover an advertising role for preannouncements in that they increase category adoption rates. In contrast, I also uncover evidence in favor of consumers postponing their purchase of existing digital cameras, as surmised in the existing literature, to wait for preannounced products. This latter finding has competing implications for manufacturers: on the one hand, product preannouncements can pre-empt purchases of competing manufacturers' existing products ("demand stealing"); on the other hand, product preannouncements can pre-empt purchases of the manufacturers' own existing products (self-cannibalization"). Correctly understanding these tradeoffs and then optimally resolving them by appropriately choosing the timing of product preannouncements would warrant the use of a "structural" model of preannouncements, an important avenue for future research.

I use numerical simulations to come up with the following substantive findings in the digital cameras category: first, for two of the three largest manufacturers in the category, product preannouncements have represented a net plus, in terms of increasing their revenues across all their products, during the study period; second, for two of the

three largest manufacturers in the category, product preannouncements exactly at the time of product launch appear to be the demand-maximizing strategy.

Some modeling caveats are in order. First, I treat the existence and timing of preannouncements in my data as *exogenous*. However, since preannouncements are deliberate strategic instruments employed by firms in the industry, they are likely to be *endogenous*. At this point, since my focus is primarily on estimating the qualitative impact (i.e., signs, rather than magnitudes) pertaining to the role of preannouncements in influencing demand, and doing this for the first time in the preannouncements literature, I hope that my empirical analysis can deflect this potential criticism. That said, correctly accounting for the endogeneity of preannouncements in the empirical analysis, by locating appropriate instruments and then correctly including these instruments in the estimation procedure, would be necessary while using my empirical framework for strategic decision-making purposes (i.e., optimizing the timing of preannouncements). I leave this as an important area for future research.

Second, I ignore the effects of unobserved heterogeneity in my demand model, which would capture differences across consumer segments in terms of how they respond to preannouncements. Since my primary interest is in estimating the qualitative impact of preannouncements on the *aggregate* demand for products, I believe that ignoring such effects of unobserved heterogeneity represents a reasonable first-order approximation. Extending the model to account for such effects of unobserved heterogeneity would be a useful next step.

Third, I model category purchase incidence by treating the no-purchase option as an additional choice option for the consumer within my utility-based discrete choice

formulation. An alternative model would treat category purchase as the first stage of a two-stage consumer decision-making process (Krishnan et al. 2012). Comparing the predictive ability of my demand model to such an alternative formulation of demand would serve to test the robustness of my findings.

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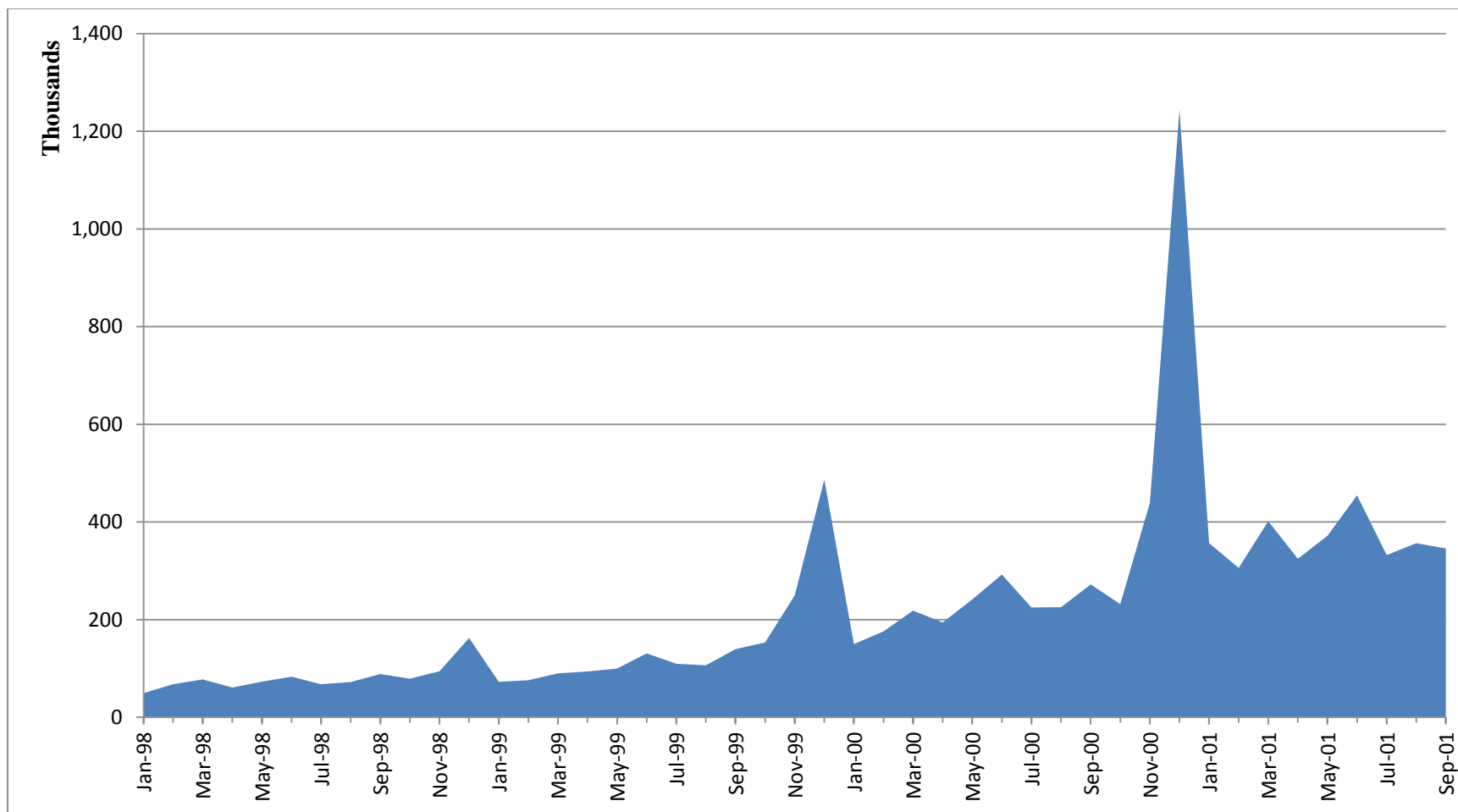
Figure 1: Digital Cameras Category Sales (in Thousands of Units)

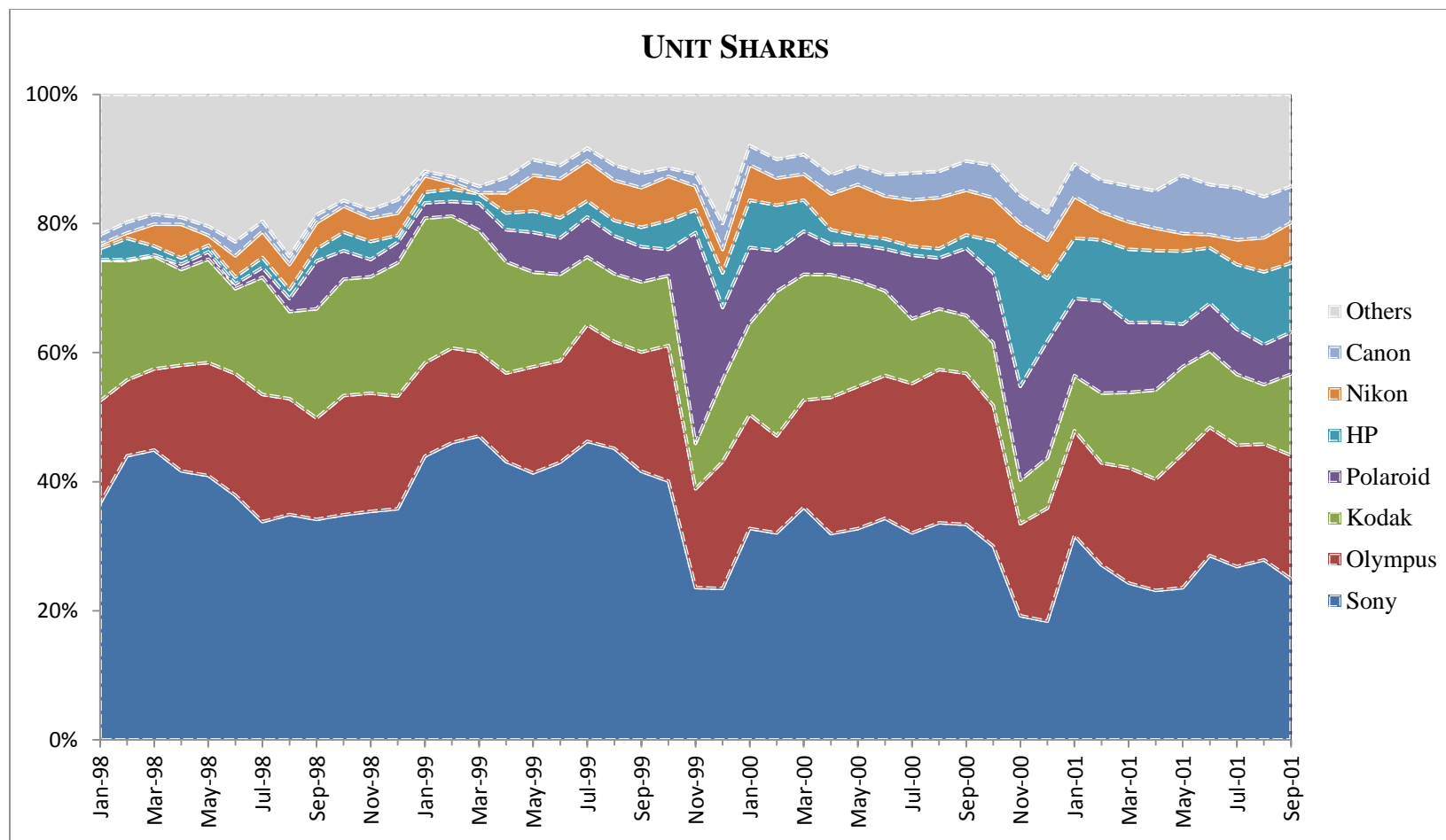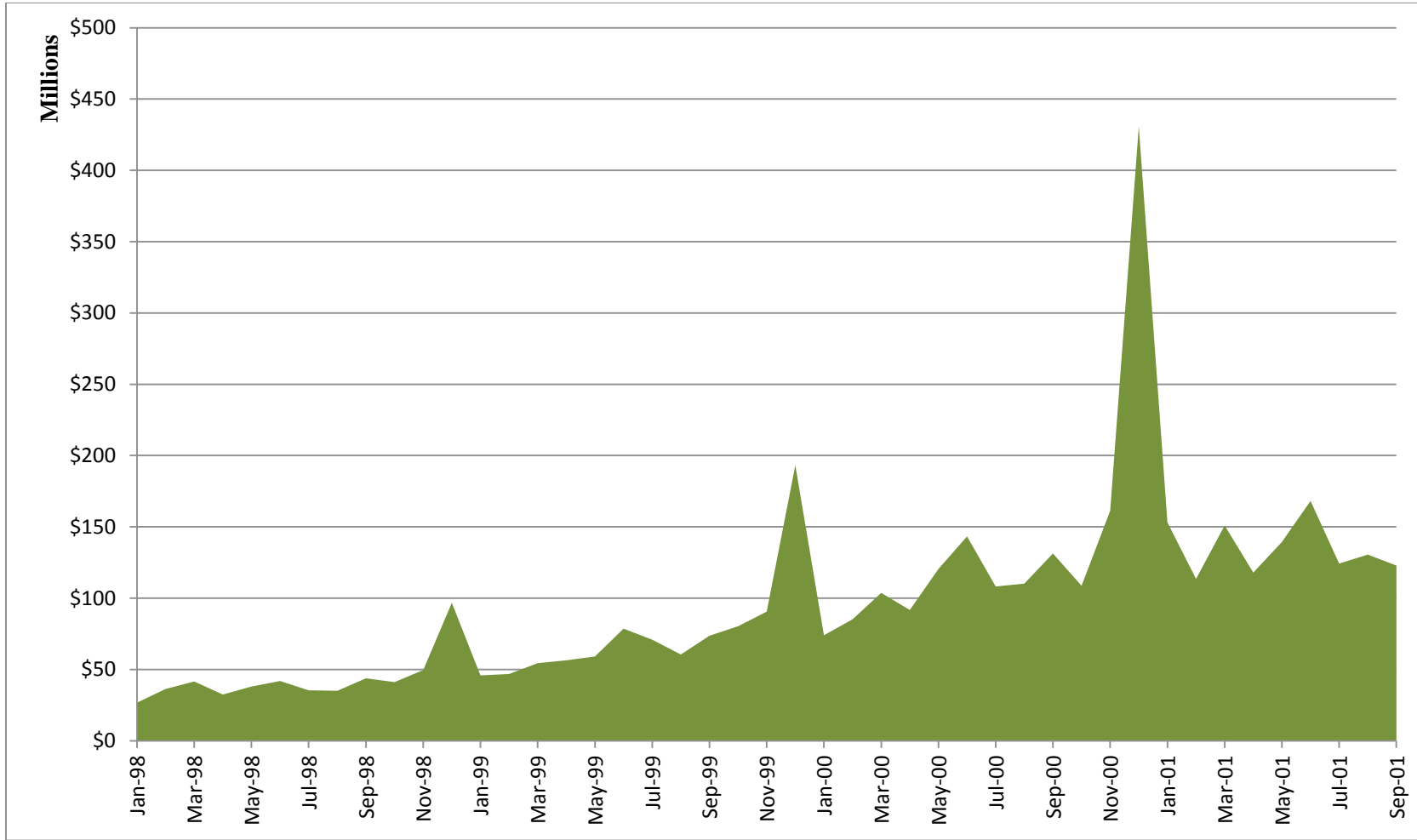**Figure 2: Unit Market Shares of Digital Camera Manufacturers**

Figure 3: Digital Cameras Category Revenues (in Millions $)
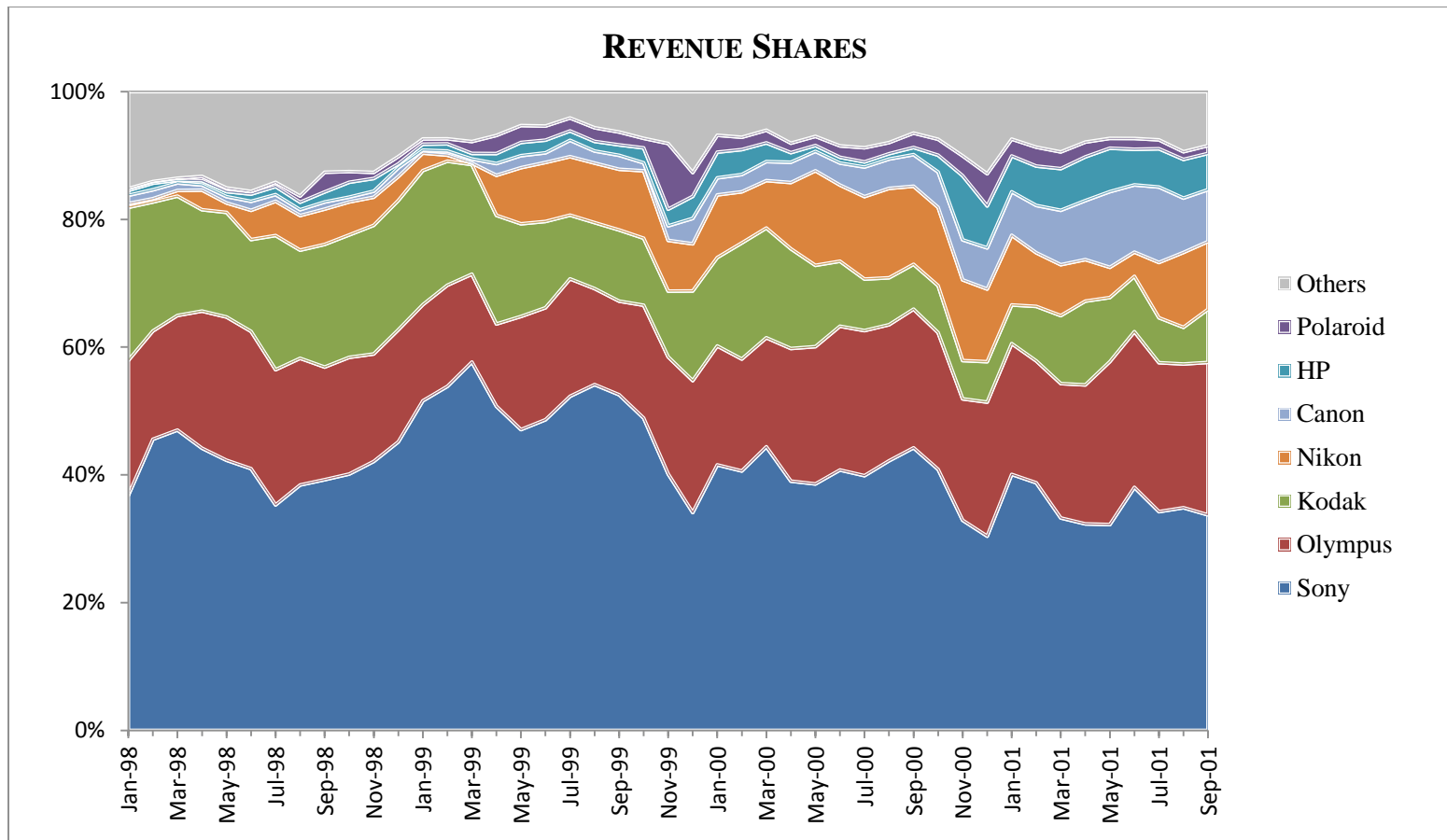
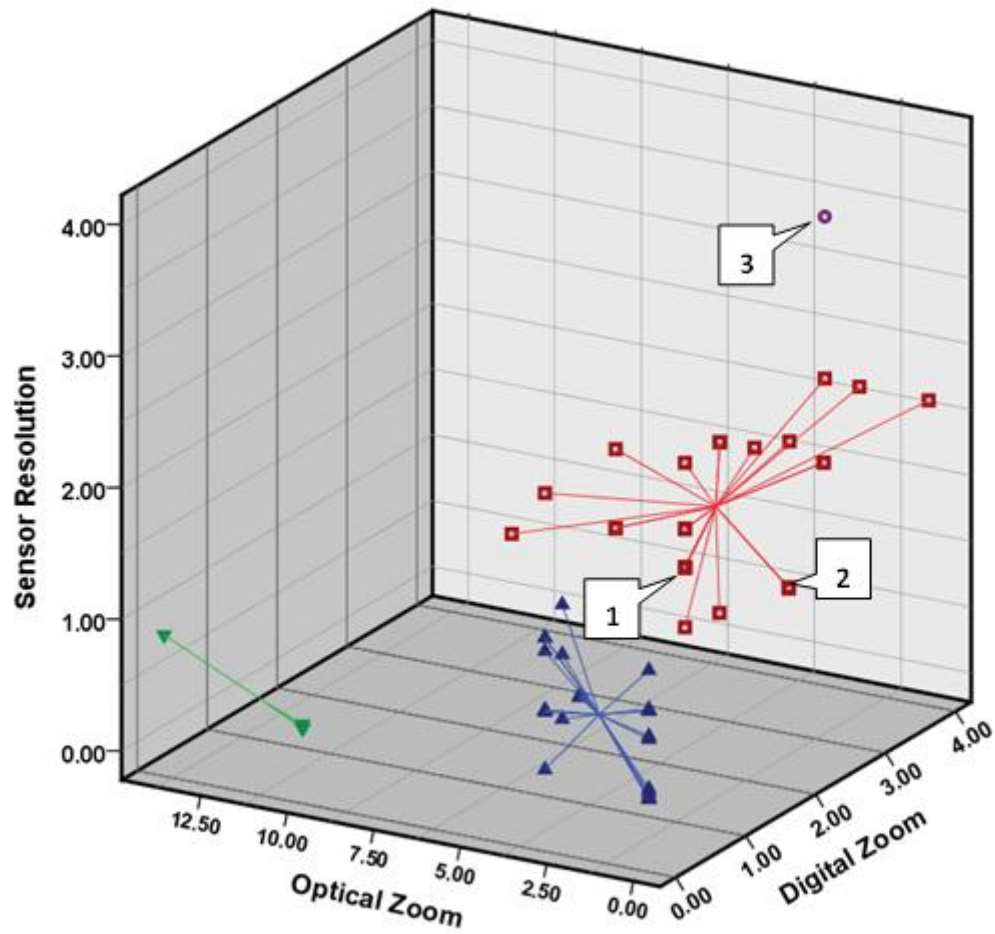**Figure 4: Revenue Market Shares of Digital Camera Manufacturers**

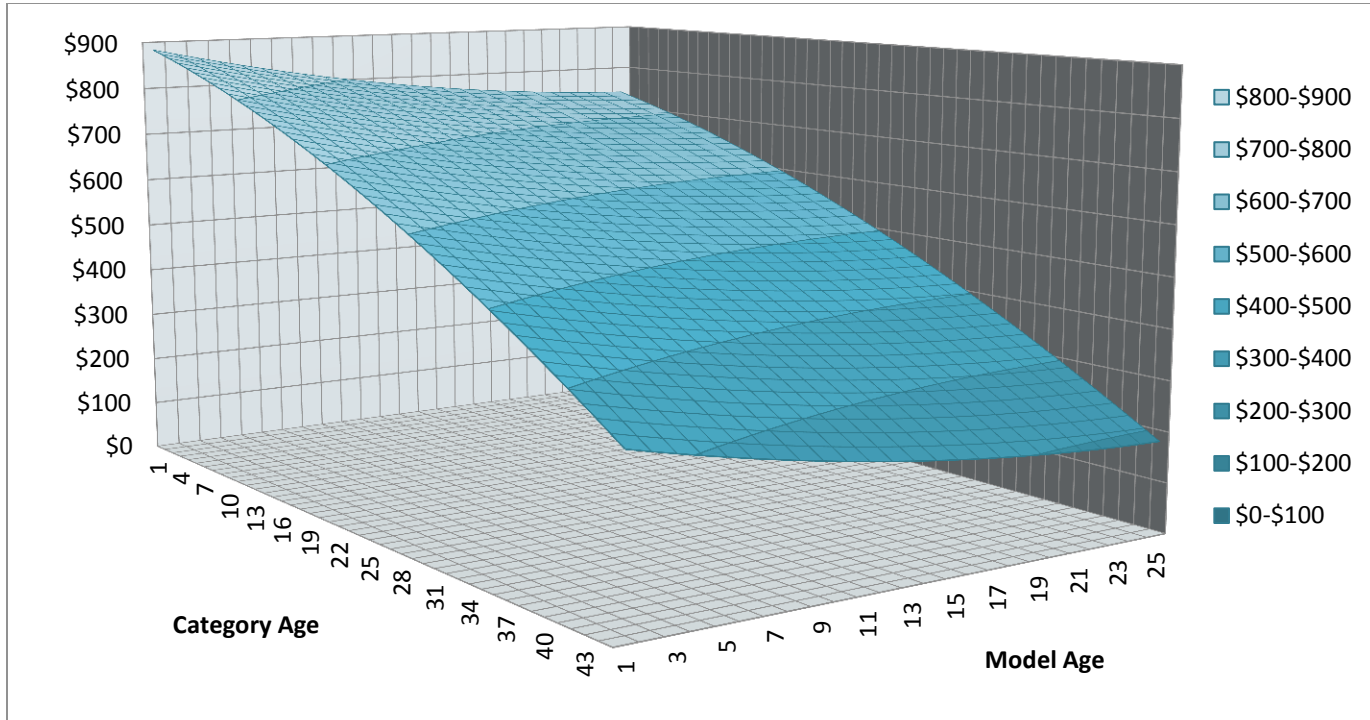**Figure 5: Product Clusters Example, February 2000 (52 Digital Cameras)**

Figure 6: Illustration of the Baseline Price Decrease in Digital Cameras Market (Numeric Simulation)

PRODUCT	SONY LAUNCHES MEGAPIXEL MAVICA, REVAMPS 1999 LINEUP
PUBLISHED DATE	3/4/1999
TITLE	Digital Cameras, Digital Still Cameras, Sony, MVC, FD73
ABSTRACT	Abstract Sony this week introduced three new Mavica digital cameras that will replace the existing Mavica MVC-FD51, MVC-FD71, and MVC-FD81 in the company's lineup. The new 1.3 megapixel MVC-FD88, MVC-FD73, and MVC-FD83 will join the existing MVC-FD91 in Sony's Mavica product line beginning in May.
DESCRIPTION	The Mavica MVC-FD73 will replace the MVC-FD51 as the entry-level camera in Sony's product line. The new model will carry a MSRP of $599, with the street price expected to be closer to $499. The MVC-FD73 will begin shipping in May. From a feature standpoint, the MVC-FD73 is very similar to the MVC-FD51 with the addition of a new 10x optical zoom. The sensor resolution on the new model is actually lower than its predecessor (350k vs. 410k), and most of the other features are carried over from the 51. These include the VGA resolution, 2.5" LCD, auto flash, 4 picture effect modes, self-timer, and bundled ArcSoft software. >>ARS ANALYSIS<< Sony has had tremendous success with its Mavica cameras over the past two years, but the appeal of the floppy disk as a storage medium may be nearing the end of its reality. The new MVC-FD83 and MVC-FD88 push the image capture quality for a floppy-disk camera farther than what was expected, but users are forced to settle for highly compressed images if they want any storage volume at all. As they have in the past, Sony does not disclose in any product literature the number of images the camera can capture in any mode, except that the camera can store "up to 40" images depending on the model selected. Furthermore, the uncompressed bitmap mode no longer exists on the models users would likely want to use it with (FD83, FD88). While it is nice the resolution has increased, users will likely be frustrated if they can only fit a very small number of images on a floppy - even if the medium is inexpensive. Even with the limitation of the floppy disk, Sony has packed a variety of features into the new Mavica cameras that will likely keep the "wow" factor in their favor. The digital and optical zooms are the most powerful in the industry, the audio / video out are features Casio proved years ago that customers want, and the MPEG video feature is still an attention getter. However, even with these strengths, the fact that two-megapixel cameras with fantastic image quality can be had for less than the price of Sony's 850K model will make it increasingly difficult for Sony to sustain its market lead.

**Figure 7: Preannouncement for Sony Mavica FD73 Digital Camera
(The Largest Selling Digital Camera From 1999 To 2001)**

PRODUCT	DIGITAL STILL CAMERAS, SONY, DSC S85
PUBLISHED DATE	6/7/2001
TITLE	Sony Officially Announces its First 4 Megapixel Camera - DSC-S85
ABSTRACT	Sony officially announced today its first 4 megapixel camera, the DSC-S85. The new DSC-S85 is expected to be available in August for $799. The new DSC-S85 features the same body design as the DSC-S75, but instead in an all-black casing. To view an image of Sony's new DSC-S85 please visit: http://www.ars1.com/cts/Images/digitalimaging/sonydscs85.htm
DESCRIPTION	Sony's new DSC-S85 features a 4.1 megapixel CCD capable of capturing images up to 2272x17040-dpi. The camera also features a Carl Zeiss 3x optical/6x digital zoom lens, 14 bit A/D converter, USB connectivity, a three-frame burst mode up to two fps, and automatic exposure bracketing that captures three images at different exposure values. Additional features include two different movie modes with sound (MPEG HQ and MPEG EX to continuously shoot video up to the capacity of the Memory Stick), a 1.8 inch LCD screen, and auto ISO or fixed at 100, 200, or 400. The DSC-S85 also offers ClipMotion, which allows users to take up to 10 pictures that the camera automatically combines to make a single animation file. The camera features an AccuPower meter to display battery time remaining in minutes. The DSC-S85 has a copy function that captures images on a Memory Stick, holds them temporarily on internal memory, and then copies the images onto another Memory Stick. The camera ships with a 16MB Memory Stick, InfoLithium Battery, AC adaptor/charger, USB cables, and software. >>ARS ANALYSIS<< Even though the DSC-S85 joins the Olympus E-10 as one of two 4 megapixel cameras that will be out on the market, the DSC-S85 is really in a class of its own. The Olympus E-10 is targeted at the prosumer-level consumer in terms of features and a hefty price tag of $1,999, whereas the DSC-S85 is for the serious as well as the amateur photographer with a much more affordable price of $799. Sony has now conquered all facets in the digital camera arena, a very popular Mavica line of cameras, two new CD-RW cameras, and now a new and very price competitive Cyber-Shot line of cameras from 1 to 4 megapixels. The price competitiveness of the new Cyber-Shot line is very uncharacteristic of Sony and creates an even bigger threat to competitors. Competing companies with 3 megapixel models, including Canon's PowerShot G1 ($799), Nikon's CoolPix 995 ($899), and Sony's own DSC-S75 ($699), will need to strongly justify why consumers should buy a comparable 3 megapixel model when a 4 megapixel is the around the same price and in some cases lower. With its broad range of digital cameras, its looks as though Sony has established itself as a dominate force within the digital camera industry.

**Figure 8: Preannouncement for Sony DSC S85 Digital Camera
(Sony's First 4-Megapixel Camera)**
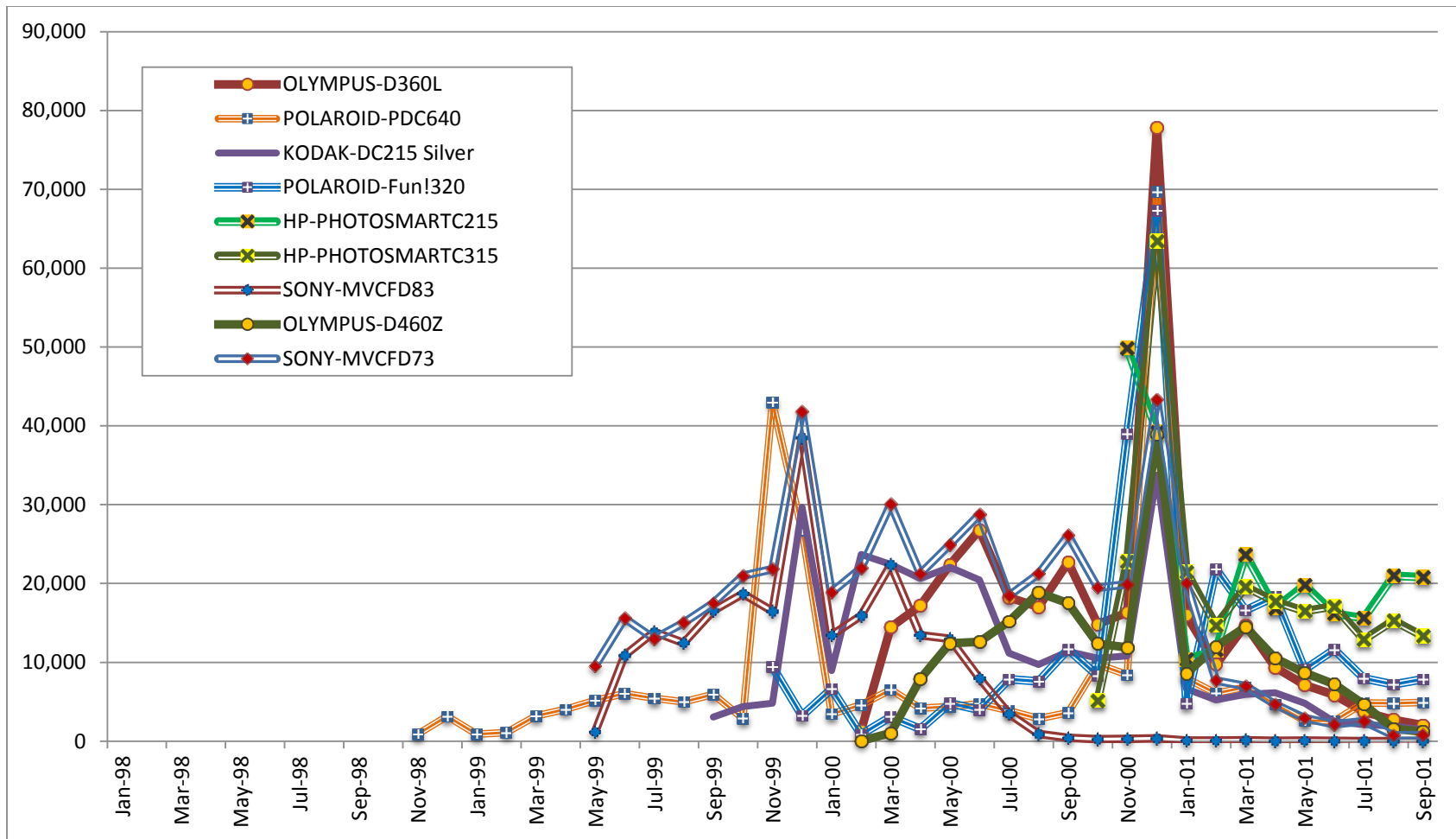
Figure 9: Unit Sales of the 9 Top Selling Digital Camera Models (Jan. 1998 – Sept. 2001)
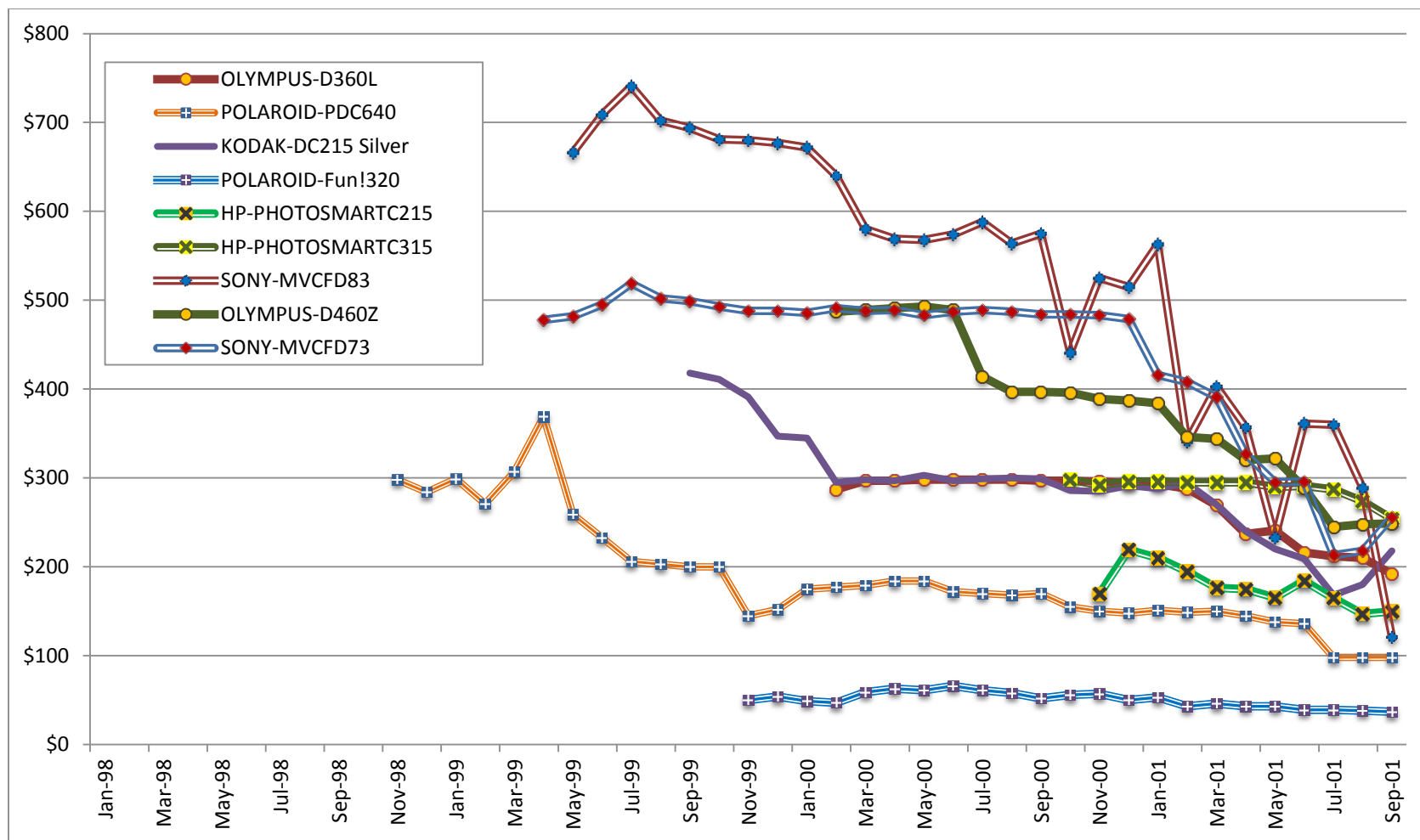
Figure 10: Prices of the 9 Top Selling Digital Camera Models (Jan. 1998 – Sept. 2001)

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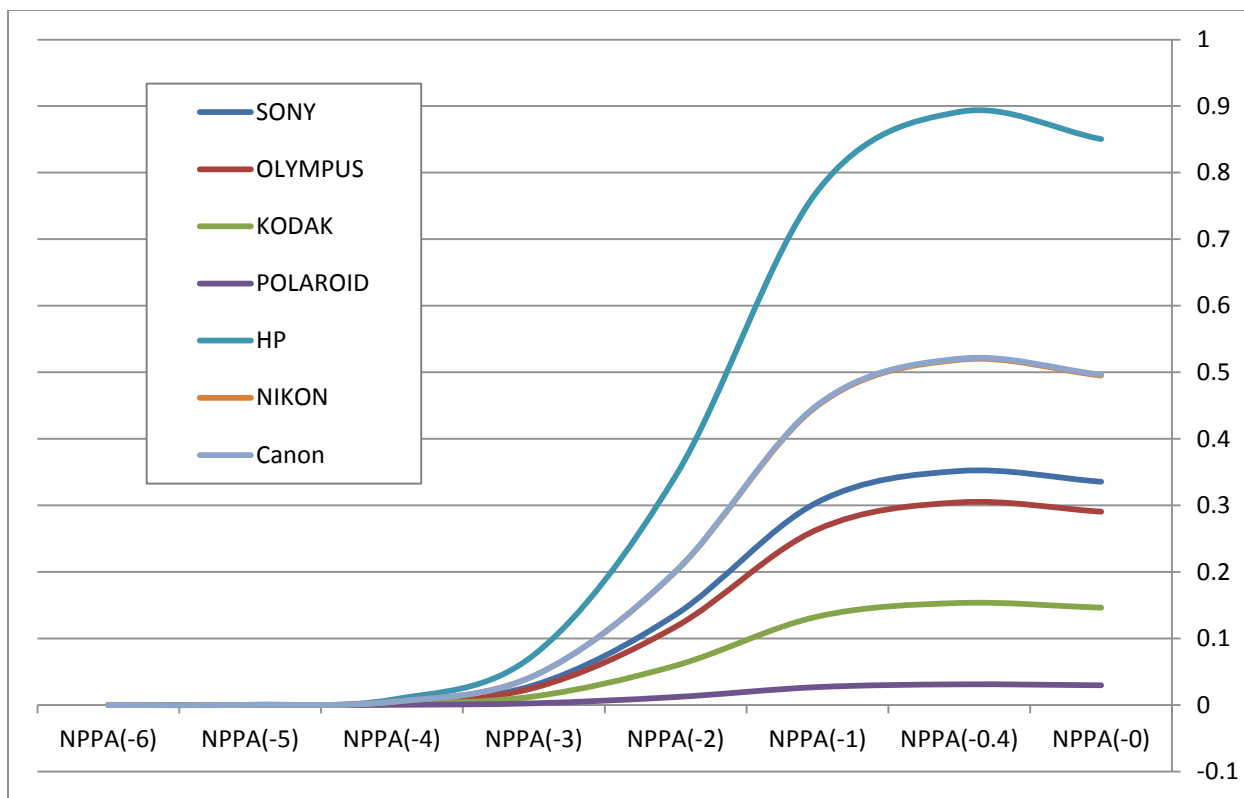
Figure 11: Bass Model Innovation Parameter (p) vs. Preannouncement Lead Time
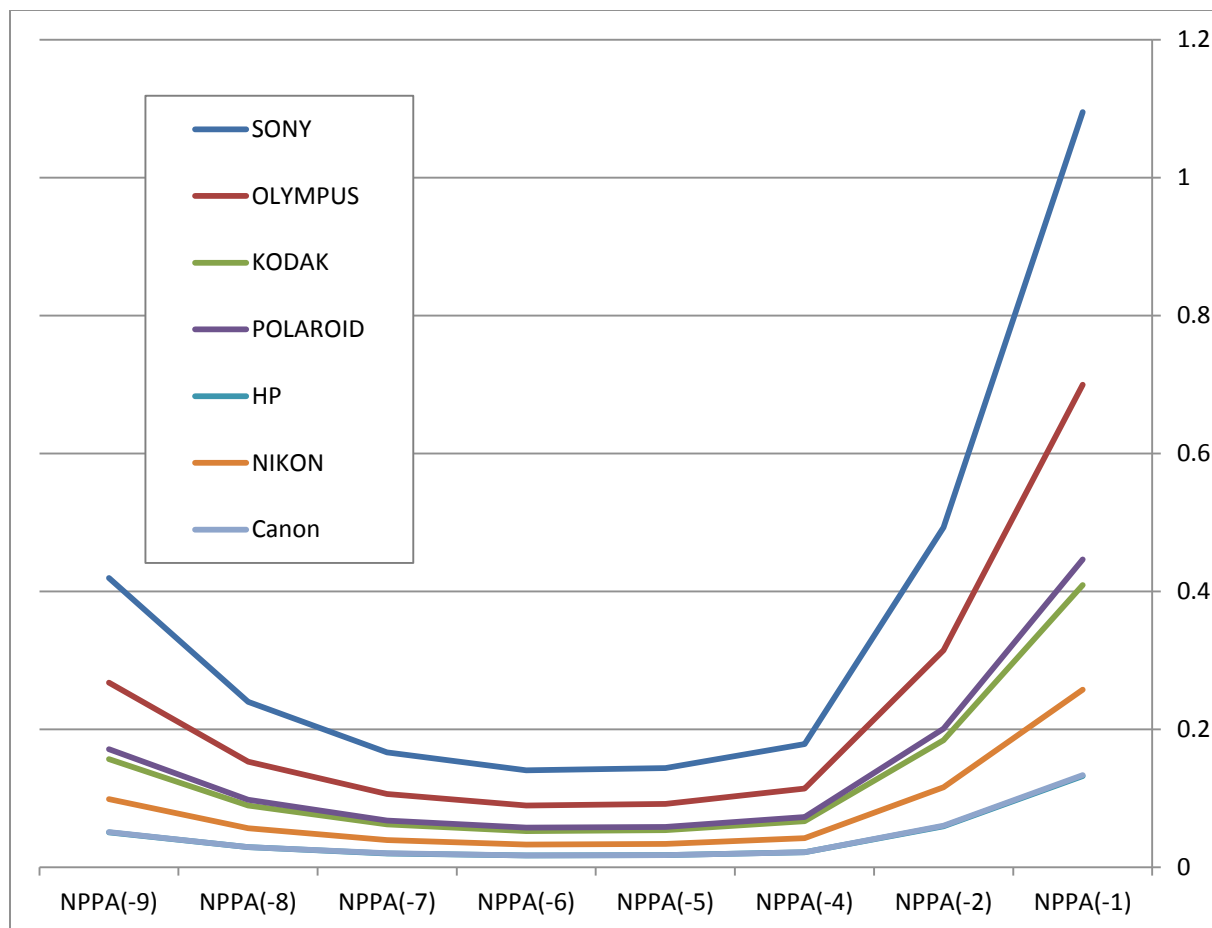
Figure 12: Bass Model Immitation Parameter (q) vs. Preannouncement Lead Time
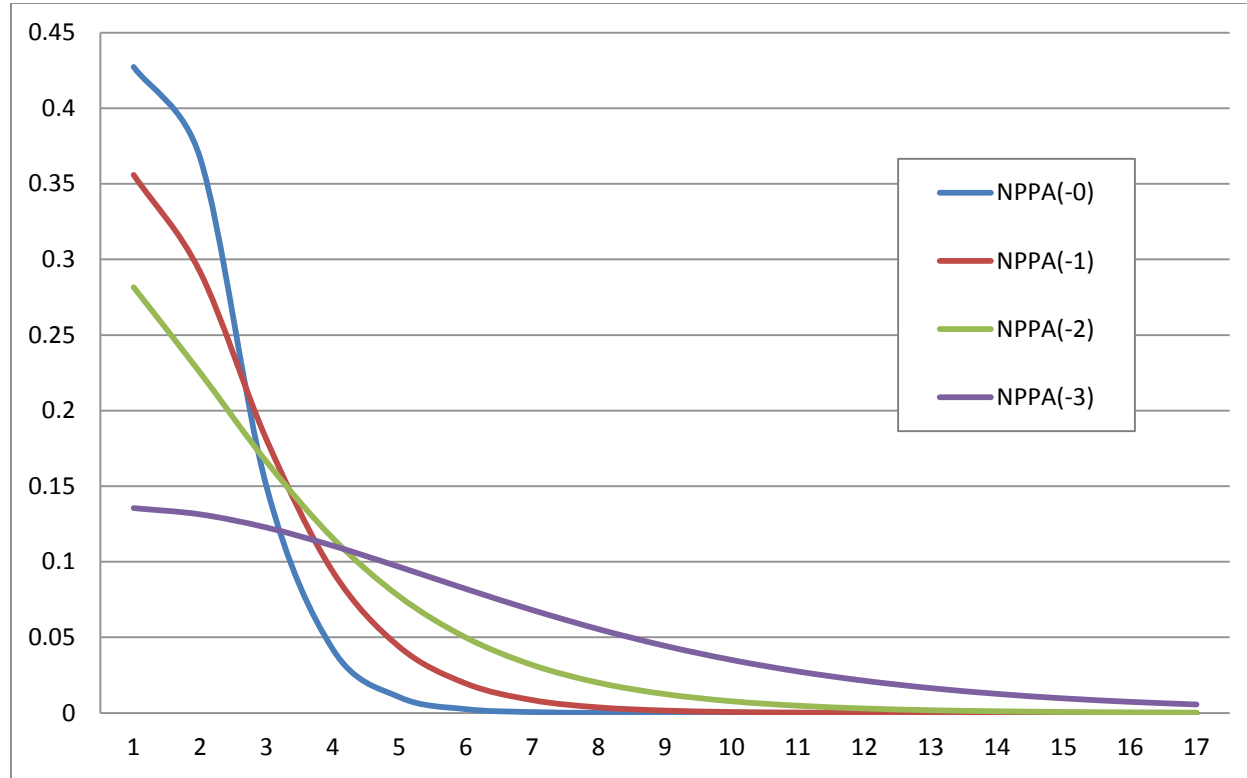
Figure 13: Estimated Baseline Adoption Density for SONY Mavica FD73

Table 1: Industry concentration, 1998-2001

	1998-2001	**1998**	**1999**	**2000**	**Q1-Q3 2001**
Herfindahl Index	0.216	0.248	0.265	0.205	1.988
Number of branded manufacturers	50	27	27	41	45

Table 2: Average annual age of the current models on the market weighted by within-brand monthly market share.

	Sony	**Olympus**	**Kodak**	**Nikon**	**Canon**
1998	8.6	9.2	8.7	4.8	11.7
1999	6.6	8.1	8.0	6.8	9.4
2000	10.9	6.4	10.9	10.8	5.9
2001 (Q1-Q3)	9.4	10.7	9.6	9.9	4.6

Table 3: Average prices of models weighted by their cumulative contribution by year of introduction

Year of introduction	Sony	Olympus	Kodak	Nikon	Canon
1998 or before	558.72	530.58	424.38	663.90	420.41
1999	676.33	602.83	485.36	611.42	440.73
2000	682.82	655.24	425.99	774.25	756.65
2001 (Q1-Q3)	567.31	478.65	296.91	707.98	589.42

Table 4: Category-level Characteristics

Variable	Range	Mean	Std. dev.
$\Delta Brand|CatShare_{kt}$	-0.78 - 6.15	0.05	0.49
$RELATIVE.AgeBrandPLine_{kt}$	0.4 - 2.0	1.04	0.28
$RELATIVE.Brand\text{-}in\text{-}CatDisp_{kt}$	0.20 - 4.85	0.92	1.03
$\Delta Category\$SalesLag_{t-1}$	-0.63 - 1.73	0.10	0.41
$NumberCompetIntros_{k(t-1)}$	0 - 8	1.81	1.58
$TimeOwnCatIntro_{kt}$	2 - 13	4.04	2.37

Table 5: Cluster-level Characteristics

Variable	Range	Mean	Std. dev.
$TimeCompClustIntro_{tkm_t}$	0 - 25	2.37	4.12
$TimeOwnClustIntro_{tkm_t}$	0 - 39	1.86	7.71
$NumberModels_{tm_t}$	0 - 45	9.53	9.28
$BrandClust|CatShare_{tkm_t}$	0 - 1	0.19	0.28
$RELATIVE.Brand\text{-}in\text{-}ClustDisp_{tkm_t}$	0 - 2.44	0.33	0.53

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Table 6: Product Attributes of Cameras in Dataset

Product Attribute	Range	Mean	Std. dev.
Image sensor resolution (in megapixels)	0.18 - 5.24	1.76	1.05
Optical Zoom	0 - 14	3.11	3.04
Digital Zoom (magnification-fold)	0 - 4	1.72	1.34
Universal Serial Bus (USB) connectivity (1 = 'available')	0 - 1	0.49	0.50
Liquid Crystal Display Size (in inches, 0=N/A)	0 - 2.5	1.86	0.49
Number of software titles shipped with the camera	0 - 6	1.98	1.52

Table 7: Product-level Characteristics

Variable	Range	Mean	Std. dev.
$ModelAge_{jt}$	1 - 52	16.06	11.38
$\Delta CompetitorPriceLag_{jm_t^{jk}}$	-221.3 - 311	-13.34	27.53
$RELATIVE.BrandClust\text{-}in\text{-}CatDisp_{j_k m_t^{jk}}$	0 - 0.58	0.16	0.10
$\Delta Brand|ClustShare_{j_k m_{t-1}^{jk}}$	-0.77 - 1.0	0.001	0.09

Table 8: Estimation Results - New Product Introduction Parameters

PARAMETER	ESTIMATE	STANDARD ERROR
Category Introduction Parameters		
Kodak	1.276	0.644
Nikon	0.724	0.738
Olympus	1.626	0.657
Sony	1.338	0.662
$\Delta CategorySalesLag_t$	0.155	0.608
$TimeOwnCatIntro_{kt}$	-0.531	0.261
$TimeOwnCatIntro^2_{kt}$	0.045	0.023
$NumberCompetCatIntros_{k(t-1)}$	-0.019	0.154
Inclusive Value	2.001	0.720
Product Cluster Entry Parameters		
$NumberModels_{tm_t}$	0.032	0.016
$BrandClust\|CatShare_{tkm_t}$	-1.807	0.711
$RELATIVE.Brand\text{-}in\text{-}ClustDisp_{km_t}$	-0.879	0.306
$RELATIVE.Brand\text{-}in\text{-}ClustDisp_{km_t}*BrandClust\|CatShare_{tkm_t}$	0.617	1.204
$TimeOwnClustIntro_{tkm_t}$	-0.048	0.080
$TimeOwnClustIntro^2_{tkm_t}$	0.001	0.004
$TimeCompClustIntro_{tkm_t}$	-0.985	0.115
$TimeCompClustIntro^2_{tkm_t}$	0.034	0.007
$RELATIVE.Brand\text{-}in\text{-}ClustDisp_{km_t}*TimeCompClustIntro_{tkm_t}$	0.198	0.102
$BrandClust\|CatShare_{tkm_t}*TimeCompClustIntro_{tkm_t}$	-0.713	0.194
Pioneer Introduction Parameters		
$\Delta Brand\|CatShare_{kt}$	0.192	0.483
$RELATIVE.AgeBrandPLine_{kt}$	-0.859	0.332
$RELATIVE.Brand\text{-}in\text{-}CatDisp_{kt}$	-0.355	0.558

-LL=200.687

Table 9: Estimation Results – Pricing Paramaters

PARAMETER	ESTIMATE	STANDARD ERROR
Intercepts		
Intercept	448.138	25.577
Kodak	-48.696	11.103
Nikon	3.166	4.931
Olympus	-5.428	5.439
Sony	27.460	12.511
Product Attribute Parameters		
Sensor Resolution	262.836	7.528
Optical Zoom	42.188	1.875
Digital Zoom	-38.359	4.725
LCD Display Size	21.659	10.772
USB connectivity	21.993	13.690
Number of software titles	-0.068	0.012
Competition and Trend Parameters		
$NewModel_{j_k t}$	-67.986	20.245
$PioneerModel_{j_k t}$	193.546	62.220
$ModelAge_{j_k t}$	-11.195	1.225
$ModelAge^2_{j_k t}$	0.202	0.028
$TimeTrend_t$	-6.674	1.573
$TimeTrend^2_t$	-0.129	0.028
$Seasonality_t$	19.843	13.911
$NoClusterCompetition_{j_k t}$	-111.223	19.167
$\Delta CompetitorPriceLag_{jm_t^{jk}}$	0.110	0.095
$\Delta CompetitorPriceLag^2_{jm_t^{jk}}$	0.001	0.001
$RELATIVE.BrandClust\text{-}in\text{-}CatDisp_{jtm_t^{jk}}$	102.330	38.371
$\Delta Brand|ClustShare_{j_k m_{t-1}^{jk}}$	79.242	45.303

-LL=15137.81

Table 10: Descriptive Statistics on Digital Cameras (Jan 1998 – Sept 2001)

Brand	Number of Models in the Study Period	Number of Preannounced Models	Cumulative Units Sold	Units-Weighted Average Price
Sony	35	30	2,913,013	$642
Olympus	33	32	1,818,920	$529
Kodak	28	22	1,208,352	$443
Polaroid	16	9	967,985	$120
HP	10	9	686,416	$259
Nikon	16	16	487,492	$850
Canon	18	18	424,153	$561
Other	147	123	1,428,720	$302

Table 11: Estimation Results – Baseline Diffusion Hazard Parameters

PARAMETER	ESTIMATE	STANDARD ERROR
Ln (p)	-1.279	0.004
Ln (q)	-2.799	0.013
Effect of Sony on p	0.589	0.006
Effect of Olympus on p	0.445	0.005
Effect of Kodak on p	-0.241	0.006
Effect of Polaroid on p	-1.836	0.005
Effect of HP on p	1.519	0.006
Effect of Nikon on p	0.978	0.006
Effect of Canon on p	0.981	0.006
Effect of Preannouncement on p	-0.402	0.005
Effect of (Preannouncement $\times$ LeadTime) on p	0.260	0.006
Effect of (Preannouncement $\times$ LeadTime^2) on p	-0.356	0.002
Effect of Sony on q	2.981	0.009
Effect of Olympus on q	2.533	0.009
Effect of Kodak on q	1.997	0.010
Effect of Polaroid on q	2.084	0.010
Effect of HP on q	0.865	0.028
Effect of Nikon on q	1.534	0.013
Effect of Canon on q	0.875	0.023
Effect of Preannouncement on q	0.902	0.005
Effect of (Preannouncement $\times$ LeadTime) on q	-1.090	0.006
Effect of (Preannouncement $\times$ LeadTime^2) on q	0.097	0.002

Table 12: Estimation Results – Product Fixed Effects

PARAMETER	ESTIMATE	STANDARD ERROR
Sony MVCFD73	2.364	0.006
Olympus D360L	1.442	0.005
Polaroid PDC640	4.497	0.008
Kodak DC215	2.007	0.003
Polaroid Fun!320	2.710	0.005
HP Photosmart C215	2.071	0.004
HP Photosmart C315	0.917	0.006
Sony MVCFD83	1.032	0.003
Olympus D460Z	2.097	0.005
Olympus D490Z	1.403	0.006
Sony MVCFD7	1.384	0.005
Sony MVCFD75	1.751	0.006
Sony DSCS70	0.608	0.004
Sony MVCFD88	0.739	0.004
Polaroid Fun!640	2.320	0.005
Canon PowerShotS100	1.177	0.005
Sony MVCFD90	1.213	0.004
Sony MVCFD91	0.923	0.006
Olympus D340R	0.682	0.004
Olympus C3000	1.139	0.004
Sony MVCFD71	0.333	0.005
Nikon Coolpix990	1.532	0.005
Sony DSCS50	0.247	0.003
Nikon Coolpix950	2.235	0.005
Intel Pocket Camera	1.281	0.005

Table 13: Estimation Results – Utility Parameters

PARAMETER	ESTIMATE	STANDARD ERROR
Luxury Model	-0.774	0.003
Price	-0.064	0.000
Price × Price Preannouncement	0.000	0.001
Price × Price Preannouncement × Lead Time	0.142	0.001
Price × Price Preannouncement × Lead Time^2	-0.046	0.000
Sensor Resolution	-0.038	0.001
Sensor Resolution × Sensor Resolution Preannouncement	0.404	0.002
Sensor Resolution × Sensor Resolution Preannouncement × Lead Time	-0.765	0.003
Sensor Resolution × Sensor Resolution Preannouncement × Lead Time^2	0.304	0.001
Optical Zoom Availability	0.387	0.002
Maximum Optical Zoom	0.048	0.001
Maximum Optical Zoom × Maximum Optical Zoom Preannouncement	-0.327	0.001
Maximum Optical Zoom × Maximum Optical Zoom Preannouncement × Lead Time	0.434	0.002
Maximum Optical Zoom × Maximum Optical Zoom Preannouncement × Lead Time^2	-0.154	0.001
LCD Display Availability	1.105	0.006
LCD Display Size	-0.937	0.003
LCD Display Size × LCD Display Size Preannouncement	0.285	0.002
LCD Display Size × LCD Display Size Preannouncement × Lead Time	-0.463	0.003
LCD Display Size × LCD Display Size Preannouncement × Lead Time^2	0.219	0.001

Table 14: Estimation Results – Utility Parameters

PARAMETER	ESTIMATE	STANDARD ERROR
Preannouncement	-0.181	0.003
Internal Storage Capacity	0.013	0.000
Internal Storage Capacity × Internal Storage Capacity Preannouncement	-0.013	0.001
Internal Storage Capacity × Internal Storage Capacity Preannouncement × Lead Time	0.062	0.001
Internal Storage Capacity × Internal Storage Capacity Preannouncement × Lead Time^2	-0.032	0.000
External Storage Shipped	-0.042	0.003
External Storage Available Not Shipped	0.231	0.002
External Storage Capacity	-0.025	0.000
External Storage Capacity × External Storage Capacity Preannouncement	-0.039	0.000
External Storage Capacity × External Storage Capacity Preannouncement × Lead Time	0.103	0.000
External Storage Capacity × External Storage Capacity Preannouncement × Lead Time^2	-0.036	0.000
Photo Flash Availability	0.393	0.003
Photo Flash Availability × Photo Flash Availability Preannouncement	-0.819	0.004
Photo Flash Availability × Photo Flash Availability Preannouncement × Lead Time	0.466	0.010
Photo Flash Availability × Photo Flash Availability Preannouncement × Lead Time^2	-0.245	0.005
Self-Timer Availability	-0.008	0.002
Self-Timer Availability × Self-Timer Availability Preannouncement	-0.090	0.006
Self-Timer Availability × Self-Timer Availability Preannouncement × Lead Time	0.050	0.013
Self-Timer Availability × Self-Timer Availability Preannouncement × Lead Time=	0.206	0.006

Table 15: Estimation Results – Utility Parameters

PARAMETER	ESTIMATE	STANDARD ERROR
USB Connectivity Availability	0.715	0.002
USB Connectivity Availability × USB Connectivity Availability Preannouncement	-0.381	0.004
USB Connectivity Availability × USB Connectivity Availability Preannouncement × Lead Time	0.086	0.006
USB Connectivity Availability × USB Connectivity Availability Preannouncement × Lead Time^2	0.018	0.002
High Season	1.655	0.001
More than 15 weeks since Launch	-1.826	0.001
Own Preannouncement Stock	-0.056	0.000
Cross Preannouncement Stock	-0.027	0.000
Category Preannouncement Stock	-0.016	0.000
Outside Good Intercept	8.353	0.064
p for Outside Good	1.199	0.047
q for Outside Good	0.732	0.100