# Skimming or Penetration?
# Strategic Dynamic Pricing for New Products

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**February 2009**

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*ABSTRACT*

The literature provides some stylized guidelines for choosing between skimming and penetration pricing for new products in simple competitive scenarios. However, these guidelines do not resolve the practical dynamic pricing problem in the current complex dynamic environments, characterized by numerous brands, each with multiple products and price points, and differentiated on a variety of product features. This study develops a structural pricing model to empirically ascertain the practice and profit implications of these alternate strategies in such complex environments. The authors apply the model to dynamic pricing over four years in one digital camera market, containing 663 cameras under 79 brand names, in one major European country. They analyze the adoption of different pricing strategies at the firm level, the factors associated with strategy choice, and the profitability of pricing strategies at the camera and firm level. The major finding is that a skimming strategy is more profitable than a penetration strategy at the camera level. However, a strategy mix appears to be preferable at the portfolio level after taking into account demand and cost interdependencies between products.

Keywords: Dynamic pricing strategy, product life cycle, durables, marketing performance, structural model

The current market environment, especially for high-tech categories, is characterized with rapid introductions of new products. In this environment, the pricing of new products is a difficult and important task affecting the financial success of a company. On the one hand, if the price is set too low, a company not only gives up potential revenues, but also sets a low value position for this new product, which can make future price increases difficult (Marn, Roegner, and Zawada 2003). On the other hand, a price set too high might harm the diffusion of the new product (Golder and Tellis 2003), limit gains from experience effects (Tellis 1986), or inhibit the product from reaching its critical mass for success (Dhebar and Oren 1985).

The literature suggests two basic dynamic pricing strategies for new products, *skimming* and *penetration* strategy (e.g., Kotler and Armstrong 2005; Monroe 2003; Nagle and Hogan 2006). A skimming strategy involves charging a high introduction price, which is subsequently lowered (Dean 1976). The rationale of this strategy is to *skim* surplus from customers early in the product life cycle in order to exploit a monopolistic position or a low price sensitivity of innovators (e.g., Dean 1976; Marn, Roegner, and Zawada 2003). A penetration strategy involves charging a low price to rapidly *penetrate* the market (Dean 1976; Nagle and Hogan 2006). Penetration pricing aims at exploiting economies of scale or experience (Tellis 1986). Further, if word-of-mouth is important in the market, then achieving large early sales increases word-of-mouth and enables rapid penetration (e.g., Clarke, Darrough, and Heineke 1982; Robinson and Lakhani 1975).

The choice of the pricing strategy is particularly important for high-tech products such as digital cameras where new products are frequently introduced and life cycles are short. Differentiation by features leads to a proliferation of products in each price tier. Text books recommend a skimming strategy for differentiated products where companies have some source of competitive protection (e.g., Kotler and Armstrong 2005; Nagle and Hogan 2006). But text books also recommend a penetration strategy for price-sensitive markets where new products usually face strong competition soon after introduction (e.g., Kotler and Armstrong 2005; Monroe 2003), which is the case for digital cameras. Hence, while the normative literature on dynamic pricing strategy provides plausible guidelines under what conditions to choose which strategy, it falls short of offering guidance in markets where conditions favor both strategy types. Unfortunately, many if not most markets for modern consumer durables (e.g., computers, mobile phones, TV sets, digital cameras) present the same dilemma: extensive feature differentiation supporting a skimming strategy concomitant with strong competition supporting a penetration strategy. Moreover, popular examples support the success of either strategy. Apple's iPhone, for example, seems to follow a skimming strategy with its recent entry into the highly competitive mobile phone market. In contrast, Lexus has been successfully competing with Mercedes and BMW in the U.S. premium *luxury car* market with its penetration pricing strategy relative to these two brands.

This study examines the practice and profit implications of the skimming and penetration strategies in a differentiated competitive market by an in-depth empirical analysis of one product market. Specifically, we analyze three price-quality segments of the market for digital cameras in Germany, the largest European market, in its early growth phase. The data cover all 663 cameras introduced under 79 brand names over a period of four years.

Our study's first contribution is that it extends an established structural model of static competition for consumer electronics to accommodate dynamic pricing strategies. Based on this model extension, we propose a method to discriminate between skimming and penetration strategies that takes demand, supply and competitive responses into account.

We apply this method to the German digital camera market and obtain a detailed picture of strategy adoption across products, firms, and market segments. So, our second contribution is an in-depth description of dynamic pricing strategy choice by manufacturers of digital cameras. We investigate several firm-level and market-level factors to describe strategy choice. The overall distribution of penetration and skimming strategies appears to be more or less balanced. A more detailed analysis, however, suggests that the adoption of dynamic strategies is strongly associated with brand positioning. Firms that target low-price segment customers with their product portfolio are more likely to adopt a penetration strategy whereas firms with a focus on higher-priced tiers prefer a skimming strategy. The likelihood of skimming also increases with distribution strength and breadth of product line, while it is lower in the early periods after product entry and in periods with increased competitive intensity.

Our third contribution is that we quantify the profit implications of strategy choice at the product level. Based on profit margin estimates obtained from our structural model, we estimate the net present value (NPV) for all analyzed 663 cameras. The results suggest that skimming is more profitable than penetration when we consider a single product. This finding is strongly corroborated by counterfactual experiments that account for the endogeneity of demand and cost and thus reduce potential causality concerns associated with a retrospective profit analysis.

Surprisingly, firms followed a penetration strategy for many cameras even though this strategy appears to be less profitable. Our fourth contribution is to resolve this contradiction by ascertaining the profit implications of strategy choice at the firm level. We conduct policy experiments in which pricing strategies are switched simultaneously, and cost and demand interdependencies between products within the product portfolio are taken into account. Our results reveal that a penetration strategy may be profitable at the firm level. We also find that even firms with preference for a skimming strategy benefit from using penetration for a few products in the lower priced tiers. These products contribute to firm profits by improving the profit margin of high-margin products via experience curve effects. Thus, our analysis indicates that the choice between skimming and penetration is not a binary decision at the product level as textbooks might suggest. It is rather a strategy mix decision to be made at the portfolio level.

The rest of the paper is organized as follows. The next section summarizes the normative literature on pricing strategies. The third section describes the data and method. The fourth and fifth sections describe the structural model of competition and the results of the model estimation. The sixth section presents the approach and results for the classification of dynamic pricing strategies. The seventh section analyzes the profit implications of these pricing strategies. The final section discusses the implications and limitations of the results.

## *LITERATURE SUMMARY*

This section reviews the literature on definitions and normative recommendations for skimming and penetration pricing.

### *Definitions*

While skimming and penetration pricing are probably the most common dynamic pricing strategies taught in almost every elementary course on marketing strategy, a closer look at popular textbooks reveals that they are not as clearly defined as one would expect. For example, Monroe (2003) writes “skimming calls for a relatively high price” and “penetration calls for a relatively low price” (pp. 380), but without further specifying what relatively high and low means. According to Nagle and Hogan (2006) “skim prices are high in relation to what most buyers in a segment can be convinced to pay” and “penetration prices […] are low relative to perceived value in the target segment” (pp. 131). Other definitions also mention a high (low) initial price for skimming (penetration) strategy (e.g., Dolan and Simon 1996; Kotler and Armstrong 2005). There is a consensus that initial prices should be evaluated relative to a benchmark to classify them as high or low, but it is unclear what the benchmark is.

Apparently, a dynamic pricing strategy should also involve a recommendation for the evolution of price over time, which we define as the dynamic component of the strategy. To our surprise, we find that textbook definitions are even more ambiguous about this aspect. Generally, definitions of skimming pricing mention that the relatively high introductory price should be reduced subsequently, whereas it remains open to which level the price should be reduced to. For penetration pricing, generally, no recommendation about the future price path is provided.

*Normative Strategy Recommendations*

The literature on normative pricing strategies is vast. The majority of these studies derive optimal dynamic pricing strategies under the monopoly condition (e.g., Balachander and Srinivasan 1998; Bass and Bultez 1982; Bayus 1992; Besanko and Winston 1990; Clarke, Darrough, and Heinecke 1982; Dhebar and Oren 1985; Dolan and Jeuland 1981; Horsky 1990; Kalish 1983; Kalish 1985; Kornish 2001; Krishnan, Bass, and Jain 1999; Narasimhan 1989; Nascimento and Vanhonacker 1988; Parker 1992b; Raman and Chatterjee 1995; Robinson and Lakhani 1975). The cost and demand assumptions of these models differ widely. For example, price may influence the diffusion rate or the market potential, products may have short (fast moving goods) or long interpurchase times (durable goods), and price elasticity increases or decreases over the product life cycle. Depending on these assumptions a skimming or a penetration strategy turns out to be optimal.

Other studies model optimal dynamic pricing strategies under duopoly (e.g., Dockner and Jorgensen 1988; Eliashberg and Jeuland 1986; Kalish and Lilien 1983; Nascimento and Vanhonacker 1993; Rao and Bass 1985; Wernerfelt 1985; Xie and Sirbu 1995). Here, cost and demand assumptions vary again widely and determine whether a skimming strategy or a penetration strategy is optimal. Hence, it is not easy to derive any generalizations that would hold in complex real markets. Moreover, even if one could, the normative guidelines might not be immediately relevant in markets which are predominantly oligopolistic or polypolistic.

A number of studies attempt to resolve the problem by an empirical analysis of pricing strategies in actual polypolistic markets (Bass, Krishnan, and Jain 1994; Gatignon and Parker 1994; Krishnan, Bass, and Kumar 2000; Mahajan, Muller, and Bass 1995; Parker 1992a; Parker and Gatignon 1996; Parker and Neelamegham 1997; Simon 1979). Most of these studies focus at the category level, i.e. they do not provide answers to managers if a specific brand pricing strategy was successful or not. The studies by Gatignon and Parker (1994), Parker and Gatignon (1996), and Simon (1979) analyze dynamic price effects on brand level diffusion. However, none of these studies compares the success of different dynamic pricing strategies with respect to profitability. Descriptive studies survey managers about perceived factors influencing their choice of strategy (Ingenbleek, Debruyne, Frambach, and Verhallen 2003; Noble and Gruca 1999). However, they do not focus on the outcome of dynamic pricing strategy for new products.

Thus, relative to the literature, this study seeks to empirically ascertain patterns of and profit rewards to various dynamic pricing strategies in the digital camera market.

## *METHOD*

This section provides an overview of the data, the descriptive statistics, and an overview of the analysis.

### *Overview of Data*

Our data set comprises the whole market for digital cameras in Germany, which we obtained from GfK, the largest provider of market research data for this category in Europe. The observation period includes 46 months (almost four complete years) of camera prices, sales, distribution, and product features between January 2000 and October 2003. Henceforth, we use the term "camera" alone to represent the most disaggregate brand and product level, with a unique alphanumeric code, that characterizes an offering on numerous features (e.g., Sony Cybershot DSC-P20). Features or product dimensions of a digital camera include among others pixel resolution, digital and optical zoom, memory, flash, auto focus, and add-ons such as MP3-player and Bluetooth. The majority of firms offer digital cameras under one brand name which may, however, encompass different product lines (e.g., Sony's Mavica and Cybershot lines). In the rest of the paper, we use the terms camera, brand, and product line as explained above but the terms product and camera interchangeably.

For our analysis, we ignore the professional segment (changeable lens products), which is less than half a percent of sales. Although the professional segment of the digital camera market already started in this country in the mid 1990's, the non-professional segment took-off only around 2000. We include only products for which we observe the complete life cycle to avoid the problem of time censoring with a product. Finally, we exclude products with life cycles shorter than 4 months. These products had no economic relevance.

The final data set consists of a total of 663 cameras marketed under 79 brand names by 74 firms. The average price of a camera in our data set is €375.42 and average monthly sales are 409 units. However, prices and monthly sales are quite dispersed, ranging from €17.40 to €2,262.60 and 1 to 30,501 units.

From discussions with industry experts, we learned that the market can be divided into three distinct segments: a low-price segment, a medium-price segment, and a high-price segment. The differences in price correspond to systematic differences in features as explained below.

Based on the observed prices, we conducted a latent class segmentation analysis. In this analysis, we control for a general price decline over time (to avoid a time-driven segmentation solution) and include product features as covariates to explain segment membership. The results corroborate the three-segment structure of the market. The segmentation procedure helps us assigning the 663 cameras to the three segments. Given the high entropy value of .987, we have much confidence in the classification of cameras (for details, see the Web appendix).

*Descriptives*

Table 1 summarizes information of the sample for the three segments. The average price for a camera in the low-price segment is €105.48. It is €321.88 in the medium-price segment and €704.01 in the high-price segment. The three segments differ also in terms of quality features. Details on product differentiation are in Table 1.

== Insert Table 1 here ==

The German digital camera market witnessed a sharp rise in firm entry, proliferation of range of products, and constant decline in prices. Growth in firm entry was highest in the low-price segment, with 15 firms being present in 2000 to 58 firms in 2003. The mean price fell by 46%. The segment share in total unit sales grew from 21% in 2000 to 36% in 2003. In contrast, the share of the high-price segment fell from 45% in 2000 to 24% in 2003; and the number of firms rose only modestly from 15 to 21. In the medium-price segment, the number of firms (share in unit sales) increased from 17 (34%) in 2000 to 39 (40%) in 2003. Prices declined by 37% in the medium-price segment and by 29% in the high-price segment. The development of unit sales, firm entries, and prices suggest that competitive intensity is significantly higher in the low-price segment compared to the other two segments.

The digital camera market is dominated by 10 mostly global manufacturers as Table 2 shows. These firms account for more than 80% of total unit sales. Canon is leader in market share both by unit and value followed by Olympus, Sony, Yakumo (by units) and Nikon (by value), respectively. Aiptek, Jenoptik (with its Concord brand), and Yakumo are almost exclusively present in the low-price segment and lead the market here. In contrast, Canon, Sony, and Nikon positioned their brands in the medium-price and high-price segments. Given the differences in competitive intensity across segments and in brand positioning across firms, we expect that competitive dynamic pricing strategies are not uniformly distributed across firms.

== Insert Table 2 here ==

*Analysis*

We apply a two-step approach to the analysis of the data. In the *first step*, we adopt the structural modeling approach to develop models of demand and competitive interaction for the digital camera market. We apply these models to the data and estimate the price conduct, i.e., the strategic price behavior of firms, and profit margins for every camera and period. We define price conduct as the deviation of a camera's price mark-up from the equilibrium-price implied mark-up under static Bertrand-Nash competition. Based on the estimated evolution of the price conduct parameter, we identify the dynamic pricing strategy of each camera.

In the *second step*, we calculate the net present value of the pricing strategy for each camera. We obtain price-cost margins over a camera's total life cycle from estimating the structural model. This metric already accounts for experience curve effects and allows us to calculate the net earnings from *pricing strategy*. In addition, we use the structural model for policy simulations to demonstrate the impact of alternative dynamic pricing strategies on NPV.

## *STRUCTURAL MODEL OF COMPETITION*

This section describes the specification, estimation, and results of our model of competition. Following Chintagunta, Erdem, Rossi, and Wedel (2006), we use structural modeling to develop demand and supply (price) functions. The estimation of these functions produces two important quantities: a direct estimate of the equilibrium market price and a direct estimate of the price-cost margin for each camera for each period.

We cover the model specification in three parts: demand model, supply model, and dynamic extension of the supply model.

*Specification of Demand Model*

Consistent with many previous studies (e.g., Besanko, Gupta, and Jain 1998; Chu, Chintagunta, and Vilcassim 2007), we assume that a consumer *h* chooses a camera *i* in market segment *s* that belongs to brand *k* among all cameras that are offered to him/her in period *t*. In addition, the consumer has the option to not purchase a digital camera, i.e., to choose the no-purchase alternative. Consumers are assumed to maximize their utility that can be divided into a deterministic part $v_{hkist}$ and a stochastic part $\varepsilon_{hkist}$. The deterministic utility of the outside good includes only a preference constant, $\beta_{00s}$, which is set to zero for identification purposes. Assuming $\varepsilon_{hkist}$ to follow an extreme value distribution, results in the well-known multinomial logit choice model and the following specification for camera *i*'s market share in segment *s* and period *t*.

$$ms_{kist} = \frac{e^{v_{kist}}}{1+\sum_{j=1}^{I} e^{v_{kjst}}},\ j=1,...,i,...,I,\ k=1,...,K\ , \tag{1}$$

$$\text{with } v_{kist} = \alpha_{st} + \beta_{0kis} + \beta_{1s} wdist_{kist} + \beta_{2s} wdist_{kist} \times \log t + \beta_{3s} p_{kist} + \beta_{4s}\ p_{kist}/t + \beta_{5s} / LCT_{kist} + \xi_{kist}\ ,$$

where $\alpha_{st}$ is month trend, $\beta_{0kis}$ measures the intrinsic preference for brand *k*'s camera *i* in segment *s*, *wdist* measures the weighted distribution of the camera, *p* is price, *LCT* is elapsed time since the launch of the camera, $\beta_{1s}$, …, $\beta_{5s}$ are utility weights associated with these variables, and $\xi_{kist}$ is unobserved (to the econometrician) product attributes. Given the total number $H_{st}$ of consumers in segment $s$ and market share $ms_{kist}$, the expected market demand $q_{kist}$ for camera $i$ in period $t$ is obtained by $q_{kist} = ms_{kist}H_{st}$.

The demand function (1) offers a number of desirable properties. It includes distribution and price, which are important marketing variables in the digital camera category. In addition, the effects of quality features, brand equity, and other time-invariant variables are reflected in the camera-specific constants.[1] We were unable to obtain advertising expenditures. Ad expenditures and other unobserved time-varying product attributes are captured by the error term $\xi_{kist}$.

Equation (1) also accounts for a number of dynamic effects of utility formation. The trend measure $\alpha_{st}$ reflects the evolution of the overall attractiveness of the digital camera segment and $\beta_{5s}$ measures the evolution of the attractiveness of a single camera. Finally, the parameters $\beta_{2s}$ and $\beta_{4s}$ measure the development of segment-specific consumer sensitivities towards distribution and price over time (Kotler and Armstrong 2005). Specification tests revealed that the interaction of distribution and price with log $t$ and $1/t$, respectively, are most appropriate for our data.

*Specification of Supply Model*

Manufacturers sell their digital cameras through retailers who set retail prices. Competition is characterized by horizontal interactions between manufacturers and retailers and by vertical interactions between manufacturers and retailers. The market for digital cameras in Germany is dominated by brands such as Canon, Olympus, and Sony at the manufacturer side and a number of nationwide retail chains such as Media Markt, Conrad, and Saturn that are specialized in selling consumer electronics. The institutional structure of the market and distribution of power among manufacturers and retailers is similar to other consumer electronics categories such as personal computers or TV sets.

Chu, Chintagunta, and Vilcassim (2007), for example, describe the situation of the U.S. market for PCs. Akin to digital cameras, computers by international firms such as IBM, Hewlett Packard, etc. are sold through nationwide retail chains (e.g., Best Buy in the U.S., Media Markt in Europe). PCs are highly differentiated, expensive and have a rather short life cycle. Competition seems to be quite intense. The data reported in Chu, Chintagunta, and Vilcassim (2007) cover the top ten players (89 % of branded PC sales) and correspond to a Herfindahl index of .124 and a C4 ratio of .592. The top ten players in the German digital camera market cover 80% of total sales. The competitive structure appears to be very similar (Table 2): .117 (Herfindahl) and .582 (C4). Because of the many similarities between the U.S. PC market and our focal digital camera market we consider the model proposed by Chu, Chintagunta, and Vilcassim (2007) as a natural candidate for further analysis. Note, however, that their model is static. We relax this assumption and extend their model to characterize dynamic pricing strategies. For the moment, let us assume static competition.

*Model assumptions*. Consistent with many other studies (e.g., Choi 1991; Sudhir 2001), Chu, Chintagunta, and Vilcassim (2007) assume a manufacturer-led Stackelberg leader-follower vertical game structure. Under this assumption, manufacturers set wholesale prices by taking into account the retailers' reaction functions that set their prices based on wholesale prices. Specifically, retailers are assumed to set retail prices by charging a brand-camera-specific mark-up. We believe that this assumption is appropriate for several reasons. Like in the U.S. PC market, a sequential process of price setting is consistent with industry practice as we learned from discussions with representatives of the Metro Group, the owner of Germany's leading consumer electronics retail chains Media Markt and Saturn. In addition, the power of retailers to negotiate prices for digital cameras was rather limited in our observation period. Digital cameras represented an innovative, fast-growing new segment of consumer durables that attracted many customers. Hence, a retailer could not credibly threaten a manufacturer with not listing its cameras because that would have probably resulted in a significant loss of overall attractiveness of the retailer.[2]

Following many previous studies (e.g., Nevo 2001; Sudhir 2001), we also assume a common retailer. Hence, we do not model horizontal interactions among retailers, which may be a shortcoming when competition is in fact strong. The assumption of a common retailer seems to be justified for several reasons. First, electronics stores in Germany are usually located far away from each other limiting potential cross-store consumer traffic effects. Second, an analysis of randomly selected retail advertisements for digital cameras in the observation period does not suggest price competition. Ads were rather focused on product assortments and the introduction of new cameras with new features. Price competition focused on other categories such as DVD players. Consistent with this result, we do not find much evidence for consumer promotions in our data (less than 2 percent).[3, 4]

Following the standard assumption for competitive product markets that seems to be justified in view of a Herfindahl index below .20 (e.g., Berry, Levinsohn, and Pakes 1995; Besanko, Gupta, and Jain 1998; Nevo 2001), we assume that the equilibrium wholesale price for each camera is set in each period according to a Bertrand-Nash game. Under this assumption, each manufacturer takes the other manufacturers' prices as given and maximizes own profits.

Finally, we need to specify the objective functions of both manufacturers and retailers. For manufacturers we assume that they maximize brand profits. This implies that prices of different cameras that are sold under the same brand name are *jointly* set. Recall that product lines such as Sony's Mavica and Cybershot fall under the Sony umbrella brand. If a manufacturer sells cameras under more than one umbrella brand, it seems reasonable to assume that their prices are not jointly set because these brands are usually positioned in different market segments (e.g., Sony's discount brand AIWA and its quality brand Sony).

The retailer's brand-camera-specific mark-up rule may involve different objectives, for example category-profit maximization. We do not make an explicit assumption here, but rather assume that the rule results from a constrained profit maximization problem the retailer faces. An important constraint in price setting is that the rule be feasible. When prices for thousands of items need to be set, a constant mark-up rule appears to be attractive because it is highly efficient in terms of time and reduction in decision complexity.

The preceding discussion offers several arguments for the appropriateness of our assumptions; however, they are still assumptions. To minimize the danger of model misspecification we later estimate a series of models with alternative assumptions about the type of vertical interaction (e.g., vertical Nash) and the objective functions of manufacturers and retailers. Among nine alternative models, the suggested model turns out to be most consistent with the data.

*Model formulation*. Let product-line profits $\Pi_{kt}$ for brand $k$ in month $t$ be

$$\Pi_{kt} = \sum_{s \in S} \sum_{i \in I_k} \left( w_{ist} - c_{it} \right) ms_{ist} H_{st} \ , \tag{2}$$

where $w_{ist}$ denotes wholesale price for camera $i$ in segment $s$, $c_{it}$ denotes marginal cost of producing camera $i$, and $ms_{ist}$ is given by Equation (1). Note that a manufacturer may offer cameras in different market segments ($S$=3) under the same umbrella brand. Manufacturers are assumed to *jointly* set camera prices by maximizing Equation (2).

Solving the Nash-game in prices, we obtain the Nash-equilibrium retail price (Besanko, Gupta, and Jain 1998; Chu, Chintagunta, and Vilcassim 2007):

$$p_{kist} = \left(1 + r_{kis}\right) c_{kit} + m_{kist}^{Bertrand}, \;\; i \in I_k, \; k = 1, \ldots, K,$$
$$\text{with } m_{kist}^{Bertrand} = -\frac{1}{\left(\beta_{3s} + \beta_{4s}/t\right)} \frac{1}{\left(1 - MS_{kst}\right)}, \tag{3}$$

where $r_{kist}$ is the retailer mark-up, $m_{kist}^{Bertrand}$ is the Bertrand margin (Sudhir, Chintagunta, and Kadiyali 2005), $MS_{kst} = \sum_{i \in I_k} ms_{ist}$ is brand $k$'s unconditional market share in segment $s$ in the equilibrium, and all other terms are defined as earlier. Note that the mark-up varies across cameras within a brand's product line via segment-specific price sensitivities reflecting consumer heterogeneity and segment-specific brand market shares.

Equation (3) provides a useful basis to explain price differences in a differentiated product market such as the digital camera market. It takes into account cost and demand conditions as well as the nature of competitive interaction. For example, we would expect higher prices if costs increase. Prices should fall when demand elasticity rises.

*Dynamic Extension of Supply Model*

The Bertrand margin is derived under the conditions of static Nash competition and forms the starting point for developing a dynamic price function. Consistent with the idea of dynamic pricing strategy, actual mark-ups should deviate from the Bertrand margin and follow a specific pattern over time. For example, a skimming strategy implies a price that exceeds the (equilibrium) market price in the beginning, which will be lowered in subsequent periods. Optimal time paths of prices may by derived from solving a dynamic game that allows for updates in a subgame perfect strategy, as an example. However, that is not an easy task in a market with 663 unique cameras, if not unfeasible with today's computer capacities. Instead of trying to solve a dynamic game and imposing further a priori restrictions under new, potentially restrictive assumptions about dynamic firm interaction, we adopt the conduct parameter framework to characterize dynamic competition (Sudhir, Chintagunta, and Kadiyali 2005; Vilcassim, Kadiyali, and

Chintagunta 1999). We still assume Nash competition among manufacturers. As a result, the set of possible strategies should nest the solution of a static game as a special case. We introduce a multiplier $\lambda_{kist}$ on the Bertrand margin that measures the extent of a camera's price deviation from the Bertrand margin. Following Vilcassim, Kadiyali, and Chintagunta (1999), we call this multiplier the conduct parameter. The dynamic pricing equation then becomes:

$$p_{kist} = \left(1 + r_{kis}\right) c_{kit} + \lambda_{kist} m_{kist}^{Bertrand} . \tag{4}$$

For $\lambda_{kist}$=1, $\forall$ $t$, we observe a market-equilibrium price that is consistent with the Bertrand-Nash price obtained from the special case of static competition. Under the assumption of a dynamic pricing strategy, firms are likely to deviate from that benchmark reflecting their dynamic equilibrium strategy. To estimate the time path of prices we parameterize the conduct parameter with a parsimonious time function (Spann and Tellis 2006):

$$\begin{aligned} &\lambda_{kist} = \lambda_{kis} + a_{1kis} LCT_{kist}^2 + a_{2kis} LCT_{kist}, \\ &\text{with } \lambda_{kis} = \bar{\lambda} + \upsilon_{kis},\ a_{1kis} = \bar{a}_1 + \kappa_{kis},\ a_{2kis} = \bar{a}_2 + \mu_{kis}, \\ &\text{and } \upsilon_{kis}, \mu_{kis}, \kappa_{kis} \sim MVN\left(0, \Sigma\right), \end{aligned} \tag{5}$$

where $\lambda_{kis}$ measures the initial conduct parameter for brand $k$'s camera $i$ in segment $s$ at the beginning of its life cycle ($LCT_{kist}$=0). $a_1$ and $a_2$ are parameters that determine the shape of the price evolution. $\bar{\lambda}$, $\bar{a}_1$, and $\bar{a}_2$ represent mean values of the parameters and are to be estimated. $\upsilon_{kis}$, $\mu_{kis}$, and $\kappa_{kis}$ are brand-camera specific deviations from the mean that are assumed to follow a multivariate normal distribution. The variance-covariance matrix $\Sigma$ is a non-diagonal matrix that needs to be estimated from the data. This specification is parsimonious but flexible enough to capture camera-specific deviations from the Bertrand margin in each period of the life cycle. Our estimation approach provides us with time and camera-specific estimates of the conduct parameter $\lambda_{kist}$ which we need for the identification of dynamic pricing strategies and estimating their NPV.

*Cost Function*

Following previous research (e.g., Berry, Levinsohn, and Pakes 1995; Besanko, Gupta, and Jain 1998; Nevo 2001), we specify marginal cost $c_{fkit}$ as a function of factor inputs, product characteristics, and cumulative production output. Since firms may produce more than one (umbrella) brand we introduce a firm index, $f$:

$$c_{fkit} = \gamma_{0fk} + \gamma_1 JPPI_t + \gamma_2 USLPI_t + \gamma_3 \log SALE_{ft-1} + \sum_{l=1}^{L} \gamma_{4+l} PF_{l,ki} \,. \tag{6}$$

$\gamma_{0fk}$ is a firm-brand-specific constant that measures the overall cost of producing one digital camera unit and all other variables measure the deviation from this cost due to changes in factor prices, production experience, and product characteristics. To the extent that $\gamma_{0fk}$ varies across brands and manufacturers it represents general differences in cost efficiency. $JPPI_t$ is the producer price index for cameras in Japan and $USLPI_t$ is an index of labor productivity in the U.S.[5] These two variables measure the change in factor prices in the countries where the majority of digital cameras is produced. $SALE_{ft-1}$ denotes unit sales for firm $f$ that have been cumulated until the start of the current period. We include this variable to account for economies of scale. $PF_{l,ki}$ represents product features of the camera such as the availability of an optical zoom or pixel resolution. The $\gamma$-parameters need to be estimated from the data.

## *ESTIMATION AND RESULTS*

*Estimation*

Following Nevo (2001), we adopt a two-step estimation approach. We first estimate the parameters of the demand equation and then the parameters of the pricing equation by using information from demand estimation. While simultaneous estimation of equation systems with imposed cross-equation restrictions can resolve potential endogeneity issues and provides efficient estimates, it is not robust against model misspecification but produces inconsistent estimates in this case (Chintagunta et al. 2006). In contrast, in a two-step approach, we can also account for potential endogeneity issues by employing instrumental variables estimation but minimize the danger of obtaining inconsistent estimates due to model misspecification.

Endogeneity issues may arise in the demand equation with respect to price and distribution. Such issues occur in the pricing equation with respect to the Bertrand-margin variable, since it incorporates the brand-segment-specific market share that is not independent of price. Following recent empirical research (e.g., Draganska, Klapper, and Villas-Boas 2009; Nevo 2001), we consider brand-camera dummies, factor prices, and product characteristics as instruments for the demand equation. In addition, we construct variables of product variety. For the pricing equation, we consider brand-camera dummies, calendar time, the number of cameras per brand, cumulated brand sales until the start of the current period, and the total number of competitive brands in the market as instruments. These instruments provide more restrictions than needed to identify the model. For the pricing equation, we also need to estimate the location and dispersion parameters for coefficients that are assumed to be randomly distributed across cameras. We employ simulated maximum likelihood estimation to obtain these estimates (Greene 2008). Our estimation procedure enables us also to derive brand-camera-specific estimates for the conduct parameter (see again Equation 5). Full estimation details are provided in the Web appendix.

*Results*

Table 3 presents the results of fitting the logit demand model in the three market segments. Recall that price and weighted distribution are instrumented to account for endogeneity. First-stage regressions produced high $R^2$s, so that we have confidence in the strength of our instruments. Model fit is high with an adjusted (Pseudo) $R^2$ ranging from .742 to .811. Price and distribution turn out to be significant drivers of brand demand in all three segments although their importance varies. We also find evidence that price and distribution sensitivities are changing over time. Specification tests showed that interacting price with $1/t$ and distribution with $\log t$ are most appropriate for the data. For both marketing instruments, we find that consumer sensitivities increase over time, which is consistent with the predictions in the literature (e.g., Kotler and Armstrong 2005).

== Insert Table 3 here ==

Table 4 provides the results from estimating the supply (price) function. Here, we do not estimate separate models for the segments because basic cost relations are determined at the firm level and not the market segment level. Among the product features, we find many features that shift marginal costs. For example, pixel resolution and the availability of an optical zoom impact marginal cost. We note that the direction of the cost impact of product features should be evaluated relative to the average camera. Consistent with our expectation, factor prices shift also costs. Higher (Japanese) producer costs increase marginal cost of a camera whereas an increase in (U.S.) labor productivity reduces marginal cost. We also find evidence for scale economies as indicated by the significant negative coefficient estimate associated with the log of cumulated manufacturer sales. Finally, we obtain significant estimates associated with the conduct parameter. The estimated mean initial value is 1.14 (SD=.71), i.e., on average and across segments, a digital camera is priced slightly higher relative to Bertrand-Nash at the beginning of its life cycle. Our estimates show also that the conduct parameter varies substantially across cameras and their life cycle. Hence, we find first evidence that firms follow dynamic pricing strategies and that these strategies differ across cameras.

== Insert Table 4 here ==

Table 5 provides interesting insights into mean marginal costs, price-cost margins, and the conduct parameter for digital cameras by segment. Note that we cannot estimate retail margins separately. As a result, marginal costs and price-cost margins still include the retail margin. Table 5 shows that the initial conduct parameter at launch is below 1 in the low-price segment and above 1 in the other two segments. Consistent with our descriptive analysis of firm entries and previous research (e.g., Berry, Levinsohn, and Pakes 1995), this suggests that competition is more fierce in the low-price segment. Average marginal costs and price-cost margins vary across segments; and it is not surprising that costs and margins increase from the low-price segment to the high-price segment. The highest margin occurs in the high-price segment with €370 per camera.

== Insert Table 5 here ==

*Robustness Checks*

To verify that the results are robust, we employed a number of analyses. First, we pooled the data from all three segments and estimated a nested logit model where market segments represent the nests. Based on the Bayesian Information Criterion, we conclude that the separate estimation of a standard logit model for each market segment is superior to the estimation of a nested logit model ($BIC_{SMNL}$=-2.85 < $BIC_{NMNL}$=-.93).[6]

Second, we changed our assumptions about manufacturers' and retailers' objectives and their vertical interaction. Specifically, we assumed that manufacturers with more than one umbrella brand (valid only for five firms) maximize their brand portfolio instead of each umbrella brand individually. Alternatively, we assumed that manufacturers maximize profits from each camera independently. We also changed the type of vertical interaction by assuming a Vertical Nash game. Under this condition, retailers are assumed to either maximize category profits or brand profits. The different behavioral assumptions resulted into eight additional alternative models of competition which we compared with our proposed model. Based on the Vuong (1989)-statistic, the proposed model appears to best represent the data generating process (see Table A-1 in the Appendix and the Web appendix for specification details). Additional robustness tests are in the Web appendix.

## *CLASSIFICATION OF DYNAMIC PRICING STRATEGIES*

This section describes the classification of the pricing strategies in three parts: method, results, and descriptors of strategy choice.

### *Method*

To capture dynamic pricing strategies, we define the price path of each camera's pricing around two broad points: the initial relative price and the subsequent relative price evolution. Previous normative research on dynamic pricing strategies has identified non-monotonic patterns such as U-shaped and inverted U-shaped price paths (e.g., Krishnan, Bass, and Jain 1999). Our approach enables us to obtain linear, nonlinear, monotonic, and non-monotonic patterns of price evolution.

*Initial relative price*. The initial relative price measures the relative difference between the actual launch price and the "fair" market price. We define the static Nash market-equilibrium price as the fair price because that price arises from reasonable demand and supply primitives and adjusts for effects of competitive responses. However, firms are assumed to behave myopically. In a dynamic game, their price is likely to differ from the static Nash price that is reflected in the conduct parameter $\lambda$ of Equation (4). To measure the initial relative price of a new camera, it is sufficient to look at the estimated initial conduct parameter, $\lambda_{kis}$, when $LCT$=0. A camera is priced relatively high at launch if $\lambda_{kis}>1$. Consistent with the literature (e.g., Dolan and Simon 1996; Monroe 2003), we call this a skimming price. A penetration price occurs if $\lambda_{kis}<1$.

*Evolution of relative price.* We evaluate the price evolution again in relative terms. Note that prices may already vary over time because of changes in marginal costs and time-varying consumer sensitivities. Since we find significant experience curve effects and increasing price sensitivities in our sample, we would expect *static* Nash equilibrium prices to fall over time. However, this temporal price pattern does not reflect dynamic strategic firm behavior as firms simply adjust their static Nash price to the new cost and demand conditions. To be consistent with the conceptualization of our dynamic price function (4) we therefore need to evaluate the evolution of prices in terms of its conduct parameter $\lambda_{kist}$ (see again Equation 5).

Depending on the estimated shape parameter values $a_{1kis}$ and $a_{2kis}$ as well as the life cycle length $LCT_{kist,max}$ of each camera, we obtain nine different patterns of a camera's price evolution (see Table A-2 in combination with Figure 1 and the Web appendix for a formal derivation of the patterns). If the absolute value of the camera-specific estimate of a shape parameter is smaller than its estimated standard deviation (t-value < 1) we set the parameter to zero, otherwise we keep the parameter estimate. When both $a_{1kis}$ and $a_{2kis}$ are equal to zero, we observe a constant price over time (pattern 2 in Figure 1). Patterns 1, 4, and 8 represent a monotonic price increase over time where the marginal rate is constant, decreasing, or increasing. Patterns 3, 5, and 7 are symmetrical patterns for decreasing prices. Patterns 6 and 9 reflect a non-monotonic price evolution.

== Insert Figure 1 here ==

*Typology of dynamic pricing strategies.* From the initial relative price as measured by the conduct parameter $\lambda_{kis}$ and the pattern of relative price evolution (see again Figure 1), we develop the following typology of dynamic pricing strategies and apply it to our data:

1. *Monotonic skimming*: If price starts off high ($\lambda_{kis}$>1) and drops with time (decreasing patterns 3, 5 or 7), then it is monotonic price skimming (e.g., Dean 1976).
2. *Non-monotonic skimming*: If price starts off high ($\lambda_{kis}$>1), decreases and then increases over time (non-monotonic pattern 9), then it is non-monotonic price skimming following a U-shape (Parker 1992b).
3. *Monotonic penetration*: If price starts off low ($\lambda_{kis}$<1) and stays low (constant pattern 2), drops with time (decreasing patterns 3, 5 or 7), or increases (increasing patterns 1, 4, or 8), then it is monotonic price penetration (e.g., Dean 1976).
4. *Non-monotonic penetration*: If price starts off low ($\lambda_{kis}$<1), decreases and then increases over time (non-monotonic pattern 9), then it is non-monotonic price penetration following a U-shape (Parker 1992b).

*Results*

Table 6 displays the distribution of dynamic pricing strategies by segment and for the total market. Across all segments, penetration strategies occur slightly more often than skimming strategies (54% versus 46%). A strong relative majority of penetration strategies appears, however, in the low-price segment (68% versus 32%). Skimming occurs more often across the medium-price and high-price segments. In terms of price evolution, we recognize that non-monotonic strategies occur less frequently than monotonic strategies across all segments. The dominant pattern is a monotonic nonlinear price decrease as Figure 1 shows. Although relative prices generally decrease (70% of all cameras) we also observe that 26% of cameras have relative price increases, albeit many of them towards the end of their life cycle (see pattern 9 in Figure 1).

We also compared the evolution patterns in Figure 1 with evolution patterns obtained from fitting a quadratic time function to observed *absolute* retail prices. Note that these prices also incorporate changes in *static* Nash prices due to evolving cost and demand conditions, which are controlled for in our conceptualization. In addition, differences may occur because of uncertainties surrounding the shape parameter estimates. Overall, we find identical strategy types for

478 cameras corresponding to a 72% hit rate. We conclude that our conduct parameter-based approach of relative price evolution is not artificial but reflects well observed retail prices.

== Insert Table 6 here ==

*Descriptors of Strategy Choice*

Table 6 reveals a quite heterogeneous choice of dynamic pricing strategies across firms, cameras, and segments. Skimming and penetration strategies are in balance, which seems to reflect the fuzziness in textbook recommendations. To better understand the factors and conditions associated with the choice of a skimming over a penetration strategy, we estimate a binomial probit model. Note that this is a descriptive analysis. We do not intend to establish causal relationships between the analyzed variables and strategy choice. The dynamic pricing strategy is assumed to be endogenously generated from dynamic competitive firm interactions.

Table 7 shows the results of our descriptive analysis. We analyze the role of seven firm-level descriptors and two market-level descriptors. At the firm level, we consider a dummy variable of *firm entry before year 2000*, the *launch date* of the camera, the *distribution strength of the brand* (measured by the focal camera's average weighted distribution), a dummy variable that classifies the (umbrella) *brand* as *established manufacturer* in consumer electronics/photography or not, the *breadth of product line* (measured by a brand's average number of cameras over the focal camera's life cycle), the *length of the* camera*'s life cycle*, and the *cumulated manufacturer sales* at launch of the focal camera. At the market level, we consider the *competitive intensity in* the *segment* (measured by the average Herfindahl index over the focal camera's life cycle) and a dummy variable that measures whether the camera was *launched in the low-price segment* or not. We discuss our sign expectations regarding theses variables together with the estimation results.

== Insert Table 7 here ==

Firms which entered before 2000 (17 out of 74) can be considered as early entrants and may enjoy competitive advantages for their products (e.g., Urban, Carter, Gaskin, and Mucha 1986). Greater distribution strength for the brand and the reputation of an established brand may create further sources of competitive protection. Following the literature (e.g., Nagle and Hogan 2006), we expect a higher likelihood for the choice of a skimming strategy in such cases. The results support our expectation, albeit the coefficient for firms entering before 2000 is not significant. We also expect a higher likelihood of occurrence of a skimming strategy for cameras launched later, for brands with broader product lines, and for cameras with longer life cycles. Firms probably use penetration more often for their first products in order to build economies of scale. With broader product lines, firms can better exploit cost advantages from a few volume cameras by using skimming strategy across other cameras. Finally, planned life cycles for cameras following a skimming strategy are likely to be longer because prices are less likely to fall below marginal costs that would signal an unprofitable product. Estimation results are consistent with these expectations. For the last firm-level descriptor, the cumulated manufacturer sales, we expect a higher likelihood for the choice of a penetration strategy. Higher cumulated sales usually lead to cost advantages which facilitate adopting a cost-oriented strategy such as penetration pricing. The negative coefficient is in line with the argument.

For the market-level descriptors, we expect that the likelihood of occurrence for penetration strategies increases with competitive intensity (e.g., Kotler and Armstrong 2005; Monroe 2003). The likelihood should also be higher when the focal camera is introduced into a market, where buyers care more about the price as is the case in the low-price segment (e.g., Kotler and Armstrong 2005). Both expectations are supported by the estimation results.

To summarize, we encounter a number of firm-level factors and market conditions that are associated with the occurrence of skimming and penetration strategies.[7] However, we do not know which profit implications are associated with the choice of the different pricing strategies, which we will analyze in the following section.

## *PROFIT IMPLICATIONS OF DYNAMIC PRICING STRATEGIES*

This section evaluates the profit implications of the dynamic pricing strategies by computing the net present value (NPV) of a camera from estimated price-cost margins and from policy simulations. Generally, we calculate the NPV for a camera as follows:

$$NPV_{fkis} = \sum_{t=\tau_{kis}}^{T_{kis}} \left[ p_{kist} - \left(1+r_{kis}\right) c_{fkit} \right] q_{kist} \left(1+d\right)^{-t} = \sum_{t=\tau_{kis}}^{T_{kis}} \left( \lambda_{kist} m_{kist}^{Bertrand} \right) q_{kist} \left(1+d\right)^{-t}, \qquad (7)$$

where $d$ is the monthly discount rate (assumed to be 1%), $\tau_{kis}$ is the launch date of the camera, $T_{kis}$ denotes the end of its life cycle, and all other terms are defined as earlier. Note that all NPVs are deflated to January 2000 to allow for a fair comparison.

### *Analysis at the Product Level*

We compare first the NPVs of individual products based on their estimated price-cost margins multiplied by the actually realized demand in the past. While this analysis provides important retrospective insights into differences in profitability for the analyzed sample of products, we cannot claim that these differences arise from strategy choice unless we test the counterfactual. Consequently, we also conduct 663 separate counterfactual pricing experiments, in which we switch the pricing strategy for each camera from skimming (penetration) to their penetration (skimming) counterpart. Specifically, we switch from monotonic skimming to monotonic penetration, from non-monotonic skimming to non-monotonic penetration, etc. An initial skimming conduct parameter (to measure the relative price at launch) that exceeds 1 by x%/100 is converted to 1-x%/100 for the corresponding penetration strategy and vice versa. For the shape parameters, $a_{1kis}$ and $a_{2kis}$, we adopt the averages across cameras from each of the four pricing strategies. Note that demand and costs are endogenously defined by the chosen pricing strategy in the policy simulations (for details of the simulation see the Web appendix).

The NPV measure in Equation (7) includes both profits to the manufacturer and retailer because we cannot estimate retail margins separately. Specifically, the profit margin $\lambda_{kist} m_{kist}^{Bertrand}$ in (7) equals the manufacturer profit margin multiplied by the retail margin $1{+}r_{kis}$. Since we consider relative profit changes in the counterfactual experiments, the retail margin cancels out and is not relevant. It may, however, matter in the comparison of estimated absolute actual profits across cameras. NPV estimates might be affected to the extent that retail margins vary with manufacturer and retailer brand strengths, product age, and price tier. To control for these potential sources of profit variance, we subject our estimates to an ANCOVA within each price tier. Here, pricing strategy serves as a quasi-experimental factor and brand dummies (brand variance), average weighted distribution (retailer variance), and the length of the camera's life cycle (age variance) are controls. We also add mean total segment sales over the camera's life cycle to control for time effects from evolving primary demand.

Table 8 displays estimated marginal means and F-values associated with pricing strategy. Overall, we find significant differences between pricing strategies in terms of NPV. It turns out that the average NPV for a camera that followed a skimming strategy in the observation period is significantly higher than for a penetration strategy. This finding is especially strong in the medium ($F_{3,258}$=5.05, $p < .01$) and the high-price ($F_{3,160}$=7.84, $p < .01$) segment. It is less strong in the low-price segment as the F-value is only marginally significant ($F_{3,233}$=2.47, $p < .10$). Although NPVs of monotonic and non-monotonic strategies also differ within a strategy type, this difference is not statistically significant (test statistics not shown in Table 8).

== Insert Table 8 here ==

As Table 9 demonstrates, the results from the counterfactual pricing experiments corroborate the findings of Table 8.[8] On the one hand, switching from a skimming to a penetration strategy would have deteriorated discounted profits considerably. On the other hand, switching from a penetration to a skimming strategy would lead to substantial profit improvements. Except for the switch of skimming to penetration in the low-price segment, all mean percentage gains and losses of Table 9 are significantly different from zero. Hence, we conclude, that for the analyzed digital camera market, a skimming price strategy at the camera level yields higher discounted profits than a penetration price strategy.

== Insert Table 9 here ==

We acknowledge that our findings are eventually derived from a structural model that is based on specific assumptions about the behavior of market agents. Even though the proposed model appears be most consistent with the data, we repeated our profit analyses for two alternative structural models in which the retailer is given more power by assuming a Vertical Nash game. Retailers maximize either category profits or brand profits. No fundamental changes in results and conclusions occurred from these analyses (see the Web appendix for details). Hence, we have some confidence that our profit implication results are not driven by model assumptions.

*Analysis at the Firm Level (Product Portfolios)*

The analysis at the camera level reveals that the NPV of an individual product can be increased if firms switch from a penetration to a skimming strategy. Table 6 shows that firms actually chose a penetration strategy for many cameras. So, a natural question arises: why do firms adopt the penetration strategy at all? The answer may be given by a profit analysis at the firm level that takes cost and demand interdependencies among cameras into account. For this analysis, we focus on the top ten manufacturers as these firms' products account for more than 80% in total sales and 47% of cameras (see Table 2 again). From Table 2, we see that firms such as Aiptek, Jenoptik (a national player), and Yakumo focused their activities on the low-price segment and established leading brands in this segment. In contrast, Canon, Nikon, Olympus, and Sony focus almost exclusively on the medium-price and high-price segments. The segment focus of Fujifilm, Eastman Kodak, and Konica Minolta is less clear.

The left half of Table 10 shows the relative distribution of pricing strategies for these firms and their brands. The dominant strategy, i.e., the most frequently used strategy by brand, is highlighted in bold figures.[9] Six out of ten firms adopted skimming as the dominant pricing strategy, which is in line with the conclusion from the product-level analysis that camera NPV is higher for skimming than for penetration. This set of firms includes the firms that are particularly focused on the medium-price and high-price segments, where buyers are less price-oriented and products more differentiated. All three firms that focus on the low-price segment adopted penetration as their dominant pricing strategy. Since consumers in this segment care more about the price and competitive intensity is higher, the results are consistent with our analysis of descriptors of strategy choice (see Table 7). Recall that profit implications from the product-level analysis were also less strong in this segment compared with the higher price tiers. The strategy focus of Konica Minolta is not readily obvious since penetration was more often used for its Konica brand and skimming more often for its Minolta brand. Interestingly, four out of eight Konica cameras were introduced into the high-price segment. All these cameras followed a penetration strategy which explains the firm's relatively high market share in this segment (see Table 2 again).

== Insert Table 10 here ==

In policy experiments, we can evaluate the appropriateness of each firm's choice of dominant strategy type in terms of firm-level NPV. For this purpose, we simulate what happens to discounted firm profits if a firm/brand that uses predominantly skimming (penetration) for their products changes to the opposite strategy for these products. Simulations are conducted as described before in the product-level analysis. However, we now evaluate the impact of a strategy switch for products of the same firm *simultaneously* and at an aggregated product portfolio level. Thus, we take cost and demand interdependencies between products into account. For example, a penetration strategy for one product may cannibalize sales from other products in the portfolio but at the same time it may also improve marginal cost of these products because of experience curve effects.

The second-last column of Table 10 displays the results from these policy simulations. For most firms, portfolio NPV decreases, indicating that the actually chosen dominant pricing strategy is more profitable. In a few cases (e.g., Aiptek, Eastman Kodak) firm profits increase; the increase is, however, marginal and basically not different from zero. We conclude from these results, the preference for penetration by firms concentrating their business in the low-price segment (Aiptek, Jenoptik, and Yakumo) where price-cost margins are typically lower seems to be justified.

The only remarkable profit increase (+76%) occurs for Konica Minolta suggesting that their actual focus in pricing strategy was suboptimal. The dominant strategy for Minolta cameras was skimming and for Konica cameras it was penetration, while both brands targeted the higher price tiers. The rise in profits is largely due to the simulated switch from penetration to skimming for Konica cameras that were introduced into the high-price segment. Noticeably, Konica Minolta gave up in 2006 and sold its digital camera business to Sony. Given that our observation period ends in 2004, we are able to anticipate this event already two years earlier, lending further support in the face validity of our results.

For firms whose brands are primarily focused on the high-margin segments, the policy simulations support their choice of skimming as the dominant strategy. The NPV of firms such as Nikon or Olympus decreases by 31.2% and 125.5%, respectively, when skimming strategies are switched to penetration. Nevertheless, these firms used penetration at least for a small number of products. We believe that it is indeed rational to use penetration for a limited number of products in the lower price tiers to move down the experience curve faster and thus improve the profit margin of products following a skimming strategy. In addition, firms may also attempt to win new customers for their brand and hope to move them up to more profitable cameras later.[10] While we cannot test the last premise with the available data, we can carry out additional policy simulations to check whether the first explanation holds. For this purpose, we switch all penetration strategies for products of these firms in the low-price and medium-price segment to a skimming strategy. The last column of Table 10 reveals that virtually no profit gains result from this switch in strategy. So, firms with a focus on skimming strategies for their quality products in the upper price tiers of the market seem to benefit from having a few volume products in their portfolio that follow a penetration strategy.

## *CONCLUSIONS AND LIMITATIONS*

Currently, the literature provides inadequate guidance about the pricing strategy that firms should adopt in complex dynamic environments characterized by hundreds of competing products. We develop a structural model to analyze the profitability of dynamic pricing strategies in such complex competitive environments. An important feature of the model is that it allows discriminating between skimming and penetration prices. We test our model in the digital camera market, a highly competitive market for differentiated consumer durables. With the help of this model, we analyze the adoption of various pricing strategies at the firm level, the factors associated with strategy choice, as well as the profitability of pricing strategies at the camera and firm level.

This analysis leads to the following main findings:

1. Firms adopt both skimming and penetration pricing strategies in the German digital camera market. In addition, firms also adopt what we term non-monotonic skimming and penetration strategies, albeit rather infrequently.

2. However, firms' choice of strategies varies substantially by segment and firm characteristics. Firms with broader product lines, greater distributional strength, and a focus on the medium- and high-price segment (e.g., Kodak, Fuji, Sony, Olympus, Nikon) predominantly choose skimming pricing for their cameras. Firms that operate primarily in the low-price segment (e.g., Aiptek, Jenoptik, Yakumo) tend to adopt penetration pricing. Firms prefer penetration pricing in the early periods after product entry and under conditions of higher competitive intensity.

3. Considering the net present value of an individual camera, a skimming strategy is, on average, more profitable than a penetration strategy.

4. However, at the firm level, consisting of a portfolio of cameras and brands, a strategy mix appears to be preferable. In particular, the use of a penetration strategy may help to maximize the net present value of cash flows from the product portfolio. A penetration strategy seems to be particularly attractive for firms with a focus on the low-price segment. But even firms that are positioned in the higher price tiers of the market may benefit from penetration pricing for cameras introduced into the lower priced high-volume segments due to cost synergies.

This study has several major implications for marketing managers. First, simple generalizations of optimal pricing strategies in complex dynamic environments may not hold. An in-depth analysis of market response to dynamic pricing strategies may be necessary in such environments. Such an analysis can yield important insights into the value of pricing strategies and enables more nuanced assessments of the profitability of penetration and skimming strategies than those in textbook recommendations. Second, the pricing strategy of a firm with a portfolio of brands and products targeted at various consumer segments may be different from that for the individual brands focusing at a single segment. The primary factor driving this difference is consumer segments with differential price points and sensitivities to price. Third, the results from Konica Minolta indicate that a suboptimal combination of brand positioning and dynamic pricing strategy may miss significant profit potential. Forth, depending on the portfolio of products and the segments of markets targeted, marketing managers should consider a mix of dynamic pricing strategies for their pricing decisions.

Our study is subject to limitations which may stimulate further research.

First, we acknowledge that any findings are strictly speaking limited to the analyzed digital camera market. An advantage of analyzing a single market is that we can avoid mingling economic primitives with idiosyncratic differences between markets. By definition, however, any generalizations remain speculative in nature. Our results are most likely to be transferred to markets that are comparable in demand and cost conditions (e.g., durable products, high product differentiation, different price-quality segments, experience curve effects) and structure of competition (e.g., number of competitors, allocation of market shares, type of distribution system, distribution of power between retailers and manufacturers). We believe that modern consumer electronics markets such as flat screen TV sets, PCs, DVD players, MP3 players, mobile phones, etc. share many conditions with the digital camera category. Future research will need to test the generalizability of our results in other markets and countries. For this purpose, our model and approach will be quite useful.

Second, we acknowledge that our results are obtained from a structural model that relies on some restrictive assumptions. One such assumption is the notion of a common and passively price-taking retailer. Recent advances in the structural modeling literature (e.g., Draganska, Klapper, and Villas-Boas 2009; Villas-Boas 2007) have offered new frameworks to analyze the bargaining process between manufacturers and retailers. For example, Draganska, Klapper, and Villas-Boas (2009) propose a model to measure the bargaining power between manufacturers and retailers. In their model, Manufacturer Stackelberg and Vertical Nash constitute two special cases at opposite sides of the bargaining continuum. Since we do not observe sales at single retailers, we cannot implement this approach. In our robustness analysis, we found that our results do not only hold under the Manufacturer Stackelberg but also under the Vertical Nash assumption. Hence, we are quite confident that our conclusions also apply to other bargaining solutions within the continuum. Provided with appropriate data, future research could extend our approach to represent the bargaining reality in markets more realistically.

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## *FOOTNOTES*

[1] Alternatively, we could have included the available product features (see Table 1 again). However, the list of features is not complete. For example, we do not observe features such as weight and size, which may introduce an omitted variable bias into the results. By using camera-specific constants, we can circumvent this problem.

[2] The mark-up rule is also in line with the observation that cost-plus pricing is the most frequently used pricing rule among retailers (Hanson 1992; see also Noble and Gruca 1999). An important reason for the attractiveness of cost-plus pricing among retailers is the fact that this rule is highly efficient in terms of execution when applied to a large product assortment. This is the case here as the average consumer electronics store carries thousands of items.

[3] Since we do not have promotion data at the store level we must infer such activities from the aggregated camera price time-series. For that purpose, we applied an algorithm that detects a temporary decrease in retail price of at least 10% while accounting for a camera-specific overall price trend.

[4] Note that, for the few cameras with potential retail price competition, we would expect lower retail margins reflected in brand-camera-specific mark-ups accommodated by our model.

[5] We considered additional factor price indexes from Japan and the U.S. relevant to the industry, but these variables turned out to be highly correlated with the factor prices included in Equation (6).

[6] To obtain the $BIC_{SMNL}$ for the proposed segment-specific MNL model we sum up the log-likelihoods, number of parameters and number of observations of all three segments.

[7] We also considered important product features such as pixel resolution as potential descriptors. While significant alone, they turned insignificant when other descriptors were added to the model.

[8] In this analysis, we exclude outlier cases that may impact the mean statistics to a large extent. All outliers stem from situations where losses turned into profits or vice versa. Relative profit changes are typically large in these cases and probably difficult to interpret. Such situations occurred in only less than 3% of cases.

[9] Canon is a special case. Even though the distribution of pricing strategies is uniform we infer from the firm's market behavior that it emphasizes skimming. First, the brand is positioned as a quality brand in Germany. Second, the initial price conduct parameter is on average higher for observed skimming than penetration strategies. Third, the firm emphasized penetration strategies in the beginning, presumably to build market share.

[10] We thank the Area Editor for bringing this explanation to our attention.

**Table 1: Descriptive Statistics**

| | **Low-Price Segment** | | **Medium-Price Segment** | | **High-Price Segment** | |
|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD |
| Price (Euro per unit ) | 105.5 | 51.3 | 321.9 | 109.9 | 704.0 | 281.5 |
| Sales (monthly units) | 307 | 1,134 | 544 | 1,174 | 357 | 735 |
| Length of life cycle (months) | 21.13 | 9.38 | 22.21 | 9.57 | 28.20 | 9.51 |
| Weighted distribution (percent) | 6.68 | 8.20 | 16.93 | 18.31 | 25.01 | 23.68 |
| Memocardslot (DV) | .47 | .50 | .99 | .11 | 1.00 | .00 |
| Optical finder (DV) | .92 | .27 | .91 | .29 | .86 | .35 |
| LCD finder (DV) | .30 | .46 | .96 | .19 | .99 | .10 |
| Auto focus (DV) | .11 | .31 | .86 | .35 | .99 | .11 |
| Flash (DV) | .60 | .49 | .98 | .15 | .98 | .14 |
| Digital zoom (DV) | .26 | .44 | .86 | .35 | .87 | .34 |
| Optical zoom (DV) | .01 | .09 | .66 | .47 | .94 | .23 |
| Pixel resolution (thsd. pixels) | 861 | 733 | 2,204 | 862 | 3,096 | 1,040 |
| CCD sensor ship (DV) | .37 | .48 | .99 | .11 | 1.00 | .05 |
| SSFDC memory (DV) | .15 | .35 | .22 | .41 | .28 | .45 |
| Comflash memory (DV) | .19 | .40 | .47 | .50 | .34 | .47 |
| SD card memory (DV) | .08 | .28 | .16 | .37 | .05 | .23 |
| XD card memory (DV) | - | - | .02 | .14 | .01 | .12 |
| PC card memory (DV) | - | - | .00 | .04 | .00 | .00 |
| Multimedia card memory (DV) | .02 | .15 | .00 | .07 | .02 | .13 |
| Memory stick (DV) | - | - | .06 | .24 | .10 | .30 |
| Floppy (DV) | - | - | .01 | .08 | .05 | .22 |
| CD-R & CD-RW (DV) | - | - | - | | .03 | .17 |
| Optical zoom factor | .03 | .28 | 1.92 | 1.54 | 3.63 | 2.22 |
| Digital zoom factor | .64 | 1.13 | 2.25 | 1.24 | 3.12 | 2.37 |
| MP3 player (DV) | .02 | .13 | .03 | .16 | .03 | .16 |
| Bluetooth (DV) | - | - | - | - | .00 | .06 |
| Number of observations | 3,547 | | 4,051 | | 3,574 | |

Notes: In total, 11,835 observations are available. Sample statistics in this table are presented for the number of observations that are effectively used for model estimation. Since the first period is lost during estimation, sample size reduces to 11,172 observations. DV indicates a dummy variable.

**Table 2: Market Shares of Top Ten Manufacturers**

| Manufacturer | Brand(s) | No. of Cameras | Low-Price Segment | | Medium-Price Segment | | High-Price Segment | | All Segments | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Units | Value | Units | Value | Units | Value | Units | Value |
| Aiptek | Aiptek | 26 | 20.6% | 12.9% | - | - | - | - | 5.5% | 0.8% |
| Canon | Canon | 32 | - | - | 14.4% | 16.5% | 23.8% | 23.2% | 13.6% | 19.1% |
| Fujifilm | Fujifilm | 36 | 5.3% | 7.9% | 8.5% | 8.0% | 5.4% | 5.0% | 6.4% | 5.8% |
| Jenoptik | Jenoptik, Concord | 42 | 11.2% | 12.4% | 5.1% | 5.2% | - | - | 5.0% | 3.3% |
| Eastman Kodak | Kodak | 28 | 6.0% | 7.9% | 11.9% | 11.5% | 3.8% | 3.3% | 7.5% | 4.9% |
| Konica Minolta | Konica, Minolta | 25 | 1.4% | 1.4% | 3.7% | 4.4% | 10.5% | 10.4% | 4.1% | 5.6% |
| Nikon | Nikon | 19 | - | - | 5.1% | 5.2% | 8.5% | 10.3% | 5.0% | 7.6% |
| Olympus | Olympus | 43 | 0.6% | 0.8% | 17.7% | 16.4% | 17.6% | 18.0% | 13.3% | 13.9% |
| Sony | Sony, Aiwa | 51 | 0.1% | 0.1% | 7.2% | 8.1% | 19.1% | 20.3% | 10.0% | 13.4% |
| Yakumo | Yakumo | 10 | 26.2% | 30.7% | 5.0% | 4.2% | - | - | 9.8% | 2.4% |

**Table 3: Estimation Results of Logit Demand Model**

| | Low-Price Segment | | Medium-Price Segment | | High-Price Segment | |
|---|---|---|---|---|---|---|
| | Coefficient estimate | Standard error | Coefficient estimate | Standard error | Coefficient estimate | Standard error |
| 1/Elapsed time since launch of product | .878 | (.163)*** | -2.026 | (.171)*** | -2.212 | (.137)*** |
| *Marketing Mix Variables* | | | | | | |
| Weighted distribution | 2.700 | (1.27)** | .972 | (.465)** | -.248 | (.341) |
| Weighted distribution × log time | 1.489 | (.473)*** | 1.010 | (.165)*** | 1.299 | (.127)*** |
| Price | -.011 | (.001)*** | -.012 | (.001)*** | -.002 | ($2.0\times10^{-4}$)*** |
| Price/time | .010 | (.006) | $3.0\times10^{-4}$ | (.001) | .003 | (.001)*** |
| Adjusted (Pseudo) $R^2$ | .811 | | .742 | | .790 | |
| No. of observations | 3,475 | | 4,018 | | 3,574 | |

Notes: Estimated fixed brand-camera effects to measure preference for camera features and trend effects to measure category attractiveness over time are not shown but may be obtained from the authors upon request.
*** $p < .01$; ** $p < .05$

**Table 4: Estimation Results of Price Equation (Standard Errors)**

| | Parameter estimate | Standard Deviation of Parameter Distribution |
|---|---|---|
| *Cost function* | | |
| Product characteristics | | |
| Memocardslot (DV) | 160.23 (2.90) | |
| Optical finder (DV) | 59.08 (1.67) | |
| LCD finder (DV) | 2.93 (2.33)[NS] | |
| Auto focus (DV) | 58.79 (2.07) | |
| Flash (DV) | -18.23 (2.35) | |
| Digital zoom (DV) | -2.31 (1.91)[NS] | |
| Optical zoom (DV) | 15.26 (2.01) | |
| Pixel resolution | .047 (.001) | |
| CCD sensor ship (DV) | 66.56 (2.49) | |
| SSFDC memory (DV) | -156.39 (1.91) | |
| Comflash memory (DV) | -132.18 (1.86) | |
| SD card memory (DV) | -190.67 (2.64) | |
| XD card memory (DV) | -140.83 (6.42) | |
| PC card memory (DV) | 93.85 (48.5)[NS] | |
| Multimedia card memory (DV) | -174.75 (5.99) | |
| Memory stick (DV) | -115.58 (2.43) | |
| Floppy (DV) | -56.48 (3.76) | |
| CD-R & CD-RW (DV) | 307.70 (3.40) | |
| Optical zoom factor | 11.39 (.388) | |
| Digital zoom factor | 2.66 (.365) | |
| MP3 player (DV) | 46.13 (2.08) | |
| Bluetooth (DV) | -92.93 (27.5) | |
| Factor prices and productivity | | |
| Japanese producer cost | 3.31 (.395) | |
| U.S. labor productivity | -.236 (.017) | |
| Log(cumulated manufacturer sales) | -12.99 (.435) | |
| *Conduct parameter* | | |
| Initial value (constant) | 1.136 (.005) | .705 (.006) |
| Elapsed time since launch | -.040 (.000) | .013 (.000) |
| Squared elapsed time since launch | .001 (.000) | .000 (.000) |
| Simulated log likelihood | -63,056.57 | |
| Number of observations | 11,172 | |

Notes: DV indicates a dummy variable. Estimated firm-brand-camera-specific effects are not shown but may be obtained from the authors upon request. Parameter estimates of the cost function include unobserved retail margin that cannot be estimated separately. For details, see the Web appendix. NS = not significant ($p > .05$)

**Table 5: Estimated Mean Prices, Conduct Parameters, Marginal Costs, and Margins**

| | Retail Price (EUR) | Initial Conduct Parameter | Marginal Cost (EUR) | Price-Cost Margin (EUR) |
|---|---|---|---|---|
| Low-price segment | 105.48 | .869 | 40.79 | 65.23 |
| Medium-price segment | 321.88 | 1.171 | 240.30 | 81.60 |
| High-price segment | 704.01 | 1.039 | 332.46 | 369.67 |
| *Total* | 375.42 | 1.030 | 206.44 | 168.56 |

Notes: Marginal cost and price-cost margin include retail margin. Marginal cost = Retail price – price-cost margin. Initial conduct parameter measures the deviation of the mark-up from static Nash-equilibrium price at launch. Number of observations: 11,172.

**Table 6: Distribution of Pricing Strategies by Segment**

| | Low-price Segment | Medium-Price Segment | High-price Segment | All Segments |
|---|---|---|---|---|
| Monotonic skimming | 65 (27.4%) | 124 (47.3%) | 54 (32.9%) | 243 (36.7%) |
| Non-monotonic skimming | 10 (4.2%) | 26 (9.9%) | 25 (15.2%) | 61 (9.2%) |
| *Skimming (overall)* | *75 (31.6%)* | *150 (57.2%)* | *79 (48.1%)* | *304 (45.9%)* |
| Monotonic penetration | 108 (45.6%) | 98 (37.4%) | 67 (40.9%) | 273 (41.2%) |
| Non-monotonic penetration | 54 (22.8%) | 14 (5.3%) | 18 (11.0%) | 86 (13.0%) |
| *Penetration (overall)* | *162 (68.4%)* | *112 (42.6%)* | *85 (51.9%)* | *359 (54.1%)* |
| *Total* | 237 (100%) | 262 (100%) | 164 (100%) | 663 (100%) |

Notes: Number of cameras (percent of cameras in specific segment).
N = 663 cameras.

**Table 7: Descriptors of Choice of Pricing Strategy (Binomial Probit Model Estimates)**

| | **Dependent Variable** Penetration = 0, Skimming = 1 | |
|---|---|---|
| | Coefficient estimate | Standard error |
| Constant | -4.23 | (1.44)*** |
| *Firm-level descriptors* | | |
| Firm entry before year 2000 | .104 | (.143) |
| Distribution strength of brand | .013 | (.005)*** |
| Established manufacturer brand | .685 | (.138)*** |
| Launch date | .085 | (.030)*** |
| Breadth of product line | .027 | (.010)*** |
| Length of camera life cycle | .088 | (.032)*** |
| Cumulated manufacturer sales | -.022 | (.005)*** |
| *Market-level descriptors* | | |
| Competitive intensity in segment[a)] | -5.98 | (3.39)* |
| Launch in low-price segment | -.539 | (.231)** |
| Number of observations (cameras) | 663 | |
| Log likelihood | -407.57 | |

Notes: Proportion of correctly classified cases = 67.4% (proportional chance = 50.3%, maximum chance = 54.1%).
*** $p < .01$; ** $p < .05$, * $p < .10$

[a)] Competitive intensity is measured by the Herfindahl index. The coefficient is reverse-coded for reading convenience.

**Table 8: Product NPV by Pricing Strategy and Segment (Estimated Marginal Means from ANCOVA)**

| | Low-price Segment | Medium-Price Segment | High-price Segment | All Segments |
|---|---|---|---|---|
| Monotonic skimming | 442,936 | 714,236 | 2,648,418 | 1,168,660 |
| Non-monotonic skimming | 308,525 | 440,365 | 1,173,806 | 676,103 |
| *Skimming (overall)* | *426,267* | *678,174* | *2,325,976* | *1,084,267* |
| Monotonic penetration | 80,888 | 422,291 | 1,406,231 | 696,840 |
| Non-monotonic penetration | 165,440 | 331,609 | 884,216 | 366,390 |
| *Penetration (overall)* | *103,149* | *397,223* | *1,270,331* | *611,019* |
| $R^2$ | .435 | .562 | .605 | .527 |
| F-value[a)] | 2.47 (.06) | 5.05 (.00) | 7.84 (.00) | 10.17 (.00) |

Notes: Mean NPV in EUR per camera (NPV-calculation based on monthly discount rate of 1%). Analysis is based on cameras' life cycles without the first period. This period is lost during estimation. N = 663 cameras.

[a)] ANCOVA-Factor: Pricing strategy, Covariates: length of life cycle, average weighted distribution, brand dummies, and average total sales of market segment. *p*-values in parentheses.

**Table 9: Change in Product Profit from Counterfactual Pricing Strategy Experiment**

| Strategy switch | | Low-price segment | | Medium-price segment | | High-price segment | |
|---|---|---|---|---|---|---|---|
| Skimming → Penetration | Mean change in discounted profits | -.4% | (.8%) [NS] | -10.1% | (3.0%) | -12.1% | (5.1%) |
| | Number of cameras | 71 | | 146 | | 77 | |
| Penetration → Skimming | Mean change in discounted profits | 10.4% | (2.0%) | 12.2% | (3.0%) | 14.7% | (3.5%) |
| | Number of cameras | 157 | | 110 | | 81 | |

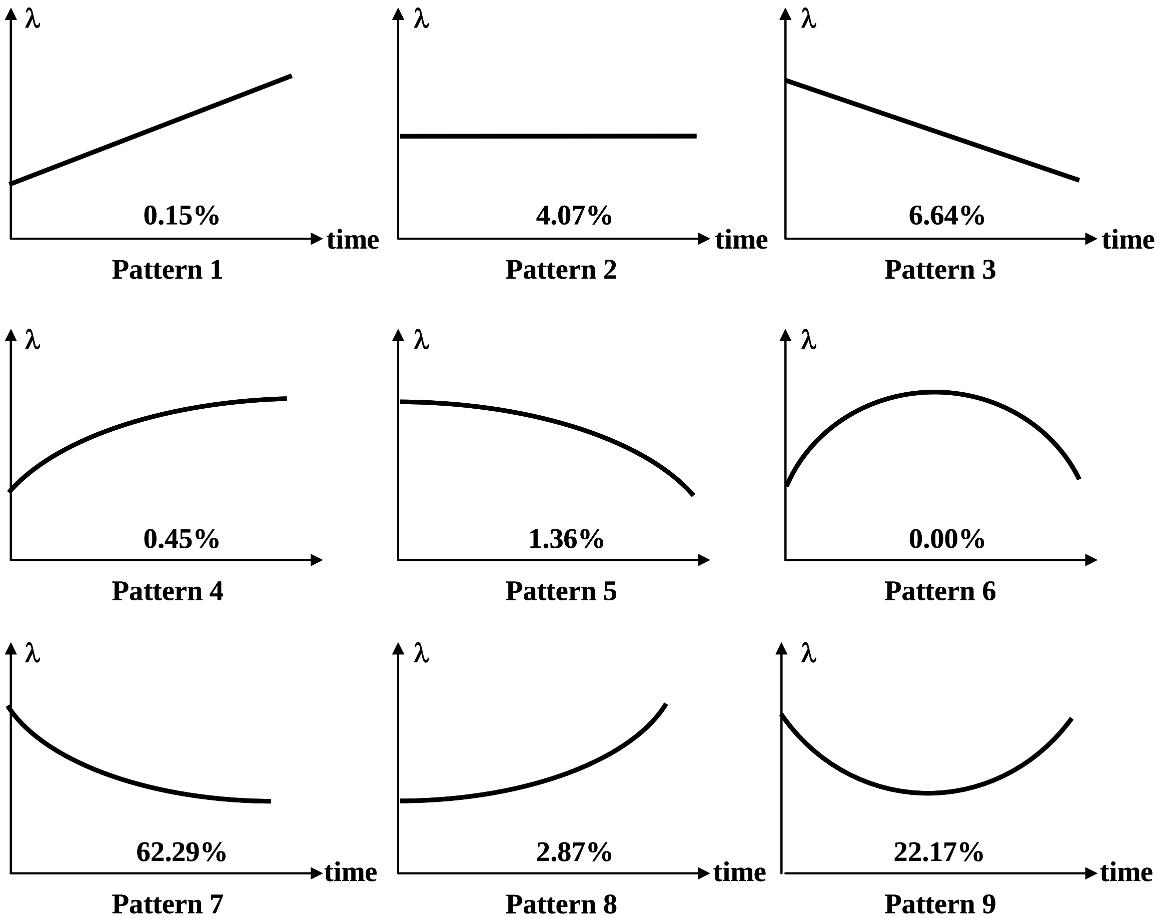
Notes: Standard errors in parentheses. Outlier observations (1 outside the 90% interval, all other outside the 95% interval) are excluded to avoid that the mean is driven by a few extreme values. All outliers occur from situations where positive (negative) profits turn into negative (positive) profits. N = 642 cameras. NS = not significant ($p > .05$)

**Table 10: Choice of Dynamic Pricing Strategies across Top Ten Manufacturers and Profit Effects from Policy Experiments**

| Manufacturer | Brand | No. of Cam-eras | Choice of Strategy Type | | Effects on Manufacturer Profit from Policy Experiments | | |
|---|---|---|---|---|---|---|---|
| | | | Skimming | Penetration | Switch to … | | Switch from penetration to skimming in low and medium price tiers |
| *Firms with focus on penetration strategy* | | | | | | | |
| Aiptek | Aiptek | 26 | 30.8% | **69.2%** | Skimming | 2.3% | - |
| Jenoptik | Concord | 17 | 41.2% | **58.8%** | Skimming | 2.9% | - |
| | Jenoptik | 25 | 48.0% | **52.0%** | Skimming | | - |
| Yakumo | Yakumo | 10 | 30.0% | **70.0%** | Skimming | .4% | - |
| *Firms with focus on skimming strategy* | | | | | | | |
| Canon | Canon | 32 | **50.0%** | 50.0% | Penetration | -5.0% | .5% |
| Eastman Kodak | Kodak | 28 | **67.9%** | 32.1% | Penetration | .2% | .2% |
| Fujifilm | Fujifilm | 36 | **63.9%** | 36.1% | Penetration | -1.8% | .9% |
| Nikon | Nikon | 19 | **73.7%** | 26.3% | Penetration | -31.2% | .6% |
| Olympus | Olympus | 43 | **60.5%** | 39.5% | Penetration | -125.5% | .0% |
| Sony | Sony | 50 | **60.0%** | 40.0% | Penetration | -9.2% | .1% |
| *Firms with unclear focus in pricing strategy* | | | | | | | |
| Konica Minolta | Konica | 8 | 12.5% | **87.5%** | Skimming | 76.0% | - |
| | Minolta | 17 | **64.7%** | 35.3% | Penetration | | |

Notes: Bold figures indicate dominant strategy type. For Canon, we assume skimming as the dominant strategy since the brand is positioned as quality brand and its initial price conduct parameter is on average higher for observed skimming than penetration strategies. For Sony, we consider only the Sony brand since only one camera was introduced under the Aiwa brand during our observation period.

**Figure 1: Distribution of Temporal Patterns of Dynamic Pricing Strategies**




Patterns are based on brand-camera specific quadratic time function of conduct parameter $\lambda$ (see Equation 5). Percentages refer to proportion of cameras whose price path follows a specific pattern.

*APPENDIX TABLES*

Table A-1 reports the test results for additional models of competition that rely on other assumptions about firm behavior than the proposed model. The first cell shows test statistics for the proposed model. Since it serves as the benchmark model the Vuong statistic is not defined.

**Table A-1: Log Likelihoods and Test Statistics for Models of Competition**

| **Manufacturer-retailer interaction** | **Manufacturer objective** | **Retailer objective** | |
|---|---|---|---|
| | | *Brand-camera-specific margin* | |
| Manufacturer leader-retailer follower | Brand profit maximization | -63,056.57 (BIC = 126,486; V = n.a.) | |
| | Brand-portfolio profit maximization | -63,611.91 (BIC = 127,597; V = 5.25, $p$ = .00) | |
| | Camera profit maximization | -63,455.13 (BIC = 127,283; V = 3.77, $p$ = .00) | |
| | | *Brand profit maximization* | *Category profit maximization* |
| Vertical Nash | Brand profit maximization | -64,005.87 (BIC = 128,385; V = 8.98, $p$ = .00) | -63,799.05 (BIC = 127,971; V = 7.02, $p$ = .00) |
| | Brand-portfolio profit maximization | -64,170.40 (BIC = 128,714; V = 10.54, $p$ = .00) | -63,835.20 (BIC = 128,043; V = 7.37, $p$ = .00) |
| | Camera profit maximization | -64,084.84 (BIC = 128,543; V = 9.73, $p$ = .00) | -63,939.47 (BIC = 128,252; V = 8.35, $p$ = .00) |

Notes: Bertrand-Nash behavior assumed for horizontal interaction between manufacturers.
BIC = Bayesian Information Criterion (lowest value indicates preferred model)
V = Vuong test statistic for non-nested model comparison.

Table A-2 summarizes the formal criteria for classification of temporal patterns as graphically shown in Figure 1.

**Table A-2: Criteria for Classifying Temporal Patterns of Dynamic Pricing Strategies**

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="3">Range of Parameter of Quadratic Term</th></tr>
<tr><th>$a_{1kis} < 0$</th><th>$a_{1kis} = 0$</th><th>$a_{1kis} > 0$</th></tr>
<tr><td rowspan="7">Range of Parameter of Linear Term</td><td rowspan="2">$a_{2kis} > 0$</td><td>$0 > a_{1kis} > \frac{-a_{2kis}}{2 \cdot LCT_{kist,\max} - 1} \wedge a_{2kis} > 0$<br>4</td><td rowspan="2">$a_{1kis} = 0 \wedge a_{2kis} > 0$<br>1</td><td rowspan="3">$0 < a_{1kis} > \frac{-a_{2kis}}{3}$<br>8</td></tr>
<tr><td>$\frac{-a_{2kis}}{3} \leq a_{1kis} \wedge a_{1kis} \leq \frac{-a_{2kis}}{2 \cdot LCT_{kist,\max} - 1}$<br>6</td></tr>
<tr><td>$a_{2kis} = 0$</td><td rowspan="3">5<br>$0 > a_{1kis} < \frac{-a_{2kis}}{3}$</td><td>$a_{1kis} = 0 \wedge a_{2kis} = 0$<br>2</td></tr>
<tr><td rowspan="2">$a_{2kis} < 0$</td><td rowspan="2">$a_{1kis} = 0 \wedge a_{2kis} < 0$<br>3</td><td>$\frac{-a_{2kis}}{2 \cdot LCT_{kist,\max} - 1} \leq a_{1kis} \wedge a_{1kis} \leq \frac{-a_{2kis}}{3} \wedge a_{2kis} < 0$<br>9</td></tr>
<tr><td>$a_{1kis} < \frac{-a_{2kis}}{2 \cdot LCT_{kist,\max} - 1} \wedge a_{2kis} < 0$<br>7</td></tr>
</table>

Note: Numbers in circles show pattern numbers (see Figure 1).