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Skimming or Penetration? Strategic Dynamic Pricing for New Products

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Current complex dynamic markets are characterized by numerous brands, each with multiple products and price points, and differentiated on a variety of product attributes plus a large number of new product introductions. This study seeks to analyze dynamic pricing paths in a highly complex branded market, consisting of 663 products under 79 brand names of digital cameras. The authors develop a method to classify dynamic pricing strategies and analyze the choice and correlates of observed pricing paths in the introduction and early growth phase of this market. The authors find that, despite numerous recommendations in the literature for skimming or penetration pricing, market pricing dominates in practice. In particular, the authors find five patterns: skimming (20% frequency), penetration (20% frequency), and three variants of market-pricing patterns (60% frequency), where new products are launched at market prices. Skimming pricing launches the new product 16% above the market price and subsequently increases the price relative to the market price. Penetration pricing launches the new product 18% below the market price and subsequently lowers the price relative to the market price. Firms exhibit a mix of these pricing paths across their portfolios. The specific pricing paths correlate with market, firm, and brand characteristics such as competitive intensity, market pioneering, brand reputation, and experience effects. The authors discuss managerial implications.

Keywords: price penetration; price skimming; dynamic pricing strategy; product life cycle; consumer durables; brand competition
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1. Introduction

The current market environment, especially for high-tech categories, is characterized by rapid introductions of new products. In this environment, the pricing of new products is a difficult and critical task affecting the financial success of the product and the company. On one hand, if the price is set too low, a company not only gives up potential revenues but also sets a perception of low quality for this new product, which can make future price increases difficult (Marn et al. 2003). On the other hand, a price set too high might harm the take-off and diffusion of the new product (Golder and Tellis 2004), limit gains from experience effects, hinder the product from reaching critical mass or necessitate embarrassing price cuts.

In response to this perennial marketing challenge, the marketing literature has formulated two fundamental marketing strategies, *skimming* and *penetration* pricing (e.g., Kotler and Armstrong 2012, p. 314; Monroe 2003, p. 380; Nagle et al. 2011, p. 125). 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 to exploit a monopolistic position or the low price sensitivity of innovators (e.g., Dean 1976, Marn et al. 2003). A penetration strategy involves charging a low price to rapidly reach a wide fraction of the market and initiate word-of-mouth (WOM) (Dean 1976, Nagle et al. 2011, p. 127). Penetration pricing is designed to enlarge market share and exploit economies of scale or experience (Tellis 1986).

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 attributes leads to a proliferation of products. Textbooks recommend a skimming strategy for differentiated products where companies have some source of competitive protection (e.g., Kotler and Armstrong 2012, p. 314;

Nagle et al. 2011, p. 125) and a penetration strategy for price-sensitive markets where new products usually face strong competition soon after introduction (e.g., Kotler and Armstrong 2012, p. 314; Monroe 2003, p. 380). However, the recommendations are unclear when both conditions prevail, such as markets differentiated with attributes yet with strong competition.

Many markets for modern consumer durables (e.g., computers, mobile phones, TVs, digital cameras, etc.) present such a dilemma, i.e., extensive attribute differentiation favoring a skimming strategy concomitant with strong competition favoring a penetration strategy. Moreover, popular examples support the success of either strategy. Apple's iPhone, for example, seems to follow a skimming strategy in the highly competitive mobile phone market. In contrast, Lexus successfully used a penetration pricing strategy when entering the U.S. premium *luxury car* market.

This study develops a method to classify observed dynamic pricing strategies or patterns and describes the choice and correlates of dynamic pricing strategies such as skimming and penetration pricing.[1] The study contains an in-depth empirical analysis of a differentiated competitive market. Specifically, we analyze the market for digital cameras in one major European country in its introduction and early growth phase. The data covers all 663 cameras introduced under 79 brand names at the monthly level over a period of four years. This combination yields a rich panel data set of 11,835 observations of cameras × months. This study makes three contributions:

First, it develops a method to identify dynamic pricing strategies such as skimming and penetration pricing. For this purpose we propose a model that specifies price as a function of product characteristics and market conditions.

Second, we apply this model to a real competitive consumer electronics market encompassing 663 products under 79 brand names. We use a latent-class approach with a priori defined classes of dynamic price patterns to infer the strategies from the data.

Third, we analyze the conditions that correlate with various pricing strategies. We want to understand which firm and market factors are associated with the choice of skimming, penetration, and market pricing.

The rest of the paper is organized as follows. Sections 2–4 describe the relationship to the literature, the method, and the data, respectively. Section 5 describes the estimation and results. Section 6 discusses the implications and limitations of the main results.

[1] We use the terms price pattern and price strategy interchangeably. Strictly speaking, we do not observe management's strategic ex-ante plan to set the price over the life cycle of a new product. It is rather the realization of that plan including the influences of changing market conditions (see, e.g., Mintzberg 1987).

2. Relationship to Literature

The literature on dynamic pricing strategies is so vast and rich that a full review is beyond the scope of this paper. Here, we highlight the relevance of the present study to this rich literature. Dynamic pricing strategies are extensively discussed in the normative diffusion and product life-cycle literature, deriving optimal dynamic pricing strategies, such as skimming or penetration pricing under monopoly (e.g., Kalish 1983, Krishnan et al. 1999) or duopoly (e.g., Eliashberg and Jeuland 1986, Xie and Sirbu 1995). Bayus (1992) and Liu (2010) analyze optimal dynamic pricing strategies by combining analytical model, simulation, and empirical analysis. These studies provide valuable insights about pricing under conditions of monopoly or duopoly.

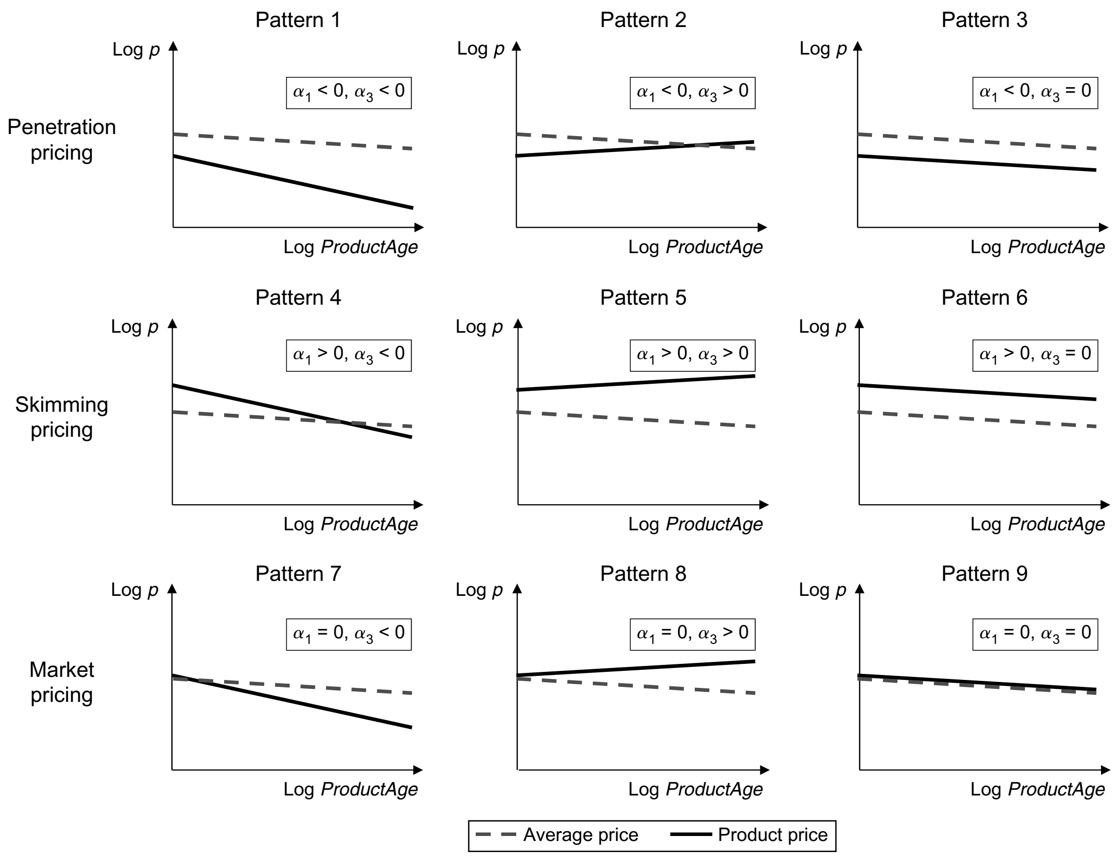
Some studies examine empirical pricing strategies in oligopolistic or competitive markets at the category level (e.g., Bass et al. 1994, Parker and Neelamegham 1997). Other studies (e.g., Gatignon and Parker 1994, Parker and Gatignon 1996, Simon 1979) analyze dynamic pricing strategies for brand diffusion. Recently, Song and Chintagunta (2003) estimated a novel micromodel of new product adoption with heterogeneous and forward-looking consumers. They calibrate their model with monthly data in a market with three brands of digital cameras and find brand-specific price effects that change over time, and which imply brand and time-specific pricing strategies. Nair (2007) derives optimal intertemporal price discrimination strategies in a model with heterogeneous forward-looking consumers and firms and tests them in the U.S. video game market. A few descriptive studies by Ingenbleek et al. (2003) and Noble and Gruca (1999) survey managers about perceived factors influencing their choice of strategy.

Relative to this full and insightful literature, this study seeks to analyze the prevalence of pricing strategies and describe the choice and correlates of dynamic pricing strategies in a complex market consisting of 663 cameras under 79 brand names exhibiting both great differentiation and intense competition. The goal is to ascertain the strategies firms choose in such complex environments and the factors that correlate with their choice.

3. Method

We develop a method to classify dynamic pricing strategies. For this purpose, we develop a latent-class regression model for the digital camera market. Our model maps the observed prices onto a rich array of product attributes, market trends, and product age. We also discuss a set of firm and market variables that are associated with a firm's choice of pricing strategies.

Figure 1 **Patterns of Dynamic Price Strategies**



Note. Parameters α_1 and α_3 are shape parameters of the price function (see Equations (1.1) to (1.3)).

3.1. Dynamic Pricing Strategies

The normative pricing literature suggests that a skimming price should be “a relatively high price” (Monroe 2003, p. 380), or prices that “are high in relation to what most buyers in a segment can be convinced to pay” (Nagle et al. 2011, p. 125), or just high introductory prices (e.g., Dolan and Simon 1996, p. 315; Kotler and Armstrong 2012, p. 314). Likewise, this literature suggests that penetration prices should be “a relatively low price” (Monroe 2003, p. 380), or prices that are “low relative to perceived value in the target segment” (Nagle et al. 2011, p. 127), or just low introductory prices (e.g., Dolan and Simon 1996, p. 278; Kotler and Armstrong 2012, p. 314). However, the literature does not specify how to empirically ascertain what is a “low” or “high” price or what consumers are willing to pay.

Our approach to discriminate between dynamic pricing strategies is based on two key observations along the price path. Specifically, we look at the *price position* for a product *at launch* (introductory price) and the *subsequent evolution* of the price. At launch, a product’s price may be above, below or equal to the market price. After launch, the price may decrease, increase or simply follow the trajectory of the market price. The crossing of three launch prices × three after-launch prices yields nine possible strategy patterns, which we illustrate in Figure 1. This is our guiding framework for classifying the observed dynamic price patterns. Consistent with Nagle et al. (2011, p. 125), we categorize these nine patterns into skimming, penetration, or market-pricing strategies.

A crucial point in any empirical application of this framework is the measurement of the market price or average price, respectively. We can identify the market price from market data provided the data covers a large range of prices, product features, and changes in firm and market conditions.

3.2. Estimating the Market Price for Digital Cameras

We define the market price as the average price consumers pay for a product given its bundle of attributes (or features). While we are not interested in developing a hedonic price model, the theory behind such models offers a well established framework to measure and infer the market price for each specific bundle of camera attributes (Rosen 1974, Pakes 2003). Here, the assumption is that heterogeneous products are aggregations of their product attributes. We can derive implicit prices for product attributes from observed prices for differentiated products, each of which represent a bundle of attributes sold in a competitive market. The actual computation of the market prices of attributes is obtained by a regression of the prices of products on the attributes of those products (Pakes 2003). Regressions of such prices on attributes have been applied many times to a broad range of product categories (for a summary see Berndt 1991). In our case, such a regression gives robust estimates of market prices because we have a large number (663) of products that differ across many (22) attributes (Rosen 1974).

3.3. Specification of Dynamic Price Equations

Our objective is to understand the various patterns and sources of dynamic price evolution. For this purpose, we specify three nested latent-class price Equations (1.1) to (1.3). We start with the simplest model that reflects the pure price dynamics

$$\log p_{it} = \sum_s \pi_s h_s(\alpha_0 + \alpha_{1s} + \alpha_2 \log ProductAge_{it} + \alpha_{3s} \log ProductAge_{it} + u_{its}),$$

$$\text{subject to}\quad \begin{array}{ll} \alpha_{1s} < 0 & \text{for } s = 1, 2, 3 \\ \alpha_{1s} > 0 & \text{for } s = 4, 5, 6 \\ \alpha_{1s} = 0 & \text{for } s = 7, 8, 9 \end{array} \tag{1.1}$$

and

$$\begin{array}{ll} \alpha_{3s} < 0 & \text{for } s = 1, 4, 7 \\ \alpha_{3s} > 0 & \text{for } s = 2, 5, 8 \\ \alpha_{3s} = 0 & \text{for } s = 3, 6, 9, \end{array}$$

where,

p_{it} = retail price of camera model i in month t;
π_s = probability of class membership;
h_s = class-specific density function;
$ProductAge_{it}$ = the camera-model-specific product age (elapsed months since launch);
u_{its} = i.i.d. error term with heteroskedastic, class-specific variance;
$i = 1, 2, \ldots, I_k$ number of camera models by brand k;
$t = 1, 2, \ldots, T_i$ number of periods (in calendar time) by camera model i;
$k = 1, 2, \ldots, K_f$ number of brands by firm f;
$f = 1, 2, \ldots, F$ number of firms; and
$s = 1, 2, \ldots, S$ number of latent classes of price patterns.

Taking the logarithm of price and product-age time allows for nonlinear price patterns. It also ensures that the predicted price is always positive. We tested a log-linear version of the model but found specification (1.1) to be superior for our data. The parameters of interest are α_0, α_{1s}, α_2, and α_{3s}, where α_0 measures the average introductory price and α_2 measures the average impact of product age on price across all camera models. Parameters α_{1s} and α_{3s} capture the deviation from the average introductory price and the average model-age effect. We assume the existence of nine dynamic pricing strategies as shown in Figure 1. These strategies are represented by nine latent classes in Equation (1.1). By imposing a priori, class-specific restrictions on α_{1s} and α_{3s}, we clearly distinguish between each strategy type in our model. For example, if $\alpha_{1s} < 0$ and $\alpha_{3s} < 0$ we obtain a penetration strategy pattern that is consistent with pattern 1 in Figure 1. In the later empirical application, we assume that these nine classes are latent. Estimation will show which latent class, i.e., which pricing pattern, best describes the data generating process for a camera model. An advantage of this approach is that we do not need to estimate parameters for each camera model separately first and use them then in a deterministic way to assign models to strategies. Parameter estimation and classification of models is done simultaneously. As a result, the classification is probabilistic and acknowledges the fact that estimated parameters are random variables.

Equation (1.1) describes the pure development of price over a camera's life cycle. Presumably, there are changes in market factors, such as overall cost decline, seasonality or improving average quality due to technological innovation, that affect all product prices. To capture these (calendar) time-varying influences, we extend the model in Equation (1.2) by including period dummies for *Month* (base: January) and *Year* (base: 2000)

$$\log p_{it} = \sum_s \pi_s h_s \begin{pmatrix} \alpha_0 + \alpha_{1s} + \alpha_2 \log ProductAge_{it} \\ + \alpha_{3s} \log ProductAge_{it} \\ + \beta_1 February_t + \beta_2 March_t \\ + \beta_3 April_t + \beta_4 May_t \\ + \beta_5 June_t + \beta_6 July_t + \beta_7 August_t \\ + \beta_8 September_t + \beta_9 October_t \\ + \beta_{10} November_t + \beta_{11} December_t \\ + \beta_{12} Year2001_t + \beta_{13} Year2002_t \\ + \beta_{14} Year2003_t + u_{its} \end{pmatrix}, \tag{1.2}$$

where the parameter restrictions of Equation (1.1) hold. For lack of a strong conceptual foundation and to keep the model parsimonious, we restrict the β-parameters to be equal across classes.

Finally, we acknowledge that camera prices are also subject to various product-level variables. Most important, technical product features create quality differences across products that need to be adjusted for in the price. We add a vector of product features, $\mathbf{PF}_i$, to Equation (1.2) that covers no fewer than 22 product attributes and thus comprehensively describes the quality of a camera model. In addition, we include brand-specific fixed effects, γ_{1k}, which capture the ability of firms to charge a price premium due to strong brand equity. Finally, we assume that manufacturers benefit from experience curve effects that may result in price decreases. We therefore include the lagged cumulated unit sales by firm in the model. Our final and *full model* is Equation (1.3)

$$\log p_{it} = \sum_s \pi_s h_s \begin{pmatrix} \alpha_0+\alpha_{1s}+\alpha_2 \log ProductAge_{it} \\ +\alpha_{3s}\log ProductAge_{it} \\ +\beta_1 February_t+\beta_2 March_t \\ +\beta_3 April_t+\beta_4 May_t+\beta_5 June_t \\ +\beta_6 July_t+\beta_7 August_t \\ +\beta_8 September_t+\beta_9 October_t \\ +\beta_{10} November_t+\beta_{11} December_t \\ +\beta_{12} Year2001_t+\beta_{13} Year2002_t \\ +\beta_{14} Year2003_t+\gamma_{1k} \\ +\gamma_2 \log CumSales_{ft-1} \\ +\sum_{l=1}^{L-1}\gamma_{l+2} PF_{li}+u_{its} \end{pmatrix}, \qquad (1.3)$$

where $CumSales_{ft-1}$ denotes an index of cumulated unit sales (initialized at 5,000 units) for firm f and period $t-1$. Because we take the log of *CumSales* the estimated parameter is an elasticity. We tried different initial levels but did not find that results are sensitive to it. Again, the parameter restrictions of Equation (1.1) also apply to Equation (1.3) and we restrict the γ-parameters to be equal across classes to keep the model parsimonious. We explain how we estimate the models of Equations (1.1) to (1.3) subsequently in §5.1.

3.4. Logic for Correlates of Choice of Pricing Strategy

In this section, we outline the logic for the selection of correlates of the choice of pricing strategies. We describe our expectations why specific firm and market variables may be associated with the likelihood of firms following a certain strategy. We do not always expect an association with each strategy, i.e., penetration, skimming, and market pricing. From the pricing literature (e.g., Monroe 2003, p. 380; Nagle et al. 2011, p. 125), we identify and consider the following variables: market stage, late firm entry status, brand reputation, distribution strength, breadth of product line, competitive intensity, and cumulative manufacturer sales. We caution against interpreting our explanations as causal claims because the research design and available data do not allow us to rigorously test such claims.

Before we start our discussion, recall that the literature (Kotler and Armstrong 2012, p. 314; Monroe 2003, p. 380; Nagle et al. 2011, p. 125) posits the following assumptions about conditions that favor a skimming or penetration strategy. A skimming strategy requires that products be differentiated where companies have some source of competitive protection (Kalish 1983). Customers should be less price sensitive (Krishnan et al. 1999). For penetration pricing, customers are assumed to be more price sensitive (Krishnan et al. 1999) and products less differentiated (Eliashberg and Jeuland 1986).

Market stage. The market stage of a high-tech category such as digital cameras is an important condition when introducing new products. As the new category matures, competitors enter with similar or identical attributes. New product entry is especially intense after the take-off of the market, which leads to a proliferation of products in the growth stage (Golder and Tellis 2004). Innovative product differentiation becomes more difficult to achieve. In addition, more price-sensitive customer segments enter the market. These conditions reduce the ability of firms to shape the market price. We therefore expect that market-pricing patterns occur more often for products launched after the take-off of the market. In addition, higher price sensitivity favors penetration pricing (e.g., Krishnan et al. 1999). Given that price sensitivity increases after the takeoff of the market, products that are launched after the take-off should be more likely to follow a penetration-pricing pattern.

Late firm entry. The literature on order-of-entry effects assigns several supply-side and demand-side advantages to first movers and early entrants over late entrants. These competitive advantages result from preference formation processes, a positive innovator image, higher customer loyalty, and command over superior or scarce resources (e.g., Carpenter and Nakamoto 1989, Urban et al. 1986). Research has also shown that the effectiveness of the marketing mix decreases with order of entry, which reduces the pricing power of late entrants (Bowman and Gatignon 1996, Hurwitz and Caves 1988). As a result, we expect that market-pricing strategies are more likely to be adopted by late entrant firms.

In addition, the first-mover advantages suggest that late entrants could offer lower prices to compensate for the disadvantage from being late to win market share (Urban et al. 1986). This reasoning suggests a higher probability of late entrant firms adopting a penetration strategy.

Brand reputation. Recall that larger product differentiation paired with a means of competitive protection favors the adoption of skimming. Brands that have established a reputation for expertise and quality in consumer electronics and (digital) photography markets over time enjoy several competitive advantages over new brands including private-label brands. The reputation of the brand provides an important intangible benefit that differentiates its cameras from competitive offerings (Nagle et al. 2011, p. 126; Wernerfelt 1991). Given these advantages, firms may want to extract consumer surplus for their brands through higher dynamic prices using a skimming strategy. Thus, we expect established, high-reputation brands to be more often associated with the occurrence of a skimming strategy.

Distribution strength. Greater distribution breadth for the brand may be another source of competitive protection. This situation arises because a broad distribution increases the likelihood of brand choice, decreases exposure to competitive brands, and increases the barriers to competitive entry (Kalyanaram and Urban 1992). These factors alone or in conjunction increase the pricing power and the price that a brand with broad distribution can charge (e.g., Nagle et al. 2011, p. 126). On the other hand, broad distribution also supports a penetration strategy. It helps boost the sales volume, which is a key objective of a penetration strategy. Thus, a broader distribution could be associated with both skimming and penetration strategies.

However, we need to acknowledge that higher prices also facilitate distribution because higher margins are more attractive to retailers. Likewise, retailers benefit from a higher product turnaround supported by a penetration strategy. These observations do not change our expectations but limit clear interpretations of the findings based only on correlational analyses.

Breadth of product line. Firms with a broad product line tend to differentiate their products to decrease internal cannibalization and increase market share (Shugan and Desiraju 2001). With a broad product line, firms can offer many low-volume highly differentiated cameras. Such product differentiation favors price skimming across the small volume of differentiated cameras (Dolan and Simon 1996, p. 211). Thus, a broad product line could be correlated with a skimming strategy.

However, a broad product line allows firms to exploit economics of scope. In addition, with a broad product line, firms can offer a few high-volume low-differentiated products, which may qualify for a penetration pricing strategy. Thus, a broad product line could be correlated with a penetration strategy.

Furthermore, a broad product line may prompt a mix of pricing strategies to mitigate risks from single pricing strategies. In particular, some products may follow a market-pricing pattern because they do not have the pricing power that is necessary to isolate them from market pressures.

So, we might find that a broad product line is not correlated at all with any single pricing pattern. Hence, the pricing strategy associated with a broad product line eventually remains an empirical issue.

Competitive intensity. High competitive intensity provides consumers with numerous alternative brands from which to choose. Such choice prompts consumers to put more weight on price differences among competing brands. As a result, under intense competition, firms compete on price rather than on product attributes. The single firm loses market power to influence the market price and competition drives profit margins down to marginal cost (Besanko et al. 2007). The firm eventually becomes a price taker. Under such conditions, we would expect that market-pricing patterns occur more often.

However, the larger customer focus on price differences between camera models also offers the chance for gaining market share through penetration pricing. The increased output helps the product to ride down the experience curve, which eventually makes the product profitable (Monroe 2003; Nagle et al. 2011, p. 128). Thus, a higher competitive intensity could also be associated with a penetration strategy.

Cumulative manufacturer sales. Finally, the volume of cumulative sales is also likely to affect the choice of strategy. A higher level of sales that a firm has accumulated prior to the launch of a new product usually leads to cost advantages that facilitate a cost-oriented strategy such as penetration pricing for the new product. So, high cumulative manufacturer sales may be associated with penetration pricing.

3.5. Multinomial Logit (MNL) Model of Strategy Choice

Note that the suggested dynamic price model of Equation (1.3) includes nine latent classes that represent the dynamic price strategies of Figure 1. An outcome of this model is the probability of which specific pricing strategy "belongs" to a camera model. We use this probability as our dependent variable in the classification model of Equation (2). Specifically

$$\pi_{fki}\ (\text{strategy } s) = \frac{\exp(\eta_{s,\,fki})}{\sum_{r=1}^{S}\exp(\eta_{r,\,fki})}, \quad s = 1, 2, \ldots, S$$

$$\begin{aligned} \text{with } \eta_{s,\,fki} = {} & \delta_{s0} + \delta_{s1} MStage_i + \delta_{s2} LateEntrant_{fi} \\ & + \delta_{s3} EstBrand_{ki} + \delta_{s4} DistStrgth_{ki} \\ & + \delta_{s5} ProdLine_{ki} + \delta_{s6} CompIntensity_i \\ & + \delta_{s7} CumSales_{fi}, \end{aligned} \tag{2}$$

where

π_{fki} (strategy s) = probability of camera model i belonging to brand k and firm f to follow pricing strategy s;
$MStage_i$ = dummy variable for market stage: 1 if camera model i was launched after take-off, 0 if launched before take-off;
$LateEntrant_{fi}$ = dummy variable for late entrant status of firm f owning camera model i: 1 if firm launched first digital camera in or after the year 2000, 0 if earlier;
$EstBrand_{ki}$ = dummy variable for brand reputation: 1 if brand k is an established brand with a reputation in consumer electronics or photography, 0 otherwise;
$DistStrgth_{ki}$ = distribution strength for brand k measured in average percent ACV (all commodity volume over camera model i's life cycle);
$ProdLine_{ki}$ = breadth of brand k's product line (measured by average number of cameras over camera model i's life cycle);
$CompIntensity_i$ = competitive intensity in market at launch of camera model i (measured by Herfindahl index);
$CumSales_{fi}$ = index of cumulated unit sales (initialized at 5,000 units) for firm f before launch of camera model i.

Note that variation in these predictor variables arises at different levels. For example, the late entrant status varies across firms whereas the market stage varies across camera models, i.e., within the same firm. These different aggregation levels help reduce collinearity issues, which we also checked more formally: The correlation between descriptors is not very high. More important, the highest variance inflation factor amounts to 4.4 and is well below the critical value of 10. In addition, the condition index is 14 and again well below its rigorous value of 20 (Greene 2010, p. 90). Thus, we did not find evidence for high levels of multicollinearity.

4. Data

This section describes the data in terms of its product and market characteristics.

4.1. Product Characteristics

Our data set comprises the whole market for digital cameras in one major European country, which we obtained from GfK. The observation period includes 46 months of camera retail prices, sales, distribution, and product attributes between January 2000 and October 2003. Retail prices are average selling prices weighted by sales volume of retailers. GfK industry experts also provided us with information on the brand reputation and late entrant dummy variables. Henceforth, we use the term "camera model" to represent the most disaggregate brand and product level, with a unique alphanumeric code that characterizes an offering on numerous attributes (e.g., Sony Cybershot DSC-P20). Thus, each camera model has a unique specification of product attributes and is associated with a unique price for each month. Attributes or product dimensions of a digital camera model include, among others, pixel resolution, digital and optical zoom, memory, flash, auto focus, and add-ons such as an MP3-player and Bluetooth. The majority of firms (93%) offer digital camera models under one brand name, which may encompass different product lines (e.g., Sony's Mavica and Cybershot lines).

For our analysis, we focus only on the consumer market and ignore the professional camera cluster (changeable lens products), which is less than half a percent of sales. We include only products for which we observe the *complete* life cycle, to estimate the dynamic price patterns at highest accuracy. Fifty percent of all cameras have a life cycle of 1.5 years or shorter.

We exclude 171 products with life cycles shorter than four months because they had no meaningful impact on the market. The share in total market unit sales by these products is 0.02%. Considering only the initial three months of all products, the average share per month is still very low at 0.08%.

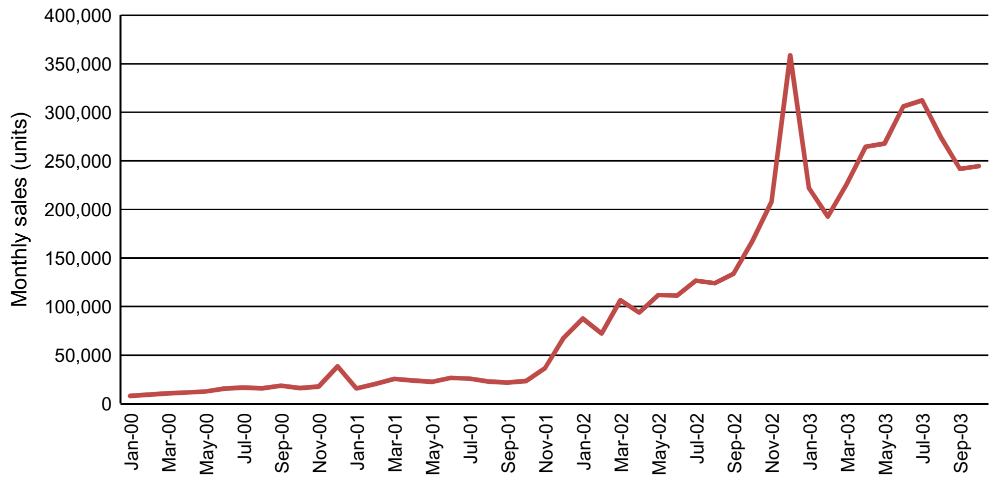
The final data set consists of 663 camera models marketed under 79 brand names by 74 firms. The average price of a camera model in our data set is €378.04 and the average monthly sales are 404 units. However, prices and monthly sales are quite dispersed, ranging from €17.40 to €2,262.60 and 1 to 31,480 units (see Table 1).

4.2. Market Characteristics

After 2000, the market witnessed a sharp rise in firm entry, proliferation of a range of products, and constant decline in prices. However, it took until November 2001 for the market to take off (see Figure 2). We identified the take-off by using the threshold-rule from Golder and Tellis (1997). Based on the take-off-date, we construct our market-stage variable *MStage*. The number of firms in the market grew from 27 in 2000 to 74 in 2003. Average prices declined by 48% during our observation period.

The structure of competition among manufacturers in our data set is similar to the digital camera market in the United States (Song and Chintagunta 2003)

Figure 2 (Color online) Monthly Market Sales During Observation Period



and other durable goods markets such as computers (Chu et al. 2007). More than 75% of total revenues are distributed among 10 manufacturers in this market leading to an average Herfindahl index of 0.12. This value indicates a highly competitive market among digital camera manufacturers.

Table 1 Descriptive Statistics

	Mean	SD	Min	Max
Price (euro per unit)	378.04	301.96	17.40	2,262.60
Sales (monthly units)	403.68	1,075.98	1.00	31,480.00
Length of life cycle (months)	20.38	12.21	4.00	46.00
Weighted distribution (percent)	16.13	19.33	0.00	95.00
Memory card slot (DV)	0.82	0.38	0.00	1.00
Optical finder (DV)	0.90	0.30	0.00	1.00
LCD finder (DV)	0.75	0.44	0.00	1.00
Auto focus (DV)	0.61	0.49	0.00	1.00
Flash (DV)	0.85	0.36	0.00	1.00
Digital zoom (DV)	0.68	0.47	0.00	1.00
Optical zoom (DV)	0.51	0.50	0.00	1.00
Pixel resolution (thousand pixels)	2,221.73	1,329.52	19.00	5,360.00
CCD sensorship (DV)	0.75	0.44	0.00	1.00
SSFDC memory (DV)	0.15	0.36	0.00	1.00
Comflash memory (DV)	0.29	0.45	0.00	1.00
SD card memory (DV)	0.21	0.41	0.00	1.00
XD card memory (DV)	0.03	0.16	0.00	1.00
PC card memory (DV)	0.00	0.04	0.00	1.00
Multimedia card memory (DV)	0.01	0.12	0.00	1.00
Memory stick (DV)	0.05	0.22	0.00	1.00
Floppy (DV)	0.01	0.12	0.00	1.00
CD-R & CD-RW (DV)	0.01	0.09	0.00	1.00
Optical zoom factor	1.72	2.05	0.00	10.00
Digital zoom factor	2.09	2.02	0.00	20.00
MP3 player (DV)	0.02	0.13	0.00	1.00
Bluetooth (DV)	0.00	0.04	0.00	1.00
Number of observations	11,835			

Note. DV indicates a dummy variable.

5. Estimation and Results

This section describes the estimation and model results, the distribution of the pricing strategies, and results from the analysis of the correlates of pricing strategy choice.

5.1. Estimation

We only discuss the estimation of our full model, Equation (1.3), because Equations (1.1) and (1.2) are nested within this model. We assume that camera prices arise from a population of camera models that is a mixture of S classes reflecting the various dynamic price patterns (see Figure 1). Following Kamakura and Russell (1989), we simultaneously identify the latent classes and estimate class-specific model parameters. Furthermore, we include the MNL model (Equation (2)) to predict class membership into the likelihood function that describes the data generation. Hence, we jointly estimate Equations (1.3) and (2) (for further details see Wedel and Kamakura 2000).

Likelihood function. The likelihood function of the estimation model is given by

$$L=\sum_{s=1}^{S}\pi(s\mid z_{fki},\boldsymbol{\delta})\prod_{f=1}^{F}\prod_{k=1}^{K_f}\prod_{i=1}^{I_k}h(\log\mathbf{p}_{fki}\mid s,\mathbf{x}_{fki},\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma}),\ \text{where}$$

$$h(\log\mathbf{p}_{fki}\mid s,\mathbf{x}_{fki},\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma})=\prod_{t=1}^{T_i}h(\log\mathbf{p}_{fkit}\mid s,\mathbf{x}_{fkit},\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma}).\qquad(3)$$

The term $h(\log\mathbf{p}_{fki}\mid s,\mathbf{x}_{fki},\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma})$ denotes the marginal density of the log of price for all camera models of brand k and firm f given class s and all exogenous information, i.e., the predictor variables $\mathbf{x}_{fki}$ and the vectors of unknown parameters $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$. The values on the latent variables s are assumed to come from a multinomial distribution. The term $\pi(s\mid z_{fki},\boldsymbol{\delta})$ describes the multinomial probability of class membership, given the cross-sectional predictor variables $\mathbf{z}_{fki}$ and unknown parameter vector $\boldsymbol{\delta}$.

We estimate Equation (3) using the maximum likelihood technique. Using the EM and Newton-Raphson algorithms combined solves the maximization problem of the likelihood function. The advantage of EM is its stability in approaching the optimum; whereas Newton-Raphson is faster than EM when it is close to the optimum. We start with 500 EM iterations at maximum and switch to the Newton-Raphson algorithm to obtain the final solution. The estimation algorithm uses an active-set method (Gill et al. 1981) to address parameter inequality constraints (see Equations (1.1) to (1.3)). For example, if the constraint on a nonnegative parameter is violated, the parameter is set to zero. Otherwise the constraint remains inactive. The parameter restrictions help to identify the model and mitigate weak identification issues. In addition, we verify that the parameters are identified by checking that the information matrix has full rank. Finally, we use 100 random sets of start parameters to minimize the danger of finding a local optimum.

Model selection. While conceptually nine dynamic price patterns or latent classes, respectively, are possible, we may not observe all patterns in the market. To infer the number of classes we proceed as follows. We first estimate the model with all nine possible latent classes. We investigate the classes for which the inequality parameter restrictions are violated. A violation implies that a camera model assigned to this class in fact follows another pattern. For example, if the restriction $\alpha_1 < 0$ is violated for class/pattern 2 this parameter is set to zero. This leads to parameter setting $\alpha_1 = 0$ and $\alpha_3 > 0$, which corresponds to pattern 8. In the next step, we reestimate the model with the reduced set of a priori defined classes. In our example, we delete Class 2 and estimate a model with only eight classes. We verify that the restricted model is supported by Bayesian Information Criterion (BIC) and Consistent Akaike Information Criterion (CAIC). We iterate this procedure until we find a stable class structure where no parameter restriction is violated. When estimating Equations (1.1) to (1.3) we always obtain a solution without further violations of parameter restrictions after just one round. Finally, we check whether restricted parameter estimates are indeed significantly different from zero. If not, they are set to zero, which again results in a reduced set of a priori defined classes/patterns. We also verify that this restricted model is supported by BIC and CAIC.

5.2. Price Regressions Results

Tables 2 and 3 summarize the estimation results for our nested pricing models in Equations (1.1) to (1.3). While Table 2 presents the estimates for the different sets of control variables added in Equations (1.2) and (1.3), Table 3 focuses on the estimation results for our key shape parameters. Unless indicated otherwise, we focus on the results of the full model Equation (1.3).

Table 2 Estimation Results for Control Variables of Price Equations (1.2) and (1.3)

Dependent variable: log(*price*)	Model (1.2)	Model (1.3)[a]
January (DV)	*Base*	*Base*
February (DV)	−0.027 (0.013)	−0.019 (0.008)
March (DV)	−0.060 (0.013)	−0.054 (0.008)
April (DV)	−0.085 (0.013)	−0.085 (0.007)
May (DV)	−0.080 (0.013)	−0.089 (0.007)
June (DV)	−0.120 (0.013)	−0.135 (0.007)
July (DV)	−0.138 (0.013)	−0.157 (0.008)
August (DV)	−0.153 (0.013)	−0.170 (0.008)
September (DV)	−0.170 (0.013)	−0.195 (0.008)
October (DV)	−0.193 (0.013)	−0.218 (0.008)
November (DV)	−0.170 (0.015)	−0.205 (0.009)
December (DV)	−0.169 (0.014)	−0.209 (0.009)
*Year*2000 (DV)	*Base*	*Base*
*Year*2001 (DV)	−0.120 (0.011)	−0.144 (0.009)
*Year*2002 (DV)	−0.337 (0.010)	−0.358 (0.012)
*Year*2003 (DV)	−0.548 (0.012)	−0.591 (0.017)
Log(*cumulative manufacturer sales*)		−0.030 (0.005)
Product characteristics		
Memory card slot (DV)		0.391 (0.011)
Optical finder (DV)		0.014 (0.007)
LCD finder (DV)		0.121 (0.009)
Auto focus (DV)		0.016 (0.007)
Flash (DV)		0.009 (0.009)[NS]
Digital zoom (DV)		0.151 (0.008)
Optical zoom (DV)		0.090 (0.007)
Pixel resolution		3×10^{-4} (2.4×10^{-6})
CCD sensor ship (DV)		0.052 (0.009)
SSFDC memory (DV)		−0.129 (0.009)
Comflash memory (DV)		−0.108 (0.008)
SD card memory (DV)		−0.157 (0.008)
PC card memory (DV)		0.117 (0.107)[NS]
Multimedia card memory (DV)		−0.094 (0.015)
Memory stick (DV)		0.154 (0.042)
Floppy (DV)		0.069 (0.044)[NS]
CD-R & CD-RW (DV)		0.598 (0.044)
Optical zoom factor		0.066 (0.001)
Digital zoom factor		−0.012 (0.001)
MP3 player (DV)		0.430 (0.012)
Bluetooth (DV)		0.271 (0.031)
Pseudo R^2	0.840	0.953
No. of obs.	11,835	11,697[b]

Notes. Standard errors are in parentheses. DV indicates a dummy variable. NS = not significant ($p > 0.05$).
[a]Brand dummies included in estimation.
[b]Some first periods lost with no prior cumulated sales.

Following our model selection procedure, we always obtain the same five-class structure for models in Equations (1.1) to (1.3). If we add more variables overall model fit increases substantially. Pseudo R^2 (squared correlation between estimated and actual dependent variable) amounts to 0.84 for Model (1.1), 0.84 for Model (1.2), and 0.95 for the full Model (1.3). The extended full model is supported by the likelihood ratio test (LRT) ($p < 0.001$). Finally, we note that the latent classes are well separated. The entropy statistic for the full model is 0.95.

Table 3 **Estimation Results for Price Positioning and Evolution Parameters of Equations (1.1) to (1.3)**

Dependent variable: log(*price*)	Parameter	Pattern 1 (Penetration pricing)	Pattern 5 (Skimming pricing)	Pattern 7 (Market pricing)	Pattern 8 (Market pricing)	Pattern 9 (Market pricing)
			Price Equation (1.1): No controls			
Average effects						
Intercept	α_0	6.231 (0.011)	6.231 (0.011)	6.231 (0.011)	6.231 (0.011)	6.231 (0.011)
Log(*ProductAge*)	α_2	−0.228 (0.005)	−0.228 (0.005)	−0.228 (0.005)	−0.228 (0.005)	−0.228 (0.005)
Deviation from average effects						
Intercept	α_1	−1.127 (0.022)	0.604 (0.024)	—[a]	—[a]	—[a]
Log(*ProductAge*)	α_3	−0.551 (0.005)	0.341 (0.004)	−0.212 (0.004)	0.167 (0.003)	—[a]
Class size: # camera models[b]		214 (32.28%)	99 (14.93%)	120 (18.10%)	115 (17.35%)	115 (17.35%)
			Price Equation (1.2): Firm and market controls			
Average effects						
Intercept	α_0	6.391 (0.016)	6.391 (0.016)	6.391 (0.016)	6.391 (0.016)	6.391 (0.016)
Log(*ProductAge*)	α_2	−0.030 (0.005)	−0.030 (0.005)	−0.030 (0.005)	−0.030 (0.005)	−0.030 (0.005)
Deviation from average effects						
Intercept	α_1	−0.982 (0.023)	0.390 (0.015)	—[a]	—[a]	—[a]
Log(*ProductAge*)	α_3	−0.546 (0.005)	0.165 (0.003)	−0.198 (0.004)	0.397 (0.007)	—[a]
Class size: # camera models[b]		205 (30.92%)	155 (23.38%)	135 (20.36%)	47 (7.09%)	121 (18.25%)
			Price Equation (1.3): Firm, market, and product controls			
Average effects						
Intercept	α_0	4.684 (0.025)	4.684 (0.025)	4.684 (0.025)	4.684 (0.025)	4.684 (0.025)
Log(*ProductAge*)	α_2	−0.042 (0.003)	−0.042 (0.003)	−0.042 (0.003)	−0.042 (0.003)	−0.042 (0.003)
Deviation from average effects						
Intercept	α_1	−0.202 (0.009)	0.148 (0.011)	—[a]	—[a]	—[a]
Log(*ProductAge*)	α_3	−0.128 (0.002)	0.085 (0.002)	−0.012 (0.003)	0.180 (0.003)	—[a]
Class size: # camera models[b]		141 (21.27%)	136 (20.51%)	79 (11.92%)	82 (12.37%)	225 (33.94%)

Notes. Standard errors are in parentheses. All estimates are significant ($p < 0.05$).
[a]Parameter restricted to zero.
[b]Percentage share of pattern on all camera models in parentheses.

Table 2 shows that we find significant influences for many control variables that are added to the model in Equations (1.2) and (1.3). Seasonality seems to be present as reflected in the significant dummy coefficients for month. Price cuts are deeper before Christmas. We also find a falling price trend over the years that reflects changes in market conditions such as overall cost decline or improvements in average quality due to technological innovation. Consistent with our expectation, we find evidence for economies of experience as indicated by the significant negative coefficient associated with the log of cumulated sales of all cameras from the start of the first period to the penultimate period of a particular manufacturer.

The full model of Equation (1.3) includes product features and brand-specific fixed effects (not shown). They contribute substantially to explain differences in market prices across camera models. For example, pixel resolution and the availability of an optical zoom are highly valued features as shown by the estimated price effects.

Table 3 summarizes the estimation results on the focal shape parameters $\alpha_0 - \alpha_3$. They reflect the type of dynamic price pattern. We find one penetration pattern (#1), one skimming pattern (#5), and three market-pricing patterns (#7, 8, and 9) in our data. Because the model of Equation (1.1) does not include any control variables it describes price evolution in its pure form. Overall, there is a substantial reduction in the magnitude of estimates when we go from Equation (1.1) to the model of Equation (1.3). For penetration Pattern 1, as an example, the deviation from the intercept, α_1 equals −1.13 in Model (1.1), −0.98 in Model (1.2), and −0.20 in Model (1.3). These results imply a deviation of the launch price from the average market price of −67% for Model (1.1), −62% for Model (1.2), and −18% for Model (1.3). The difference is especially significant when we move to Model (1.3). This result underlines the importance of controlling for quality features and brand effects for measuring the price position in the market.

Considering the class sizes in Table 3, it is apparent that the sizes for the five identified price patterns vary across the price models. However, it does not appear to be extreme. Most noticeable is that penetration Pattern 1 includes most cameras (32%) under Model (1.1) compared to the full Model (1.3), where most cameras follow market-pricing Pattern 9 (34%).

Overall, the results of the model estimation identify a stable structure of dynamic price patterns in the analyzed digital camera market. The number and type of price patterns are consistent across model specifications. Class sizes and shape parameters vary across model specification but not to an extent that

Table 4 Estimation Results for Descriptor Variables of Multinomial Logit Model (Equation (2))

Dependent variable: Probability of pattern (strategy) choice	Pattern 1 (Penetration pricing)	Pattern 5 (Skimming pricing)	Pattern 7 (Market pricing)	Pattern 8 (Market pricing)	Pattern 9 (Market pricing)
Intercept	−0.475 (0.554)	0.108 (0.397)	−0.354 (0.466)	−0.427 (0.473)	1.148 (0.429)*
Market level					
Market stage (DV)[a]	0.953 (0.323)**	0.273 (0.258)	−1.019 (0.334)**	−0.629 (0.330)	0.422 (0.248)
Competitive intensity[b]	32.098 (14.29)*	−12.677 (8.56)	−29.412 (9.56)**	−30.947 (9.53)**	40.938 (11.55)**
Firm level					
Late entrant (DV)[c]	0.445 (0.250)	−0.339 (0.219)	−0.256 (0.289)	−0.306 (0.280)	0.456 (0.206)*
Cumulated manufacturer sales	0.025 (0.010)*	−0.025 (0.013)	−0.019 (0.019)	0.001 (0.015)	0.017 (0.009)
Brand/product level					
Established brand (DV)	−0.021 (0.240)	0.445 (0.220)*	−0.082 (0.282)	−0.097 (0.279)	−0.246 (0.194)
Distribution strength	0.026 (0.009)**	0.015 (0.010)	−0.019 (0.014)	−0.060 (0.016)**	0.039 (0.009)**
Breadth of product line	0.013 (0.019)	−0.002 (0.020)	0.005 (0.027)	0.016 (0.024)	−0.033 (0.017)
Class size: # camera models	141	136	79	82	225
# observations = 663; classification rate = 43.2%; proportional chance = 23.2%; maximum chance = 33.9%					

Notes. For identification purposes the parameter estimates for each variable sum to zero across the five patterns. They should be interpreted as deviation from the overall mean of zero. Standard errors are in parentheses. DV indicates a dummy variable.
[a] 1 = Launch after takeoff; 0 = before takeoff.
[b] Competitive intensity is measured by the Herfindahl index at launch of model. The coefficient is reverse coded for reading convenience.
[c] 1 = Entry in or after 2000; 0 = before 2000.
$^*p < 0.05$; $^{**}p < 0.01$.

would alter our interpretation. Rather, the differences reflect the explanatory power of important control variables.

5.3. Prevalence of Pricing Strategies

Figure 3 summarizes our findings on the prevalence of pricing strategies. It shows that the majority, i.e., roughly 60% of camera models, follow a market-pricing strategy in this market. Thirty-four percent of cameras set the introductory price at launch at market level and also subsequently move in sync with the market price (Pattern 9). Thus, Pattern 9 appears to be the dominant market-pricing strategy. Another 21% follow a penetration strategy consistent with Pattern 1. About 20% follow a skimming strategy consistent with Pattern 5. We do not find evidence for other skimming or penetration patterns. Using the results from Table 3, the dominant penetration strategy in this market is to launch the product 18% below market price ($= 100 \times [\exp(\alpha_{1s}) - 1]$) and further lower the price over the life cycle. The monthly rate of decrease starts highest after the introductory period with −12.8% and reduces over time ($= 100 \times \alpha_{3s}/ProductAge$). The dominant skimming strategy is to launch at a price 16% above market price and further increase the price relative to the market price. The rate of monthly increase starts with 8.5% per month and reduces over time.

Figure 4 shows the fit between estimated and actual price paths for selected cameras. It includes two pairs of actual and estimated price paths for a skimming, penetration, and market-pricing strategy. Note that these are actual prices, not relative to the market. Predicted price follows actual price quite well.

5.4. Results for Correlates of Choice of Pricing Strategy

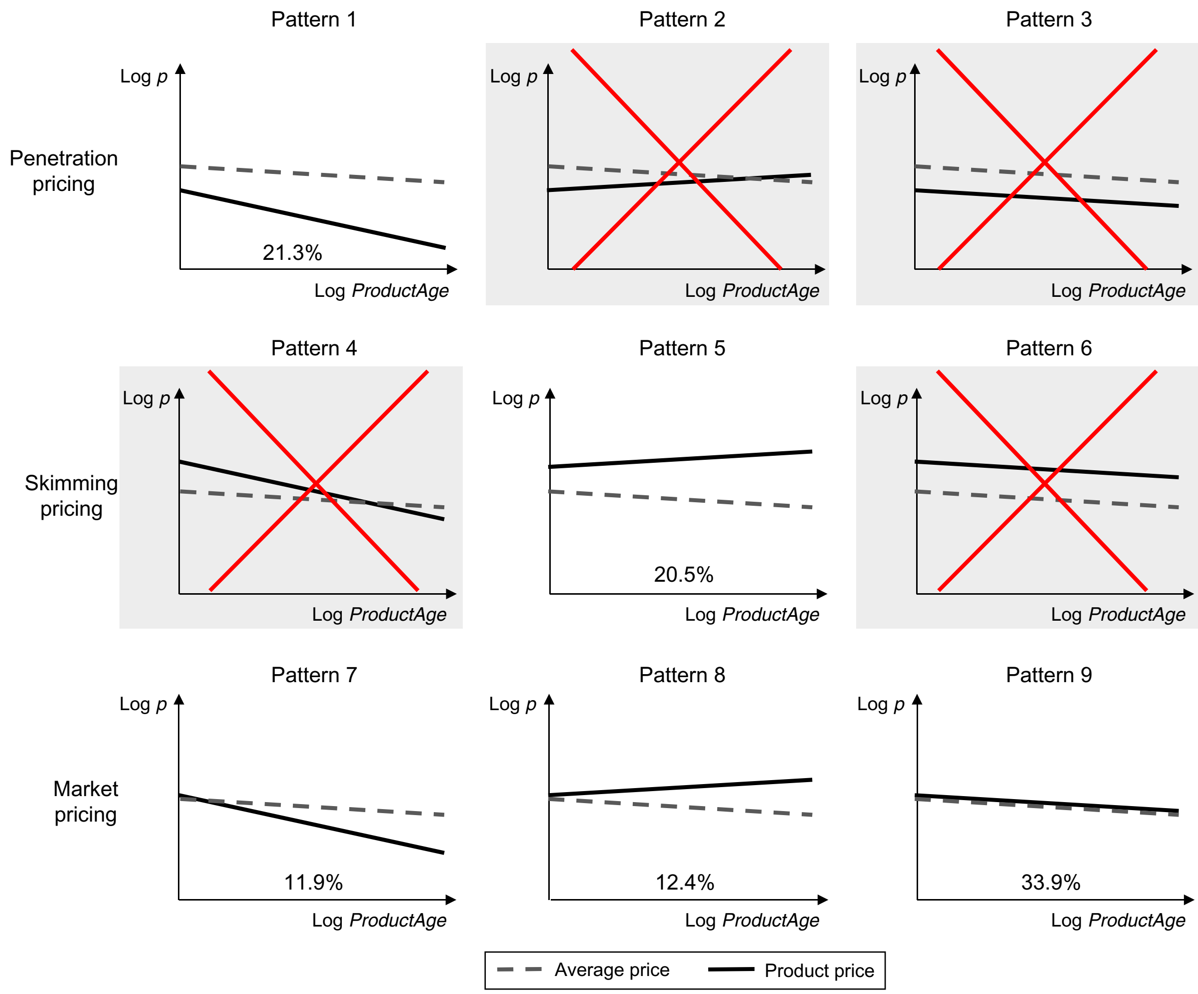
Table 4 shows the results of the MNL model. Although many coefficients do not reach statistical significance, this does not limit the insights from this analysis.[2] It is unlikely that each descriptor variable can be associated with all five strategy patterns. We consider the classification rate of 43% to be moderate and acceptable. The seven descriptor variables substantially improve the prediction of strategy use. The MNL model beats the prediction of the maximum chance criterion by 27% and the proportional chance criterion by 86% (Table 4).

Our results show that use of a skimming strategy is significantly correlated with brand reputation. Consistent with our expectation, established consumer electronics/photography brands seem to exploit their reputation advantage and are more likely to follow a skimming strategy. In addition, a skimming strategy seems more likely in less competitive market periods and by early entrants. However, the estimated effects are not significant.

Most significant estimates are associated with penetration Pattern 1 and market-pricing Pattern 9. Consistent with our expectation, we find that a penetration strategy and a market-pricing strategy are more likely to occur if competitive intensity is higher. Both strategies also occur more often after the take-off of the new product, whereas the effect is only marginally significant ($p < 0.10$) with respect to

[2] Note that for identification purposes the parameter estimates for each variable sum to zero across the five patterns. They should be interpreted as deviation from the overall mean of zero.

Figure 3 (Color online) Prevalence of Dynamic Price Strategy Patterns in the Analyzed Digital Camera Market



Note. Percentages refer to the relative number of cameras following a specific price trajectory (based on estimation of full model Equation (1.3)).

market-pricing Pattern 9. If the firm is a late entrant into the digital camera market, a market-pricing strategy is more likely to occur. We also find a higher likelihood of penetration pricing for late entrants at marginal significance. Finally, we find evidence for the expected positive correlation between cumulated firm output and the use of a penetration strategy.

In our discussion of the distribution strength (measured in percent all commodity volume (ACV)), we develop arguments that suggest a positive correlation with both penetration pricing and skimming pricing. Our results support the expected associations, although the coefficient with respect to skimming does not reach significance. On the other hand, we also find a significant correlation with market pricing. Finally, we do not obtain significant estimates for the association of strategy patterns with the breadth of product line. For this variable, we had conflicting arguments that may explain the nonsignificant result.

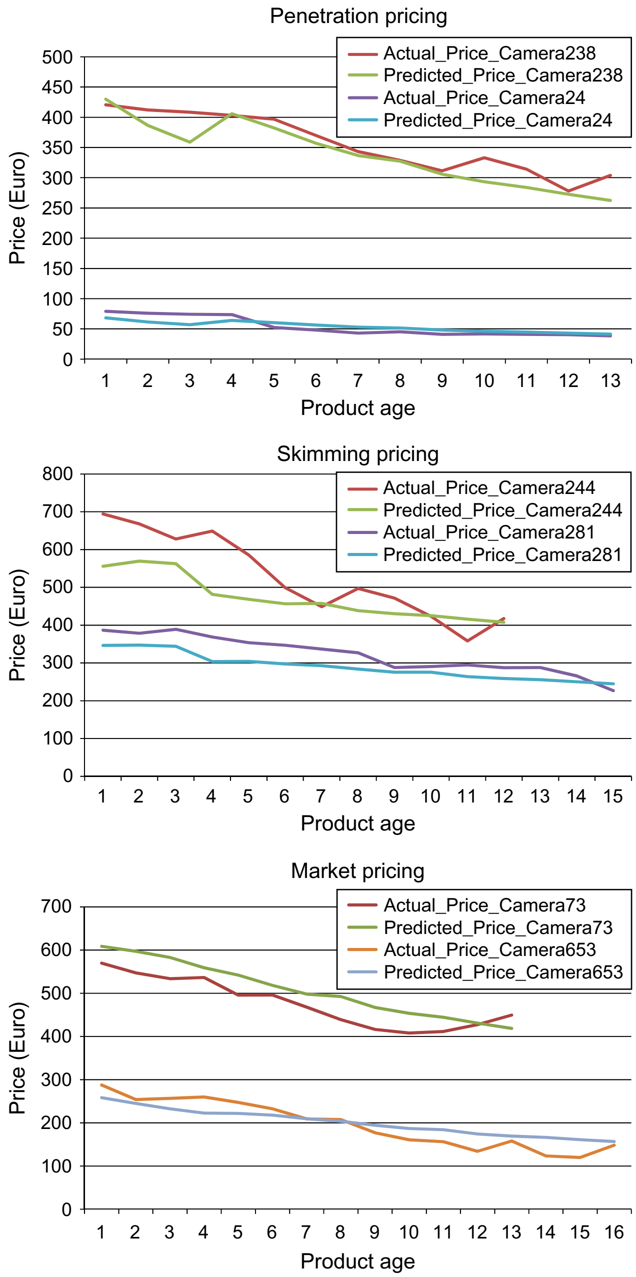
To summarize, the results for the correlations of conditions with various pricing strategies are predominantly in line with our expectations.

5.5. Robustness and Holdout Validation

We tested the robustness of our results and conclusions in various ways. First, we compared a log-linear specification of the price equation with the suggested specification. The Davidson and MacKinnon non-nested model test (Greene 2010, p. 136) is inconclusive, suggesting that none of the specifications is superior to the other. However, BIC (−5,541.18 versus −4,804.69) and CAIC (−5,382.18 versus −4,645.69) statistics favor the log–log specification. Pseudo R^2 is also higher for the log–log model (0.952 versus 0.948).

Second, we added firm dummies or brand dummies (most firms have only one brand) to the MNL model. This is to control for the impact of other descriptor variables at the firm/brand level, which we do not observe. If we include only these dummies into the MNL model of Equation (2) we obtain

Figure 4 (Color online) Illustration of Actual and Predicted Prices of Selected Cameras



Notes. The number refers to a camera identifier. Product age in elapsed months since launch.

quite a number of significant fixed effects. The explanatory power of these dummy variables, however, completely vanishes when we add our descriptor variables. Consequently, the likelihood ratio test rejects extending the MNL model of Equation (2) by firm/brand dummies ($p > 0.10$).

Finally, we tested the predictive performance of our model in various holdout samples. Specifically, we ask to what extent our results and conclusions are robust to variations in the set of periods, products, and firms. Table 5 summarizes common prediction

Table 5 Prediction Statistics for Holdout Validation

Holdout sets	Pseudo R^2	MSE	RMSE	MAE	MAPE (%)
Periods					
Estimation sample	0.963	0.028	0.168	0.123	2.17
Holdout sample	0.918	0.063	0.251	0.187	3.48
Products					
Estimation sample	0.953	0.035	0.187	0.137	2.45
Holdout sample	0.942	0.052	0.228	0.158	2.81
Firms					
Estimation sample	0.958	0.035	0.188	0.138	2.44
Holdout sample	0.776	0.136	0.369	0.289	5.25

Notes. Holdout sets are obtained as follows. *Periods*: the last 25% of periods for each camera's life cycle are excluded from estimation. *Products*: 25% of cameras are randomly selected and excluded from estimation. *Firms*: 20 out of 74 firms are randomly selected and excluded from estimation.

Pseudo R^2, squared correlation of predicted with actual values of log(*price*); MSE, mean squared error; RMSE, root mean squared error; MAE, mean absolute error; MAPE, mean absolute percentage error.

statistics for three different holdout sets. In the *period* set, we remove the last 25% of periods of each camera's life cycle (ca. 25% of observations) from the sample and keep them for the holdout sample. In the *product* set, we randomly assign 25% of camera models to the holdout sample. In the *firm* set, the holdout sample includes 20 randomly chosen firms (from a total of 74 firms). We apply a stratified approach to the selection of products and firms. We randomly select firms or products from each class proportional to their size. This sampling is necessary to ensure sufficient observations to identify a certain class in the estimation sample. In the holdout sample, however, we need to know the class membership for a camera model a priori for prediction purposes. As Table 5 shows, we observe very good model performance in all holdout sets and across all predictions statistics. This strongly supports the robustness of our results.

6. Discussion

We develop a method to classify dynamic pricing strategies (skimming, penetration, and market-pricing) and analyze correlates of choice of strategies in complex branded new product markets. Such markets are characterized by extensive differentiation and intense competition from numerous competing brands and products plus a large number of new product introductions. An important attribute of this method is that it allows us to discriminate between potentially nine pricing patterns. We test this method by an in-depth empirical analysis of the digital camera market consisting of 663 products under 79 brand names in digital cameras. This analysis leads to several findings on the pricing strategies in this high-tech market:

1. Firms follow five of nine possible dynamic pricing strategies in the digital camera market. The majority of cameras (60%) follow a market-pricing pattern.

Skimming and penetration strategies are also quite frequently adopted. Each strategy accounts for 20% of all strategies.

2. The dominant skimming pattern is to launch the new product 16% above market price and subsequently increase the price relative to the market price. The dominant penetration pattern is to launch the new product 18% below market price and subsequently lower the price relative to the market price. The dominant market-pricing pattern is to launch the new product at market price level and subsequently move in sync with the market price.

3. Firms simultaneously exhibit various dynamic pricing strategies over a portfolio of products. Market conditions such as the stage of market and the level of competitive intensity are associated with the choice of strategies. Market-pricing and penetration strategies occur more often after the take-off of the market and under increased competitive intensity.

4. Firm-level variables also correlate with the adoption of strategies. Market pricing is more likely to be adopted by late entrants, whereas firms that have established a reputation in the market are associated with a skimming strategy. Penetration strategies occur more often in firms with larger cumulated sales.

This study has several major implications for marketing managers. First, generalizations of optimal pricing strategies drawn from analytical models may not hold in real, complex, and dynamic environments characterized by a large number of differentiated brands and products with intense competition plus many new product introductions. 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 drivers and value of pricing strategies, enabling nuanced recommendations of market-pricing, penetration, or skimming strategies.

Second, our analysis does not find idiosyncratic preferences of firms for a certain strategy. Rather, firms seem to follow a portfolio approach with various products in their product line launched at various times and probably targeted at various consumer segments. In this case, the application of penetration pricing for some products can exploit economies of scale and experience that may cross-subsidize costs for the skimming strategy for other products. Concomitantly, price skimming for some products exploits margin that can complement the low margin from price penetration for other products.

Third, marketing managers in other markets can easily apply our method to analyze the prevalence and use of pricing strategies in their respective market. They need only adapt variables such as product features to the specific characteristics of their market.

Our study is subject to some limitations that need discussion and would benefit from further research. First, our findings are based on one market. However, it is typical of a large number of modern markets characterized by numerous brands, differentiated products, numerous new product introductions, and intense competition. Thus, the results may extend to other modern consumer markets such as video games, cars, TVs, mobile phones or computers. However, future research will need to test the generalizability of our results in other markets and countries. Additionally, future research may study the mark-up behavior of manufacturers versus retailers in such markets.

Second, we observe manufacturer sales in only one major country. We use an index variable for measuring cumulated manufacturer sales that eliminates issues of a different global scale. As a result, we only assume that the dynamics in sales accumulation are similar in the focal market and the global market because in a "flat world" and global economy, economies of experience are quickly shared across major markets. It would be interesting to test this assumption with extended data.

Third, we acknowledge that our results are descriptive and drawn from the average firm and product. The benefit of this descriptive approach is that endogeneity is not a critical concern. Conceptualizing the market price as the market average implies that product prices may deviate in both directions from the average, which does not need to correspond to every market. In addition, conclusions for the average firm and product may not apply as generalized normative guidelines for individual firms.

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