# The Effects of Product Ageing on Demand: The Case of Digital Cameras

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**Abstract:** The static differentiated product demand model when applied to products with rapid product turnover and declining prices, yields implausible results. One response is to explicitly model the inter-temporal choices of consumers but computational demands require restrictive assumptions on consumer heterogeneity and limits on the characteristics included in the model. We propose, instead, to supplement the static model with a control for the age that each product has been in the market. This approach is applied to the US digital camera market and we find we obtain more plausible estimates. Our results are consistent with inter-temporal price discrimination by firms. Furthermore, our results suggest that ignoring the effects of product ageing may result in substantially overestimated price elasticities and technological progress and underestimated price-cost markups.

**Keywords:** Discrete Choice, Demand Dynamics, Forward-Looking Behavior, Heterogeneous Preferences.

**JEL Classification:** D12, D24, L63

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## The Effects of Product Ageing on Demand: The Case of Digital Cameras

### 1. Introduction

New products entering into and old products retiring from markets is a prevailing phenomenon. It is more noticeable in markets where the price of a distinct variety of the product falls steeply and persistently over its limited lifetime. Examples of such markets include consumer electronics like personal computers, television sets, mobile phones, digital camcorders and digital cameras. Although the static differentiated product demand model applied to products like cars yields satisfactory estimates and predictions (e.g., Berry, Levinsohn and Pakes 1995, (hereafter BLP), Petrin 2002), it has been observed that this model is likely to deliver counterintuitive estimates or predictions in markets with rapid product turnover and substantial price changes like consumer electronics (Melnikov 2001, Gowrisankaran and Rysman 2007). To address the problem, these researchers, and other more recent papers, such as Zhao (2007) and Carranza (2008), focus on explicitly modeling inter-temporal consumption choices, which are clearly an important feature of these markets, using a dynamic programming approach.

However, it is not clear that the inter-temporal nature of these products is the sole source of the problem as there is a strong inter-temporal aspect for products like cars too. Furthermore, compared with a static differentiated product demand model, computational feasibility requires a specification that is simplified in several ways. The extent of randomness of the coefficients is limited, as well as the set of characteristics included in the models, and further simplifying assumptions are made, all apparently to reduce the computational burden. Until there is further improvement in computational technology, this leaves open the empirical question whether a restricted dynamic model or a more general static-style model will best capture substitution patterns in such markets. This is particularly the case as computational complexity further discourages the wide adoption of these dynamic models by economic analysts.

This paper proposes an alternative approach to tackling demand dynamics by explicitly introducing into the standard static differentiated product demand model a set of controls for demand dynamics and product life cycle factors. To control for demand dynamics and price evolution, this paper extends the static demand model by adding an age variable into the utility function, where the age of a product is the time elapsed since the product is introduced into the market.[1] This preserves the ability of this framework to capture the contribution of product heterogeneity to determining the patterns of substitutability, whilst simultaneously controlling for dynamics on both the demand and supply sides. It also significantly reduces the computation burden in the estimation procedure and the approach can be easily nested into a more sophisticated dynamic modeling framework. The coefficient on age can be interpreted in two ways. First, it can be interpreted as a structural coefficient reflecting the change in consumer valuations over the life-cycle of the product identified as firms engage in inter-temporal price discrimination. In equilibrium, consumers anticipate the decline of prices and wait until the price reaches their reservation price, and it is profitable for firms to sell in this way. This is the interpretation highlighted in the recent dynamic demand models such as Gowrisankaran and Rysman (2007), Zhao (2007) and Carranza (2008). Alternatively the age variable can be seen as a reduced form control for dynamics resulting from the supply side, e.g. through advertising (Ackerberg, 2003), which might also be contributing to the problematic results from the standard static model.

This approach is applied to the US digital camera market from January 2003 to May 2006, when the market experienced fast technological progress and considerable price declines. The effects of introducing the age variable are consistent with controlling for dynamic aspects of demand and supply. The estimated demand system and price elasticity matrix become more

[1] As we discuss in more detail below, Xiao (2008) independently used age as a control in a non-random coefficients model of demand for differentiated camera. However, it is included without any specific interpretation beyond a standard control.

reasonable and reliable, and the estimated price-cost markups are also more consistent with firms' inter-temporal pricing behavior. Ignoring product level dynamics results in overestimating own-price and cross-price elasticities, the magnitude of overestimation being higher for newly introduced and highly priced products. In our application, the predicted price-cost markups are significantly underestimated by up to 70%, and underestimation appears to be the greatest for mid and low-end cameras at their introduction period. Consequently, welfare gains from the cost reduction due to technological progress could be considerably overestimated. It should also be noted that as well as affecting the value of the price coefficient, the coefficients on most product characteristics become more plausible after the ageing effect is taken into account. Hence our approach can be seen as either providing an alternative to estimating a full dynamic model, if controlling for a wider set of product characteristics (with random coefficients) is important, or at the very least, providing a first step in estimation that would ease the computational demands of estimating a full dynamic differentiated product demand system.

The rest of the paper is organized as follows. The next section provides the conceptual foundations for including product ageing in a BLP differentiated product demand system. Section 3 details the specification of demand models, with both logit demand and random coefficient models, and the pricing and cost equations on the supply side. Section 4 discusses the choice of instruments and the GMM estimation procedure. Data statistics are given in Section 5 while estimation results are compiled in Section 6. The final section concludes the paper.

## 2. Product Ageing in Differentiated Product Demand models.

The majority of the most prominent applications of the BLP framework for estimating differentiated product demand systems are to relatively mature markets like automobiles and breakfast cereals (BLP; Berry et al, 1999; Nevo, 2000a, 2000b, 2001; Petrin, 2002). However, when the BLP framework is applied to new consumer electronics, the literature shows that the predictability performance of a static model is quite poor. For instance, Gowrisankaran and

Rysman (2007) report an insignificant positive price coefficient in the estimation of a static demand model for digital camcorders. Hence, they, as well as Carranza (2008) and Zhao (2007), explicitly model demand dynamics. This work focuses on the product-level demand dynamics resulted from consumer heterogeneity in willingness-to-pay as exhibited in the form of delayed purchases.[2] For many durables such as consumer electronics their prices are not far beyond most consumers' affordability. Given the durable nature of these goods, consumers could purchase as soon as their preferred products are introduced into the market and gain immediately the subsequent stream of utility flows. If the rate of product innovation and obsolescence is high, however, many consumers may deliberately wait and do not purchase until the particular variety enters into the later stage of its life cycle. One of the main reasons for postponing purchase is that consumers are forward-looking and they anticipate that the product's price will decline quickly and permanently as time goes by. In consequence, consumers who have a high willingness-to-pay for their favored goods enter the market soon after the new products have been launched. High price-elastic consumers with a low willingness-to-pay tend to delay their purchases and wait until their preferred alternatives are priced below their reservation prices. The heterogeneity in consumption preferences also provides oligopolistic firms with incentives to inter-temporally price discriminate by setting a higher initial price for a new product.

This forward looking behavior is modeled formally as an optimal stopping problem in the dynamic approach (see Melnikov 2001), exploiting information in the sales data. In particular, demand dynamics are captured by separating a purchase into two sequential decisions: choose the appropriate purchase time and then find the best option. All consumers are assumed to have the same constant discount factor to exponentially discount the expected stream of future utilities. Two further simplifying assumptions are usually imposed to make the analysis tractable:

[2] In the recent empirical IO literature, many econometricians attribute demand dynamics in consumer electronics markets to the delay of purchase by forward-looking consumers as they anticipate future prices will drop (see Melnikov 2002, Song and Chintagunta 2003, Erdem et al. 2005).

a Markov process assumption for the transition of future states (Rust 1994); and an "Inclusive Value Sufficiency" assumption (Gowrisankaran and Rysman 2007, Hendel and Nevo 2006). Using a scalar logit inclusive value to index for all products that exist in each time period, these assumptions reduce the state space of purchase decision from many dimensions (equal to the number of products in each market plus the outside alternative) to two. As well as these formal simplifications though, the complexity of the problem appears to limit the extent of diversity in preferences and the range of characteristics that can be included in the econometric model as these models typically allow either limited randomness in preferences for characteristics or a limited set of characteristics or both.

Rather than building in, albeit in a restricted way, consideration of future alternatives directly into the decision problem as in the demand dynamics literature, we propose including a variable for the age of the product as an additional attribute to control for these dynamic factors. It is worthwhile to notice that to a certain extent, the age variable can be considered as a "characteristic" of a camera model. Consumers may view two cameras with identical characteristics as differentiated goods if one was launched after the other. They may discount the value of a camera purely because it has been in the market "too long". Since the mean utility of a camera declines as time goes by, two consumers buying the exact same camera at different time points reveal their difference in willingness-to-pay. Thus, the age variable can depict the evolution of consumer willingness-to-pay which gives rise to dynamics in demand and pricing.

Including the age variable in the regression model provides an easy and flexible way to control for the forward-looking behavior of consumers when estimating solely with market-level data. A concern with including this variable is that the life of a product is an endogenous variable – the determination of which we do not explicitly model. We will address this concern below by instrumenting for age. Rather than specifically assuming that the heterogeneity works through an effect on the response to a particular change (like price), our approach allows for direct shifts in the quantity demanded at each price.[3] Of course, it would be possible to interact the age variable with other variables such as price if of interest.

Unlike other characteristics that are time-independent, the age of a camera model increases as time elapses so that it is time-dependent. This means that the age variable could also be picking up other influences on demand that vary through time (and that are not captured by the price). For example, if a brand is launched with a considerable amount of advertising, the value of which diminishes over time, then the age variable will also pick up this influence. Though not necessarily a direct determinant of utility, under this interpretation, we follow earlier papers, such as Ackerberg (2003), in including such determinants in the demand equation. However, the interpretation of the results will tend to emphasize the demand side interpretation as the patterns are consistent with a well established theory. To a certain extent, activities like advertising are likely to be done so to support the strategy of inter-temporal price discrimination which we believe is occurring here.

Before proceeding, it is worth noting that the digital camera market is a natural market with which to explore these questions as, presumably due to data availability, many dynamic differentiated product demand studies use data on digital cameras in the same way as the early studies of static models used data on cars.[4] Xiao (2008) applies static logit-type model to the digital camera market, including age as one of a set of exogenous characteristics, while focusing on other characteristics to analyze the welfare implications of features that improve usability. Other papers on digital cameras, such as Song and Chingtahua (2003), Carranza (2008) and Zhao (2007) build on the dynamic programming approach developed by Melnikov (2001). The interest of Song and Chingtahua (2003) is in how consumers adopt new products and their data cover the

[3] Income is another possibility. Without consumer level data as used, for example, in Petrin (2002), interacting age with income over such a short period is unlikely to be revealing.

[4] Though Gowrisankaran and Rysman (2007) use camcorders, they too used digital cameras in an early version of the paper.

infant period of the digital camera industry (April 1996 to May 1999) with three brands (Sony, Casio and Kodak). Carranza (2008) estimates the joint distribution of utility function and participation function by a reduced-form solution to account for the dynamic optimization problem. Zhao (2007) intends to explain the reasons for the fast price decline in the US digital camera market from 2001 to 2004 and finds that cost savings by technological progress contributes two thirds of the price fall and shrinking price-cost markup explains the remaining. However, Zhao's (2007) model focuses on overall market trends rather than price dynamics of individual products. Moreover, all these studies, except for Xiao (2008) and Carranza (2008) (who uses resolution and zoom), use only one characteristic of digital camera—image resolution. Our data of prices and sales is from the same source as used by all of these authors (except, perhaps, for Carranza who does not state the source) but supplemented with more characteristics of cameras.

## 3. Model Specification

### *3.1 The demand side*

Suppose there are $J^t$ distinct camera models marketed in period *t*, and each model is indexed by $j = 1, 2, ..., J^t$. Suppose further that there are $I^t$ consumers/households in market *t* and the utility of household $i \in I^t$ achieving from consuming model *j* is

$$U_{i,j}^t = -\alpha p_j^t + \sum_{k=1}^{K} \beta_k x_{j,k} + \beta_{age} x_{j,age}^t + \xi_j + \varepsilon_{i,j}\,, \tag{1}$$

where $p_j^t$ is the price of camera model *j* in period *t*, $x_{j,k}$ is its quality measure of observable characteristic *k* (*k* = 1, 2, …, *K*, including brand dummy), $x_{j,age}^t$ is the camera's age—the time between its first introduction and *t*, $\xi_j$ is product-specific characteristics observable to consumers but unobservable or immeasurable to researchers, and $\varepsilon_{i,j}$ represents the idiosyncratic shock to utility. The coefficients $\alpha$, $\beta_k$ and $\beta_{age}$ in (1) measure the marginal (dis)utility of price, characteristic *k* and age. Denote $\delta_j^t$ as the mean utility of model *j* at time *t*:

$$\delta_j^t \equiv \sum_{k=1}^{K} \beta_k x_{j,k} + \beta_{age} x_{j,age}^t + \xi_j . \tag{2}$$

Of course, consumers are not forced to buy a camera and they may opt not to enter into the market; i.e., there is an outside option, indexed by $j = 0$. The utility of the outside choice is:

$$U_{i,0}^t = \delta_0^t + \varepsilon_{i,0} . \tag{3}$$

The mean utility of the outside alternative $\delta_0^t$ is not well defined without further assumptions so we normalize it to be zero. If the additive structural term $\varepsilon_{i,j}$ ($j$ = 0, 1, …, $J^t$) follows the type-I extreme value distribution, the market share of model $j$ can be determined by

$$s_j^t = \frac{\exp\left( -\alpha p_j^t + \sum_{k=1}^{K} \beta_k x_{j,k} + \beta_{age} x_{j,age}^t + \xi_j \right)}{1 + \sum_{l=1}^{J^t} \exp\left( -\alpha p_l^t + \sum_{k=1}^{K} \beta_k x_{l,k} + \beta_{age} x_{l,age}^t + \xi_l \right)}, \qquad j = 1, 2, ..., J^t \tag{4}$$

$$s_0^t = \frac{1}{1 + \sum_{l=1}^{J^t} \exp\left( -\alpha p_l^t + \sum_{k=1}^{K} \beta_k x_{l,k} + \beta_{age} x_{l,age}^t + \xi_l \right)} . \tag{5}$$

This logit demand structure not only provides a closed-form of market shares but also facilitates the use of ordinary least squares to estimate the coefficients in utility function (1). The results reported in Subsection 6.1 are based on the following regression equation

$$\ln(s_j^t) - \ln(s_0^t) = -\alpha p_j^t + \sum_{k=1}^{K} \beta_k x_{j,k} + \beta_{age} x_{j,age}^t + \xi_j . \tag{6}$$

However, utility specification (1) ignores the income effect. It is also subject to the problem of the IIA property, as well discussed in the discrete choice literature.[5] Define $v^t = (y_i^t, v_{i,1}, v_{i,2}, ..., v_{i,K}, v_{i,age})$ to depict a consumer's characteristics, representing idiosyncratic variations from population means, $\beta_k$ and $\beta_{age}$ , and income, $y_i^t$ . The extent of the taste variations around their means is measured by $\sigma_k$ and $\sigma_{age}$, respectively. The consumer's utility function is now given by:

[5] The IIA property implies that own-price elasticity is almost proportional to own price and the cross-price elasticity depends only on the substitute's price and market share. See Nevo (2000a) for a review.

$$U_{i,j}^{t} = \alpha \ln(y_i^t - p_j^t) + \sum_{k=1}^{K} (\beta_k + \sigma_k v_{i,k}) x_{j,k} + (\beta_{age} + \sigma_{age} v_{i,age}) x_{j,age}^{t} + \xi_j + \varepsilon_{i,j}. \tag{7}$$

The utility of the outside choice is given by

$$U_{i,0}^{t} = \alpha \ln(y_i^t) + \sigma_0 v_{i,0} + \xi_0 + \varepsilon_{i,0}^{t}. \tag{8}$$

Conditional on the realization of $v^t$, the probability of consumer $i$ choosing product $j$ out of choice set $J^t$ is:

$$\Pr_j(v^t) = \frac{\exp\left( \alpha \ln(y_i^t - p_j^t) + \sum_{k=1}^{K} (\beta_k + \sigma_k v_{i,k}) x_{j,k} + (\beta_{age} + \sigma_{age} v_{i,age}) x_{j,age}^{t} + \xi_j \right)}{1 + \sum_{l=1}^{J^t} \exp\left( \alpha \ln(y_i^t - p_l^t) + \sum_{k=1}^{K} (\beta_k + \sigma_k v_{i,k}) x_{l,k} + (\beta_{age} + \sigma_{age} v_{i,age}) x_{l,age}^{t} + \xi_l \right)}. \tag{9}$$

Given the joint probability density function $P(v^t)$, the aggregated probability of consumers choosing camera model *j*, or the market share of model *j* is obtained by integration:

$$s_j(p^t, x^t, \xi; \alpha, \beta, \sigma) = \int \Pr_j(v^t) P(v^t) dv^t, \tag{10}$$

where $p^t$ is the price vector, $x^t$ represents the collection of all observable characteristics and ages $(x_{j,1}, ..., x_{j,K}, x_{j,age}^t, j = 1, ..., J^t)$, $\beta$ and $\sigma$ are the collections of all beta and sigma parameters, $\xi$ is the vector of all unobservable characteristics, which will form the error term required for the GMM estimator.

### 3.2 *The Supply Side*

The production of product *j* incurs a constant marginal cost $mc_j^t$. For a multi-product firm, *f*, the profit at period *t* can be expressed as:

$$\Pi_f = \sum_{j \in J_f^t} (p_j^t - mc_j^t) T^t s_j(p^t, x^t, \xi),$$

where $T^t$ is the aggregate market size in market (time) *t* and $J_f^t$ is the product set of firm *f*. The first-order condition for profit maximization implies that,

$$s_j(p^t, x^t, \xi) + \sum_{l \in J_f^t} (p_l^t - mc_l^t) \frac{\partial s_l(p^t, x^t, \xi)}{\partial p_j^t} = 0, \qquad j = 1, 2, ..., J^t. \tag{11}$$

Define a $J^t \times J^t$ matrix $\Delta(p^t, x^t, \xi)$, where each element in the matrix is given by

$$\varDelta_{j,l}(p^t,x^t,\xi)=\begin{cases}\dfrac{-\partial s_l(p^t,x^t,\xi)}{\partial p_j^t}, & l,j\in J_f^t\\ 0, & \text{otherwise}\end{cases}.$$

The $J^t$ first-order conditions can be written as:

$$s(p^t,x^t,\xi)-(p^t-mc^t)\Delta(p^t,x^t,\xi)=0. \tag{12}$$

Rewriting the above equation, the price of each product in market $t$ is equal to the sum of marginal cost and markup:

$$p^t=mc^t+\varDelta(p^t,x^t,\xi)^{-1}s(p^t,x^t,\xi). \tag{13}$$

In the empirical analysis, the markup term $\Delta(\cdot)^{-1}s(\cdot)$ is estimated jointly with the demand side equations. For marginal cost, a hedonic cost function is defined, which relates the marginal cost of a product to a set of broadly available quality measures, $\chi_j$, a time trend, *t,* to control for technological progress, and unobservable cost characteristics, $\varpi_j$,

$$\ln(mc_j^t)=\gamma\chi_j+\lambda_f t+\varpi_j, \qquad j\in J_f^t, \tag{14}$$

where $\gamma$ is a vector of coefficients measuring the marginal effect of a particular observable characteristic on the logarithm of the product's marginal cost. The observable part of characteristics $\chi_j$ can include part or all of those included in the demand equations, $x_j$. From (12) and (14), we can write a supply side moment condition:

$$\varpi=\ln(p^t-\varDelta(p^t,x^t,\xi)^{-1}s(p^t,x^t,\xi))-\gamma\chi-\lambda t. \tag{15}$$

The cost side moment condition given by (15) is used jointly with the demand side condition to generate the objective function in the GMM estimation routine. By minimizing the GMM objective function, estimates for both demand and supply equations are derived simultaneously as shown in the next section.

## 4. Instruments and Estimation Procedure

### *4.1 Appropriate Instruments*

There are three variables for which there are potential endogeneity problems. First, the disturbances $\xi_j$ in (6) or (10) and $\varpi_j$ in (15) are correlated with price $p_j^t$ because, as is modeled, the price is chosen by the firm knowing the value of the unobservable characteristics. Second, though we do not model this explicitly, it is clear that the age of a product, i.e. how long the product has been in the market, is potentially influenced by unobservable characteristics. Finally, it has often been argued in the hedonics literature that the weight of a product also proxies for unobserved features which, when included, increase the weight of a product. Hence we also treat the weight variable as potentially correlated with the unobservable characteristics of the products.

The instrumental variable technique is a conventional solution to solve this kind of endogeneity problem. In cases where only aggregated product level sales data are available, the data generated BLP-type instruments are the usual option to control for the endogeneity problem. The instruments for the price of product *j* produced by firm *f* include some characteristics of model *j*, the sums of characteristics of all other products produced by firm *f* and the sums of those that are produced by all other firms excluding *f*. In other words, for each camera model $j \in F_f^t$, $z_{j,k}^t$, $\sum_{l \neq j, l \in F_f} z_{l,k}^t$ and $\sum_{l \notin F_f} z_{l,k}^t$ are calculated separately for each characteristic $k$ that is orthogonal to $\xi_j$ or $\varpi_j$ and are used as instrument variables for the price of model $j$.

We supplement the BLP-type instruments with some new instruments. We include two measures of the number of products in the market (with suitable deletions to avoid the collinearity problem) - the number of products offered by the firm and the number of products offered by their competitors. On the demand side, the change in the number of available options can affect the probability of a consumer purchasing a particular model (Ackerberg and Rysman (2005) make a related argument). On the supply side, the numbers of products provided by the single firm and that produced by all other firms affect pricing strategies since firms have to set appropriate prices simultaneously for all their products.

Furthermore, due to fast technological progress, appropriate instruments should be constructed by using the observations within the associated market (period) that each observation is drawn from, rather than using all information over different time periods. This treatment also reflects the feature that price-setting strategies in oligopoly are often time specific and consumers adjust their preference rankings over time. The time superscript *t* in the instruments indicates that only observations in market *t*, constructed by interacting each variable with time-dummies, are used to generate the BLP-type instruments for price $p_j^t$.

## 4.2 Estimation Procedure

The coefficients in the logit demand equation (6) can be estimated by OLS or 2SLS controlling for the endogeneity of price. For the random coefficient logit model, simulation estimation is required. Since BLP, the required steps have been presented in various forms from Nevo (2001) to Ackerberg et al (2007). We briefly review the steps of the algorithm

First we simulate the market share for camera *j*:

$$s_j^{ns}(\delta^t, x^t; \alpha, \beta, \sigma) = \frac{1}{ns}\sum_{i=1}^{ns} \frac{\exp[\delta_j^t + \alpha \ln(y_i^t - p_j^t) + \sum_k \sigma_k x_{j,k} v_{ik} + \sigma_{age} x_{j,age}^t v_{i,age}]}{1 + \sum_{l=1}^{J} \exp\left[\delta_l^t + \alpha \ln(y_i^t - p_l^t) + \sum_k \sigma_k x_{l,k} v_{l,k} + \sigma_{age} x_{l,age}^t v_{i,age}\right]}, \quad (16)$$

where $(y_i^t, v_{i,1}, ..., v_{i,K}, v_{i,age})$ are obtained by drawing a sample of *ns* draws from the consumer population distribution $P(v^t)$ and an initial estimate of $\delta_j^t$ is obtained from the logit model. Berry (1994) and BLP show that the set of market mean utilities, $\delta_j^t$, that set the simulated market share equal to the actual market shares can be recovered using a contraction mapping operator which takes the form of following recursive algorithm:

$$\delta_j^t =: \delta_j^t + \ln(S_j^t) - \ln(s_j^{ns}(\delta^t, x^t; \alpha, \beta, \sigma)), \quad (17)$$

where $S_j^t$ is the observed market share of camera *j*. Upon the completion of calculating this set of $\delta_j^t$, we can use equations (2) and (15) to compile the error terms required for GMM. Define

$\omega \equiv \{\xi, \varpi\}$ and $z \equiv \{z_1, z_2\}$, where $z$ are the instruments we have mentioned in the previous subsection. If the true values of the model parameters, $\theta^*$, are known, the orthogonality condition between unobservable characteristics and instruments is that $E[z'\omega(\theta^*)] = 0$. Accordingly, the GMM parameter estimates ($\hat{\theta}$) are obtained by minimizing the following objective function:

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \omega(\theta)' z \Phi^{-1} z' \omega(\theta), \tag{18}$$

where $\theta$ includes all parameters of the model, $\alpha, \beta_k, \beta_{age}, \sigma, \gamma$ and $\lambda$. In the above objective function, $\Phi^{-1}$ is a weight matrix, which is computed as the inverse of the variance-covariance matrix of the moments. The Nelder-Mead (1965) non-derivative "simplex" search method is utilized to search over all possible parameter values in the parameter space $\Theta$. Some recent papers raise questions on the computational practices when performing simulation estimation in the BLP framework (e.g., Dube et al. 2008, Knittel and Metaxoglou 2008), particularly, the "nested fixed point" procedure involved in the contraction mapping technique. As a start on minimizing the vulnerability of our results to computational concerns, this paper estimates the parameters for the differentiated product demand models, with and without the control for product age, using the same starting values and same stopping criteria. We also use a stricter convergence criterion than BLP (1.0E-8) and do not have to resort to loosening the criterion to achieve convergence.

## 5. Data statistics

### *5.1 Data on Sales and Quality Measures*

Data on digital camera prices and sales volumes were purchased from NPD Market Research, a US market research company – the same source as used by Song and Chingtahua (2003), Zhao (2007) and Xiao (2008). This data set includes monthly prices and sales quantities at the camera model level, covering the period from January 2003 to May 2006. The reported prices and sales are nation-wide, accounting for more than 80% of the US digital camera market.

No information on geographically separated markets is observed. The original NPD dataset also lists a number of quality measures for most digital camera models. But they are quite brief and do not meet our requirements. To get a clearer picture for each model, the data on product characteristics are supplemented with much more detailed specifications through extensive web searching. In the final dataset, each camera is defined more accurately by: the type of digital camera (Single-Lens-Reflex (SLR), SLR-alike, Point-and-Shoot (P&S)), the exact number of mega pixels of image resolution, the size of LCD screen, the numbers of optical and digital zoom ranges, the size of camera (three-dimension measures), the weight of camera, etc. The structural estimation focuses on point-and-shoot digital cameras manufactured by top six brands (Canon, Fujifilm, Kodak, Nikon, Olympus and Sony).[6] This comes to a total of 4253 model/month observations, representing 351 distinct models.

Table 1 summarizes the sales of the top six brands during the sample period. In general, the combined sales volume of P&S digital cameras from the top six brands exceeds 32 million units, taking up more than 83% of the entire US P&S market. Three leading brands represent nearly 60% of the market, indicating a highly concentrated market.

Table 1 is about here

The sales of digital cameras grew significantly during the sample period, as demonstrated clearly by Figure 1. For instance, the total sales were below 0.3 million units in January 2003 but it doubled to about 0.59 million units in the same period three years later. Along with the general upward trend in sales, there is a significant seasonal effect. For the three Christmas seasons included in the data set, P&S camera sales in each December was approximately three (five) times of that in the November (October) before, illustrating that the Christmas sales are extremely important for the digital camera industry. Unlike the growth in sales, digital cameras'

[6] More details on data collection and statistics are provided in the Appendix. It also offers a justification for choosing the top six brands for the analysis.

prices declined considerably over the sample period. The mean price in the beginning of 2003 was around US$360 per unit, and ended up at around $250 in May 2006.

Figure 1 is about here

The variables that enter the demand and supply estimation include product characteristics, age, time (month) dummies as well as brand dummies. There are six product characteristics in the analysis: image resolution, optical zoom rang of lens, the size of LCD screen, size and weight of camera, and digital zoom. While the first five are continuous variables, the last is a dummy variable with 1 indicating a camera has a digital zoom and 0 indicating no digital zoom. The volume weighted average characteristics and age for selected months are reported in Table 2. On average, camera models included in the sample featured a 4.2 mega pixel resolution, 3 times optical zoom range and 1.8 inch LCD screen. The average size and weight from January 2003 to May 2006 were 14.77 in.$^3$ and 6.8 oz., respectively.

Table 2 is about here

Table 2 demonstrates an overall upward trend in the characteristics of resolution, LCD and optical zoom. The average resolution, LCD size and the optical zoom range increased by approximately 99%, 25% and 29%, respectively, in the sample period. However, camera size and weight fell continuously until the end of sample period. The two measures started at 24.56 in.$^3$ in size and 9.86 oz. in weight and then dropped dramatically to less than or nearly a half of their initial values, reaching 11.33 in.$^3$ and 5.49 oz. respectively. A clear picture of the time trends of all these features can be seen in Figures 2a and 2b.

Figures 2a and 2b are about here

## *5.2 The Age Variable*

Apart from product quality, the demand for each particular option is also determined by the age factor. For each camera model, its age is measured as the time elapsed (in month) since the model was launched. For all models that had been introduced into the market before the beginning of the sample period, their actual introduction dates are collected by searching web resources, based upon which ages are calculated. As Table 2 shows, sales weighted age generally declined during the sample period, although the reported statistics varied dramatically from time to time. The highest age was 11.36 months which appeared in February 2004 (See Figure 2b) while the lowest was only 6.55 months and appeared in May 2006.

Figure 3 illustrates average price and sales of the US digital cameras, where observations of the top six brands over the 41-month sample period are grouped by their ages. It reveals that the mean price exhibits a sharp downward trend as cameras get older until they reach their age of 20 months. However, beyond that age, the mean price trends up. Examining our sample data, it shows that cameras which survived longer than two years were usually high-end products. They were initially priced well above five hundred dollars when they were introduced to the market. Even after nearly two years of declining prices, their prices were still higher than those of new low-end entrants. Hence, the age groups older than 20 months have a higher mean price.

Figure 3 is about here

Along with the falling prices, sales exhibit, to certain extent, a bell-shaped life pattern (see Figure 3). In particular, after the introduction of a new model, the sales volume climbs up quickly until it reaches a certain high level, and this sales level would be maintained for about half a year. Very interestingly, there is a huge jump of average sales at the age of 10 months more than 30% greater than that at any other age.[7] After the volume peaks, sales drop continuously until extinction, although prices fall persistently. Most digital camera models had a relatively significant level of sales for less than two years. Beyond this age, the average sales

[7] The "PMA International Convention and Trade Show" is held annually in the end of February or early March. This is an important time for most digital camera producers to release new camera models or other information regarding technology advance in digital photographing. This is probably the key factor that results in a large increase of average model level sales at the age of 10, when many models face their first Christmas season after introduction.

volume becomes negligible. Very few P&S digital cameras survive in the US market for more than three years after their introduction.

## 6. Estimation Results

### *6.1 Results from the Logit Demand Model*

Although the focus of this paper is on the random coefficient structural model, estimation results from the logit model are reported in Table 3,[8] where each column lists the estimated parameters and the standard errors, distinguished by whether the utility function includes the age variable or not and whether OLS regression or two-step least squares (2SLS) estimation is adopted. As we can see, the results are generally satisfactory in the sense that all characteristic variables in the models are highly significant. Using OLS or 2SLS does not yield substantial differences in the coefficient estimates, but including age causes substantial changes in the estimates. The improvement by the introduction of age variable is also demonstrated, for OLS, by the changes in $R^2$ and adjusted $R^2$ statistics.

Table 3 is about here

The price coefficient estimates documented in Table 3 are all significantly negative across four different settings. However, the absolute value of the price coefficient from the 2SLS estimates in Column (4) is only one third of its counterpart where age is omitted. The significantly negative parameter estimates for age indicate that the marginal value or consumers' willingness-to-pay for a particular product generally falls as it gets older. The coefficients on resolution, LCD, optical zoom and digital zoom are all of the expected positive sign. In comparison with their counterparts in Columns in (1) and (3), the OLS estimate of the marginal value of resolution in Column (2) is reduced by more than two thirds, and the 2SLS estimate in

[8] The results of time dummies are not listed for the sake of space.

Column (4) is small and insignificantly different from zero. The 2SLS estimates of marginal values for LCD and optical zoom all drop considerably by more than 50%.

The specifications reported in columns (1) and (3), which do not include age, return significantly positive coefficients on camera size. This suggests that consumers prefer large to small cameras. However, this result contradicts the trend to miniaturization in digital camera (and other electronic device) markets, in which manufacturers produce smaller and smaller cameras. Note that using the BLP-type instruments to control for endogeneity in column (3) does not alter this result. In the specifications, reported in columns (2) and (4), which include age, the coefficients on camera size shrink substantially. For the 2SLS results, size has a negative coefficient, albeit insignificantly different from zero.

Also note that the coefficients on weight under both OLS and 2SLS in Columns (1) and (3) are significantly negative, implying that consumers dislike heavier cameras. Interestingly though, after including the age variable, the magnitude of coefficient estimates for weight also drops dramatically, remaining negative, but not significantly different from zero, in the 2SLS results.

Since the logit model imposes that all consumers have identical marginal valuations of product characteristics and age, it fails to account for consumer heterogeneity in preferences. In terms of the size of digital camera, for example, some amateur consumers may prefer smaller devices for their portability when traveling, while others may like relatively larger cameras which are easier to hold or are more professional looking. To find out a more accurate picture, a random coefficient structural model is estimated below. The random coefficients together with the age variable can resolve the counterintuitive predictions from the logit model.

### *6.2 Results from the Random Coefficient Structural Model*

Table 4 reports the estimated demand parameters from the structural model with a random coefficients specification, with and without the ageing effect. The left columns list parameter estimates and the right columns report the standard errors. In general, both price coefficients and mean parameters associated with characteristics (except for LCD screen size) in the demand model are significantly different from zero. As expected, the marginal utility of age reported under Column (2) is strongly significant with mean -0.2253, suggesting that the older is the camera in the market, the less are consumers willing to pay for it. Comparing the estimation results derived from the two models, the reported marginal value of income is 0.6707 without age and only 0.3240 after age is included. Similarly, the magnitude of the mean coefficients of resolution, LCD screen and optical zoom range all become considerably smaller after the age variable is included. This suggests that when the age variable is omitted in the demand model, the ageing effect is then captured partially by other variables, leading to upwardly biased estimates of the coefficients on prices and other characteristics. The parameters for LCD screen are insignificant for both models. This may reflect the divergence of preferences and when the LCD screen reaches certain size photographers seem not to pursue a larger LCD screen.

Table 4 is about here

Surprisingly, for weight and size, the two models yield substantial differences in the estimated mean parameters. As Column (1) shows, the mean coefficient of size is insignificantly positive (0.093) and that of weight is significantly negative (-0.2799). These results may be interpreted as that the size of a camera is a marginally desired feature to consumers but not the weight. The prediction for size effect in column (1) seems not completely sensible, because the majority of P&S camera consumers are amateur photographers who are more likely to choose a smaller camera, other things being equal. However, when age is incorporated into the model, the marginal value for size becomes significantly negative (-0.2577). This correction makes the estimate more consistent with the common perception and the move by manufacturers to produce smaller cameras. In column (2) the effect of weight is positive and insignificantly different from zero.

The coefficients on the brand dummies measure consumers' subjective value on each brand of digital cameras. The brand dummy coefficients in Column (1), range from -1.2 to 0.73, which is much wider than those in Column (2), ranging from -0.82 to 0.53. The estimates from both models show that consumers, on average, prefer Sony and Canon to other brands, while Fujifilm is the least favored brand. The coefficient on the Nikon brand dummy is statistically insignificant in both random coefficients models

The lower part of Table 4 demonstrates that there exists substantial variation in the marginal value of some camera features, suggesting that we can reject the hypothesis that the random coefficient model is equivalent to the logit model. For instance, the standard deviations for LCD and size are strongly significant in Column (1), while after the age variable is introduced, the standard deviations for digital zoom and age become highly significant. On the other hand, consumers' preferences for resolution and optical zoom range seem relatively uniform, as the standard deviations of these coefficients do not differ significantly from zero. While not conclusive, these results are suggestive that dynamic models of the digital camera market that use a limited set of characteristics are potentially affected by omitted variable bias.

Results from estimating the marginal cost equations are reported in Table 5, based on the full random coefficient model. As shown in the table, except for digital zoom, all variables enter the cost side equations significantly at the 1% level. The coefficients on the log of resolution, optical zoom and the log of LCD size are all positive and highly significant.[9] This implies, the higher the value for these features, the more costly it is for firms to produce a camera. On the contrary, the cost of digital camera is negatively related to cameras' size, which suggests that smaller cameras can only produced at a higher marginal cost.

The parameters associated with log weight are positive and significantly different from zero. Thus, it is generally more costly for firms to produce cameras with more robust material and extra components, confirming that the weight signals some favored unobservable

[9] No logarithm of optical zoom range is taken because many cameras do not have optical zoom so that their zoom range is zero.

components or quality of a camera. This contradicts the result from random coefficients demand model without age, where, the weight is seen to be a disfavored characteristic. Also, the cost estimate for digital zoom without age is significantly negative (-0.485). It is inconsistent with the fact that only low-end and cheapest cameras are not featured with digital zoom range options during our sample period. The coefficient for digital zoom is still negative in Column (2), but it enters the cost function insignificantly different from zero.

Table 5 is about here

The estimated coefficients for brand dummies in Table 5 are much smaller when the ageing effect is considered. The magnitudes of parameters for the log of resolution and LCD also drop considerably after age is incorporated. Both trend parameters are negative, indicating a downward time trend in production costs. This is in accordance with the dramatic technological progress in the digital camera industry over the sampling period. Nevertheless, the result shows that the magnitude of the trend measure is 0.0204 in Column (1), and the scale falls substantially to 0.0122 after the age variable is included. This implies that the predicted reduction in production costs over time is much higher if the ageing effect is not accounted. This issue will be investigated further in Subsection 6.5.

### *6.3 The Ageing Effect and Age Elasticity*

As demonstrated by Figures 1 and 3, many camera models' prices dropped to below half of their initial prices within one to two years. For instance, Canon PowershotA520 was priced at \$293.13 in March 2005 when it was just launched but its price slipped down to \$147.00 in April 2006. Similarly, the price of Kodak CX7430 dropped from \$272.53 when it entered into the market in February 2004 to only \$110.14 two years later. Given the durable nature and affordability of P&S cameras, consumers could buy their preferred products soon after introduction. However, forward-looking consumers, aware of the persistent downward trend of prices could choose to purchase the same item at different ages, depending on how they value the camera. In particular, earlier adopters purchase soon after products are launched and pay a relatively higher price because they have a higher reservation price. On the other hand, consumers with a lower willingness-to-pay choose to postpone their purchases because waiting means they can obtain the same product at a lower price. Hence, the time when a consumer chooses to buy an identical product directly reveals his idiosyncratic willingness-to-pay for the product. This is consistent with the estimation result reported in Table 3 earlier, in that the $R^2$ and adjusted $R^2$ rise considerably after bringing in the age variable into the logit demand model. Furthermore, the predicted mean coefficient in Table 4, from the random-coefficients model, for age is -0.2253 and is statistically significant at the 1% level. The estimated standard deviation for the age is also highly significant, indicating a substantial variation in the marginal value for age from its overall market mean. To see the effect of product ageing on demand more clearly, Figure 4 plots the estimated age elasticity of demand against age at the time of observation. Obviously, there is an overall downward trend in the predicted elasticity, which means the demand becomes more sensitive to the age when a camera gets older.

Figure 4 is about here

*6.4 The Price Elasticity of Demand*

Turning to the price elasticity of demand, products with a short life cycle such as consumer electronics display quite different properties from products with a long life cycle. For the latter, the product-level price drop is often temporary and consumers response sensitively and significantly to a price shock. On the contrary, the response to a periodic price drop in consumer electronics is smaller and the demand for a particular product is quite sensitive to its age because of its short life cycle and the persistent downward price trend. Particularly, after a product is introduced into the market for a certain period, its sales volume declines continuously despite the fall in its price. Such sales pattern implies that the short life cycle of a product also influences purchasing decisions as well as firm’s strategies in pricing and product characteristics provision.

To investigate the price elasticity of demand more closely, we have calculated the elasticity using estimated data from the two random coefficient structural models, with and without the age variable.

Both Figures 5a and 5b have five panels to organize elasticities into five different age groups. Interestingly, Figure 5a displays quite different patterns from Figure 5b. Particularly, in Figure 5a, where no age variable is incorporated, the predicted price elasticity of demand is more or less independent of age, represented by similar patterns of the scatters across the five panels of different age groups. In Figure 5b, however, each of the five panels depicts a very different scatter from the others. Generally, the predicted elasticity is relatively small (in absolute term) when the product is young and it goes up gradually as the product gets older. For instance, within the first 6 months of introduction, the price elasticity is small and similar across the whole price range; almost no product is highly price elastic. Then, there are a few mid-range products whose price elasticities jump up during the next 6 months period (see panel titled 12). In the meantime, the price elasticities for most low- to mid-end cameras climb up slightly (in absolute term). In the third panel, where products age from 13 to 18 months, a lot more products become more price elastic, and on average the predicted elasticities for the low- to mid-end cameras increase. Such growth trend continues for older age groups. In the last panel, where observations are of 25 months or older, the number of products with a high price elasticity is larger despite a smaller number of total observations. These characteristics of price elasticity are also observable by the median belt plotted in the graphs. Figure 5b demonstrates that earlier buyers of a camera are much less price-sensitive than later purchasers, which seems to be consistent with conventional beliefs that impatient and price insensitive consumers enter the market early. Therefore, the inclusion of the age factor appears to effectively control for the variation in the consumer group that purchases each of the identical products.[10] Typically, higher-priced fresh and young

[10] It is hard to think of a supply side phenomenon which would generate this outcome.

products are more likely to be purchased by price insensitive consumers with a higher willingness-to-pay. Out-dated models, even with extensive price reductions, are likely to be attractive mostly to more price-sensitive consumers. Since most empirical studies on the new durable products are based upon product-level data, the result of Figure 5b calls for the attention to the product-level dynamics associated with the timing of purchasing each identical product and its effect on the demand system, either through a dynamic model, or through a suitably adjusted static model.

Figures 5a and 5b are about here

To see the effects of price change on demand more clearly, Table 6a reports the own- and cross-price elasticity estimates from the random coefficients model for 15 randomly selected camera models marketed in May 2006, which is the last month of our sample period. The upper part of each row reports the own-price elasticity and the Sum of Cross-price Elasticities (SCE) without considering the ageing effect while the lower counterpart considers the ageing effect. The SCE depicts the overall effect of one percentage price rise of a product on the sales of all other products. The mean and median of both own-price elasticities and SCEs are of much larger magnitude than those predictions when the ageing effect is included and the difference tends to increase when prices get higher. The average of SCEs is 0.947, which is only more than half of that without the ageing effect. The variation pattern of SCE is similar to own-price elasticity. The semi-cross price elasticities of 15 selected products are reported in Table 6b, where semi-cross price elasticity measures the percentage change of sales of a product in each row in response to a $10 price increase of each column product.

Tables 6a and 6b are about here

*6.5 Measuring Market Power*

One application of the demand estimation is to use the estimated price elasticities to predict the firms' price-cost markups. Facing consumers with heterogeneous willingness-to-pay, firms are likely to inter-temporally price discriminate. By setting prices higher when products are just launched, firms can extract more profits from the consumers with high valuations. Then, they gradually reduce prices to make their products more affordable and appealing to those who are more price sensitive. To examine the issue, Figure 6 illustrates the observed prices and estimated markups of six top selling models within the sample period. Apparently, all six cameras in the figure exhibit a significant decline in their prices during their lifetimes. Furthermore, the markups predicted from both versions of the model (with and without age) also drops.

Figure 6 is about here

Nevertheless, the magnitudes of markups predicted from two structural models differ dramatically. The downward trends of markups estimated from the model excluding the age variable are much flatter than the decline of prices, indicating that there is very small change in profitability as the prices go down steeply. Therefore, the large drops of prices have to be mainly explained by savings from production costs. Take the Canon PowershotA520, for example. Its price drops from $293 to $147 one year after its introduction. The predicted markup for the product falls by less than $50.00, leaving a large proportion of price decrease to be explained by cost reduction. Numerically, this implies that the marginal cost of producing a Canon PowershotA520 falls from around $200 dollars to $100 dollars within one year. Similarly, when Nikon Coolpix320's price declines sharply from $280 to $130 over two years, its predicted markup drops by only $52 and the gap of $98 drop in prices would have to be attributed to the cost reduction as well. These results are consistent with the estimates of the cost trend reported in Table 5, where much faster speed in cost reduction is predicted when the age effect is omitted. However, they are hardly believable from a practical point of view.

After the ageing effect is incorporated into the regression model, the predicted markups in Figure 6 show very similar downward patterns to those of prices, and the change in the gap between price and price-cost markup is much smaller as time passes, consistent with the predictions of a model of inter-temporal price discrimination. When the price of each product falls, a product’s markup shrinks a lot more than the cost reduction. Comparing the markups predicted by two regression models, the difference between them is the largest when a product is just launched. Towards the end of a product’s life, the two predictions have little difference. Hence, ignoring the ageing effect is likely to result in a significantly underestimated markup and an overestimated marginal cost, during the early stages of a product’s life.

To see the relation between markup and age at firm level, Figure 7 plots each manufacturer’s average markup of its products for a given age. Evidently, the predicted markups without accounting for the ageing effect show quite small downward trends while mean prices fall significantly as products get older. On the contrary, the estimated markups decline quite steeply after incorporating the ageing effect and it seems more plausible. On average, the predicted markups are about 35% smaller if the age variable is excluded. The extent of underestimation, up to more than 70%, appears to be the greatest when products are very young.

Figure 7 is about here

## 7. Concluding Remarks

This study estimates a structural model of demand and supply for the US digital camera market, where there is considerable product turnover and prices have dropped significantly and persistently over time. Forward-looking consumers expect the price to fall and choose an optimal time to enter the market. While most recent studies modeling such dynamics in the demand for new durable products use a dynamic programming approach, this is at the cost, due to computational constraints, of more restrictive assumptions and limitations on the data used. This paper analyzes the dynamic issue using a simple adaptation of the standard static structural model. This enables including a rich set of characteristics and a flexible specification of the heterogeneity of consumers, as reflected by allowing randomness in the coefficients of more characteristics. The coefficient on age can be interpreted as tracking the evolution of the changing consumer mix associated with firms inter-temporally price discriminating. Hence, the purchase time associated with each particular camera directly reveals consumers' willingness-to-pay. Alternatively, the age variable can also control for supply side dynamics in, for example, advertising. We find introducing the age variable overcomes the problems identified for the static demand models, by yielding more reasonable coefficient estimates and markups. Furthermore, our results suggest the consequences of ignoring the ageing effect are substantial with over-estimates of price elasticities, technological progress and underestimates of markups. Our approach is relatively easy to implement, with a significantly reduced computational burden. It is suitable for applications where allowing for rich patterns of substitution are more important than controlling explicitly for inter-temporal choice, or as a first step in estimating a full dynamic differentiated product demand system.

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**Table 1. Sales and market share of the top six brands in the US P&S market**

| Brand | Observations | Units | Market Share within Six Brands | Overall Market Share |
|---|---|---|---|---|
| CANON | 924 | 8,508,226 | 25.91% | 21.71% |
| SONY | 946 | 7,677,646 | 23.38% | 19.59% |
| KODAK | 695 | 6,711,926 | 20.44% | 17.13% |
| OLYMPUS | 761 | 4,064,932 | 12.38% | 10.37% |
| NIKON | 470 | 3,615,261 | 11.01% | 9.23% |
| FUJIFILM | 457 | 2,256,409 | 6.87% | 5.76% |
| **Total** | **4253** | **32,834,400** | **100.00%** | **83.79%** |

Source: NPD Market Research Company. The reported sales for each brand is the sum over a 41-month period from January 2003 to May 2006. The sales volume of the overall market is calculated upon observations of all P&S cameras by 46 brands listed in the original dataset, which takes up above 80% of overall sales in the US market during this period.

**Table 2. Product characteristics of P&S cameras**

| Time | Resolution (MP) | Optical Zoom | LCD (Inch) | Size (Inch^3) | Weight (Oz) | Age (Months) |
|---|---|---|---|---|---|---|
| **All Observations** | | | | | | |
| | 4.20 | 3.03 | 1.80 | 14.77 | 6.80 | 8.31 |
| **Monthly Observations** | | | | | | |
| 200301 | 2.81 | 2.72 | 1.69 | 24.56 | 9.65 | 9.90 |
| 200307 | 3.30 | 2.87 | 1.60 | 18.61 | 8.19 | 8.01 |
| 200401 | 3.66 | 2.93 | 1.59 | 18.51 | 8.33 | 10.65 |
| 200407 | 3.86 | 3.03 | 1.70 | 15.21 | 7.17 | 7.53 |
| 200501 | 4.33 | 3.12 | 1.78 | 14.59 | 6.86 | 9.34 |
| 200507 | 4.66 | 3.34 | 1.92 | 13.07 | 6.29 | 7.40 |
| 200601 | 5.10 | 3.29 | 2.04 | 12.33 | 6.18 | 9.05 |
| 200605 | 5.59 | 3.41 | 2.19 | 11.33 | 5.49 | 6.55 |

All statistics reported in the table are the means of the characteristics of products weighted by their sales within each month.

**Table 3. Demand estimation results from the logit model**

| | OLS | | 2SLS | |
|---|---|---|---|---|
| **Variable** | **(1) Without Age** | **(2) With Age** | **(3) Without Age** | **(4) With Age** |
| Price | -0.0023* | -0.0024* | -0.0042* | -0.0014* |
| | (0.0003) | (0.0003) | (0.0008) | (0.0006) |
| Constant | -12.2940* | -11.4826* | -12.3054* | -11.4960* |
| | (0.2937) | (0.2728) | (0.2957) | (0.2740) |
| Resolution | 0.4430* | 0.1226* | 0.5534* | 0.0184 |
| | (0.0279) | (0.0284) | (0.0556) | (0.0454) |
| LCD | 0.4312* | 0.2572* | 0.5032* | 0.1761* |
| | (0.0838) | (0.0777) | (0.0908) | (0.0818) |
| Opt. Zoom | 0.2593* | 0.1606* | 0.2735* | 0.1264* |
| | (0.0175) | (0.0166) | (0.0197) | (0.0181) |
| Size | 0.5318* | 0.1023* | 0.4620* | -0.0338 |
| | (0.0581) | (0.0560) | (0.0629) | (0.0651) |
| Weight | -0.3399* | -0.0625* | -0.2916* | -0.0031 |
| | (0.0249) | (0.0252) | (0.0291) | (0.0310) |
| Dig. Zoom | 1.5882* | 1.8483* | 1.5548* | 1.8831* |
| | (0.2007) | (0.1855) | (0.2021) | (0.1863) |
| Age | - | -0.0906* | - | -0.0988* |
| | - | (0.0034) | - | (0.0035) |
| Canon | 0.2681* | 0.1114* | 0.3070* | 0.0385 |
| | (0.0507) | (0.0472) | (0.0556) | (0.0503) |
| Fujifilm | -0.8201* | -0.5834* | -0.8593* | -0.4976* |
| | (0.0746) | (0.0694) | (0.0785) | (0.0721) |
| Kodak | -0.0492 | -0.1307* | -0.1009 | -0.0813 |
| | (0.0585) | (0.0541) | (0.0642) | (0.0573) |
| Nikon | -0.3560* | -0.0923 | -0.2446* | -0.0796 |
| | (0.0747) | (0.0697) | (0.0851) | (0.0773) |
| Olympus | -0.4503* | -0.2350* | -0.4396* | -0.1790* |
| | (0.0559) | (0.0522) | (0.0566) | (0.0534) |
| Sony | 0.7096* | 0.5040* | 0.6646* | 0.4461* |
| | (0.0576) | (0.0537) | (0.0595) | (0.0566) |
| $R^2$ | 0.18 | 0.301 | - | - |
| Adjusted $R^2$ | 0.169 | 0.292 | - | - |

1. The standard errors are reported in parentheses below each parameter estimate.
2. * Coefficient significantly different from zero at the 1% level.
3. Time dummies are included in the estimation but their parameter estimates are not reported for the sake of space.

**Table 4. Demand estimates from the random coefficient model**

| Variables | Parameter Estimate | Standard Error | Parameter Estimate | Standard Error |
|---|---|---|---|---|
| | (1) Without Age | | (2) With Age | |
| ***Alpha: Term on Price*** | | | | |
| ln($y$-$p$) | 0.6707* | (0.0702) | 0.3240* | (0.1157) |
| ***Beta: Mean Coefficient*** | | | | |
| Constant | -8.0837* | (0.6283) | -7.4278* | (0.5955) |
| Resolution | 0.7970* | (0.0672) | 0.3825* | (0.1187) |
| LCD | 0.5038 | (0.4310) | 0.2472 | (0.1427) |
| Opt. Zoom | 0.4133* | (0.0201) | 0.2492* | (0.0297) |
| Size | 0.0930 | (0.1226) | -0.2577* | (0.1250) |
| Weight | -0.2799* | (0.0331) | 0.0232 | (0.0621) |
| Dig. Zoom | 1.4859* | (0.3142) | 1.5229* | (0.5736) |
| Age | - | - | -0.2253* | (0.0130) |
| Canon | 0.5201* | (0.0570) | 0.2401* | (0.0620) |
| Fujifilm | -1.2024* | (0.0797) | -0.8256* | (0.0879) |
| Kodak | -0.2639* | (0.0693) | -0.3068* | (0.0705) |
| Nikon | -0.1197 | (0.0819) | 0.0984 | (0.0861) |
| Olympus | -0.5003* | (0.0604) | -0.2324* | (0.0572) |
| Sony | 0.7287* | (0.0651) | 0.5277* | (0.0627) |
| ***Sigma: Standard deviation of Beta*** | | | | |
| Constant | 0.8375 | (0.6661) | 0.8424 | (1.1050) |
| Resolution | 0.0664 | (0.1497) | 0.0372 | (0.3615) |
| LCD | 1.0195* | (0.3029) | 0.2922 | (0.2031) |
| Opt. Zoom | 0.0256 | (0.0520) | 0.0052 | (0.0987) |
| Size | 0.2461* | (0.0701) | 0.1809 | (0.1037) |
| Weight | 0.0228 | (0.0227) | 0.0774 | (0.0529) |
| Dig. Zoom | 0.9169 | (1.0149) | 1.5235* | (0.5015) |
| Age | - | - | 0.0950* | (0.0058) |

1, The standard errors are reported in parentheses; * denotes the 1% significance level.
2, Time dummies are included in the estimation, but their estimates are not listed for the sake of space.

**Table 5. Cost estimation results from the random coefficients model**

| Variable | Parameter Estimates | Standard Error | Parameter Estimates | Standard Error |
|---|---|---|---|---|
| | (1) Without Age | | (2) With Age | |
| Canon | 3.0067* | (0.1201) | 1.7735* | (0.2125) |
| Fujifilm | 2.9557* | (0.1175) | 1.7951* | (0.2103) |
| Kodak | 2.9285* | (0.1164) | 1.7158* | (0.2132) |
| Nikon | 3.2716* | (0.1108) | 2.1474* | (0.2006) |
| Olympus | 3.0672* | (0.1147) | 1.9107* | (0.2120) |
| Sony | 2.8673* | (0.1239) | 1.6834* | (0.2218) |
| Ln(Resolution) | 0.6490* | (0.0322) | 0.4333* | (0.0958) |
| Ln(LCD) | 0.6113* | (0.0558) | 0.4187* | (0.0457) |
| Opt. Zoom | 0.0473* | (0.0073) | 0.0191* | (0.0084) |
| Ln(Size) | -0.5667* | (0.0300) | -0.6601* | (0.0394) |
| Ln(Weight) | 0.9598* | (0.0591) | 1.4230* | (0.0791) |
| Dig. Zoom | -0.4850* | (0.0765) | -0.0114 | (0.1618) |
| Trend | -0.0204* | (0.0010) | -0.0122* | (0.0019) |

The standard errors are reported in parentheses; * denotes significant at the 1% level.

**Table 6a. Own-price elasticity and the sum of cross-price elasticities**

| | Model | Price | Own-price elasticity | Sum of cross-price elasticity |
|---|---|---|---|---|
| (1) | OLYMPUS D425 | $74.07 | -0.965<br>**-0.714** | 0.558<br>**0.352** |
| (2) | KODAK C300 | $90.55 | -1.249<br>**-0.656** | 0.713<br>**0.255** |
| (3) | CANON PSA400 | $102.78 | -1.209<br>**-1.171** | 0.722<br>**0.467** |
| (4) | FUJIFI FINEPIXA400 | $135.29 | -1.873<br>**-2.175** | 1.085<br>**0.676** |
| (5) | NIKON COOLPIXL4 | $147.46 | -0.633<br>**-2.946** | 0.415<br>**0.950** |
| (6) | FUJIFI FINEPIXA500 | $155.38 | -2.428<br>**-2.181** | 1.333<br>**0.705** |
| (7) | NIKON COOLPIXL3 | $182.58 | -2.331<br>**-1.183** | 0.993<br>**0.741** |
| (8) | OLYMPU SP310 | $220.11 | -4.120<br>**-2.896** | 1.465<br>**1.311** |
| (9) | KODAK C340BD | $245.59 | -1.895<br>**-2.644** | 1.226<br>**1.306** |
| (10) | SONY DSCW70 | $292.03 | -2.659<br>**-4.367** | 1.657<br>**1.292** |
| (11) | OLYMPU STYLUS710 | $321.45 | -6.612<br>**-3.642** | 2.523<br>**1.283** |
| (12) | SONY DSCT9 | $389.65 | -7.569<br>**-3.431** | 2.618<br>**1.402** |
| (13) | FUJIFI FINEPIXE900 | $392.80 | -9.217<br>**-2.139** | 3.390<br>**0.960** |
| (14) | OLYMPU C7000 | $453.51 | -8.910<br>**-3.004** | 3.028<br>**1.396** |
| (15) | CANON PSS3IS | $485.00 | -9.275<br>**-2.603** | 3.734<br>**2.067** |
| | MARKET MEAN | | -3.531<br>**-2.581** | 1.615<br>**0.947** |
| | MARKET MEDIAN | | -2.885<br>**-2.179** | 1.465<br>**0.863** |
| | MARKET MINIMUM | | -12.347<br>**8.904** | 0.320<br>**2.202** |
| | MARKET MAXIMUM | | -0.425<br>**-0.438** | 4.427<br>**2.742** |

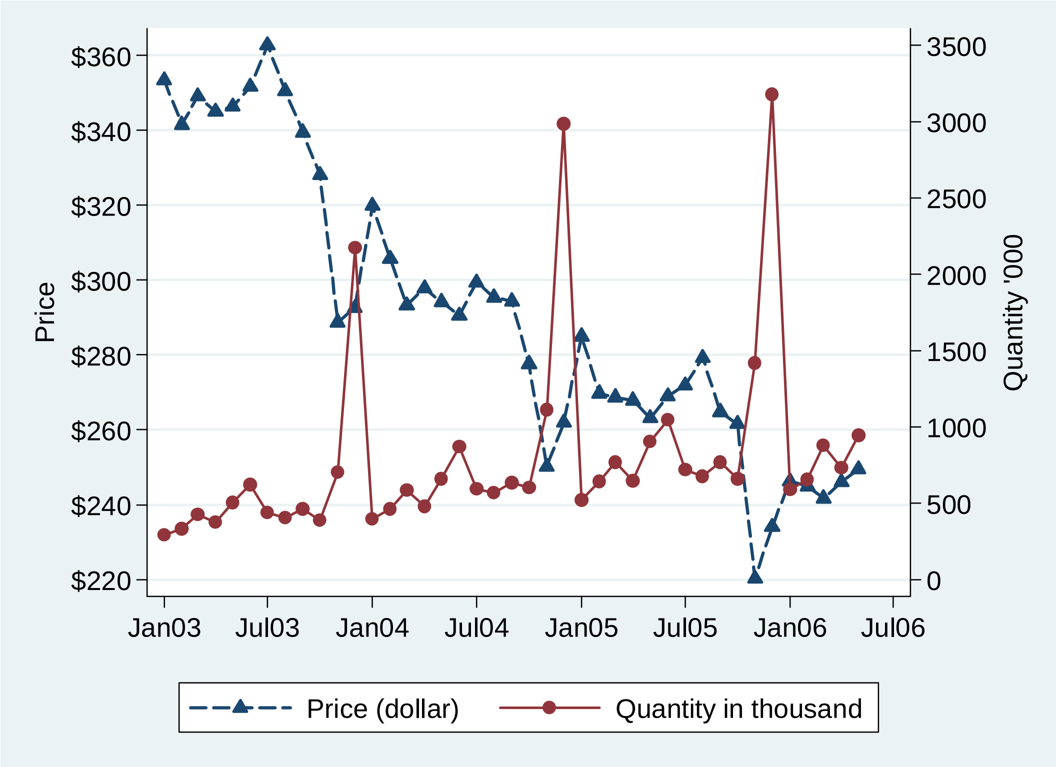
The upper entries in each row are elasticities when the ageing effect is excluded while the lower entries are elasticities when the ageing effect is included in the calculation.

## Table 6b: Semi-price elasticity

| | Model | Price | Semi-cross-price elasticity | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| (1) | OLYMPUS | 74.07 | -13.030 | 0.019 | 0.002 | 0.016 | 0.000 | 0.005 | 0.001 | 0.001 | 0.097 | 0.181 | 0.002 | 0.003 | 0.005 | 0.012 | 0.003 |
| | D425 | | **-9.646** | **0.063** | **0.038** | **0.003** | **0.005** | **0.107** | **0.006** | **0.015** | **0.015** | **0.157** | **0.014** | **0.069** | **0.005** | **0.001** | **0.058** |
| (2) | KODAK | 90.55 | 0.072 | -13.788 | 0.002 | 0.017 | 0.000 | 0.005 | 0.001 | 0.002 | 0.094 | 0.178 | 0.002 | 0.004 | 0.006 | 0.013 | 0.003 |
| | C300 | | **0.002** | **-7.245** | **0.010** | **0.001** | **0.000** | **0.027** | **0.000** | **0.001** | **0.001** | **0.042** | **0.006** | **0.039** | **0.008** | **0.001** | **0.001** |
| (3) | CANON | 102.78 | 0.065 | 0.017 | -11.759 | 0.015 | 0.000 | 0.004 | 0.001 | 0.001 | 0.101 | 0.182 | 0.002 | 0.003 | 0.004 | 0.010 | 0.002 |
| | PSA400 | | **0.008** | **0.080** | **-11.390** | **0.002** | **0.004** | **0.094** | **0.001** | **0.007** | **0.006** | **0.146** | **0.013** | **0.064** | **0.006** | **0.001** | **0.009** |
| (4) | FUJIFI | 135.29 | 0.072 | 0.019 | 0.002 | -13.844 | 0.000 | 0.005 | 0.001 | 0.002 | 0.093 | 0.177 | 0.002 | 0.004 | 0.006 | 0.013 | 0.003 |
| | FINEPIXA400 | | **0.007** | **0.066** | **0.034** | **-16.079** | **0.006** | **0.122** | **0.001** | **0.008** | **0.006** | **0.203** | **0.015** | **0.062** | **0.004** | **0.001** | **0.006** |
| (5) | NIKON | 147.46 | 0.020 | 0.005 | 0.001 | 0.005 | -4.294 | 0.001 | 0.000 | 0.000 | 0.070 | 0.099 | 0.000 | 0.001 | 0.001 | 0.002 | 0.000 |
| | COOLPIXL4 | | **0.016** | **0.048** | **0.060** | **0.006** | **-19.975** | **0.211** | **0.002** | **0.020** | **0.014** | **0.336** | **0.021** | **0.072** | **0.002** | **0.000** | **0.020** |
| (6) | FUJIFI | 155.38 | 0.077 | 0.021 | 0.002 | 0.018 | 0.000 | -15.623 | 0.001 | 0.002 | 0.086 | 0.172 | 0.003 | 0.005 | 0.007 | 0.015 | 0.003 |
| | FINEPIXA500 | | **0.007** | **0.069** | **0.031** | **0.003** | **0.005** | **-14.038** | **0.001** | **0.007** | **0.006** | **0.173** | **0.014** | **0.060** | **0.004** | **0.001** | **0.007** |
| (7) | NIKON | 182.58 | 0.044 | 0.011 | 0.001 | 0.010 | 0.000 | 0.003 | -12.766 | 0.001 | 0.062 | 0.115 | 0.001 | 0.003 | 0.004 | 0.011 | 0.002 |
| | COOLPIXL3 | | **0.021** | **0.053** | **0.025** | **0.001** | **0.003** | **0.063** | **-6.478** | **0.015** | **0.017** | **0.086** | **0.010** | **0.069** | **0.005** | **0.001** | **0.101** |
| (8) | OLYMPU | 220.11 | 0.050 | 0.014 | 0.001 | 0.013 | 0.000 | 0.004 | 0.001 | -18.719 | 0.046 | 0.098 | 0.002 | 0.005 | 0.007 | 0.016 | 0.003 |
| | SP310 | | **0.022** | **0.055** | **0.055** | **0.004** | **0.010** | **0.170** | **0.006** | **-13.156** | **0.020** | **0.254** | **0.018** | **0.078** | **0.003** | **0.001** | **0.066** |
| (9) | KODAK | 245.59 | 0.047 | 0.012 | 0.001 | 0.010 | 0.001 | 0.003 | 0.000 | 0.001 | -7.715 | 0.175 | 0.001 | 0.001 | 0.002 | 0.005 | 0.001 |
| | C340BD | | **0.023** | **0.056** | **0.046** | **0.003** | **0.007** | **0.136** | **0.007** | **0.021** | **-10.765** | **0.197** | **0.016** | **0.074** | **0.004** | **0.001** | **0.087** |
| (10) | SONY | 292.03 | 0.054 | 0.014 | 0.001 | 0.012 | 0.001 | 0.003 | 0.001 | 0.001 | 0.108 | -9.106 | 0.001 | 0.002 | 0.002 | 0.007 | 0.001 |
| | DSCW70 | | **0.006** | **0.067** | **0.029** | **0.003** | **0.004** | **0.106** | **0.001** | **0.007** | **0.005** | **-14.955** | **0.013** | **0.058** | **0.004** | **0.001** | **0.005** |
| (11) | OLYMPU | 321.45 | 0.061 | 0.017 | 0.001 | 0.015 | 0.000 | 0.005 | 0.001 | 0.002 | 0.048 | 0.108 | -20.569 | 0.006 | 0.009 | 0.019 | 0.004 |
| | STYLUS710 | | **0.005** | **0.079** | **0.022** | **0.002** | **0.002** | **0.071** | **0.001** | **0.004** | **0.003** | **0.115** | **-11.331** | **0.055** | **0.006** | **0.001** | **0.005** |
| (12) | SONY | 389.65 | 0.051 | 0.014 | 0.001 | 0.013 | 0.000 | 0.004 | 0.001 | 0.002 | 0.045 | 0.097 | 0.003 | -19.426 | 0.007 | 0.016 | 0.003 |
| | DSCT9 | | **0.004** | **0.086** | **0.018** | **0.001** | **0.001** | **0.051** | **0.001** | **0.003** | **0.003** | **0.080** | **0.009** | **-8.806** | **0.007** | **0.001** | **0.004** |
| (13) | FUJIFI | 392.80 | 0.066 | 0.019 | 0.001 | 0.017 | 0.000 | 0.006 | 0.001 | 0.003 | 0.044 | 0.104 | 0.004 | 0.006 | -23.465 | 0.021 | 0.005 |
| | FINEPIXE900 | | **0.001** | **0.082** | **0.008** | **0.000** | **0.000** | **0.018** | **0.000** | **0.001** | **0.001** | **0.028** | **0.004** | **0.033** | **-5.445** | **0.001** | **0.001** |
| (14) | OLYMPU | 453.51 | 0.051 | 0.014 | 0.001 | 0.013 | 0.000 | 0.004 | 0.001 | 0.002 | 0.044 | 0.096 | 0.003 | 0.005 | 0.007 | -19.647 | 0.003 |
| | C7000 | | **0.003** | **0.085** | **0.013** | **0.001** | **0.001** | **0.032** | **0.001** | **0.002** | **0.002** | **0.050** | **0.007** | **0.046** | **0.008** | **-6.624** | **0.003** |
| (15) | CANON | 485.00 | 0.060 | 0.017 | 0.001 | 0.015 | 0.000 | 0.005 | 0.001 | 0.002 | 0.052 | 0.113 | 0.003 | 0.005 | 0.008 | 0.018 | -19.123 |
| | PSS3IS | | **0.047** | **0.032** | **0.036** | **0.002** | **0.005** | **0.090** | **0.021** | **0.035** | **0.044** | **0.107** | **0.011** | **0.059** | **0.003** | **0.001** | **-5.368** |

The upper entries in each row are semi-price elasticities when the ageing effect is excluded while the lower entries are semi-price elasticities when the ageing effect is included in the calculation.

**Figure 1. P&S sales volume and price of top six brands**




Based on 4253 observations, covering all P&S cameras of top six brands (Canon, Fujifilm, Kodak, Nikon, Olympus and Sony). The sales figures plotted are the monthly sum. The prices are sales weighted average prices in US dollars.

**Figure 2a. Evolution of characteristics: resolution, optical zoom and LCD screen**

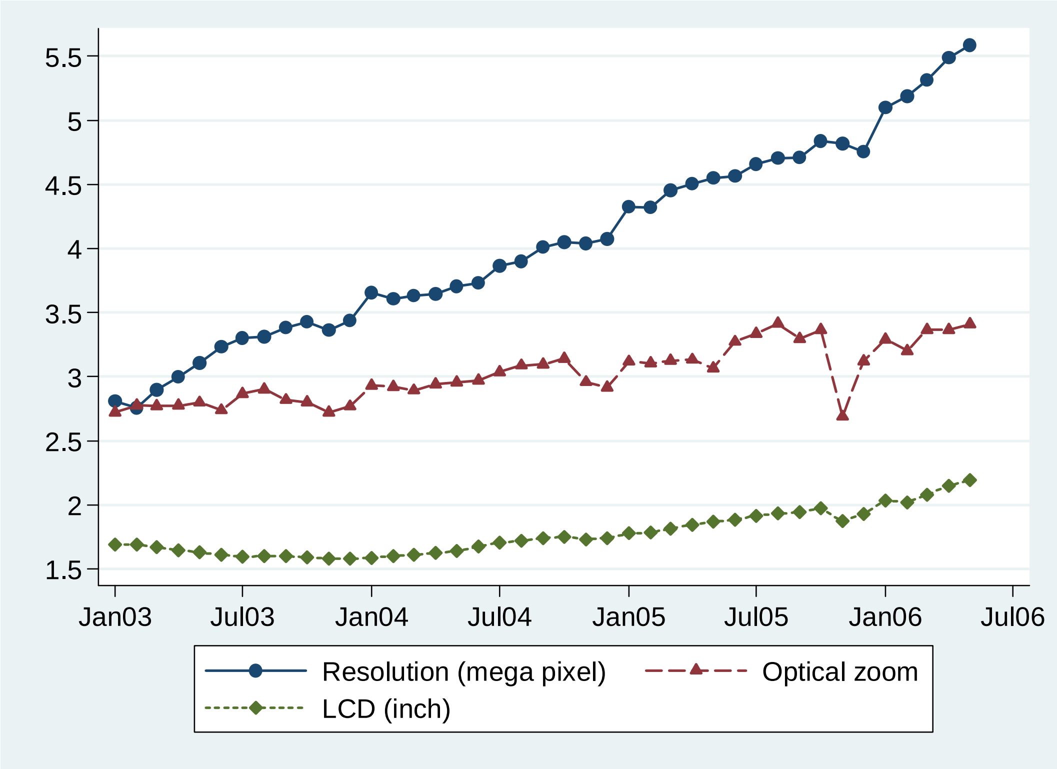



**Figure 2b. Evolution of camera characteristics: size, weight and age**

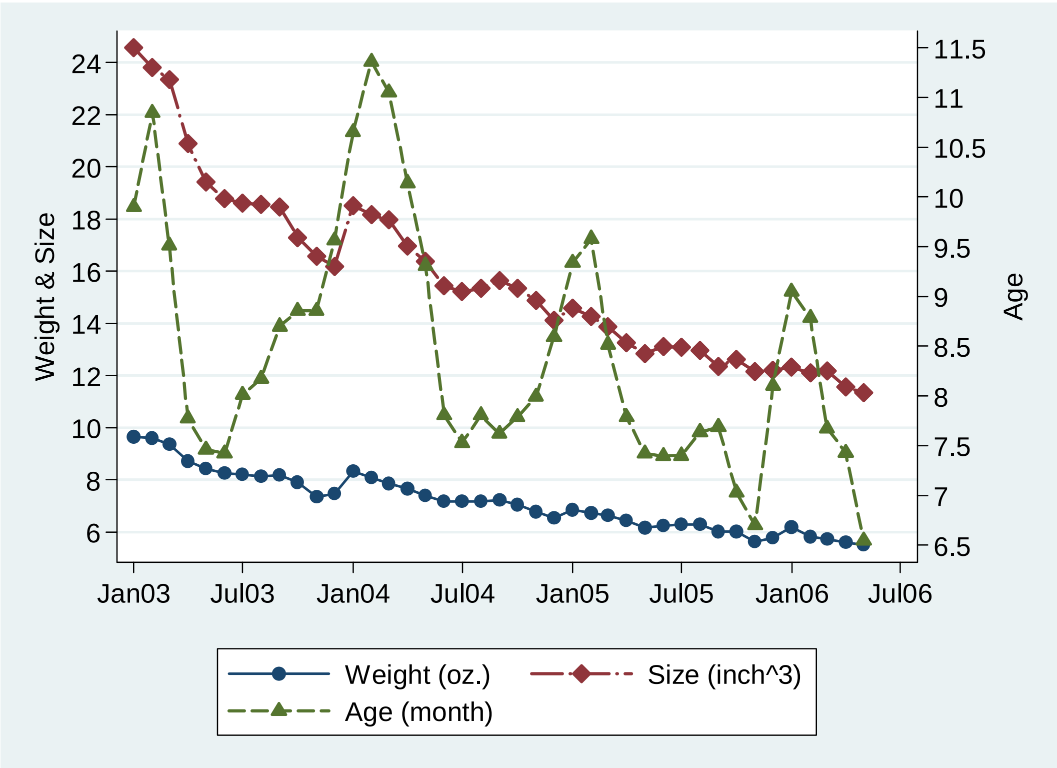
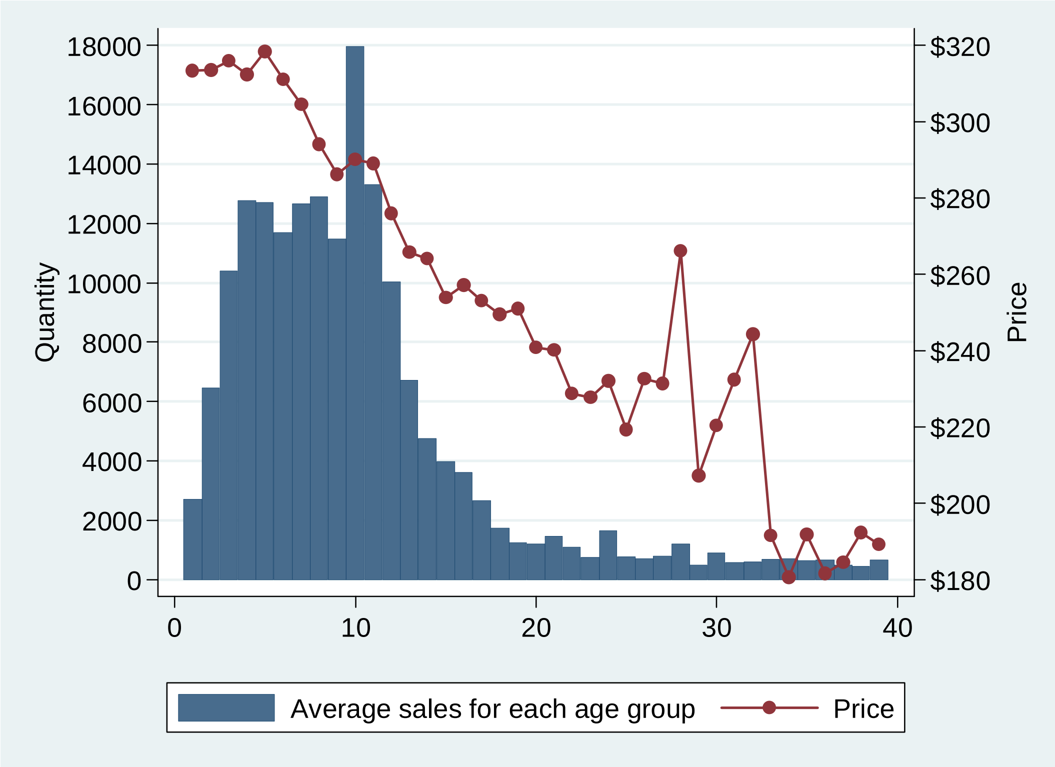
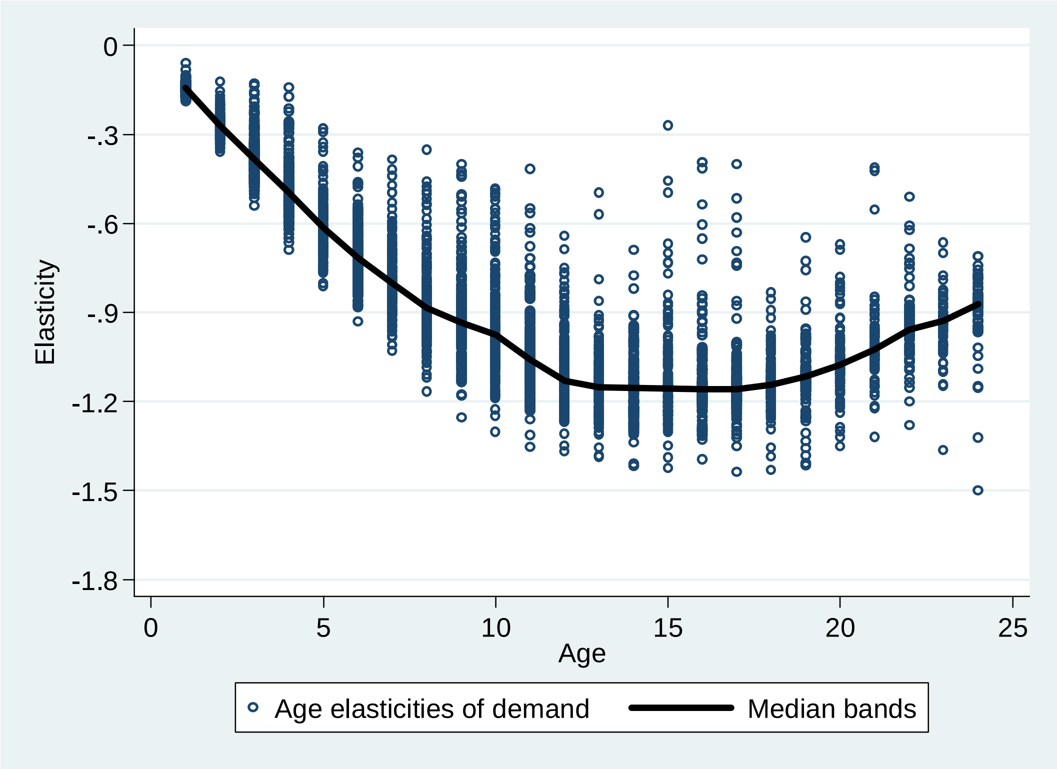


**Figure 3. Average sales and prices at different ages**




1. The age reported for each model is determined upon the actual first on-market date, not subject to the first-time observed sales in the dataset. The information regarding actual introduction date is obtained from the internet; including firms' own websites and other public ones, e.g. www.dpreview.com.
2. Only the top six brands of P&S cameras (4253 observations) are reported.
3. The reported sales are the total sales volume at each age averaged by the number of models within each age group.
4. The prices are the average prices of models within each age group.

**Figure 4. Age elasticity of demand**




The figure plots the percentage change in demand with respect to the percentage change in age for all observations included in the estimation. The age in the x-axis represents the number of months at the time of observation after a product is introduced into the market. The age elasticity in the y-axis is in percentage terms.

**Figure 5a. Price elasticity of demand excluding the age variable**

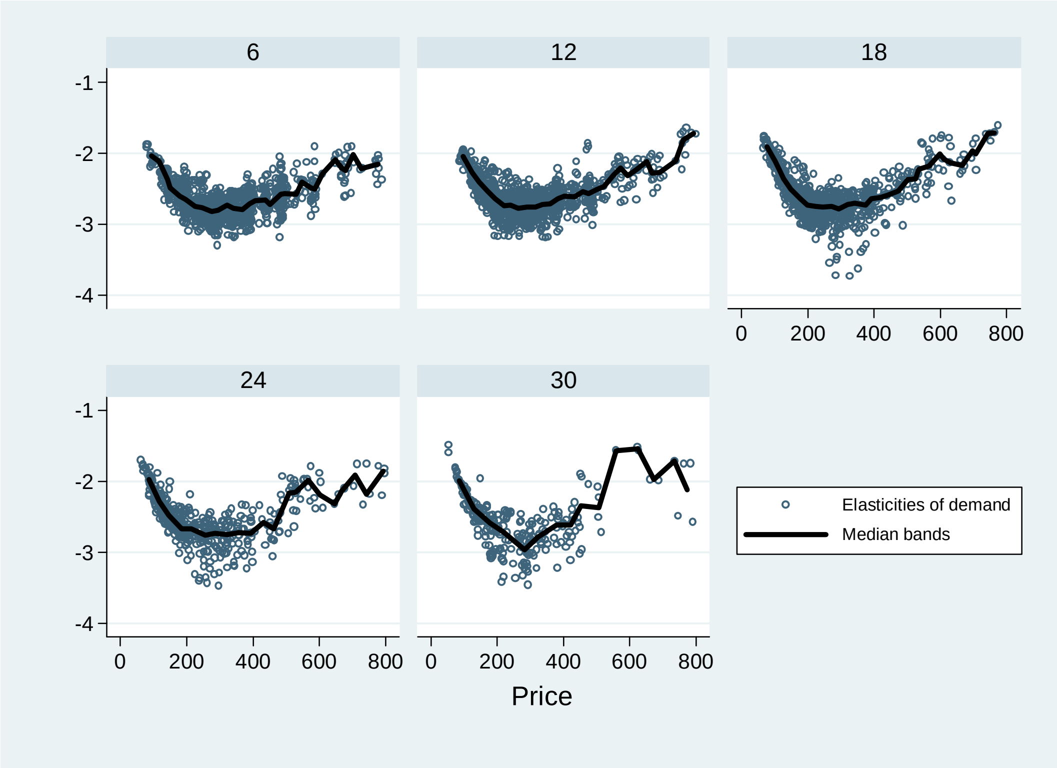
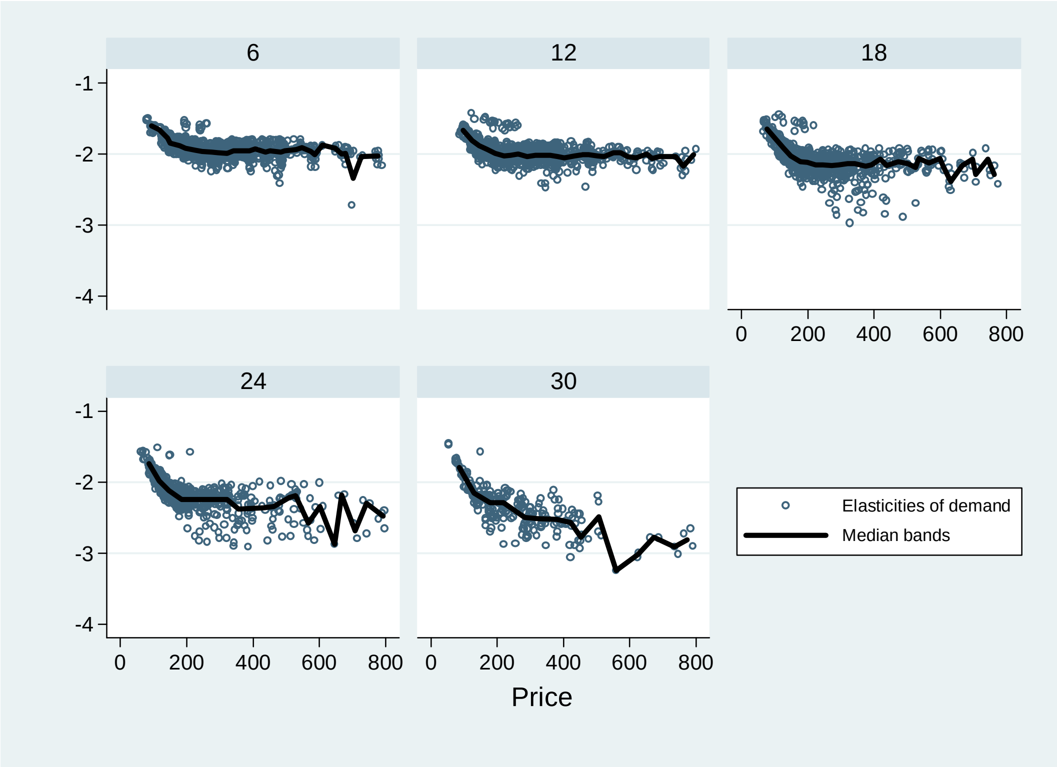



**Figure 5b. Price elasticity of demand including the age variable**




Figures 5a and 5b plot the price elasticity of demand, where the former excludes the age variable but the latter includes it. All observations are organized into 5 groups according to their ages, i.e. age 1~6, age 7~12, age 13~18, age19~24 and age > 24. Each group is plotted in a separate panel. The scatters are associated with individual elasticities, while the belts show the median predictions.

**Figure 6. Observed prices and estimated markups for six top selling models**

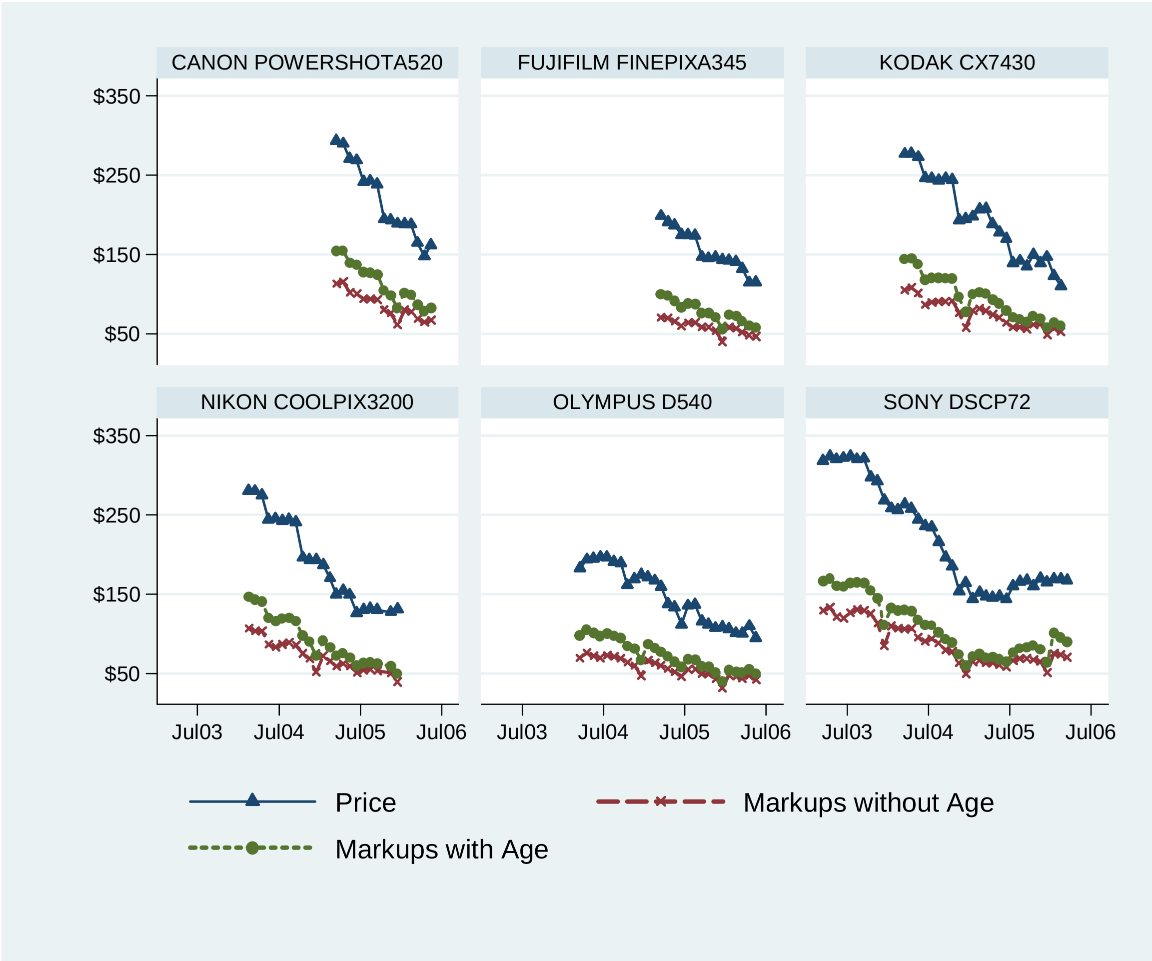
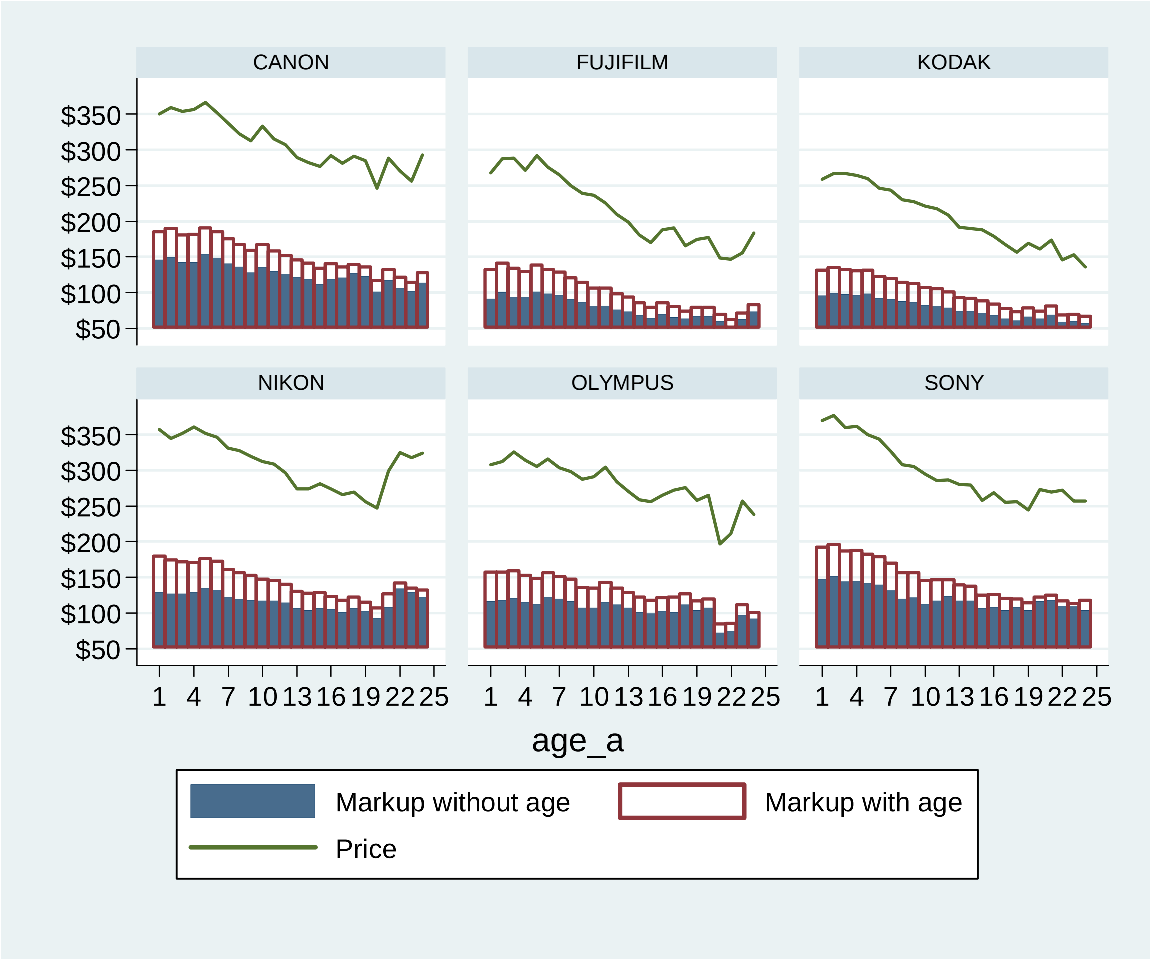


**Figure 7. Average prices and markup predictions for the top six brands**




Data plotted in the figure corresponds to average prices and markup predictions for each of the top six brands, grouped by the age of sales observations.

**Appendix: Data on US digital camera market (for reviewing only)**

In the original NPD data, there are a total of 1350 camera models. After checking for repetition of models, we find 1338 distinct models. Figure A1 below plots the sales volumes for the top 20 brands, showing a clear picture of steep declines in market shares. Listed characteristics of products include image resolution; weight and thickness of cameras; dummy showing whether a camera features an optical zoom range or not; dummy showing whether a camera has an LCD screen or not; dummies for built-in-flash and the type of memory devices.

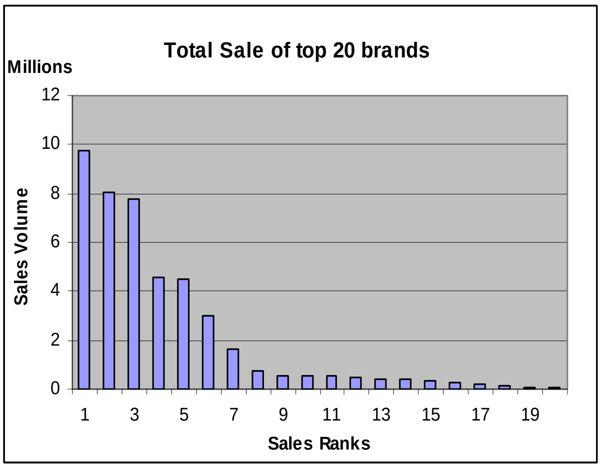



**Figure A1**

For attributes listed in the original dataset, there is a considerable amount of missing values, especially for the attribute measures for weight and thickness. Moreover, the data on characteristics of digital cameras are relatively raw. For example, with the key quality measure on cameras' resolution, image quality is reported by ranges of resolution (e.g., 3-3.99 mega-pixel), not the exact value. Although dummies are reported for features like LCD and optical zoom range, in many cases, these dummies are not sufficient to indicate the quality of digital cameras. For instance, more than 90% of the cameras have the value of one for "built-in-flash" and "with optical zoom range", making these cameras incomparable.

To derive accurate estimation, the original NPD data on camera features are supplemented by extensive searching through the website. To ensure the accuracy in definition of each model, observations derived from different sources are compared and matched. The features listed in the final dataset include the type of camera (Single-Lens-Reflex (SLR), SLR-alike, Point-and-Shoot cameras (P&S); the exact pixel number of image resolution, the size of LCD screen, the number of optical zoom range, the size of built-in-memory, the size (three-dimension measures) of camera, the battery type (rechargeable or not); the number of digital zoom, etc. Our final sample has 1127 distinct models, with 22,527 observations, representing more than 96% of total sales of original 1338 models reported by NPD. To construct the age variable, we obtain the introduction date for all models included in the final sample. Most of the information comes from the website www.dpreview.com and the websites of the manufacturers. Hence, each observation in this study will be assigned a precise age value to indicate how long the product has been marketed since its introduction.

The study focuses on the standard point-and-shoot (P&S) digital cameras manufactured by top six brands. Other brands are not included in the analysis due to three empirical facts. First, the output of the top six brands takes up about 83.79% of total sales of P&S cameras reported in the whole sample. The remaining 16.21% sales are shared by 40 smaller brands, with the aggregate market share of the $7^{th}$ to $10^{th}$ largest brands representing a total of less than 8% of market share. Second, we include observations belonging to the top six brands in part because of the lack of accurate price information of some smaller brands' models. For instance, the seventh largest seller Hewlett Packard takes up about 3.62% of the P&S market but most HP products are sold in packages or bundles. Therefore, the observed prices are for the whole bundle including other items such as printers. Accurate prices for the digital camera within the bundle are not observed. Finally, functionality and quality measures for products provided by smaller firms/brands may not be comparable with popular brands. For example, some of the digital cameras in the original data are PC video camera (e.g. MICRO INNOVATIONS), while others feature special functions (e.g. Sealife DC250 and DC310 can be used under water). It is difficult to specify a cut-off on choosing comparable products from these manufacturers. Rather than making an ad hoc selection, the study uses only observations from the top six brands.