

Product innovation and adoption in market equilibrium: The case of digital cameras.

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Abstract

This paper contains an empirical dynamic model of supply and demand in the market for digital cameras with endogenous product innovation. On the demand side, heterogeneous consumers time optimally the purchase of goods depending on the expected evolution of prices and characteristics of available cameras. On the supply side, firms introduce new camera models accounting for the dynamic value of new products and the optimal behavior of consumers. The model is estimated using data from the market for digital cameras and the estimated model replicates rich dynamic features of the data. The estimated model is used to perform counterfactual computations, which suggest that more competition or lower product introduction costs generate more product variety but lower average product quality.

Keywords: Durable goods; Dynamic demand; Innovation

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1 Introduction

This paper develops an empirical model of demand and supply for durable goods that accounts for the dynamic incentives of both consumers and firms and that allows endogenous product innovation over time. The model is tailored to the case of the market for digital cameras during the early stages of the diffusion of digital cameras between 1998 and 2001, when the quality of cameras was increasing rapidly and their price was falling. The model accounts for the incentives of consumers to time optimally the purchase of a digital camera depending on the perceived evolution of product characteristics and prices. On the supply side, the model focuses on the incentives of firms to introduce new products accounting for the dynamics of the market.

On the demand side, the paper contributes to a growing literature on estimation of dynamic models of demand for differentiated products which includes Chintagunta and Song (2003), Erdem, Imai and Keane (2003), Gowrisankaran and Rysman (2006) and Hendel and Nevo (2006). Instead of using a nested fixed point algorithm that requires the computation of the dynamic problem of individuals along the estimation algorithm, this paper proposes a novel technique that uses a reduced form of the dynamic problem solution. The specification facilitates dramatically the estimation of dynamic demand, specially when using product-level data; it also nests the standard model as described in Berry, Levinsohn and Pakes (1995)—henceforth referred to as BLP.

Similarly to some of the papers mentioned above, this paper relies on restricting the dynamic behavior of consumers. Specifically, the model allows them to condition their decision to purchase *any* product only on the current realization of a scalar state variable that is a sufficient statistic for distribution of expected payoffs. In other words, it is assumed that the maximum expected payoff that consumers can get from participating in the market is Markovian. As already recognized by others (e.g. Hendel and Nevo (2006)), consumers are expected to condition their behavior on *all* the variables that affect firm behavior. Therefore, such assumption (first proposed in the context of durable goods demand by Melnikov (2000)) is difficult to reconcile with a general supply model, in which firms condition their actions on the actions of each individual competitor.

This paper constructs a supply model that is consistent with the adopted demand

model. Specifically, it takes advantage of the large number of different products with very low market shares and the very rapid innovation in the market for digital cameras, which imply that firms' decisions regarding the introduction and pricing of individual products have a negligible effect on overall market variables. The model also requires that the expectations of firms be consistent with observed behavior in a manner that is similar to the models of social interactions as described, for example, in Brock and Durlauf (2001). The approach can also be related to recent work by Weintraub, Benkard and Van Roy (2007) on "oblivious equilibria" in which agents condition their strategies on average industry information.

There is a growing literature on the estimation of *static* models of strategic quality choice based on static models, e.g. Mazzeo (2002), Seim (2007) and Jia (2006). While there is a growing body of empirical literature on the estimation of dynamic games, such techniques require the availability of a long history of repeated interactions across firms and are not applicable in the context of our data set. Instead, this paper focuses on the dynamics of product innovation in the market for digital cameras¹. The result is an estimable model of endogenous product innovation in a market for differentiated products that has no precedent in the empirical microeconomic literature².

The paper is organized as follows: in the next section, the data set on which the estimation is based will be introduced and described. In the third section, the detailed model of market equilibrium is discussed. In the fourth section the empirical implementation and the estimation results are presented. The last section contains a concluding discussion.

¹See Holmes (2005) for dynamic a model of location choice that also abstracts from strategic interactions.

²There are two recent unpublished empirical papers that endogenize the behavior of firms in dynamic environments: Chen, Esteban and Shum (2008) construct a model of dynamic pricing that is calibrated using U.S. data. The recent work by Goettler and Gordon (2008) endogenizes innovation in the U.S. market for PC processors.

2 Data: the U.S. digital cameras market

The methodology proposed in this paper is tailored specifically to study the digital photocameras market, which is a perfect example of a growing durable good market with a rapidly improving technology, and its study may give insights onto similar cases. The data on which the estimation is based is a panel of monthly sales, prices and characteristics of more than 350 camera models aggregated into quarterly data. It spans the months between January of 1998 and September of 2001 and has coverage of around 90% of the market.

The centerpiece of a digital photocamera is a chip called Charge Coupled Device (CCD)³. A CCD is an integrated circuit comprising an array of photosites. The higher the number of these photosites (“pixels”), the better the quality of the picture (i.e. the resolution). Other main components of a camera are its lenses, which may have an adjustable focal length (optical zoom), a built-in liquid crystal display (LCD) of varying size and a magnetic storage device, which may be fixed or removable.

As can be seen from table 1, which puts together some illustrative summary statistics, the volume of sales of digital cameras increased throughout the whole sample span, going from 215000 units sold in the first quarter of 1998 to the more than one million sold in the first quarter of 2001⁴. The growth of the size of the market is paralleled by the increase of the quality of the sold cameras. The main indicator of the quality of a camera, in particular during the time span of the sample, is its resolution. As can be seen, the resolution of average available and sold cameras increased from around 0.5 to slightly more than 1.5 megapixels.

On the other hand, prices fell significantly over time: the average price paid for sold cameras fell from more than \$600 at the beginning of the sample to less than \$400 at the end, without controlling for the change in quality. A hedonic price regression was

³An alternative technology called CMOS has recently gained importance in low-quality/low-cost applications, such as cell phone and PDA cameras. It was no factor, though, during the time span of this study, and its ability to compete with CCD technology in the cameras market is still to be seen.

⁴There is a big seasonal effect in December of each year; for example, December sales accounted in 2000 for 30% of yearly sales.

Table 1: Summary statistics

Quarter	Units sold	Sales in million \$	# of models	Average price	Average resolution	Average zoom	Product concentration	Average share
1998:1	0.22	131	86	609.4	0.52	4.56	0.14	1.2%
1998:2	0.23	134	95	585.0	0.61	4.13	0.10	1.1%
1998:3	0.27	154	98	577.2	0.70	3.73	0.07	1.0%
1998:4	0.31	208	101	668.5	0.83	4.27	0.07	1.0%
1999:1	0.28	181	112	647.8	0.86	4.74	0.07	0.9%
1999:2	0.34	220	126	641.2	0.97	4.58	0.06	0.8%
1999:3	0.54	263	139	483.9	0.93	3.65	0.06	0.7%
1999:4	0.90	393	143	436.8	0.97	3.09	0.06	0.7%
2000:1	0.73	341	172	463.9	1.11	3.54	0.05	0.6%
2000:2	0.80	392	185	490.4	1.39	3.32	0.04	0.5%
2000:3	0.98	434	216	444.6	1.41	2.91	0.03	0.5%
2000:4	1.91	782	210	408.8	1.45	2.59	0.03	0.5%
2001:1	1.12	445	221	396.0	1.53	3.04	0.02	0.5%
2001:2	1.17	451	245	384.1	1.58	3.17	0.02	0.4%
Total	9.81	4528	352	461.7	1.26	3.27	0.02	0.7%

Table 2: Hedonic Regression Estimation
(dependent variable: $\log(p_{jt})$)

variable	coefficient	t-stat
resolution (mPix)	0.5839	56.1413
zoom	0.3229	22.6011
card	0.342	14.9491

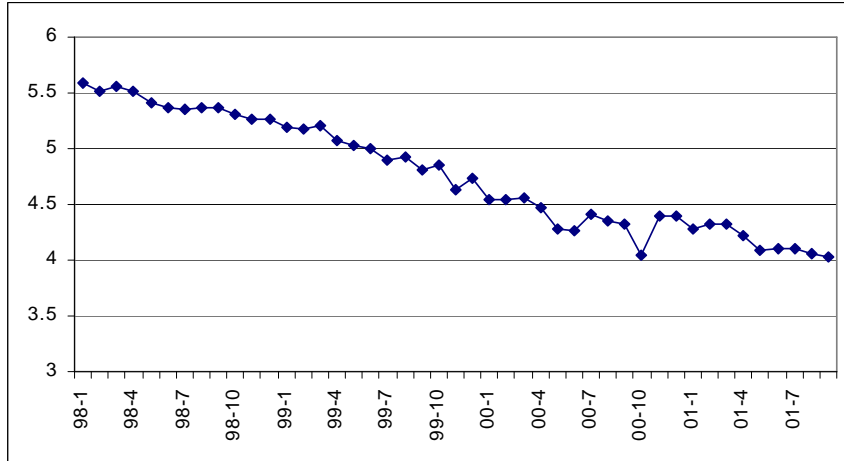


Figure 1: Hedonic regression fixed time effects

estimated using the following specification:

$$\log(p_{jt}) = a_t + a_1 x_j^{res} + a_2 x_j^{zoom} + a_3 x_j^{card}$$

where x_j^{res} is the resolution (in megapixels) of camera j , x_j^{zoom} is the log of its optical zoom and x_j^{card} is an indicator variable that takes value one when the camera has a mobile storage device. The time-changing variable a_t is estimated as a fixed time effect that captures the part of price variation that is not explained by the other included characteristics. The coefficients of the included characteristics are shown in table 2 and the estimated time effects, which are all significant, are displayed in figure 1. The clearly decreasing trend of the estimated fixed time effects confirms the observation that camera prices fell dramatically over time, more so after controlling for the improving quality.

Figure 2 shows a measure of the average behavior of prices and sales of camera models after introduction⁵. Notice that sales tend to grow during the first months after introduction and then fall, while prices fall on average steadily since introduction⁶. As will be shown below, the model proposed in this paper will be able to reproduce well these general patterns.

⁵The used average measures are the percent deviation of price and share from the average for each individual model. Notice that the sample had to be reduced in order to include only the models for which the introduction date and the following fourteen months were included in the sample.

⁶Behavior of prices and sales of individual products is less smooth but still conforms to this general

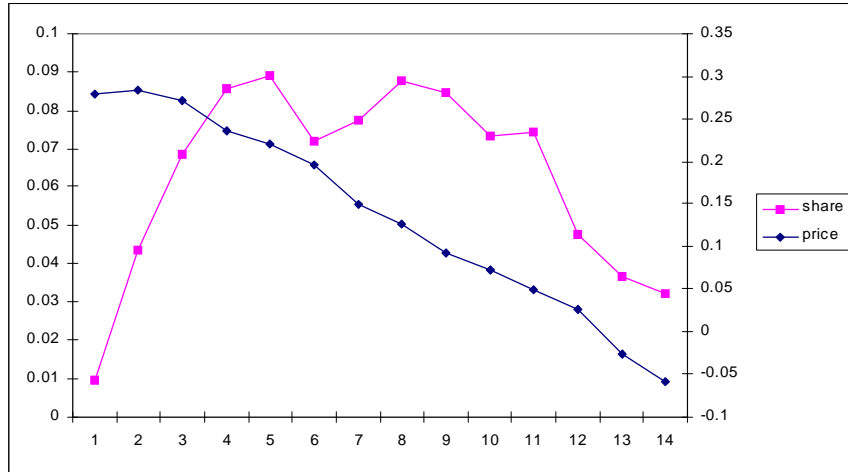


Figure 2: Evolution of price and share after introduction

As seen in table 3, the market is concentrated at the brand level, but it is very disperse at the level of individual products, which is the level at which it is assumed that firms make their pricing and innovation decisions. As seen in the right columns of table 1, the product-level Herfindahl index is below 0.1 throughout the sample period and is in average below 0.05 during the last ten quarters of the sample, on which the estimation of the supply model will be based. Notice that the average market share of individual camera models at any time after the fourth quarter of the sample is less than 1%. Some products can have very high market shares, reaching above 20% at times, but never for more than a quarter.

Moreover, in a market for durable goods, static market shares are misleading, since firms compete against products that are being introduced over time. Since consumers who purchase a product stay out of the market at least for a while, manufacturers compete against the products that have been released in the past and against products that consumers expect to be released in the future. If we compute market shares of individual camera models across the whole sample as shown in the bottom rows of the table, the market shares of most individual products are much lower than 1% and never reach 5%.

The estimation of the supply side of the market will take advantage of the low market shares of individual products to assume that the introduction and pricing of

pattern.

Table 3: Value Shares by Manufacturer

Jan/98		Sep/01	
Sony	36.1%	Sony	33.0%
Kodak	23.5%	Olympus	23.4%
Olympus	20.7%	Nikon	10.4%
Epson	4.8%	Kodak	9.0%
Ricoh	3.5%	Canon	8.0%
Casio	3.4%	HP	5.6%
Canon	1.3%	Fuji	2.8%
Minolta	0.8%	Minolta	1.5%
HP	0.8%	Toshiba	1.3%
Agfa	0.7%	Polaroid	1.2%

individual products have a negligible expected effect on overall market variables. This notion will also be supported by the demand estimates, which will show that cross price elasticities are economically insignificant in the data.

3 An equilibrium model of product adoption and innovation

3.1 Demand

The demand model assumes that at each point in time, consumers who have *not* purchased any camera decide whether to buy a camera or not among available cameras in the market. If they buy a camera they leave the market. If they don't buy any camera, they get the chance to make the decision the following period. Therefore, the specification of demand is similar to the standard specification of a BLP-style model nested inside an optimal stopping problem.

Specifically, at each point in time a consumer i , who has not yet purchased any camera, has to decide whether to purchase a camera and leave the market, or delay the decision one period to see whether cheaper and/or better cameras become available; if

she purchases any product j at time t , she gets a lifetime utility $u_{ijt} + \epsilon_{ijt}$, where ϵ_{ijt} is an *iid* unobserved preference shock that changes across time, consumers and products. Each period t the problem of a consumer i who has not purchased a camera is described by the following value function:

$$C(S_{it}) = \max\{\max_{j \in \mathfrak{S}_t} \{u_{ijt} + \epsilon_{ijt}\}, \epsilon_{i0t} + \beta E[C(S_{it+1})|S_{it}]\} \quad (1)$$

where the consumer decides to purchase a camera if the maximum lifetime utility she can get from the set \mathfrak{S}_t of available cameras at time t is higher than a reservation value $\bar{R}_{it}(S_{it}) \equiv \epsilon_{i0t} + \beta E[C(S_{it+1})|S_{it}]$. This reservation utility contains the option value of deciding on the purchase of the camera next period, discounted by a constant discount rate β , and an unobserved idiosyncratic *iid* shock ϵ_{i0t} that changes across consumers and time. The purchase decision is made based on a state vector S_{it} that contains all the variables that the consumer uses to construct her expectations of the payoff she can get from delaying her purchase decision one period.

This model is equivalent to a standard BLP-style model nested in an optimal stopping problem. It is identical to the standard BLP-style model when the reservation utility is a constant. The estimation of the model should therefore enable us to test whether the data support the notion that consumers are timing optimally their purchases, rather than just reacting myopically to changes in the prices and quality of available products.

The assumption that consumers leave the market after a purchase ignores the possibility of repeated purchases. This assumption implies that purchasing a camera leads to an absorbing state and facilitates the computation of the model. It is also justified by the short span of the sample, which doesn't allow the identification of any meaningful repeated purchasing behavior.

Let the lifetime utility of consumer i when purchasing camera model j be given by the following linear function:

$$\begin{aligned} u_{ijt} + \epsilon_{ijt} &= [\xi_{jt}^u + \gamma_0 + D_{B_j} \gamma^B + x_j^{res} \gamma^{res} + x_j^{zoom} \gamma^{zoom} - \alpha p_{jt}] + x_j^{res} \sigma_\gamma \epsilon_{\gamma i} + \epsilon_{ijt} \\ &\equiv \delta_{jt} + x_j^{res} \sigma_\gamma \epsilon_{\gamma i} + \epsilon_{ijt} \end{aligned} \quad (2)$$

Where the mean utility δ_{jt} of purchasing camera j at t depends on the camera resolution x_j^{res} , its optical zoom x_j^{zoom} , a matrix of brand dummies D_{B_j} multiplied by a vector of

brand effects γ^B , an unobserved product attribute ξ_{jt}^u and its price p_{jt} . The term $x_j^{res} \sigma_\gamma \varepsilon_i$, where $\varepsilon_i \sim N(0, 1)$, is an unobserved consumer-specific error that is correlated with the resolution x_j^{res} of the camera.

This specification is equivalent to a model where consumers have heterogeneous tastes for resolution as in Berry (1994) or in BLP and implies that the individual resolution coefficient in the utility function is distributed $N(\gamma^{res}, \sigma_\gamma^2)$. This correlated unobserved state will generate cross-price substitutions among products that are higher for cameras with similar resolution. Notice that it is assumed that consumers have heterogeneous taste coefficients but homogeneous price coefficients. This is similar to the original BLP formulation and is mainly justified by the difficulty associated with the separate identification of the two types of heterogeneity from product-level data.

Assume, as it is usual in the literature, that ε_{ijt} and ε_{i0t} are distributed *iid* according to the Type I extreme value distribution. Then, the probability that a consumer will purchase *any* product is given by the probability that the reservation utility is higher than the expected value of participating in the market (also known as the “inclusive value”):

$$r_{it}(\cdot) = \log \sum_{k \in \mathfrak{S}_t} e^{(\delta_{kt} + x_k^{res} \sigma_\gamma \varepsilon_i)} \quad (3)$$

Where \mathfrak{S}_t is the set of available products at time t . Due to the heterogeneity of the consumers’ taste for camera resolution, this value is different for every individual.

Specifically, let $R_{it} = E_t [\bar{R}_{it}] = \beta E[C(S_{it+1})|S_{it}]$ be the “expected” reservation utility of consumer i at time t . The probability that consumer i purchases product j at time t is:

$$Pr_{ijt} = \left[\frac{e^{r_{it}}}{e^{R_{it}} + e^{r_{it}}} \right] \left[\frac{e^{\delta_{jt} + x_j^{res} \sigma_\gamma \varepsilon_i}}{e^{r_{it}}} \right] \equiv \left[\frac{1}{1 + e^{R_{it} - r_{it}}} \right] \left[\frac{e^{\delta_{jt} + x_j^{res} \sigma_\gamma \varepsilon_i}}{e^{r_{it}}} \right] \quad (4)$$

where the first term of this expression is the probability that the consumer buys *any* camera at time t (i.e. the *participation probability*) and the second term is the probability she buys specifically model j , conditional on purchasing a camera.

Therefore, when timing optimally the purchase of a camera the consumer only cares about forecasting the evolution of r_{it} . It follows that the reservation utility of consumer i is a function of the state variables that the consumer uses to forecast the evolution of r_{it} . Assume that r_{it} follows a first order Markov process, so that r_{it} is a sufficient

statistic for the distribution of r_{it+1} :

$$E[r_{it+1}] = \Phi^r(r_{it}) \quad (5)$$

This assumption implies that $S_{it} \equiv r_{it}$, so that consumers don't have to keep track of the behavior of individual firms when forecasting the evolution of the market. This assumption was first proposed by Melnikov (2000) when estimating the demand for computer printers and has been used, more recently, by Hendel and Nevo (2006) and Gowrisankaran and Rysman (2006).

Given (5), the reservation value for each active consumer depends only on her realized inclusive value, i.e. $R_{it}(S_{it}) \equiv R_{it}(r_{it})$. We obtain demand for product j by integrating the individual demand (4) over the distribution of the consumers attributes:

$$q_{jt}(x_j, p_{jt}, \xi_{jt}^u) = M_t \int \left[\frac{1}{1 + e^{R_{it}(r_{it}(\varepsilon_i)) - r_{it}(\varepsilon_i)}} \right] \left[\frac{e^{\delta_{jt} + x_j^{res} \sigma_\gamma \varepsilon_i}}{e^{r_{it}(\varepsilon_i)}} \right] dG_t(\varepsilon_i) \quad (6)$$

where M_t is the total number of active consumers in the market, which is obtained by taking the exogenous number of potential consumers and subtracting those who have purchased a camera in previous periods. Since the data set spans the initial stages of the diffusion of digital cameras, the initial market size is going to be set equal to the total number of households in the U.S.. G_t is the distribution of consumers' attributes ε , which is initially standard normal but then changes over time as consumers of different types select themselves out of the market by buying a camera. Notice that as the quality of available products increases over time and their price decreases, the inclusive value r_{it} increases and demand for any given camera model falls towards zero.

To facilitate the computation of (6), the individual expected reservation utility R_{it} will be approximated locally around its current value using a polynomial on the individual states and attributes⁷:

$$\tilde{R}(r_{it}; \varepsilon_i) = \pi_0 + \pi_1 \varepsilon_i + (\pi_2 + 1)r_{it} + \pi_3 r_{it} \varepsilon_i \quad (7)$$

which implies that $\tilde{R}_{it}(r_{it}) - r_{it} = \pi_0 + \pi_1 \varepsilon_i + \pi_2 r_{it} + \pi_3 r_{it} \varepsilon_i$. Higher-order polynomials could be used to make the approximation more precise, but results will show that in this case the last interaction term has no impact on the structural preference estimates

⁷A similar idea was used by Park (2004) to approximate the expected network externalities when estimating demand for VCR's.

and that the linear polynomial is a good local approximation of this value function. Notice also that any approximation error is not separately identified from the idiosyncratic extreme value shock ϵ_{i0t} . The parameters $\pi = \{\pi_0, \pi_1, \pi_2, \pi_3\}'$ have no structural meaning and are not important themselves; they just serve as a control for the dynamic incentives of consumers. In this particular specification they are interesting because when $\{\pi_1 = 0, \pi_2 = -1, \pi_3 = 0\}$ the model collapses to the “static” BLP model. The nested specification will therefore allow us to test formally the validity of the standard model in the given data.

Let $h_{it}(\cdot) = \frac{1}{1 + e^{\tilde{R}_{it}(\cdot) - r_{it}}}$ be the participation probability of consumer i at time t , i.e. the probability that consumer i purchases *any* product at time t . Let $\gamma = \{\gamma_0, \gamma^B, \gamma^{res}, \gamma^{zoom}\}'$ and $\xi_t^u = \{\xi_{jt}^u\}_{j \in \mathfrak{S}_t}$. For any set of parameters $\theta = \{\pi, \gamma, \alpha, \sigma_\gamma\}$ and given the vector of unobserved product characteristics ξ_t^u , a consistent estimate of product j demand (6) can be computed by simulating N times the errors $\varepsilon_i \sim N(0, 1)$ at the initial period and then updating their distribution over time using the following formula:

$$\begin{aligned} \tilde{q}_{jt}(\xi_t^u \theta) &= M_t \frac{1}{N} \sum_{n=1}^N \left[\psi_{nt} h_{nt}(r_{nt}(\theta, \varepsilon_n), \varepsilon_n; \pi) \frac{e^{(\delta_{jt}(\theta) + x_j^{res} \sigma_\gamma \varepsilon_n)}}{e^{(r_{nt}(\theta, \varepsilon_n))}} \right] \\ &= M_t \frac{1}{N} \sum_{n=1}^N \psi_{nt} \left[\frac{1}{1 + e^{\tilde{R}_{nt}(\cdot) - r_{nt}(\theta, \varepsilon_n)}} \right] \left[\frac{e^{(\delta_{jt}(\theta) + x_j^{res} \sigma_\gamma \varepsilon_n)}}{e^{(r_{nt}(\theta, \varepsilon_n))}} \right] \\ &= M_t \frac{1}{N} \sum_{n=1}^N \psi_{nt} \left[\frac{1}{1 + e^{\pi_0 + \pi_1 \varepsilon_i + \pi_2 r_{nt} + \pi_3 r_{nt} \varepsilon_n}} \right] \left[\frac{e^{(\delta_{jt}(\theta) + x_j^{res} \sigma_\gamma \varepsilon_n)}}{e^{r_{nt}}} \right] \end{aligned} \quad (8)$$

where the last equality is obtained after replacing R_{it} with its approximation. $\psi_{n,t}$ is the “density” of consumer n at time t . At $t = 1$, $\psi_{n,1} = 1$; at $t > 1$, each consumer leaves the market with probability h_{nt} and $\psi_{n,t>1} = \psi_{n,t-1}(1 - h_{n,t-1})$, so that the distribution of consumer attributes is correlated over time. Notice that the participation probability has a logistic functional, which conforms with the standard notion of product adoption behavior.

The formulation of (8) is identical to the standard BLP demand when $\{\pi_1 = 0, \pi_2 = -1, \pi_3 = 0\}$. Moreover, it can be estimated using the same algorithm: for any vector θ_0 , the implied vector of unobserved product attributes $\xi_t^u(\theta_0)$ is solved from the equality of predicted demand $\tilde{q}_{jt}(\theta_0)$ and observed demand Q_{jt} :

$$\tilde{q}_{jt}(\xi_t^u(\theta_0), \theta_0) \equiv Q_{jt} \quad (9)$$

The implied unobserved product attributes correspond to the structural errors of this system of non-linear equations and can be interacted with a matrix Z_t of instruments that vary across products to construct moment conditions based on a set of orthogonality conditions:

$$m_t = E [\xi_t^u(\theta^*)' Z_t] = 0 \forall t \quad (10)$$

where θ^* is the vector of true parameters θ and m_t is a vector of moment conditions.

3.2 The model of firm behavior

In the demand model above, consumers were assumed to use current realizations of their inclusive values to predict the value of delaying their purchase of a camera. This assumption, which made the demand model tractable, implies that firms also use these inclusive values to condition their actions. Otherwise, if firms were conditioning their behavior on the prices and product innovation decisions of individual firms, consumers would also condition their dynamic behavior on these variables.

In order to construct a supply model that is consistent with the demand model, we'll assume that the effect of individual firms' decisions on each consumer's inclusive value is negligible. These inclusive values are endogenous in the sense that the behavior of firms relies on their expectations regarding their evolution and should be consistent with it. But when making individual product introduction and pricing decisions, firms will take these inclusive values and their distribution across consumers at the observed dynamic equilibrium as given. This assumption insures that neither firms nor consumers have to keep track of the actions of individual firms. It will follow that firms, consistently with the assumed demand model, condition their decisions only on the realizations of the inclusive value.

The fundamental exogenous force that drives the innovation decisions of firms is the evolution of technology, reflected in the changing –presumably decreasing– production costs. Let the marginal cost of producing one camera with observed characteristics $x_j = \{x_j^{res}, x_j^{zoom}\}'$ at time t be described by the following linear function:

$$mc_t(x_j, \xi_{jt}^{mc}) = \eta_t x_j + \xi_{jt}^{mc} \quad (11)$$

where ξ_{jt}^{mc} is a zero-mean unobserved to the econometrician cost shifter that is uncor-

related with the other cost and demand shifters, and $\eta_t = \{\eta_t^{res}, \eta_t^{zoom}\}'$ is the vector of cost parameters at time t . Assume that the cost parameters $\eta \equiv \{\eta_{t=1\dots T}\}$ follow an exogenous time-changing distribution:

$$Prob[\eta_t < \eta^0] = \Phi_t^\eta(\eta^0) \quad (12)$$

The marginal cost has been assumed to be constant on the produced quantity of each product and to vary systematically only with respect to the observed characteristics. The technology that generates this cost function is assumed to be available to all firms and to be unobserved by consumers.

Assume that demand is described by (6) and that firms choose the observed attributes x_j before introducing a new camera model. Consistently with the data set, these attributes stay constant throughout the commercial life of the product. It is assumed that the unobserved product characteristics ξ_{jt}^u and unobserved cost shifters ξ_{jt}^u are random and unknown at the time the firm decides to introduce the new product. After introduction, camera model j introduced by firm B with observed attributes x_j is expected at the time of introduction τ to generate an expected net present value of payoffs given by:

$$\tilde{V}_{j\tau}^B = \tilde{V}_{j\tau}^B(x_j, \{p_{t=\tau\dots T_j}\}, \cdot) = E_\tau \sum_{t=\tau}^{T_j} \beta^{t-\tau} (p_{jt} - mc_t(x_j, \cdot)) q_{jt}(x_j, p_{jt}, \cdot) \quad (13)$$

where β is the discount rate and the sum is taken up to the time T_j at which product j drops endogenously off the market, which occurs when demand falls close enough to zero. Notice that this value is affected by the expected evolution of the quality and price of available cameras as captured by the expected evolution of the inclusive values, which in turn affect demand q_{jt} .

Consider the general problem of firm B at time $t = \tau$. Let \mathbb{I}_{l_t} be an indicator function that takes value 1 if product l_t is introduced into the market at time t and is zero otherwise. Given the set $\mathfrak{S}_{\tau-1}^B$ of products that the firm has already introduced in the past, the firm maximizes the net present value of profits Π_τ^B :

$$\begin{aligned} \Pi_\tau^B &= \sum_{k \in \mathfrak{S}_{\tau-1}^B} \tilde{V}_{k\tau}^B(x_k) \\ &+ E_\tau \sum_{t=\tau}^{\infty} \sum_{l_t=1}^{L_t^B} \beta^{t-\tau} \mathbb{I}_{l_t} \max_{x_{l_t}} \{ \tilde{V}_{l_t t}^B(x_{l_t}, \cdot) - F_t^B(x_{l_t}, \xi_{l_t}^F) \} \end{aligned} \quad (14)$$

where the first term corresponds to the expected profits from sales of existing products and the second term corresponds to the expected profits of products to be introduced at τ and in later periods, whose observed quality is to be chosen by the firm at the time of introduction. It is assumed that the firm gets to introduce an exogenous maximum number L_t^B of products every period t and that the firm incurs fixed introduction costs given by $F_t^B(\cdot)$, which depend on the chosen characteristics of the product x_{l_t} and on an unobserved state $\xi_{l_t}^F$.

Each period τ the firm has to decide whether to introduce new camera models or not; if so, it has to decide the optimal set of observed attributes. Then it has to choose the price of new and old products. The set of control variables is therefore $d_\tau = \{\mathbb{I}_{l_\tau=1,\dots,L_\tau^B}, x_{l_\tau=1,\dots,L_\tau^B}, p_{l_\tau=1,\dots,L_\tau^B}, p_{k \in \mathfrak{S}_{\tau-1}^B}\}$ and the firm's problem is:

$$\max_{d_\tau} E_\tau [\Pi_\tau^B | d_\tau] \quad (15)$$

The solution to this general maximum problem is difficult because, in principle, every pricing and product introduction decision of the firm has to account for its potential effects on the profitability of other products that the firm has introduced in the past or that the firm may introduce in the future. It also has to take into account the potential strategic responses of other firms.

Notice, though, that all effects of pricing and product introduction on the demand of other products or the demand of the same product over time occur via changes on the inclusive values of the consumers. Assuming that the inclusive values are given eliminates all these cross-demand effects and turns the very complicated optimization problem described above into a set of separate relatively simple maximization problems. On one hand, firms set prices for each product at each point in time individually, solving a static profit maximization problem. On the other hand, firms compute the expected profitability of introduced products assuming that the evolution of the inclusive values is exogenous and decide separately whether to introduce each new product or not if its maximum expected profitability is higher than the corresponding introduction costs. The solution to each of these two separate problems is described in the following two subsections.

3.2.1 Pricing

In the context of each firm's pricing problem, the assumption that take the inclusive values as given is equivalent to the following condition:

$$\frac{\partial r_{it}}{\partial p_{j\tau}} = 0 \forall i, t, j, \tau \quad (16)$$

In terms of the application below, the actual values of these derivatives are very close to zero, due to the fact that most of the time there are more than 150 available camera models in the market.

This condition in turn implies that the derivatives of demand for individual camera models (6) with respect to camera prices are given by:

$$\begin{aligned} \frac{\partial q_{jt}}{\partial p_{jt}} &= -\alpha q_{jt} - \int \left[\frac{1}{(e^{R_{it}} - e^{r_{it}})^2} (e^{R_{it}} \frac{\partial R_{it}}{\partial r_{it}} \frac{\partial r_{it}}{\partial p_{jt}} - e^{r_{it}} \frac{\partial r_{it}}{\partial p_{jt}}) \right] dG_t(\varepsilon_i) = -\alpha q_{jt} \\ \frac{\partial q_{kt}}{\partial p_{jt}} &= - \int \left[\frac{1}{(e^{R_{it}} - e^{r_{it}})^2} (e^{R_{it}} \frac{\partial R_{it}}{\partial r_{it}} \frac{\partial r_{it}}{\partial p_{jt}} - e^{r_{it}} \frac{\partial r_{it}}{\partial p_{jt}}) \right] dG_t(\varepsilon_i) = 0 \end{aligned} \quad (17)$$

where the first equality is the derivative of model j demand with respect to its own current price. The second term is the derivative of model j demand with respect to the current price of other cameras and is equal to zero. Therefore, changes in p_{jt} only affect demand for product j at time t . This in turn implies that $\frac{\partial V_{kt}}{\partial p_{j\tau}} = 0$ for $k \neq j$ and $t \neq \tau$.

Given (16) and (17), the first order conditions of (14) with respect to prices yield a separate pricing equation for each camera model j that has already been introduced into the market:

$$\begin{aligned} \frac{\partial \Pi_\tau^B}{\partial p_{jt}} &= \frac{\partial V_{jt}^B}{\partial p_{jt}} = q_{jt} + (p_{jt} - mc_t(x_j, \xi_{jt}^{mc})) \frac{\partial q_{jt}}{\partial p_{jt}} = 0 \\ &= 1 - \alpha(p_{jt} - mc_t(x_j, \xi_{jt}^{mc})) = 0 \end{aligned} \quad (18)$$

Which is exactly equivalent to a static monopolistic optimization condition equating marginal revenue and marginal cost. Indeed, in this model each firm acts as a monopolist of each of the camera models it has already introduced. Given the adopted demand, this implies that the price of any camera j is given by its marginal cost plus a constant markup:

$$\begin{aligned} p_{jt}^* &= mc_t(x_{jt}, \xi_{jt}^{mc}) + \frac{1}{\alpha} \\ &= x_j^{res} \eta_t^{res} + x_j^{zoom} \eta_t^{zoom} + \xi_{jt}^{mc} + \frac{1}{\alpha} \end{aligned} \quad (19)$$

This equation can be estimated using standard linear techniques. It implies that prices vary across cameras depending on their observed characteristics and vary over time as production costs decrease.

Notice that once a camera model has been introduced, its price is determined endogenously by (19). Moreover, expected prices can be computed by taking the expectations of the production costs, which are exogenous to the firms. The expected sales of any given camera model can also be computed replacing the expected price in the demand function (6). Therefore, the expected profits generated by any product j introduced at τ by firm B can be written only as a function of the observed characteristics x_j by replacing (19) and (6) in (13):

$$V_\tau^B(x_j) = E \left[\sum_{t=\tau}^{T_j} \beta^{t-\tau} \frac{1}{\alpha} M_t \int \left[\frac{e^{\gamma_0 + D_{Bj} \gamma^B + (\gamma - \alpha \eta t) x_j - 1 + x_j^{res} \sigma_\gamma \varepsilon_i}}{e^{r_{it}(\varepsilon_i)} + e^{R_{it}(r_{it}(\varepsilon_i))}} \right] dG_t(\varepsilon_i) | \{r_{i\tau}\}, \eta_t \right] \quad (20)$$

where it is assumed that before introduction the firm expects both the unobserved product attributes and cost shocks to be zero over time, i.e. $\xi_{jt}^u = 0$ and $\xi_{jt}^{mc} = 0$ for all t . As indicated before, as the inclusive values increase gradually over time, demand for any product drops asymptotically towards zero. The sum is taken up to the time T_j , when predicted demand for model j is sufficiently close to zero.

3.2.2 New product introduction

The objective function (14) of firms assumes that each firm B has an exogenous maximum number L_t^B of product introductions per-period. In addition, the assumption that inclusive values are taken as given implies that the expected profitability of individual products is not affected by individual introduction decisions:

$$E_t \frac{\partial r_{it}}{\partial \mathbb{I}_{l_t}^B} = 0 \forall i, t, l_t \quad (21)$$

As a consequence, the decision to introduce one new product doesn't affect the profitability of other products in the market. Moreover, it doesn't affect the decision to introduce other products in the current period and in the future. Given the very high number of available camera model at any point in time, this assumption is not very strong but facilitates significantly the estimation of the model.

Given (21), the first order conditions of the objective function (14) with respect to the decision to introduce a new product and its corresponding vector of observed characteristics imply that a new product is introduced if and only if it generates expected profits higher than its introduction costs:

$$\mathbb{I}_{l_t}^{B*} = 1 \Leftrightarrow \max_{x_{l_t}} \{V_{l_t}^B(x_{l_t}) - F_t^B(x_{l_t}, \xi_{l_t}^F)\} \geq 0 \quad (22)$$

The condition above contains two decisions: on one hand, for each prospective product introduction the firm has to choose the vector of observed product characteristics that maximizes the expected net profits. On the other hand, if these net profits are greater than zero, the firm introduces the new product. We can therefore rewrite (22) as the following pair of conditions:

$$\mathbb{I}_{l_t}^{B*} = 1 \Leftrightarrow \{V_{l_t}^B(x_{l_t}^*) - F_t^B(x_{l_t}^*, \xi_{l_t}^F)\} \geq 0 \quad (23)$$

where $x_{l_t}^*$ solves a system of first order conditions, one for every product characteristic:

$$\frac{\partial V_{l_t}^B(x_{l_t}^*)}{\partial x_{l_t}} = \frac{\partial F_t^B(x_{l_t}^*, \xi_{l_t}^F)}{\partial x_{l_t}} \quad (24)$$

Since conditions (23) and (24) must hold for all products at the time of introduction, they can be used to construct an estimator of the introduction costs $F(\cdot)$, given an estimate of $V(\cdot)$. The estimation has to account for the fact that observed introductions are a selected sample that includes only the successful product introduction for which (23) held.

4 Estimation and results

The equilibrium model of supply and demand of digital cameras is described by the demand equation (6), the cost equation (19), the product introduction conditions (23) and (24), the transition of the production costs (12) and the transition of the inclusive values (5). The model is estimated using the product-level data set described in section 2.

The estimation involves the following steps, each described in a separate subsection: first, marginal costs are estimated from equation (19) using standard linear techniques and the results are used to estimate the time-changing distribution (12) of marginal

costs. Second, demand is estimated using a variation of the standard BLP technique that accounts for the dynamics of consumer behavior. Demand estimates are also used to estimate the transition of the inclusive values (5).

Third, the estimates of the transition of the dynamic states obtained above are used to compute the function $V(\cdot)$ for every firm and every period. Fourth, the estimated function $V(\cdot)$ is used to estimate introduction costs from (23) and (24) using simulation methods. The following subsections describe these steps separately and in detail.

The identification of the model takes advantage of the assumption that inclusive values are exogenous. On the demand side, mean taste coefficients are identified from the covariation of individual products' market shares and characteristics; the distribution of the taste coefficients is identified from the covariation of market shares across similar products⁸. The identification of the consumers' participation probabilities comes from the covariation of *total* sales and the exogenous inclusive values, which is usually unexploited in standard applications of BLP.

On the supply side, cost parameters are identified from the covariation of prices and product characteristics at any point in time. Given demand and cost parameters, the expected profitability of introduced products is identified. Therefore, the product introduction costs are identified from the covariation of these inferred measures of profitability and the observed product introduction behavior, across firms and over time.

4.1 Estimation of markups and marginal cost

Cost parameters are estimated using equation (19). Given the linear marginal costs and the assumption that the unobserved cost states ξ_{jt}^{mc} are uncorrelated with observed states, estimating (19) is straightforward using OLS with observed prices and characteristics.

Table 4 contains estimates of $\{\eta_{t=1..T}\}$ and α obtained from (19). Results, as shown, are very precise and intuitive. The first column contains estimates of an equation with only the resolution (in megapixels) as an observed camera attribute. The second column contains estimates with both resolution and the log of the optical zoom as observed

⁸This identification argument is identical in any application of BLP to product-level data.

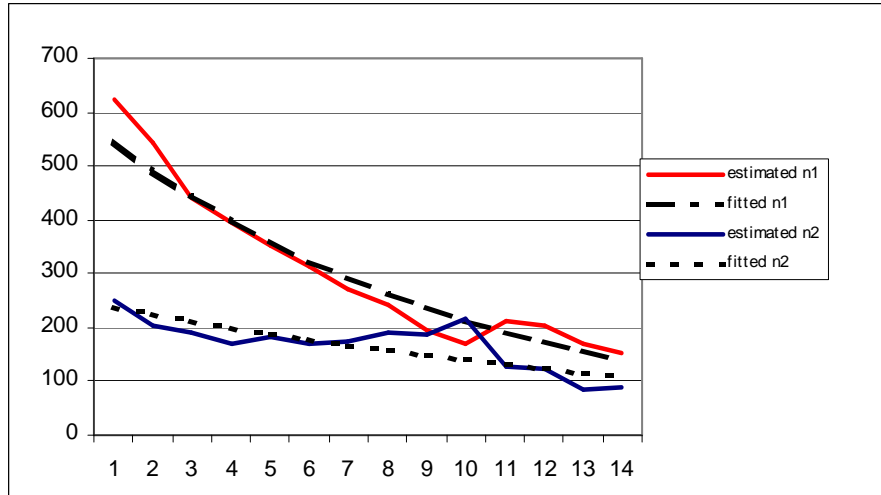


Figure 3: Estimated and fitted cost of resolution and zoom

attributes.

These results are consistent with the notion that the cost of technology is falling substantially over time. The “cost” of one megapixel (i.e. the cost of the CCD divided by its capability) at the beginning of the sample in the first quarter of 1998 was around \$700, and it fell to less than \$200 by the end of the sample in the second quarter of 2001. The estimates of the cost of the optical zoom (i.e. the cost of lenses) imply that a lens with 3X optical zoom added around \$200 to the cost of a camera over a lens with no zoom, whereas this incremental cost was only around \$70 by the end of the sample.

The estimate of $1/\alpha$, which corresponds to the inverse of the price coefficient in the utility function, implies that firms charged a markup of \$80-\$100 over the cost of the camera. The estimate of α will be replaced on the demand equation (6) to estimate the remaining demand parameters. Notice that estimating α from this equation facilitates the estimation of the demand model, given the lack of adequate instruments for the prices of individual products.

The estimates of the cost parameters are used to estimate its distribution over time, which firms use to compute the expected evolution of production costs and prices. Assume that the mean of each of these parameters follows an independent logarithmic time trend, so that they tend to fall asymptotically towards zero:

$$\log(\eta_t^{res}) = \rho_0^{res} + \rho_1^{res}t + \mu_t^{res}$$

Table 4: Estimation of markups and marginal cost

Parameter	$x_j = \{x_j^{res}\}$	$x_j = \{x_j^{res}, x_j^{zoom}\}$	
	Estimate (s.e)	Estimate (s.e)	
$1/\alpha$	102.3 (9.119)	81.7 (8.8)	
	$\eta_t \equiv \eta_t^{res}$	$\eta_t \equiv \{\eta_t^{res}, \eta_t^{zoom}\}$	
η_1	741.2 (45.7)	674.6 (49.3)	209.3 (52.5)
η_2	658.4 (41.6)	601.4 (43.9)	181.2 (42.4)
η_3	547.6 (36.7)	474.8 (40.8)	172.4 (38.5)
η_4	467.9 (34.4)	397.5 (38.7)	168.0 (38.1)
η_5	454.5 (28.0)	380.5 (32.8)	169.1 (35.3)
η_6	391.3 (24.2)	329.1 (27.9)	166.5 (33.8)
η_7	359.9 (20.7)	291.6 (26.0)	159.3 (32.6)
η_8	314.2 (19.2)	246.5 (24.1)	170.7 (33.2)
η_9	257.5 (14.8)	200.2 (19.1)	152.2 (29.3)
η_{10}	234.3 (13.7)	181.7 (17.9)	145.7 (28.6)
η_{11}	229.0 (11.6)	205.5 (14.3)	93.1 (26.1)
η_{12}	239.0 (11.3)	212.4 (14.0)	100.2 (25.3)
η_{13}	199.9 (10.3)	178.4 (12.8)	84.8 (23.4)
η_{14}	176.9 (9.2)	161.4 (11.8)	68.8 (23.4)
ρ_0^{res}	6.64 (0.041)	6.48 (0.0723)	
ρ_1^{res}	-0.11 (0.005)	-0.11 (0.0085)	
ρ_0^{zoom}		5.48 (0.088)	
ρ_1^{zoom}		-0.07 (0.010)	

$$\log(\eta_t^{zoom}) = \rho_0^{zoom} + \rho_1^{zoom}t + \mu_t^{zoom} \quad (25)$$

where $\{\mu_t^{res}, \mu_t^{res}\}$ are non-persistent mean-zero errors. Estimates of $\{\rho_0^{res}, \rho_1^{res}, \rho_0^{zoom}, \rho_1^{zoom}\}$ obtained from (25) are very precise, as seen at the bottom of Table 4. The estimated cost parameters corresponding to the estimation with two observed characteristics are displayed in figure 3, together with the fitted values obtained from (25).

It has been assumed that all firms share the same marginal production costs under the understanding that camera components are traded openly in the market. Equation (19) could have included firm effects to account for possible differences in the levels of marginal costs across firms. There's nothing in the data, though, that would allow the identification of such effects separately from the brand effects on the demand side. Therefore, any systematic differences in profitability across manufacturers are captured by the differences in demand, as illustrated below.

4.2 Estimation of demand

Demand is estimated using an algorithm almost identical to the standard BLP algorithm. The only difference is that the demand equation (6) accounts for a non-constant reservation utility and a time-changing distribution of consumers' attributes. For any set of demand parameters, the vectors of unobserved product characteristics are solved period by period to compute a GMM criterion function based on the moment conditions (10).

Specifically, a number of $N = 1000$ draws of $\varepsilon_n \sim N(0, 1)$ are simulated. Set $\psi_{n1} = 1$ for all n and set the demand parameters $\theta^0 = \{\hat{\alpha}, \pi^0, \gamma^0, \sigma_\gamma^0\}$, where the price coefficient α has been replaced by its estimate obtained above. Given the equality of predicted and observed demand (9), where the predicted demand is given by (8), the vector of implied mean utility levels $\delta_{t=1}^0 \equiv \{\delta_{j \in \mathfrak{S}_1, t=1}^0\}$ is obtained numerically using the fixed point algorithm proposed in BLP:

$$\delta_t^1 = \delta_t^0 + \log(Q_t/M_t) - \log(\tilde{q}_t/M_t) \quad (26)$$

The appendix contains a description of the conditions under which this mapping is a contraction and its fixed point unique. As discussed below, these conditions are met in all but one of the estimated specifications of the model. The computation of

the implied unobserved product attributes is straightforward from the definition of the mean utilities:

$$\xi_{t=1}^{u0}(\theta_0) = \delta_{t=1}^0 - \gamma_0 - D_{B_j}\gamma^B - x_{t=1}^{res}\gamma^{res} - x_{t=1}^{zoom}\gamma^{zoom} + p_{t=1}\hat{\alpha} \quad (27)$$

where $x_{t=1}^{res} \equiv \{x_{j \in \mathfrak{S}_1}^{res}\}$, $x_{t=1}^{zoom} \equiv \{x_{j \in \mathfrak{S}_1}^{zoom}\}$ and $p_{t=1} \equiv \{p_{j \in \mathfrak{S}_1}\}$.

To obtain $\xi_{t>1}(\theta_0)$, the participation probabilities h_{nt} associated with each draw ε_n are computed to get the survival probabilities $\psi_{nt+1} = \psi_{nt}(1 - h_{nt})$ for each simulated consumer. Then, the vector of mean utilities and the associated unobserved product attributes can be computed in the same way as in $t = 1$. This procedure is repeated for every t until $t = T$.

With the unobserved product attributes at hand, matrices of instruments Z_t are used to compute the sample analog of the vector of moment conditions (10) for each t :

$$\tilde{m}_t(\theta^0) = \xi_t^u(\theta^0)' Z_t \quad (28)$$

The estimation algorithm looks for the set of parameters $\hat{\theta}$ that minimizes a GMM metric:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \{ \tilde{m}(\theta)' \tilde{m}(\theta) \} \quad (29)$$

where \tilde{m} is a vector of vertically stacked moment conditions \tilde{m}_t . The instruments used to estimate the model include vectors of ones and the observed characteristics of available products at any point in time, which as usual are assumed to be uncorrelated with the unobserved attributes.

Estimates of $\{\pi, \gamma, \sigma_\gamma\}$ were obtained following the described procedure and are shown on Table 5. The displayed standard errors were obtained bootstrapping the random components of the model. The initial market size was set to 100 million which was the approximate number of U.S. households and then was adjusted period by period according to observed sales. The parameter π_0 is not separately identified from the constant γ_0 of the utility function and was therefore normalized to zero⁹. Eight versions of the model were estimated –four specifications (I, II, III and IV) each with one observed characteristic (resolution) and two characteristics (resolution and optical zoom) as follows:

⁹This normalization is equivalent to the usual normalization of the outside utility in discrete choice models.

Table 5: Preference estimates(standard errors in parenthesis)

	I: Constant coefficients		II: Random coefficients	
π_1	0	0	0.43 (0.15)	0.33 (0.09)
π_2	-0.37 (0.04)	-0.31 (0.03)	-0.60 (0.15)	-0.78 (0.13)
π_3	0	0	-0.83 (0.23)	-0.49 (0.16)
γ_1	3.04 (0.13)	3.24 (0.18)	3.13 (0.12)	3.03 (0.19)
γ_0	-10.20 (7.798)	64.64 (30.4)	-23.11 (4.6)	-22.19 (6.73)
γ_2	-	2.25 (0.17)		2.24 (0.17)
σ_x	0	0	0.07 (0.025)	0.22 (0.03)
	III: Random coefficients (restricted)		IV: Static model (BLP)	
π_1	0.08 (0.03)	0.13 (0.05)	0	0
π_2	-0.36 (0.04)	-0.30 (0.02)	-1	-1
π_3	0	0	0	0
γ_1	3.09 (0.13)	3.24 (0.15)	2.56 (0.10)	2.58 (0.15)
γ_0	-11.09 (3.11)	-11.28 (3.16)	-12.33 (0.12)	-12.18 (0.13)
γ_2	-	2.25 (0.18)	-	2.20 (0.18)
σ_x	0.01 (0.00)	0.05 (0.01)	0.00 (0.00)	0.00 (0.00)

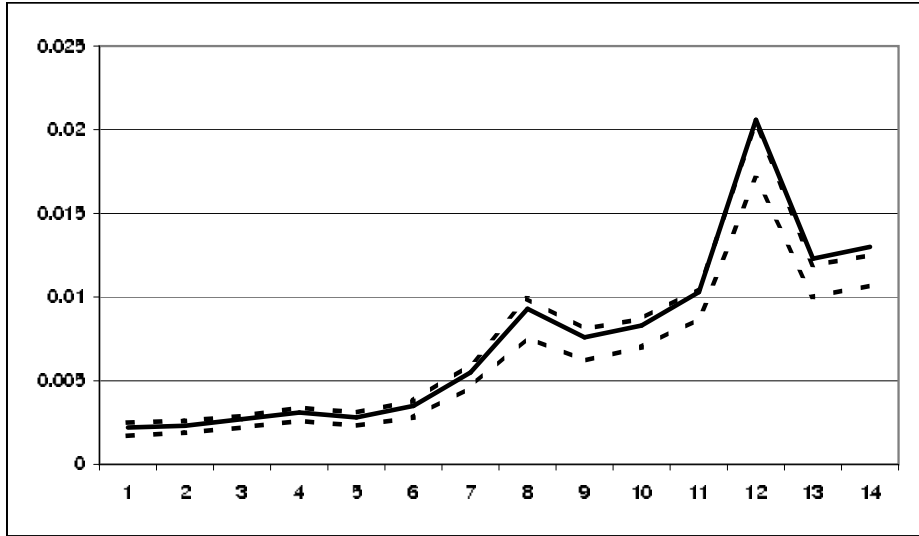


Figure 4: Observed market participation and 95% predicted interval

- Models I have no random taste coefficients. Therefore, $\sigma_\gamma = 0$, $\pi_1 = 0$ and $\pi_3 = 0$.
- Models II correspond to the full model. As shown in the appendix, depending on the draws of ε_n the mapping (26) may not be a contraction and therefore the algorithm failed to find a solution to the model for some parameter values.
- Models III are a restricted specification with $\pi_3 = 0$ that satisfies the sufficient conditions for (26) to be a contraction with a unique fixed point.
- Models IV are equivalent to the standard BLP estimation, which is a particular case of the model with $\pi_1 = 0$, $\pi_2 = -1$ and $\pi_3 = 0$.

Estimates of the taste coefficients are positive and reasonable. The estimates of the parameters π , though non-structural, are illustrative of the response of consumer behavior to changes in overall quality at the given equilibrium. Estimates $\hat{\pi}_2 < 0$ obtained from the dynamic models (I, II and III) imply that the participation function is positively correlated with the average consumer's valuation of "quality", so that as the quality of cameras increases, so does the probability of adoption. Nevertheless, when unobserved heterogeneity is incorporated (models II and III), the estimate $\hat{\pi}_1 > 0$ which implies that, given a set of available products and prices, a higher than average taste for camera resolution has a negative effect on the purchase probability.

To see how the model is able to reproduce the aggregate pattern of sales over time, figure 4 shows the series of observed aggregate camera sales over time and a band containing a 95% interval of simulated camera sales. The band was obtained simulating the joint distribution of the unobserved components of the model with no random coefficients and two characteristics (models I on Table 5, second column).

Now we discuss two salient features of the results. First, the contrast between the dynamic specifications of the model (models I, II and III) and the “static” specification (models IV), which allows the rejection of the standard “static” model. Second, the very low estimated randomness of the taste coefficient, which will facilitate the computation of the model of product introduction.

The first and most salient feature of the estimation is that they allow the rejection of the standard BLP model in favor of the more general dynamic specifications. Specifically, estimates of π in models I, II and III allow the easy rejection of the hypothesis that $\pi_1 = 0$, $\pi_2 = -1$ and $\pi_3 = 0$. This means that the participation behavior of consumers in this market is consistent with a non-constant reservation utility. Moreover, the data is consistent with the hypothesis that this reservation utility is tied to the changing quality of products.

In addition, estimates of γ^{res} obtained in I, II and III are significantly higher (both statistically and economically) than the estimates of γ^{res} obtained in IV. This bias is the result of the underlying assumption of the standard BLP model that non-participating consumers don’t value available products enough to buy them, whereas the truth may be that they may be waiting for better products to become available in the future. Notice that price parameters, which are identified from the pricing equation are the same across specifications, so that the differences in taste parameters reflect the essential difference between the static and the dynamic model.

As discussed before, the improvement of CCD chips over time is constant and quite dramatic, as well as the fall in prices. As a consequence of such change, consumers have strong incentives to delay the purchase of a digital camera. It is therefore no surprise that the static model yields a lower preference for CCD resolution than the dynamic model. On the other hand, notice that the estimate of the optical zoom coefficient doesn’t differ between the static and dynamic versions of the model; it is

also the case that the technology of lenses hasn't changed significantly over the last decade. Results are therefore consistent with the premise, that a static specification of consumer behavior is a misleading approach in environments with rapidly changing quality that imply nontrivial dynamic concerns for the consumers.

The second salient feature of the results is that the estimates of σ_γ in models II, III and IV are very low, which implies that there is little evidence of any economically significant heterogeneity of the taste for camera resolution, which was the main measure of the quality of an individual camera. In fact, the estimate of σ_γ obtained from models IV (the BLP specification) collapses literally to zero.

The reason why a model with random coefficients is generally better able to fit a panel of sales data is that it takes advantage of the correlation of market shares of similar products over time. In this case, the results indicate that the variation of the unobserved determinants of choices in the data has a very low correlation with the resolution of the cameras.

Consequently, for the estimation of the model of product introduction below it will be assumed that $\sigma_\gamma = 0$. This implies that all consumers share the same inclusive value:

$$\sigma_\gamma = 0 \Leftrightarrow r_{nt} = r_t \forall n \quad (30)$$

Therefore, firms should only keep track of one inclusive value over time when computing their expected evolution. Specifically, let the inclusive values evolve according to a first order autoregressive process:

$$r_t = \rho_0^r + \rho_1^r r_{t-1} + \epsilon_t^r \quad (31)$$

where ϵ_t^r is a non-persistent normal error, so that (31) can be estimated using OLS.

Table 6 contains the estimates of $\rho^r \equiv \{\rho_0^r, \rho_1^r\}$ obtained from (31) using the two different versions of models I. The estimates are precise and consistent with the upward trend of quality and variety of camera models over time. Figure 5 displays computed and fitted values of r_t , obtained from the model with two observed characteristics. Notice that the adopted transition of r_t , which is very close to a random walk, is consistent with the Markovian assumption on which the estimation of demand was based.

Table 6 also contains the estimates of the fixed brand-effects γ^B obtained from models I. These effects capture the systematic variation of unobserved quality across

Table 6: Estimates of γ^B and ρ^r
(standard errors in parenthesis)

	$x_j = \{x_j^{res}\}$	$x_j = \{x_j^{res}, x_j^{zoom}\}$
	$\sigma_\gamma = 0$	$\sigma_\gamma = 0$
agfa	0.50 (0.38)	0.38 (0.40)
canon	2.98 (0.30)	3.40 (0.41)
fuji	-0.21 (0.42)	-0.23 (0.33)
hp	0.74 (0.26)	0.90 (0.45)
kodak	1.36 (0.39)	1.05 (0.28)
nikon	1.10 (0.26)	1.10 (0.42)
olympus	2.52 (0.37)	2.43 (0.28)
polaroid	4.54 (0.26)	5.21 (0.40)
sony	5.08 (0.39)	4.06 (0.32)
toshiba	0.34 (0.37)	0.29 (0.43)
ρ_0^r	0.90 (0.27)	1.03 (0.27)
ρ_1^r	0.97 (0.03)	0.96 (0.03)

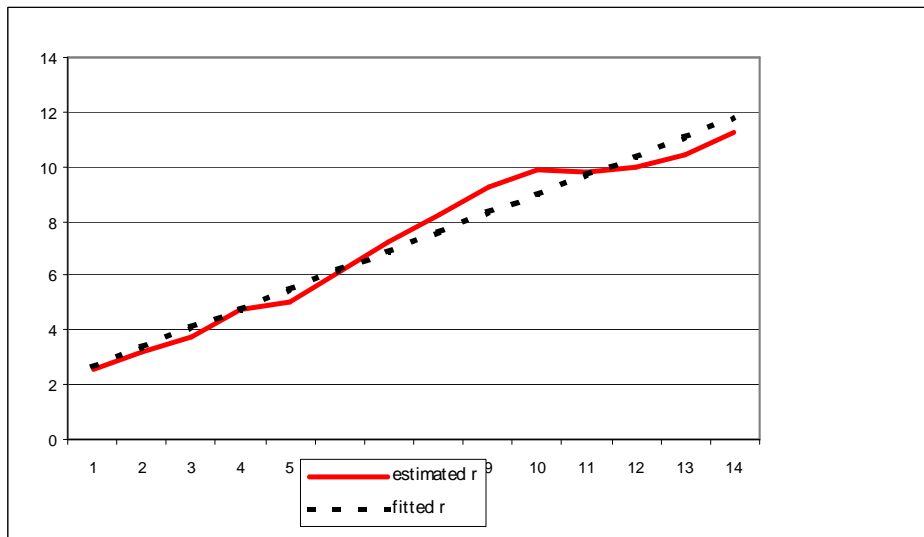


Figure 5: Estimated and fitted r

brands. Effects were included for the 10 top-selling brands and are measured with respect to the remaining brands. These ten biggest firms comprise around 90% of the market during the time span of the sample. Most of these effects are significantly different from zero. According to the estimates, Sony and Polaroid have the highest brand attributes.

4.3 Computation of $V(\cdot)$

We can use the estimates obtained above to compute the expected profitability at the time of introduction of any camera model. Consider the estimates obtained from models I for which $\sigma_\gamma = 0$ and use $\{\hat{\pi}, \hat{\gamma}, \hat{\alpha}, \hat{\eta}\}$ to compute the inclusive values as defined in (3). Then replace these values in (20) to obtain the expected value of a camera model with observed characteristics x_j to be introduced by firm B_j at time τ :

$$V_\tau^{B_j}(x_j) = E_{r_t, \eta_t} \left[\sum_{t=\tau}^{T_j} \beta^{t-\tau} \frac{1}{\hat{\alpha}} M_t \left[\frac{e^{\hat{\gamma}_0 + D_{B_j} \hat{\gamma}^B + (\hat{\gamma}^{res} - \hat{\alpha} \hat{\eta}_t^{res}) x_j^{res} + (\hat{\gamma}^{zoom} - \hat{\alpha} \hat{\eta}_t^{zoom}) x_j^{zoom} - 1}}{e^{\hat{r}t} + e^{\hat{\pi}_2 \hat{r}t}} \right] \right] \quad (32)$$

where the expectations with respect to the evolution of r_t and η_t are computed using the estimated distribution of $\{\hat{\rho}^r, \hat{\rho}^{zoom}, \hat{\rho}^{res}\}$ obtained above from (25) and (31).

The function (32) can be computed up to the time T_j at which the expected demand for the product falls close enough to zero. In practice, the maximum lifetime of any product was set to ten quarters, i.e. $T_j = \tau + 10$. This assumption has absolutely no effect on the results of the model because ten quarters is much more than the commercial life of any camera model in the sample. The quarterly discount rate was set at 0.97, and it was verified that results were not very sensitive to other choices. Also, to reduce the dimension of the problem, it was assumed that firms can perfectly anticipate the evolution of the total number of potential buyers, since it didn't have any significant effect on the results.

Figure 6 depicts the computed $V(\cdot)$ as a function of $x_j = \{resolution_j, \log(zoom_j)\}$ during the second quarter of 2000. Notice that the function is increasing and convex, as a consequence of the static demand functions being also convex on the characteristics space. For illustration purposes, the fixed-brand effect was set equal to zero. To provide

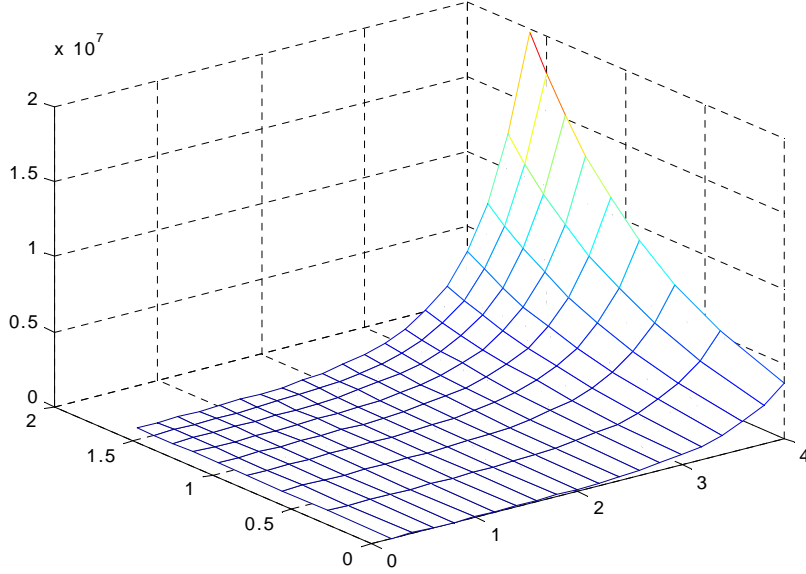


Figure 6: Value of quality as a function of resolution and optical zoom

an idea of the order of magnitude of this functions, this example indicates that a 2 megapixel average digital camera to be introduced by a less-known brand in mid-2000 was expected to generate discounted profits of 0.5 million dollars over the course of its commercial life, while a 3 megapixel camera was expected to generate around 3 million dollars.

The function $V(\cdot)$ is going to be used below for the estimation of the product introduction costs. Despite the fact that the computation of (32) above is an easy computational task for a given set of product characteristics, the estimation of the product introduction problem (22) requires that we compute the function $V(\cdot)$ and its derivatives repeatedly along the estimation algorithm. To facilitate these computations, a parametric approximation of the computed function $V(\cdot)$ was obtained. The computed $V(\cdot)$ is very smooth and could be approximated well by an exponential polynomial:

$$V_t^{B_j}(x_j) \approx \exp(\lambda_{0t}^B + \lambda_{1t}^B x_j) \quad (33)$$

Notice that the parameters are time- and brand-specific, since the function varies over time and across brands. It will be assumed that firms cannot anticipate or choose the value of a new product's unobserved attribute so that they expect it to be zero, which is its assumed mean. Estimates $\{\hat{\lambda}_{0t=1,\dots}^B, \hat{\lambda}_{1t=1,\dots}^B\}$ are obtained by successively computing $V(\cdot)$ over a grid of product characteristics and firms, and then using OLS

on its logs. The estimates of the approximation (not shown) are very precise, which is not surprising given the smoothness of $V(\cdot)$.

4.4 Estimation of product introduction costs

Now we turn back to the estimation of the product introduction costs $F(\cdot)$ given our approximation of $V(\cdot)$. As in standard empirical entry models, the maximum number of potential product introductions per period is set exogenously by assuming a maximum number of introductions L_t^B that each firm B can make at each period t . Even though the set of participating firms is fixed, a firm can endogenously exit (and enter back) the market depending on the success of its new product introductions. The model is estimated based on the behavior of the ten biggest firms in the market during the last ten quarters of the sample, taking the behavior of the remaining firms as given. It is assumed that the number of new products that any firm can introduce into the market each period is eight, i.e. $L_t^B = L = 8$. Eight is the maximum number of camera models introduced by any firm in the same quarter at any point during the time span of the sample.

Consider the problem of firms choosing only the resolution of the camera, so that $x_j \equiv x_j^{res}$. As indicated before, resolution was by far the most important quality indicator of individual camera models during the time span of the sample. Let the fixed introduction costs be given by the following flexible convex specification:

$$F_t(x_j, \xi_j^{F0}, \xi_j^{F1}; \zeta, \sigma_F) = \exp(\zeta_q + \zeta_V t + \sigma_{F0} \xi_j^{F0}) + \exp(\zeta_x x_j + \zeta_H t + \sigma_{F1} \xi_j^{F1}) \quad (34)$$

where $\xi_j^F \equiv \{\xi_j^{F0}, \xi_j^{F1}\}$ are standard normal unobserved errors that are associated with the two choices of the firm, i.e. introduction and camera quality. The introduction costs depend on the chosen observed quality x_j of the camera, a time trend t which captures the drift of the function over time, and parameter vectors $\zeta \equiv \{\zeta_x, \zeta_V, \zeta_H, \zeta_{q1}, \zeta_{q2}, \zeta_{q3}, \zeta_{q4}\}$ and $\sigma_F \equiv \{\sigma_{F0}, \sigma_{F1}\}$.

There are two terms in $F(\cdot)$: graphically, the first term indicates its position across the vertical axis, while the second one determines its curvature and potential horizontal shift. The first time trend parameter ζ_V causes the function to drift vertically as time

passes by. The second time trend parameter ζ_H shifts the function horizontally as time passes by. Parameter $\zeta_q \in \{\zeta_{q1}, \zeta_{q2}, \zeta_{q3}, \zeta_{q4}\}$ is a fixed-quarter effect that approximates the specific seasonal concerns that are not included explicitly in the model.

Each period τ , firm B gets to “try” to introduce up to $L = 8$ new camera models taking $l = 1, \dots, L$ independent draws of the standard normal errors $\xi_{lB\tau}^F \equiv \{\xi_{lB\tau}^{F0}, \xi_{lB\tau}^{F1}\}$. For each of these binomial draws the firm can introduce one new product. Given the assumptions above, each new product introduction is decided independently. Therefore, for each set $\xi_{lB\tau}^F$ of draws, the optimal introduction decision is given by the solution to (23) and (24).

The model is estimated using a simulated method of moments as follows: Fix the vector of parameters $\{\zeta^0, \sigma_F^0\}$. For each of the ten biggest firms in the sample $B = 1, \dots, 10$ and each period $\tau = 1, \dots, 10$, eight independent sets of errors $\xi_{lB\tau}^F$ are simulated (i.e. $l = 1, \dots, 8$). For each set of random draws we can obtain the optimal resolution $x_{lB\tau}^*$ of the new camera models to be considered for introduction replacing (33) and (34) in (24):

$$\hat{\lambda}_{1\tau}^B \exp(\hat{\lambda}_{0\tau}^B + \hat{\lambda}_{1\tau}^B x_{lB\tau}^*) = \zeta_1^0 \exp(\zeta_x^0 x_{lB\tau}^* + \zeta_H^0 \tau + \sigma_{F1}^0 \xi_{lB\tau}^{F1}) \quad (35)$$

Given the optimal resolution $x_{lB\tau}^*$ of the new camera model, the firm will introduce it *iff* its net expected profitability is positive. The optimal introduction decision \mathbb{I}_l^* can be obtained replacing $x_{lB\tau}^*$, (33) and (34) in (23):

$$\begin{aligned} \mathbb{I}_{lB\tau}^* = 1 &\Leftrightarrow \exp(\hat{\lambda}_{0\tau}^B + \hat{\lambda}_{1\tau}^B x_{lB\tau}^*) \\ &- \exp(\zeta_q^0 + \zeta_V^0 \tau + \sigma_{F0}^0 \xi_{lB\tau}^{F0}) - \exp(\zeta_x^0 x_{lB\tau}^* + \zeta_H^0 \tau + \sigma_{F1}^0 \xi_{lB\tau}^{F1}) > 0 \end{aligned} \quad (36)$$

Each simulation $s = 1, \dots, S$ yields optimal introduction decisions $\{\mathbb{I}_{lB\tau}^*, x_{lB\tau}^*\}^s$ for $l = 1, \dots, 8$, $B = 1, \dots, 10$ and $\tau = 1, \dots, 10$. The simulation was repeated $S = 100$ times to obtain a number of predicted moment conditions. Specifically, we obtain average predictions of the number of products introduced at each point in time and of the predicted inclusive values of the demand function:

$$\bar{K}_\tau(\zeta^0, \sigma_F^0) = \frac{1}{S} \sum_{s=1}^S \sum_{B=1}^{10} \sum_{l=1}^{10} [\mathbb{I}_{lB\tau}^{*s}] \quad (37)$$

$$\bar{r}_\tau(\zeta^0, \sigma_F^0) = \frac{1}{S} \left[\sum_{s=1}^S \log \sum_{B=1}^{10} \sum_{l=1}^{10} \mathbb{I}_{lB\tau}^{*s} \exp\left(\hat{\delta}(x_{lB\tau}^{*s})\right) \right] \quad (38)$$

where

$$\hat{\delta}(x_{lB\tau}^{*s}) = \hat{\xi}_{lB\tau}^u + \hat{\gamma}_0 + D_{B_j} \hat{\gamma}^B + (\hat{\gamma}^{res} - \hat{\alpha} \hat{\eta}_t^{res}) x_{lB\tau}^{*s} - 1$$

The average of the predicted inclusive value across the S simulations \bar{r}_τ in (38) contains random realizations of the unobserved product attributes $\hat{\xi}_{lB\tau}^u$ drawn from its empirical distribution, estimated in section 4.2. \bar{K}_τ is the predicted number of products introduced each period τ , averaged across simulations.

The choice of these moments is not arbitrary. The consistency of the model requires that the inclusive values predicted by the model $\bar{r} \equiv \{\bar{r}_1, \dots, \bar{r}_{10}\}$ match the observed inclusive values $r \equiv \{r_1, \dots, r_{10}\}$. On the other hand, matching the predicted number of introductions $\bar{K} \equiv \{\bar{K}_1, \dots, \bar{K}_{10}\}$ with its observed counterpart $K \equiv \{K_1, \dots, K_{10}\}$ guarantees that, given the inclusive values, the predicted quality of introduced products resembles the quality of products that are introduced in the data.

The estimation algorithm looks for the sets of parameters that match predicted and observed moments according to the following quadratic form:

$$\max_{\{\zeta, \sigma_F\}} \left(\{\bar{r}(\zeta, \sigma_F) - r, \bar{K}(\zeta, \sigma_F) - K\} * \{\bar{r}(\zeta, \sigma_F) - r, \bar{K}(\zeta, \sigma_F) - K\}' \right) \quad (39)$$

The standard errors of the estimates were obtained bootstrapping the random elements of the model.

Results of the estimation are presented on the middle column of table 7. The parameter estimates are precise and have the expected signs, with the exception of ζ_V which is very close to zero. The negative estimate of ζ_H indicates that for any given resolution, introduction is becoming cheaper over time and that the function is shifting to the right over time. Moreover, at any time introduction is more costly the higher the resolution of the model to be introduced (i.e. $\zeta_{res} > 0$). This may occur because, at any point in time, higher resolutions are technologically more complex and its adoption is therefore more expensive.

Estimates of ζ_q indicate that there are significant seasonal differences in introduction costs. Estimates indicate that introduction costs are higher during the summer and during the Christmas season. These differences may be a reflection of seasonal increases in competition for shelf space or in marketing costs. Finally, the simulated and observed moment conditions are displayed in figures 7 and 8 to illustrate the ability of the model to replicate the rich behavior observed in the data.

Table 7: Introduction Cost Estimation

Parameter	Estimate(s.e.)	Estimate (s.e.)
ζ_{q1}	15.8815 (0.20)	15.585 (0.48)
ζ_{q2}	17.2818 (0.30)	17.064 (0.63)
ζ_{q3}	15.6535 (0.23)	15.833 (0.49)
ζ_{q4}	17.7867 (0.41)	17.594 (0.70)
ζ_{res}	8.2197 (1.11)	11.499 (0.98)
ζ_V	0.024 (0.04)	-0.171 (0.08)
ζ_H	-0.9626 (0.23)	-1.062 (0.30)
σ_0	1.4957 (0.53)	2.036 (0.59)
σ_1	2.5798 (0.54)	2.562 (0.80)
ζ_{c1}		12154 (396.29)
ζ_{c2}		335 (40.19)

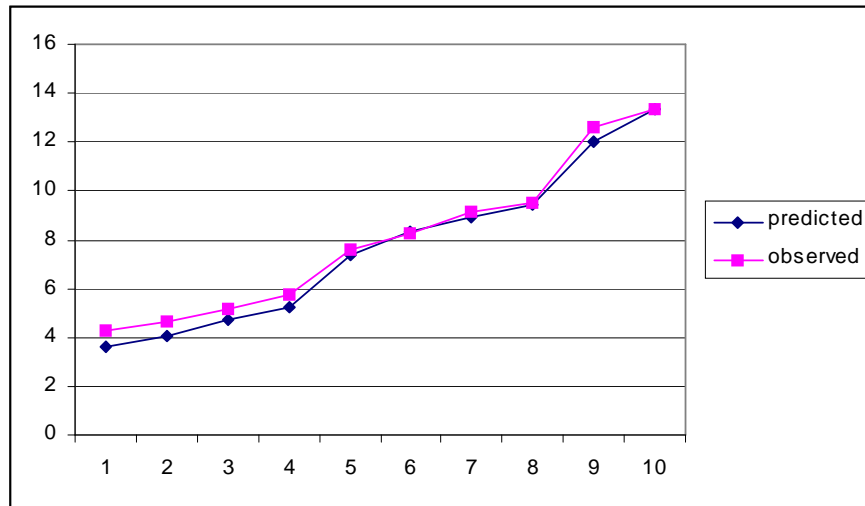


Figure 7: Predicted and observed inclusive value

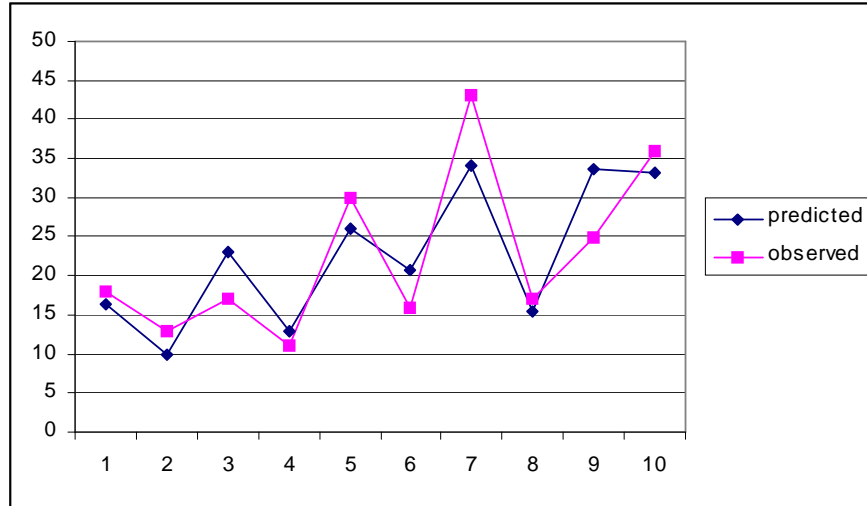


Figure 8: Predicted and observed number of introductions

Notably, the model can be used to generate predicted paths for prices and market shares of cameras with given quality. Figure 9 displays prices and market shares of a camera model chosen arbitrarily. As illustrated in the figure, the model generates the inverse-U shaped pattern of the market share that is observed in the data and that was documented in figure 2. Prices, on the other hand, decline monotonically over time, which is also consistent with the data as seen in figure 2. The figure corresponds to a camera with 1.1 megapixel introduced in mid 1999, but the general pattern is the same across qualities and brands.

Notice that in the model pricing behavior has no built-in dynamic mechanism and is purely the result of static profit maximization. The endogenous evolution of the market shares is generated by the interaction of consumer's dynamic behavior and the evolution of prices: in early periods, the technology is too costly and therefore the prices are high. As the technology of the camera becomes cheaper, so do prices and sales increase. At some point, though, the decrease of its relative quality –compared with competing models –induces the monotonic decrease of the market share of the given model.

The estimation has been based on the competitive assumptions detailed through the previous sections of the paper, which ruled out any strategic and/or cannibalization effects on firms' decisions. If these assumptions are not valid, product introduction

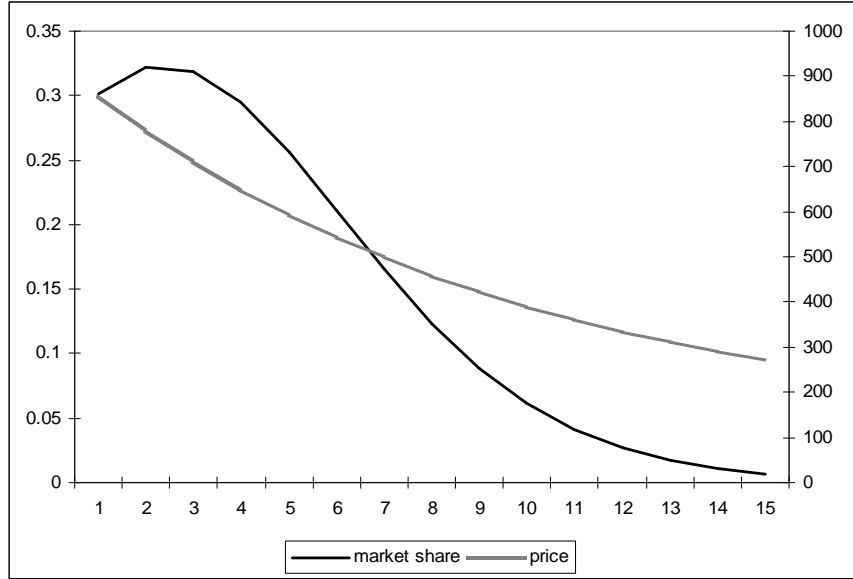


Figure 9: Predicted monthly prices and market shares after introduction

decisions are not independent of each other, both within and across firms, and estimates obtained from conditions (35) and (36) may be incorrect. To test the potential significance of this correlation and its impact on the estimation, a modified version of the model was estimated.

The correlation of the product introduction decisions and the market shares of individual firms can be estimated by modifying (36) as follows:

$$\begin{aligned} \mathbb{I}_{lB\tau}^* = 1 \Leftrightarrow & \exp(\hat{\lambda}_{0\tau}^B + \hat{\lambda}_{1\tau}^B x_{lB\tau}^*) - \exp(\zeta_q^0 + \zeta_V^0 \tau + \sigma_{F0}^0 \xi_{0lB\tau}^F) \\ & - \exp(\zeta_x^0 x_{lB\tau}^* + \zeta_H^0 \tau + \sigma_{F1}^0 \xi_{lB\tau}^F) + \zeta_{c1} s_{B\tau} + \zeta_{c2} s_{B\tau}^2 > 0 \end{aligned} \quad (40)$$

where $s_{B\tau}$ is the market share of firm B at time τ . The parameters ζ_{c1} and ζ_{c2} capture any statistical correlation between product introduction and the relative size of the firms which would be inconsistent with the assumptions of the model.

Results of this modified estimation are displayed on the right column of table 7. Notice that in general the estimated parameters of the introduction costs are similar to the ones obtained from the model without firm-size effects. Accounting for these effects implies a bigger coefficient of camera resolution and a significant downward shift over time of the introduction costs. This negative effect is compensated by the additional costs associated with the size of individual firms.

The estimates imply that there is a statistically significant negative effect of firm’s market shares on their product introduction decisions. There is a positive second order effect which implies that the effect is worse for larger firms. Nevertheless, the magnitude of the effect is negligible. For a firm with a 35% market share –which is around the highest any firm in the sample has at any point in time–the additional “costs” of product introduction implied by their market shares are estimated to be around \$4500, which is almost negligible compared with the estimated value of products.

These results suggest that the assumptions on which the estimation is based are adequate. In the following section the estimated model without firm-size effects is used to characterize the behavior of the model around the observed equilibrium and to illustrate the computation of counterfactual equilibria.

4.5 Computation of counterfactual equilibria

The estimated model above allows the computation of counterfactual equilibria in a manner that is consistent with a structural behavioral model. Computing the counterfactual behavior of the model is useful to understand its mechanics and illustrates the counterfactual implications of the model.

Computing such equilibria is not trivial, though, due to the fact that behavior of firms is determined crucially by their expectations regarding the evolution of overall market quality and variety as indexed by the inclusive values $r \equiv \{r_{t=1,\dots,T}\}$. The computed values of product introduction $V(\cdot)$ described in (32) are specific to the given dynamic equilibrium. In any counterfactual equilibrium, the expected evolution of r should be consistent with its counterfactual intertemporal distribution.

The estimation is in fact based on a rational expectations assumption implying that expectations are consistent with observed behavior. The model implies that if firms expect the inclusive value r_t to increase slowly over time, the value of individual innovations is higher and therefore incentives to introduce new products are higher; on the other hand, as all firms introduce more and better products, they should expect r_t to increase more rapidly over time. In an equilibrium with rational expectations, though, expectations should coincide with the observed behavior.

More precisely, given any observed sequence r^0 , and any assumed set A of exogenous

assumptions, the estimated model generates a mapping Ψ of simulated r' :

$$r' = \Psi(r^0, A) \tag{41}$$

In equilibrium, for the beliefs to be consistent we need $r' \equiv r^0$. For any given $A' \neq A$, therefore, consistent beliefs can be found by computing the fixed point of $r' = \Psi(r^0, A')$.

The computation of the fixed point above was done in the following way: given an initial guess for r , we can compute its transition probability, which we can use to compute the value of product introduction for each firm, at each point in time and for any quality choice. These computed values of $V(\cdot)$ are then used to obtain the parametric approximation (33)—one for every period and for every firm. With these parametric approximations at hand we simulate 200 times the behavior of firms under the counterfactual assumptions A' to and obtain a new predicted set of r' by taking its average prediction across simulations. For each iteration along the fixed point algorithm, these steps are repeated until convergence, which is assumed to be reached as soon as the norm of $(r' - r)$ is sufficiently small.

The value of the parameters of the model correspond to estimates obtained above as follows:

- Cost and markup estimates from the left column on table 4.
- Preference estimates from the left column of model I on table 5 and the left column of table 6.
- Introduction cost parameters from the left column on table 7.
- Set the starting values for r equal to its values in the estimated equilibrium.

In other words, the computations are based on the model with only one observed product characteristic and no unobserved persistent taste heterogeneity. The computations are based on the behavior of ten biggest firms over the last ten quarters of the sample and take the behavior of the smaller firms as given. They also take the dynamic behavior of consumers as given by the reduced form approximation implied by the demand estimates.

Tables 8 and 9 report the number of new model introductions per quarter and its average quality averaged across 200 simulations computed using the fixed point

Table 8: Simulated number of introductions

<i>Quarter</i>	<i>Baseline</i>	I	II	III	IV	V	VI
t=1	17.06	144.71	17.33	22.95	14.77	12.65	23.21
t=2	8.76	51.38	8.53	13.90	7.46	5.96	13.79
t=3	18.03	134.36	18.78	25.25	17.07	13.71	24.50
t=4	8.56	31.50	7.95	13.75	7.86	5.60	13.18
t=5	21.55	137.64	23.46	29.22	21.31	16.97	27.61
t=6	13.72	56.57	13.42	20.02	13.99	9.87	19.43
t=7	24.42	137.75	28.10	32.68	24.70	19.73	31.14
t=8	14.68	44.26	14.28	20.46	14.97	10.55	19.44
t=9	28.98	150.54	38.31	37.99	30.35	24.24	36.13
t=10	20.45	74.93	22.46	27.73	21.44	16.50	26.45

algorithm discussed above. The baseline values correspond to a simulated version of the observed equilibrium obtained from a first run of the algorithm under the observed conditions. Each other column corresponds to a different experiment: in I and II, the number of participating firms is altered. In III and IV, the introduction costs are changed across existing firms. Finally, in V and VI the exogenous potential market size is changed. Each experiment and its results is discussed below.

Notice that these experiments involve the variation of exogenous variables that don't vary in the data. The model identifies the effects of such variation in the following way: Given that each firm has a limited number of products, the model can predict the effect of varying the number of firms (experiments I and II) through its effect on the potential number of successful product introductions, which has direct implications on the value of later product introductions.

Given the structure of the model, on the other hand, the observed variation in product introduction across time and firms implies different introduction costs, which can therefore be changed counterfactually (experiments III and IV). Finally, as time passes by and consumers purchase cameras, the market size shrinks and affects directly the value of introduction, which can be therefore evaluated counterfactually for different market sizes (experiments V and VI).

Table 9: Simulated average resolution

<i>Quarter</i>	<i>Baseline</i>	I	II	III	IV	V	VI
t=1	2.10	2.00	2.08	2.04	2.13	2.07	2.14
t=2	2.20	2.07	2.18	2.15	2.23	2.17	2.25
t=3	2.33	2.20	2.31	2.26	2.35	2.30	2.36
t=4	2.41	2.25	2.39	2.34	2.44	2.38	2.45
t=5	2.55	2.39	2.54	2.47	2.57	2.53	2.58
t=6	2.65	2.46	2.63	2.57	2.68	2.62	2.68
t=7	2.78	2.59	2.78	2.69	2.81	2.76	2.80
t=8	2.87	2.65	2.87	2.78	2.91	2.86	2.90
t=9	3.01	2.79	3.03	2.91	3.05	3.01	3.03
t=10	3.12	2.87	3.14	3.01	3.15	3.12	3.13

4.5.1 Changing the number of competing firms

Columns I and II in tables 8 and 9 display the number of counterfactual new product introductions per period and the average camera resolution of the new products over the ten last quarters of the sample, when 30 additional firms of two different types are added to the market¹⁰. The two chosen types were Sony (column I) and Toshiba (column II) which are, correspondingly, the firms with the highest and lowest unobserved brand-specific “quality” so that the contrast is more evident¹¹.

This experiment is equivalent to increasing the maximum number of product introductions per period for two different firm-types. Such change induces two offsetting effects: one one hand, the increased “competition” allows the introduction of more and better products. On the other hand, it erodes the dynamic value of innovation, because firms expect to have lower market shares.

By comparing the results of column I and column II in both tables, it can be seen that the net effect of having more firms competing in the market depends heavily on

¹⁰Simulations were performed increasing gradually the number of competing firms and results are qualitatively equivalent.

¹¹The unobserved brand-effect of Sony is 5.02 and Toshiba’s is 0.3, measured with respect to the average of the smaller firms; in this sense, Toshiba is very much an “average” firm.

the type of the firms. As can be seen, the number of product introductions, compared to the observed baseline only increases slightly when lower-type firms are added to the market, whereas it increases dramatically when higher-type firms are added.

What happens is that low-type firms cannot successfully introduce new products. In this sense, increased “competition” by average firms (i.e. similar to Toshiba) has no effect on the observed performance of the market: new firms just have a lower rate of product introduction, or just fail to introduce any new products at all. On the other hand and as seen in table 9, the average resolution of new cameras doesn’t change much with respect to the baseline when low-type firms are added to the market (column II). Surprisingly, it is lower when more higher-type firms are competing with each other (column I). The highest resolution (not shown) of new cameras doesn’t change across simulated regimes, whereas the lowest resolution (not shown) is lower when more high-quality firms are competing. The higher successful competition of high-quality firms skews the distribution of quality of new camera models, because of the convexity of introduction costs, which makes it less likely the introduction of new high quality camera models than the introduction low quality camera models.

In sum, the counterfactual computation of the model suggests that competition, per se, has no necessary effect on the performance of the market. As illustrated, the increased presence of average competitors only causes average firms to be displaced from the market and to have more difficulties introducing new products. On the other side, increased competition by higher quality firms has a significative impact on product introduction and variety and causes average quality to be actually lower, because increased competition decreases the value of high-quality product introduction. Simulating a high number of high-quality firms has just an illustrative meaning, in the sense that the exogenous “quality” of brands is the reflection of the underlying scarcity of technological and managerial talents.

4.5.2 Changing market size and introduction costs

This section explores the counterfactual effects of changing the product introduction costs and the market size. Columns III and IV in tables 8 and 9 contain the counterfactual effects of changes in the fixed introduction costs. Column III corresponds to

the experiment in which introduction costs are halved across firms and across quality choices, while column IV corresponds to the counterfactual doubling of introduction costs across firms and across quality choices.

As can be seen, both in terms of the number of introductions and the average resolution of cameras, the effects of a decrease in the introduction costs as seen in column III are more significant than the effects of an increase of costs displayed in column IV.

When introduction costs decrease (column III), the number of new product introductions increases so that the effective competition increases. The average quality of new cameras *decreases*, due to the fact that more effective competition decreases the value of innovation and therefore more of the new cameras tend to have *lower* quality.

When the introduction costs are doubled (column IV), the number of introductions is lower during the earlier periods. The average quality of cameras does not change much, because the effective lower competition is offset by the increased introduction costs.

This asymmetry of the effects on the product introduction behavior of counterfactual changes in introduction costs is due in part to the convexity of the introduction costs with respect to the choice of camera resolution. It implies that introducing high quality cameras becomes prohibitively expensive very rapidly as the quality increases. Therefore, when the market is able to absorb more camera models, the distribution of their quality will tend to be skewed towards lower quality cameras.

The effects of changes in total market size, on the other side, are more balanced. Column V in tables 8 and 9 reports the effects of halving the total market size, and column VI reports the effects of doubling the total market size. As expected, the number of introductions increases when the market size is bigger, whereas it decreases when the market size is smaller. Remarkably, average quality stays fairly constant across experiments. This is a reflection of the offsetting impact of competition and innovation opportunities.

The described experiments illustrate the very complex relationship between market performance and market structure implied by the model. Some of the results are surprising: for example, the fact that increased presence of competitors doesn't necessarily

have any effect on product variety or quality. Or the result that increased introduction costs lead to higher average camera quality. The richness of the results highlight also the importance of addressing the innovation behavior of firms accounting for the the specifics of the environment.

5 Conclusion

An empirical framework was developed to study product innovation and adoption in markets for digital cameras. The framework was based on an equilibrium model of supply and demand for durable goods that accounts for the dynamic incentives of both consumers and firms. Estimates were obtained of the value of products for firms and consumers accounting for the dynamics of the environment. The model was not only able to reproduce the dramatic improvement in camera quality over the time span of the sample, but was also able to reproduce the rich pattern of pricing and sales of individual products that is observed in the data.

Counterfactual computations illustrate the need for addressing the innovation behavior of firms using an empirical technique that accounts for the structural complexities of the market. For example, it is shown that increasing competition doesn't necessarily increase the average quality of introduced products. Or that increased market size or reduced innovation costs do not necessarily lead to higher average quality, due to technological restrictions and the perverse effects of increased competition on the value of innovation.

There is no precedent in the literature of an empirical structural model of dynamic product innovation and adoption. The paper illustrates the difficulties for estimating a general model of product innovation and adoption that accounts for all the strategic and product cannibalization concerns of firms. Therefore, the identification of the model relied on a monopolistic competition assumption, which was argued to be adequate for the case of the market for digital cameras.

The supply side of the model illustrates how a competitive model can reproduce the dramatic improvement in quality and decrease in prices observed in the data. Product innovation decisions were shown to be loosely correlated with the firms' overall market

shares, which is consistent with the competitive assumption. Future research should ascertain whether it is possible to identify a richer model of firm competition from product-level data.

Finally, the paper contributes to the empirical literature on estimation of demand for differentiated products by implementing a simple extension of the standard BLP technique that incorporates both dynamics and unobserved consumer heterogeneity. It was found that persistent unobserved heterogeneity was not significant and that consumers had strong dynamic incentives to time optimally their purchases. Specifically, it was found that the standard BLP specification was rejected by the data.

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Appendix I: Computation of the mean utilities

The computation of the mean utility levels is based on the solution for the fixed point of the mapping (26), $f(\delta_t) = \delta_t + \log(Q_t/M_t) - \log(\tilde{q}_t/M_t)$, which is identical to the function (6.8) in BLP except for the fact that demand \tilde{q} is given by (6). The appendix in BLP spells out three assumptions that (26) must satisfy in order to be a contraction with a unique interior fixed point.

It is shown below that a sufficient condition for these assumptions to hold is that $0 \leq \partial R_{it}/\partial r_{it} < 1$. This condition guarantees that $f(\cdot)$ is monotonic; if it doesn't hold

$f(\cdot)$ may fail to converge, and the algorithm would be systematically ruling out points in the parameter space. This restriction makes economic sense: it means that the reservation value of a consumer should not be affected negatively or disproportionately by movements in the current value of participating in the market.

From (6), predicted demand can be rewritten as follows:

$$\frac{q_{jt}(\delta_t)}{M_t} = \int Pr_{ijt}(\delta_t, \varepsilon_i) dG_t(\varepsilon_i)$$

where individual choice probabilities are given by:

$$Pr_{ijt} = \left[\frac{e^{\delta_{jt} + x_j^{res} \sigma_\gamma \varepsilon_i - R_{it}(r_{it}(\delta_t, \varepsilon_i))}}{1 + e^{r_{it}(\delta_t, \varepsilon_i) - R_{it}(r_{it}(\delta_t, \varepsilon_i))}} \right]$$

As in BLP, the derivatives of the function $f(\cdot)$ are given by:

$$\begin{aligned} \frac{\partial f_{jt}}{\partial \delta_{jt}} &= 1 - \frac{1}{q_{jt}/M_t} \frac{\partial(q_{jt}/M_t)}{\partial \delta_{jt}} = 1 - \frac{\int (\partial Pr_{ijt}(\delta_t, \varepsilon_i) / \partial \delta_{jt}) dG_t(\varepsilon_i)}{\int Pr_{ijt}(\delta_t, \varepsilon_i) dG_t(\varepsilon_i)} \\ \frac{\partial f_{jt}}{\partial \delta_{kt}} &= \frac{1}{q_{jt}/M_t} \frac{\partial(q_{jt}/M_t)}{\partial \delta_{kt}} = \frac{\int (\partial Pr_{ijt}(\delta_t, \varepsilon_i) / \partial \delta_{kt}) dG_t(\varepsilon_i)}{\int Pr_{ijt}(\delta_t, \varepsilon_i) dG_t(\varepsilon_i)} \end{aligned}$$

The first assumption that $f(\cdot)$ must satisfy is the following set of conditions: $\partial f_{jt} / \partial \delta_{jt} > 0$ and $\partial f_{jt} / \partial \delta_{kt} > 0$ for all $j, k \in \mathfrak{S}_t$, and that $\sum_{k \in \mathfrak{S}_t} \partial f_{jt} / \partial \delta_{kt} < (q_{jt}/M_t)$ for all $j \in \mathfrak{S}_t$. Note that these derivatives correspond to integrals over properties of individual choice probabilities. Therefore, it is sufficient to show that the conditions hold point by point as follows:

$$\begin{aligned} \frac{\partial Pr_{ijt}}{\partial \delta_{kt}} &= -Pr_{ijt} Pr_{ikt} \left(1 - \frac{\partial R_{it}}{\partial r_{it}} \right) < 0 \\ \frac{\partial Pr_{ijt}}{\partial \delta_{jt}} &= Pr_{ijt} \left(1 - \frac{\partial R_{it}}{\partial r_{it}} \frac{e^{\delta_{jt} + x_j^{res} \sigma_\gamma \varepsilon_i}}{e^{r_{it}(\delta_t, \varepsilon_i)}} \right) - Pr_{ijt}^2 \left(1 - \frac{\partial R_{it}}{\partial r_{it}} \right) < Pr_{ijt} \\ \sum_{k \in \mathfrak{S}_t} \frac{\partial Pr_{ijt}}{\partial \delta_{kt}} &= Pr_{ijt} \left(1 - \frac{\partial R_{it}}{\partial r_{it}} \frac{e^{\delta_{jt} + x_j^{res} \sigma_\gamma \varepsilon_i}}{e^{r_{it}(\delta_t, \varepsilon_i)}} \right) - Pr_{ijt} \left(1 - \frac{\partial R_{it}}{\partial r_{it}} \right) \sum_{k \in \mathfrak{S}_t} Pr_{ikt} < Pr_{ijt} \end{aligned}$$

Since by definition $0 < \frac{e^{\delta_{jt} + x_j^{res} \sigma_\gamma \varepsilon_i}}{e^{r_{it}(\delta_t, \varepsilon_i)}} < 1$ for all realizations of ε_i , it can be easily seen that whenever $0 \leq \partial R_{it} / \partial r_{it} < 1$ the conditions above hold. Notice that in BLP $\partial R_{it} / \partial r_{it} = 0$ and therefore these conditions always hold.

The second and third assumptions for $f(\cdot)$ to satisfy according to BLP guarantee that its fixed point is interior. How these assumptions hold can be shown using an argument identical as in BLP.

The second assumption is that $f(\cdot)$ has a finite lower bound. To show this, rewrite $f(\cdot)$ as follows:

$$f(\delta_t) = \log(Q_t/M_t) - \log \int \frac{e^{x_j^{res} \sigma_\gamma \varepsilon_i - R_{it}(r_{it}(\delta_t, \varepsilon_i))}}{1 + e^{r_{it}(\delta_t, \varepsilon_i) - R_{it}(r_{it}(\delta_t, \varepsilon_i))}} dG_t(\varepsilon_i)$$

Note that as $\delta_t \rightarrow -\infty$, $r_{it} \rightarrow \infty$ and, by definition, $R_{it} \rightarrow 0$. Therefore, as $\delta_t \rightarrow -\infty$, $f(\delta_t) \rightarrow \log(Q_t/M_t) - \log \int e^{x_j^{res} \sigma_\gamma \varepsilon_i} dG_t(\varepsilon_i)$.

The third assumption is that $f(\cdot)$ is bounded away from ∞ . Specifically, we show that there exists a value $\bar{\delta}$, such that if any element in δ_t is greater than $\bar{\delta}$, then there is some $k \in \mathfrak{S}_t$ such that $q_{kt}(\delta)/M_t > Q_{kt}/M_t$ and $f(\delta_{kt}) < \delta_{kt}$. For each $j \in \mathfrak{S}_t$ find the value $\bar{\delta}_j$ that makes the share of the outside option equal to its observed value assuming that j is the only product in the market, and set $\bar{\delta} = \max_{k \in \mathfrak{S}_t} \bar{\delta}_j$. Notice that if there is an element in δ_t that is above $\bar{\delta}$ then it must be that $\sum_k q_{kt} > \sum_k Q_{kt}$ and for some $k \in \mathfrak{S}_t$ $q_{kt} > Q_{kt}$ therefore $f_k(\delta_t) < \delta_k$.

Four specifications of the model were estimated (labelled models I, II, III and IV). Models I, III and IV satisfy the restriction that $0 \leq \partial R_{it}/\partial r_{it} < 1$. In models IV, this restriction may be violated for particular realizations of ε_i and sometimes lead to non-convergence of (26).