Why are Prices Falling Fast? An Empirical Study of the US Digital Camera Market

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Abstract

This paper aims to address the reasons behind the rapid price declines generally experienced in new durable goods markets. It develops an equilibrium model that separates price declines caused by cost reductions from those caused by declines in markups. The model distinguishes itself from the existing literature by explicitly incorporating the interaction between consumers' forward-looking behavior and firms' dynamic pricing policies. In the model, heterogeneous consumers adopt the products in diverse patterns and the changing consumer mix in residual demand is taken into account in firms' price decisions. The actual prices are thus the equilibrium outcome consistent with both demand and supply dynamics. The paper also proposes tractable estimation strategies that are free of solving for equilibrium and the large dimensionality of the state space. Using a newly collected dataset from the US digital camera market, the paper finds that cost reductions account for an average of only two thirds of the price declines in this market. The remaining one third of the price declines are due to the declines in markups. Further decomposition of the sources of falling markups can be conducted in a variety of counterfactual analyses.

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1 Introduction

New durable goods markets, especially those consumer goods markets associated with quickly improving technologies, are characterized by rapid declines in price paths. In the digital camera market, the first four megapixel digital cameras sold to consumers in mid-2001 cost nearly $800. By the end of 2004, however, their prices had declined to less than $150. Other notable examples of this phenomenon include DVD players, VCRs and personal digital assistants. A natural explanation for the fast price declines is the advance in cost saving technologies. Image-capture chips see constant and quick improvement in their ability to transform images in greater detail, and their production costs are constantly reduced. Digital camera producers are thus able to charge lower prices for the same products over time.

However, cost reduction is not the only factor that drives down product prices in new durable goods markets. Markups may decline at the same time as costs and account for part of the price declines. The reasons for declining markups are multiple. Intensifying price competition over time may be a generically plausible explanation, but the unique features of durable goods markets imply another even more important one – the interaction between the dynamic behavior on the demand and supply sides of the economy. While this interaction has been intensively studied in a large body of theoretical literature since Coase (1972) and Stokey (1978, 1981), very few studies have developed formal empirical models that incorporate the dynamic behavior of both consumers and firms in a satisfactory way. In this paper, I aim to fill this void in the empirical literature by building an equilibrium model, where demand and supply dynamics in durable goods markets are integrated and the contributions of different sources to the price declines can be separated.

The theoretical issues in durable goods markets that may give rise to falling markups are familiar. On the demand side in these markets, consumers make purchase decisions by comparing the utility from the current purchase with the expected discounted utility from postponing the purchase to the future if they believe prices will fall or quality will improve. Their dynamic purchase decisions are therefore dynamic and affected by the price paths set by firms. On the supply side, firms' pricing policies are also essentially dynamic in that they care about both the current and future profits and must consider the impact of the current period price decisions on the residual demand left in the market for future periods. To trade off optimally between the current and future profits requires firms to know how the residual demand among heterogeneous consumers is shaped by their price decisions, and more crucially, how the consumer mix in residual demand is changing over time. The reason for the changing consumer mix is the diverse adoption patterns across different consumer groups. Early adopters possess higher valuations for the products and are less price elastic. Once they have purchased, they drop out of the market and their exit will leave for future periods a pool of consumers that are more price elastic and have lower valuations for the product. Faced with an increasingly elastic demand, firms have an incentive to cut prices to appeal to remaining consumers. But this incentive may work against firms because, by the Coasian argument, strategic consumers may delay their purchases even longer, forseeing falling price paths. As a result, big price cuts are needed to counteract strategic procrastination. This interaction between demand and supply dynamics generate complex market outcomes, especially with regard to price paths. In equilibrium, the actual price paths reflect both consumers' and firms' forward-looking behavior, and their correct beliefs about the behavior of one another. In other words, the price paths are consistent with consumers' expectation about future prices, and consumers' optimal purchase decisions based on their expectations are consistent with firms' perception of the changing consumer mix affected by their dynamic pricing policies. It is reasonable to anticipate that this interaction might result in price declines larger than that induced by cost reductions alone.

Most empirical studies on the dynamics of durable goods markets examine only the demand-side dynamics, with varying degrees of complexity in demand specification and estimation techniques. One seminal paper is Melnikov (2001), which characterizes each consumer's purchase decision as an optimal stopping problem. In this framework, a representative consumer decides whether to exit the market by comparing the average market values of all existing products, indexed by *the logit inclusive value*, in the current and the next periods. Pre-assumed to be a Markov process, the evolution of this statistic completely characterizes the transition of consumers' state space and determines their choice probabilities in each period. Building upon the same approach, Carranza (2006) and Gowrisankaran and Rysman (2006) extend Melnikov's framework to allow for consumer heterogeneity.[1] Other papers that fall into the same group include Song and Chintagunta (2005). In all these studies, the price paths from which

[1] They differ from each other in terms of their estimation strategies. While Carranza chooses parameterized reduced-form hazard rate functions to ease the computation burden, Gowrisankaran and Rysman combine Melnikov's framework with the findings in Rust (1984) and are able to solve directly for each individual's purchase probabilities in any period.

consumers form their expectations are exogenous. An account of how the price paths are set by firms, and more crucially, how consumer expectations are transmitted into the endogenized price decisions is still missing. So far, the attempts to address both demand and supply dynamics are limited. Carranza (2005) focuses on firms' dynamic innovation decisions and the setting of his model assumes away the dynamic concern of firms' pricing strategies and the possible changes in markups. Nair (2004) simulates the equilibrium price paths in the US video-game industry given the estimate of a simple demand system and the available cost information. Although the results shed light on the qualitative pattern of declining equilibrium prices, this paper does not treat market outcomes as in equilibrium and therefore does not separate the price declines due to cost reductions and the price declines due to markup changes. It also excludes the possibility of quantifying consumer welfare and market power in both real markets and counterfactual scenarios.

The omission of the supply-side dynamics in the equilibrium framework likely arises from two principal difficulties in investigating firm behavior. On the one hand, the conventional algorithm for supply-side estimation requires numeric policy iterations like the techniques in Nair (2004) to solve firms' Bellman equations, and the algorithm is often confronted with the problem of multiple equilibria. On the other hand, the analysis of firm behavior has to face the challenge from the large dimensionality of firms' state space. The state variables relevant to firms' pricing policies include the residual demand in each consumer group, the competitors' product innovations and the information on cost structures. The transition of all these variables are hard to characterize or calculate.

In this paper, I tackle these difficulties with two strategies. First, I draw on Berry and Pakes (2001) to base the supply-side estimation directly on the necessary optimality conditions that the equilibrium prices must satisfy. Orthogonality conditions implied by the assumed rational expectations of firms identify the cost parameters. There is no need to solve Bellman equations and the problem of multiple equilibria is therefore avoided. Second, I simplify the transition of firms' state space by introducing a novel market shock process. The special feature of this process is that it contains all the uncertainty as to how much in each consumer group the current price decisions can influence the current demand and thus the residual demand in the future. With exogenous evolution of cost structures and product innovations, the transition of firms' state space is fully characterized by this market shock process.

The empirical estimation of the model is cast in the US digital camera market, although the framework developed is potentially applicable to a variety of durable goods markets. I use a newly collected dataset, in which the standard market level sales and price data is supplemented with household level penetration data. I start with the estimation of a complex demand system with forward-looking and heterogeneous consumers. The estimation strategies are built on Gowrisankaran and Rysman (2006) but improve upon their techniques by following Berry, Levinsohn and Pakes (2004) and Petrin (2002) to create extra micro moments from the household level observations. Consumer heterogeneity is therefore identified in a more accurate way. The estimation results support the conjecture that different income groups differ considerably in their price elasticities. The estimated demand system then serves as an input into firms' dynamic pricing problems, where the optimality conditions for prices and the assumption of rational expectations generate the moment conditions that cost parameters are associated with.

With a rich set of instruments, I obtain reasonable estimates of the cost structures using the GMM method. Strikingly, my results illustrate that it is not only the costs, but the markups that are declining rapidly over the observation period. On average, markups decrease by nearly two percent each month and account for about one third of the price declines. This finding corroborates what is predicted in the theoretical literature – the interaction between demand and supply dynamics limits the profitability of firms' dynamic pricing policies, and thus their market power. Further evaluation of the contributions by demand and supply dynamics to the price declines are allowed by the developed equilibrium model and the estimated parameters. In particular, I can simulate new equilibrium price paths in the counterfactual scenarios with myopic and/or static firms. How much less steep the simulated price paths become compared to the observed ones will speak for the importance of the dynamics shut down.

The remainder of this paper is organized as follows: Section 2 develops the equilibrium model and proposes the estimation strategies; Section 3 provides an overview of the US digital camera market and a description of the dataset; Section 4 makes empirical specifications and discusses estimation details; Section 5 shows the estimation results and Section 6 concludes.

2 An Equilibrium Dynamic Model and its Estimation

This paper aims to address how prices in durable goods markets are driven down by different sources, especially how the interaction between consumers' strategic purchase decisions and firms' dynamic pricing policies curtails markups and thus contributes to the price declines over time. In the section below, this interaction is incorporated in an equilibrium model, in which actual prices are consistent with consumers' expectations and firms' dynamic pricing policies, as well as their correct beliefs about the behavior of one another. The section starts with an introduction of firms' dynamic pricing problems, and proceeds with a study of how the residual demand is shaped by firms' price decisions. It then looks at how equilibrium prices are generated by both supply and demand dynamics.

2.1 Supply-side Dynamics

On the supply side, durable goods producers are assumed to be playing among themselves an infinitely repeated Bertrand pricing game. At the beginning of time t, each firm f chooses the prices of their products, denoted by vector p_{ft}, to achieve the highest net present value of its expected profit flow. The price decisions are made simultaneously and there is no private information about any firm's product qualities, demand structure, cost evolution or price history. The knowledge about any demand uncertainty is also shared among all firms. The state vector σ_t,which represents all the information available at the beginning of time t, is thus invariant across firms.

In this setting, each firm f's price decision can be described as below:

$$V_f(\sigma_t) = \max_{p_{ft}>0} E[\sum_{\tau=1}^{\infty} \beta^\tau \pi_{f,t+\tau} | \sigma_t, p_{ft}], \tag{2.1}$$

where $\pi_{f,t+\tau}$ is the single-period profit at time $t+\tau$, β is the common discount factor shared by all firms, and $V_f(\sigma_t)$ is the maximized net present value of the expected profit flow from time t. In Bertrand equilibrium, firm f's pricing strategies p_{ft} are optimal given its correct belief about rival firms' actual price decisions.

With the regular assumptions that $0 \leq \beta < 1$, $\{\pi_{f,t+\tau}\}_{\tau\geq 0}$ are bounded, and $\{\sigma_t\}_{t>0}$ follows a Markov process with transition kernel $F(\sigma_{t+1}|\sigma_t, p_{ft})$ conditional on firm f's price decision p_{ft}, the solution to the above problem is the unique fixed-point value function that solves the Bellman equation

$$V_f(\sigma_t) = \max_{p_{ft}>0}\{E\pi_{ft}(\sigma_t, p_{ft}) + \beta \int V_f(\sigma_{t+1}) dF(\sigma_{t+1}|\sigma_t, p_{ft}) \ . \tag{2.2}$$

Essentially the price decisions are dynamic, since the current prices not only affect firm f's current period profit, but also influence the transition of the state that determines the value function in the next period.

The profit function of firm f usually involves parameters to be estimated, especially parameters underlying the marginal cost function. The profit function is given as follows:

$$\pi_{ft}(\sigma_t, p_{ft}) = \sum_{j \in J_{ft}} (p_{jt} - mc_{jt}(\theta^s)) s_{jt}(\theta^d) M, \tag{2.3}$$

where J_{ft} is the set of products produced by firm f, and mc_{jt} is the marginal cost to produce a certain product j with unknown parameters θ^s. M is the size of the entire market, and s_{jt} is product j's market share with demand parameters θ^d. In the pricing game played among firms, each firm has full knowledge about how the market shares of both its own products and its rivals' products are determined by demand dynamics and price decisions. In particular, θ^d are known to all firms when they set prices.

Ideally, the conventional dynamic optimization technique may help us obtain estimates of θ^s by computing each firm's equilibrium pricing policy as the fixed-point function of its Bellman equation and choosing the set of parameters that generates equilibrium prices closest to what we observe in the real data. However, this technique is hard to implement for practical reasons. In the first place, searching for the fixed-point value function is computationally burdensome. In the second place, the large dimensionality of firms' state space is difficult to deal with. Moreover, repeated oligopolistic price competition in many cases leads to multiple equilibria. To identify which equilibrium is the market outcome is a hard task. Recent literature such as Pakes and McGuire (1994, 2001) have proposed different ways to get around these difficulties, but they are still too demanding to use in empirical studies. Therefore, I adopt the approach proposed in Berry and Pakes (2001), which bases the supply-side estimation purely on the optimality conditions for prices. With this technique, there is no need to solve for equilibrium pricing policies and the problem of multiple equilibria is thus avoided.

I impose the standard assumptions for this technique to be applied:

A1. *Rational Expectation:* $\sum_{\tau=0}^{\infty}\beta^{\tau}\pi_{f,t+\tau}=V_f(\sigma_t)+\nu_t$, and $E[\nu_t|\sigma_t]=0$.

A2. *Smoothness:* $F(\sigma_{t+1}|\sigma_t,p)$ has support which is independent of p, Its density function $f(\sigma_{t+1}|\sigma_t,p)$ is differentiable in p for almost all $\sigma_t.\pi(\sigma_t,p)$ is also differentiable in p for almost all σ_t.

A1 is the standard assumption of rational expectations, which says that the discounted actual profit flow from time t differs from the firm's expectation at time t only by a random error. This error is uncorrelated with the information available to firms when they make decisions. A2, as discussed in the next subsection, is satisfied with the special feature of demand dynamics. These two assumptions altogether render the following optimality conditions for prices:

$$\begin{aligned}
& \frac{\partial E\pi_{ft}(\sigma_t,p_{ft})}{\partial p_{jt}}+\beta\int V_f(\sigma_{t+1})\frac{\partial f(\sigma_{t+1}|\sigma_t,p_{ft})}{\partial p_{jt}}d\sigma_{t+1} \\
= & \frac{\partial E\pi_{ft}(\sigma_t,p_{ft})}{\partial p_{jt}}+\beta E[V_f(\sigma_{t+1})\frac{\partial \ln f(\sigma_{t+1}|\sigma_t,p_{ft})}{\partial p_{jt}}|\sigma_t] \\
= & \frac{\partial E\pi_{ft}(\sigma_t,p_{ft})}{\partial p_{jt}}+\sum_{\tau=1}^{\infty}\beta^{\tau}\pi_{f,t+\tau}\frac{\partial \ln f(\sigma_{t+1}|\sigma_t,p_{ft})}{\partial p_{jt}}+\epsilon_{jt} \\
= & 0, \text{ for any } j\in J_{ft},
\end{aligned} \tag{2.4}$$

where the second line is a manipulation of the formula for expectation and the third an application of A1. $\epsilon_{jt}=\beta E[V_f(\sigma_{t+1})\frac{\partial \ln f(\sigma_{t+1}|\sigma_t,p_{ft})}{\partial p_{jt}}|\sigma_t]-\sum_{\tau=1}^{\infty}\beta^{\tau}\pi_{f,t+\tau}\frac{\partial \ln f(\sigma_{t+1}|\sigma_t,p_{ft})}{\partial p_{jt}}$ by construction and $E[\epsilon_{jt}|\sigma_t]=0$ as implied by the assumption of rational expectations. The property of conditional zero mean of the random error generates a moment condition and validates the use of the GMM method. With appropriate instruments to interact with the error, θ^s can be consistently estimated. To be specific, let $h(\sigma_t;\theta^s)$ be a sufficiently rich function of all state variables observed by firms. Then a consistent and asymptotically normal estimate of θ^s can be found by minimizing a norm of the following moments.

$$G_T(\theta^s)=\frac{1}{T}\sum_{j,t}\epsilon_{jt}h(\sigma_t;\theta^s), \tag{2.5}$$

where T is the total number of observations in the data available. Moreover, as proposed in Hansen (1982), this consistent estimate can be further used to obtain an efficient estimate of θ^s. Namely, the estimate that minimizes $||a(\theta^s)G_T(\theta^s)||$ is optimal, where $a(\theta^s)$ is the square root of the inverse of the asymptotic variance-covariance matrix of the moments evaluated at the original consistent estimate. The variance of this estimate is calculated as

$$\frac{1}{T}(\Gamma'\Gamma)^{-1}\Gamma' V \Gamma(\Gamma'\Gamma)^{-1}, \tag{2.6}$$

where V is the sample analog of $E[(a(\theta^s)G_T(\theta^s))(a(\theta^s)G_T(\theta^s))']$ and Γ of $E[\frac{\partial(a(\theta^s)G_T(\theta^s))}{\partial\theta^s}]$, both evaluated at the new optimal estimate of θ^s.

The remaining issue involved is the transition of the state space from one period to the next. The transition may be hard to calculate since the state vector σ_t potentially has a large number of elements that can affect firms' profits. Apart from the residual demand left from the previous period, cost structure, product innovations and entry/exit are also determinants of profit level. Nevertheless, the equilibrium model proposed here focuses particularly on firms' pricing behavior, and it is reasonable to allow only the transition of residual demand to depend on price decisions. The transitions of all other state variables are assumed to follow certain processes independent of price decisions, and they drop out from the optimality conditions for prices. Let d_t denote the residual demand in the market at time t, the condition underlying the supply-side estimation boils down as below:

$$E[\sum_{k\in J_{ft}}(p_{kt}-mc_{kt})\frac{\partial Es_{kt}(\sigma_t,p_t)}{\partial p_{jt}}M+Es_{jt}(\sigma_t,p_t)M+\sum_{\tau=1}^{\infty}\beta^{\tau}\pi_{f,t+\tau}\frac{\partial \ln f(d_{t+1}|d_t,p_{ft})}{\partial p_{jt}}|\sigma_t]=0. \tag{2.7}$$

It is clear in (2.7) that firm f's price decision at time t needs to balance two effects: the effect on the current profit and the effect on future profit flow through the transition of residual demand. The optimality conditions require that the sum of these two effects are orthogonal to the information available to firm f at time t.

Two issues in (2.7) remain to be solved: The first is how the current market shares are affected by price decisions; the second is how prices influence the transition probability of residual demand. The analysis of demand-side dynamics in the next subsection will help us address these two issues.

2.2 Demand-side Dynamics

Consumers in durable goods markets make strategic purchase decisions by comparing the utility from a purchase in the current period with that from a purchase in the future when prices are lower. Heterogeneous consumers with differing price elasticities and intrinsic valuations will choose diverse adoption patterns, which leads to the varying consumer mix in residual demand over time. Since price-inelastic and high-valuation consumers drop out of the market after their adoptions, the consumer mix each period contains a larger proportion of price-elastic and low-valuation consumers. Firms thus have an incentive to cut prices in order to attract remaining consumers. Moreover, the price decisions need to take into consideration their impact on the current sales, as well as on the transition of residual demand where future sales are collected. This subsection therefore is devoted to the study of how residual demand is shaped in a durable good market.

Suppose each consumer in the market starts thinking of purchasing a unit of the considered durable good from the time the good is introduced. Once she makes a purchase, the consumer drops out of the market and never comes back.[2] Let i index the consumer and j the product she buys. The net utility she obtains from the purchase at time t is expressed as below:

$$u_{ijt} = \alpha_i^x x_j - \alpha_i^p \ln(p_{jt}) + \psi_t + \xi_{jt} + \epsilon_{ijt},$$

where x_j represents the time-invarying characteristics of product j and p_{jt} the price charged for product j at time t. ψ_t is the market demand shock at time t to the entire product category, and is assumed to follow a Markov process. In each period, the value of the market shock is observed by all consumers but is not realized yet when firms make their price decisions. The component of the market shock process that is unobserved by firms may come from the changes in the national taste for the entire product category due to factors such as word-of-mouth. Although the value of market shock is revealed to firms later in the period, at the time of price decisions, firms can only form their rational expectations about its value based on the value revealed in the last period. ξ_{jt} is the typical unobserved (by researchers) product quality that is potentially correlated with prices. ϵ_{ijt} is the idiosyncratic random error that is distributed as Type I extreme value and independent over all i, j, and t. α_i^x and α_i^p denote the intrinsic valuation for product characteristics and the disutility of prices, both of which are varying across consumers. If only market level data is available, these two forms of consumer heterogeneity can be specified to be drawn from certain distributions with underlying parameters to be estimated. If more detailed individual level data is available, interactions between consumer attributes and product characteristics can be allowed. The literature utilizing micro observations includes

[2] My framework does not allow yet the possibility of replacement purchases. Studies addressing this issue include Gordon (2006) and Prince (2005).

Berry, Levinsohn and Pakes (2004) and Petrin (2004). In the empirical specification later on, I allow the disutility of prices to differ across different income groups but exclude the heterogeneity in consumers' intrinsic valuations of the products.

The outside option for remaining consumers who are not making a purchase at time t is to postpone the purchase until a future period. Although consumers do not have exact knowledge about the future product characteristics and prices, they can form their own expectations about the future market situation based on what they observe in the the current period. Let σ_{it}^{d} denote the set of state variables affecting consumers' purchase decisions at time t, such as product characteristics and prices. Each consumer' purchase decision at time t, given that she has not made a purchase in previous periods, is given by the following Bellman equation:

$$V_i(\sigma_{it}^{d}, \epsilon_{i.t}) = \max\{\max_{j=1,\ldots J_t} u_{ijt}, \beta E[V_i(\sigma_{i,t+1}^{d}, \epsilon_{i.,t+1})|\sigma_{it}^{d}]\},$$

where the common discount factor is assumed to be the same as that of firms, and the utility of purchasing nothing is normalized to zero. To decide whether to buy or not at time t, each consumer compares the highest utility she can obtain from all existing products with the expected utility she can obtain if she delays the decision until the next period.

Similar consumer problems have been analyzed in a small group of recent literature. Melnikov (2001) is the seminal paper that first proposes how to frame consumers' adoption decisions as optimal stopping problems. Carranza (2005), Song and Chintagunta (2005), and Gowrisankaran and Rysman (2006) all build on this approach and extend the framework in different ways. The demand-side analysis in this paper is closest to Gowrisankaran and Rysman (2006), although I use micro observations to obtain more accurate estimates of consumer heterogeneity, and the extra market shock process is added to facilitate the study of supply dynamics.

The key point of Gowrisankaran and Rysman (2006) is the combination of Melnikov (2001) and Rust (1987) to derive each consumer's adoption pattern. Following Melnikov (2001), define *the logit inclusive value* $R_{it} = \ln(\sum_{j \in J_t} \exp r_{ijt})$, where $r_{ijt} = \alpha_i^x x_j - \alpha_i^p \ln(p_{jt}) + \psi_t + \xi_{jt}$. Also define *the expected value function* $EV_i(\sigma_{it}^{d}) = \int V_i(\sigma_{it}^{d}, \epsilon) dF_\epsilon$, which by taking advantage of the logit distribution is a fixed-point function to the following equation:

$$EV_i(\sigma_{it}^{d}) = \ln(\exp(R_{it}) + \exp(\beta E[EV_i(\sigma_{i,t+1}^{d}|\sigma_{it}^{d}])). \tag{2.8}$$

Then the purchase probability at time t of consumer i who has not purchased prior to time t is determined as:

$$P_{it} = \frac{\exp(R_{it})}{\exp(R_{it}) + \exp(\beta E[EV_i(\sigma^d_{i,t+1})|\sigma^d_{it})])}, \tag{2.9}$$

and given consumer i is purchasing at time t, the probability that she chooses product j is given by

$$P_{ijt} = \frac{\exp(r_{ijt})}{\exp(R_{it})}. \tag{2.10}$$

Similar to firms' pricing problems, consumers' adoption decisions involve evaluating the transition $F(\sigma^d_{i,t+1}|\sigma^d_{it})$, and the large dimensionality of the state space is still hard to deal with. Following the treatment in Melnikov (2001), I assume that this transition is fully determined by a one dimensional Markov process in the logit inclusive value, i.e. $F(\sigma^d_{i,t+1}|\sigma^d_{it}) = F(R_{i,t+1}|R_{it})$.Therefore, the above purchase probability can be simplified as

$$P_{it} = \frac{\exp(R_{it})}{\exp(R_{it}) + \exp(\beta E[EV_i(R_{i,t+1})|R_{it})])}, \tag{2.11}$$

where

$$EV_i(R_{it}) = \ln(\exp(R_{it}) + \exp(\beta E[EV_i(R_{i,t+1})|R_{it})])). \tag{2.12}$$

With an appropriately parameterized Markov process of R_{it}, demand-side parameters can be estimated with the procedures discussed in detail in the next section. Each consumer's adoption pattern determined by observed prices and qualities is thus obtained. The resulting consumer mix in residual demand in any time period is also derived. Now I move on to discuss how the equilibrium market prices are generated by the interaction between demand and supply dynamics.

2.3 The Interaction between Demand and Supply Dynamics

The main feature of the equilibrium model proposed here is that the actual prices are consistent with firms' dynamic pricing strategies and consumer expectations. The study of demand dynamics demonstrates how firms' price decisions affect consumers' forward-looking behavior and thus their adoption pattern. These diverse adoption patterns are next taken into account in firms' pricing problems so that both the demand and supply sides arrive in their equilibrium behavior. As discussed before, any firm's price decision at time t is a trade-off between two effects: the effect on time t's profit and the effect on future profit flow at time $t+1$ through the transition of residual demand from t to $t+1$. These two effects are examined next.

In the framework considered, firms know everything about the demand system except that the current period market shock is not realized at the time of their price decisions. If the market shocks follow a Markov process, firms expect the probability of consumer i choosing product j at time t, denoted by Es_{ijt}, to be given as

$$Es_{ijt} = s^0_{i,t-1} \int P_{it}(\psi_t) * P_{ijt}(\psi_t) dF(\psi_t | \psi_{t-1}),$$

where $s^0_{i,t-1} = \prod_{\tau=1}^{t-1}(1 - P_{i\tau}(\psi_\tau))$ is the residual demand of consumer i at the beginning of time t, i.e., the probability that consumer i still remains in the market at the beginning of time t. Es_{jt}, the expected market share for product j is simply the average of Es_{ijt} over all consumers. The effect of price p_{jt} on firm f's time t profit is therefore as below:

$$\frac{\partial E\pi_{ft}(\sigma_t, p_{ft})}{\partial p_{jt}} = \sum_{k \in J_{ft}} (p_{kt} - mc_{kt}) \frac{\partial Es_{kt}(\sigma_t, p_t)}{\partial p_{jt}} M + Es_{jt}(\sigma_t, p_t) M, \text{ for any } j \in J_{ft}. \tag{2.13}$$

The second effect of p_{jt}, the effect on future profit flow, is indicated in (2.5) as below:

$$\sum_{\tau=1}^{\infty} \beta^\tau \pi_{f,t+\tau} \frac{\partial \ln f(d_{t+1} | d_t, p_{ft})}{\partial p_{jt}}. \tag{2.14}$$

The way that the the current prices impact future profit is through their effects on the transition probability from the current residual demand to the residual demand in the next period. From the perspective of firms, the magnitude of the price effect on residual demand is uncertain due to unrealized market shock, but the transition probability of residual demand can be estimated at each price decision given firms' knowledge of the market shock process. As can be seen from the study of consumer behavior, heterogeneous consumers adopt products at different times and the residual demand is inherently individual-specific. Therefore, $d_t = \{s^0_{i,t-1}\}_{i=1}^M$ has a large dimension and its transition seems to impose another barrier in the framework. However, the market shock process makes the calculation of this transition manageable. Before the realization of the market shock at time t, the transition probability from d_t to d_{t+1}

given firm f's price decision p_{ft} is as below:

$$\begin{aligned} f(d_{t+1}|d_t, p_{ft}) &= f(s^0_{1,t}, ..., s^0_{M,t}|s^0_{1,t-1}, ..., s^0_{M,t-1}, p_{ft}) \\ &= f(s^0_{1,t-1}(1 - P_{1t}(p_{ft}, \psi_t)), ..., s^0_{M,t-1}(1 - P_{Mt}(p_{ft}, \psi_t))|s^0_{1,t-1}, ..., s^0_{M,t-1}, p_{ft}) \\ &= f(\psi_t(s^0_{i,t}, s^0_{i,t-1}, p_{ft})), \text{ for any } i = 1, ..., M. \end{aligned}$$

This is to say that the joint transition density of residual demand of all consumers is the distribution density of the underlying market shock. In other words, each consumer's residual demand transitions from one period to the next according to exactly the same distribution of market shocks. The market shock process relieves us of the difficulty in dealing with the large dimensionality of residual demand. The expression (2.7) is now a lot easier to calculate: With the residual demand for each consumer at its actual (equilibrium) value at time t and time $t+1$, a marginal change in price decisions results in a new density for the residual demand to achieve the actual transition. The change in the density is what needs to be calculated in (2.7).

With both (2.6) and (2.7) ready to use, the supply-side estimation can be implemented with the GMM method using the moment condition (2.5). The estimates of cost parameters will illustrate the magnitude of cost reductions relative to price declines and help us identify other sources that contribute to price declines.

3 Overview of the US Digital Camera Market

The equilibrium model developed here is potentially applicable to a large variety of new durable goods markets. However, in this paper, the empirical estimation of the model is embedded in the US digital camera market. The relevance of this market to the study here is obvious: product prices have been falling rapidly since the inception of this market, which may result not only from the cost reductions induced by the fast improving digital technologies, but also from the dynamic behavior on both the demand and supply sides of this market.

The US digital camera market has achieved the second highest growth rate in the IT sector in less than a decade since its debut in the mid 1990's. According to a report by the NPD Group, the sales of the US digital camera market are projected at a record-breaking 29.5 million units in 2006, which amounts to more than two thirds of the total camera sales. It translates into \$5 billion revenues, a nearly eight percent increase over 2005. Meanwhile, as announced by the PMA US Industry Trends Report, the US household penetration of digital cameras is estimated to reach 63% by 2006 while it was less than 30% in 2003.

The empirical estimation of the proposed model uses a newly collected dataset from the US digital camera market. It contains information on monthly aggregate sales and prices for all the products marketed from January 2001 to December 2004, and on household end-of-year penetration from 2000 to 2004.[3] The market level data is provided by the NPD Group and covers about 80% of the market using point-of-sale reports from major consumer electronics retailers. The household level data is collected from the PMA Annual Survey, which is conducted in January among a rotating panel of 10,000 US households every year.

The market-level data captures a panorama of the US digital camera market from 2001 to 2004. Figure 3.1 shows the total sales of the top twenty brands over these 48 months. Sony was the leading brand in this period, followed by Canon and Kodak, and the market was dominated by the top seven brands altogether.[4] However, competition was intensifying over time due to the entry of brands at both existing and higher resolution levels. Table 3.1 lists by resolution level the maximum number of competing brands in each year, as well as the average prices across brands within a year. The table illustrates that competition was generally getting fierce at all resolution levels, and the core of the competition was moving toward high-quality product categories. In the meanwhile, the average price of each product category was decreasing rapidly, although the speed slowed down as time passed. Competition, as suggested in this table, may explain part of the declines in markups, and the equilibrium model proposed in this paper is potentially able to isolate the contribution of intensifying competition from that of the interaction between demand and supply dynamics.

The household penetration data provides information on the household ownerships of digital cameras. One of the questions asked in the PMA Annual Survey is whether the surveyed households own any digital cameras or not. Given the fact that the survey panel each year is a nationally representative sample and the responses are believed to be random, the ownership among respondents can be generalized to the penetration rate among the entire population. The survey results show that the observation pe-

[3]Since the macro data does not start from the inception of the market, I need the penetration data at the end of 2000 to control for the probability that a household remained in the market at the beginning of 2001.

[4]The brands not displayed are aggregated as the 21st brand in the empirical estimation.

Figure 3.1: 2001-2004 Total Sales by Brand

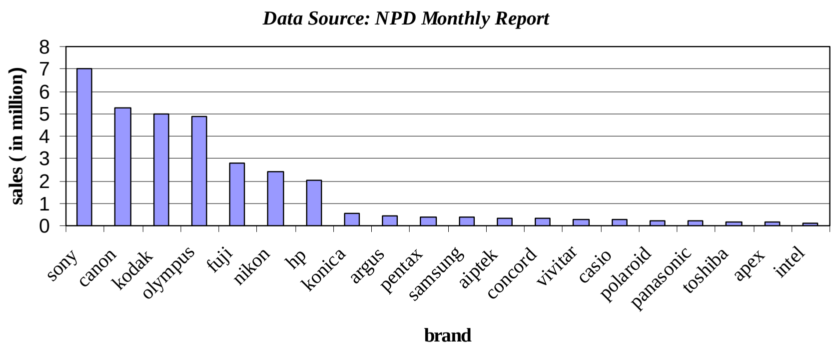
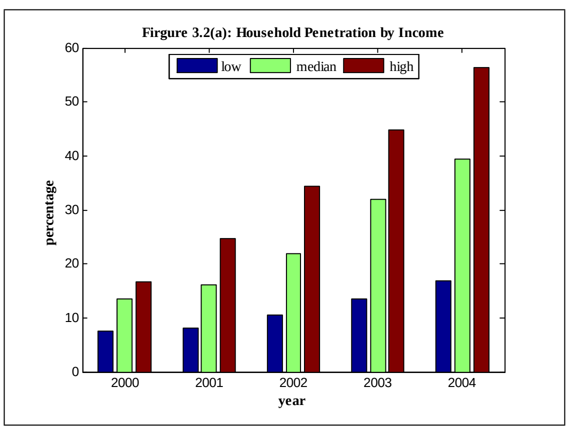


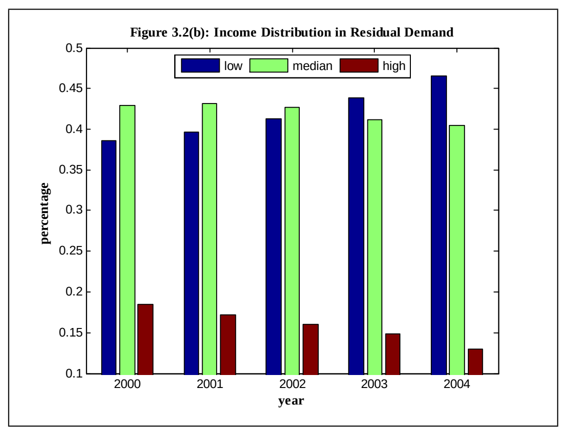
Table 3.1: Brand Numbers and Average Prices by Resolution Level

Megapixel	2001		2002		2003		2004	
Range	(A)	(B)	(A)	(B)	(A)	(B)	(A)	(B)
<1	13	\$171	15	\$99	15	\$81	14	\$62
[1, 2)	17	\$293	20	\$167	20	\$121	17	\$89
[2, 3)	15	\$439	18	\$267	19	\$180	19	\$120
[3, 4)	12	\$659	15	\$413	18	\$298	18	\$202
[4, 5)	7	\$736	12	\$565	13	\$402	17	\$282
[5, 6)	1	\$1078	3	\$965	10	\$593	16	\$410
[6, 7)	0	n/a	0	n/a	1	\$282	6	\$504
[7, 8)	0	n/a	0	n/a	0	n/a	5	\$253
[8, 9)	0	n/a	0	n/a	0	n/a	1	\$747

NOTES: Column As list the maximum number of brands competing at a certain resolution level in each year, and Column Bs the corresponding average prices across brands. Data is collected from the NPD Monthly Report.

riod witnessed fast penetration of the digital camera category into the US population. Compared to the 11.95% at the end of 2000, the penetration rate more than doubled by 2004, arriving at 34.15%. However, if the whole population is divided into different demographic groups, the penetration rates across these groups differ substantially. Figure 3.2(a) graphs the penetration rates by household income at the end of observation years. The household heterogeneity is striking: Digital cameras were adopted by high-income households at a quick speed, with the penetration rate in this group going from under 20% to more than 50%; but digital cameras had a hard time penetrating into low-income households, with the penetration rate increasing by less then 10% within these four years. This fact implies that the consumer mix in the residual demand for digital cameras was changing over time. As illustrated in Figure 3.2(b), the households without digital cameras had an increasing proportion of low incomers but diminishing proportions of median and high incomers. If low-income households are believed to be more price-elastic, it is not surprising that the markups, generally a negative function of demand price elasticity, were falling over time if firms' pricing policies correctly took into account the changing income distribution of remaining households.





NOTES: Figure 3.2(a) shows the proportion of digital camera owners among each income group at the end of all observation years, and Figure 3.2(b) the proportion of non-owners in each income group among all non-owners. Data is collected from the PMA Annual Survey. The ownership among survey respondents is nationally representative.

4 The Empirical Specification and Estimation

4.1 Demand Specification and Estimation

Consumer i's net utility obtained from a purchase of product j at time t is specified as below:[5]

$$\begin{aligned} u_{ijt} &= \textstyle\sum_{g=1}^{7} b\,\mathrm{rand}_j^g\,\beta_b^g + meg_j\beta_m - \beta_p \ln p_{jt} + \psi_t + \xi_{jt} \\ &\quad +(median_i\beta_p^1 + high_i\beta_p^2 - \nu_i\beta_p^u)\ln p_{jt} + \epsilon_{ijt}. \end{aligned} \tag{4.1}$$

The mean utility of product j common to all consumers has five components: the brand effect (β_b^g) of firm b that produces product j and is one of the top seven manufacturers, the preference for product j's quality measured by resolution level (β_m), the mean disutility of j's price (β_p), market shock realized at the time of purchase decisions (ψ_t), and the unobserved (to researchers) quality (ξ_{jt}) that may include time-varying attributes such as marketing efforts.[6] As stressed in Berry (1994) and in Berry, Levinsohn and Pakes (1995), ξ_{jt} picks up the impact of all other non-included attributes of product j and is potentially correlated with p_{jt}.

Consumer heterogeneity is specified to exist only in the disutility of prices. $median_i$ is the dummy that takes one if household i belongs to the median income group ($y_i \in (\$35,000, \$75,000)$), and $high_i$ takes one if i is a high-income household ($y_i > \$75,000$). These two income groups have less average disutility of prices compared to the low-income group by β_p^1 and β_p^2, respectively. Unobserved household heterogeneity is represented by the coefficient $\nu_i\beta_p^u$ of log prices, where $\{\nu_i\}$ are assumed to be $\chi^2(2)$ distributed.[7] Unobserved factors that may influence price elasticity include family size, and householder's age, education and occupation. With the unobserved ν_i, each household is essentially its own type. As elaborated in Berry, Levinsohn and Pakes (1995), allowing for both observed ($median_i$ and $high_i$) and unobserved (ν_i) heterogeneity generates more reasonable and accurate measures of substitution patterns. $\{\epsilon_{ijt}\}$ are the standard i.i.d logit errors.

[5] I aggregate models according to their brands and integer resolution levels in order to limit the choice set of consumers. A product therefore refers to a group of models that are produced by the same firm and are at the same integer resolution level. Product prices are the average model prices within groups.

[6] Other excluded attributes such as optical zoom and weight turn out to have little variation at their averages across categories.

[7] I use χ^2 distribution instead of the standard normal distribution used in other literature mainly to guarantee negative coefficients of log prices. Robustness needs to be checked.

As in previous section, let θ^d denote the set of demand parameters to be estimated. Then $\theta^d = \{\theta_1^d, \theta_2^d\}$,where $\theta_1^d = \{\{\beta_b^g\}_{g=1}^7, \beta_m, \beta_p\}$ is the set of parameters for mean tastes and $\theta_2^d = \{\beta_p^1, \beta_p^2, \beta_p^u\}$ is that for heterogeneous tastes. The strategies to estimate these demand parameters are built on Gowrisankaran and Rysman (2006), but I will use micro observations to obtain more accurate estimates of heterogeneous tastes, namely the parameters contained in θ_2^d. The procedures are summarized as below.

The first step is to derive the mean utility $\delta_{jt} = \sum_{g=1}^7 b_j^g \beta_b^g + meg_j \beta_m - \beta_p \ln p_{jt} + \psi_t + \xi_{jt}$ given an initial conjecture of $\theta_2^d = \{\beta_p^1, \beta_p^2, \beta_p^u\}$. As in Berry, Levinsohn and Pakes (1995, 2004), δ_{jt} can be located using the contraction mapping defined as

$$\delta_{jt}^{new} = \delta_{jt}^{old} + (\ln(s_{jt}^N) - \ln(s_{jt}^{ns}(\delta_{jt}^{old}; \theta_2^d)) \tag{4.2}$$

where s_{jt}^N is the observed market share of product j at time t, and s_{jt}^{ns} is the simulated counterpart. To derive s_{jt}^{ns} at $(\delta_{jt}^{old}; \theta_2^d)$, a series of random draws $\{y_i, v_i\}_{i=1}^{ns}$ is first drawn from their corresponding distributions. I use the empirical income distribution in Census 2000 to make draws of y_i, and therefore $median_i = 1$ if $y_i \in (\$35,000, \$75,000)$ and $high_i = 1$ if $y_i \geq \$75,000$.[8] $\{v_i\}$ are drawn from $\chi^2(2)$ distribution as mentioned before. $P_{it}(\delta_{jt}^{old}; \theta_2^d)$, the conditional purchase probability of household i at time t, and $P_{ijt}(\delta_{jt}^{old}; \theta_2^d)$, the conditional choice probability for product j are calculated using the results in equations (2.11) and (2.10) respectively. The involved continuation value $EV_i(R_{it})$ is calculated as the fixed-point function in equation (2.12), with the evolution of R_{it} assumed to be a Markov process as below

$$R_{i,t+1} = \gamma_{1i} + \gamma_{2i} R_{it} + \omega_{it}, \text{ where } \omega_{it} \sim i.i.d.N(0, \sigma_\omega). \tag{4.3}$$

The model predicted market share of product j at time t is therefore simulated as

$$s_{jt}^{ns} = \frac{1}{ns} \sum_{i=1}^{ns} \prod_{\tau=1}^{t-1} P_{i0}(1 - P_{i\tau}) P_{it} * P_{ijt} \tag{4.4}$$

where P_{i0} is the empirical probability for household i to remain in the market at the beginning of 2001 according to its income level, and all other probabilities are evaluated at $(\delta_{jt}^{old}; \theta_2^d)$.[9] Plugging (4.4) into (4.2) and replacing δ_{jt}^{old} with δ_{jt}^{new} in each iteration will

[8] The model developed requires that household characteristics and the consumer mix in the whole population are stable over time. Empirically, I am assuming that income level for each household is constant and the national income distribution remains the same as in Census 2000, i.e. with the proportion of median-income households at 43.76% and high-income households 19.52%.

[9] The penetration rate observed at the end of 2000 in PMA Annual Survey is 7.49%, 13.58% and

quickly locate the mean utilities in all periods given the conjecture of θ_2^d.

With the derived correspondence between δ_{jt} and θ_2^d, θ_2^d can be searched next by matching the model predicted end-of-year penetrations across income groups with those observed in the micro data. This methodology is similar to Petrin (2002), in which household level choice data facilitate the estimation of heterogeneity parameters. Specifically, with each guess of $\theta_2^d = \{\beta_p^1, \beta_p^2, \beta_p^u\}$ and the located δ_{jt} , the model predicted end-of-year penetration of low-income household is given as below:

$$
\begin{aligned}
& E[\{i \text{ owns a digital camera by time } t\}|\{i \text{ is a low-income household}\} \\
= \;\; & 1 - \textstyle\prod_{\tau=1}^{t}(1 - P_{i\tau}(median_i = high_i = 0)).
\end{aligned}
$$

With four year observations of three income groups, I have twelve micro moments to estimate θ_2^d. The two-step GMM method proposed in Hansen (1982) promises efficient and consistent estimates of these parameters.

The set of demand parameters remains to be estimated is $\theta_1^d = \{\{\beta_b^g\}_{g=1}^7, \beta_m, \beta_p\}$. They are obtained easily with a linear regression of δ_{jt}, using the IV method that controls for the correlation between the unobservable ξ_{jt} and p_{jt}. The values of market shocks $\{\psi_t\}$ are estimated as time fixed effects in the regression. I approximate the process of market shocks using a Markov process as below

$$\psi_t = h(\psi_{t-1}) + \varsigma_t, \text{ where } \varsigma_t \sim i.i.d.N(0, \sigma_\varsigma). \tag{4.5}$$

Therefore, the transition density of market shocks is calculated as $f(\psi_t|\psi_{t-1}) = \phi(\psi_t - h(\psi_{t-1}))$, where $\phi(.)$ stands for the standard normal density.

4.2 Cost Specification and Estimation

The estimated demand parameters, except the realized value of the current market shock are primitives known to all firms at the time of their dynamic price decisions. As discussed in the development of the general model, estimation of the cost parameters relies on the moment condition (2.7), in which the relevant terms (2.13) and (2.14) are derived given firms' knowledge of the demand system. A few notes about the condition (2.7) need to be mentioned. First, the condition is only about the price decisions for those products marketed at time t. The product entry/exit decisions are beyond the

16.60% for low-, median- and high-income households respectively.

scope of the current framework. Second, the future profit flows are approximated by summing up all profits of the considered product until the end of the observation period. With the time span of observations not long enough, the truncation problem may exist.

I specify the marginal cost of product j at time t as below:

$$mc_{jt} = [\exp(\kappa^0_{b_j} - \kappa^1_{b_j} * t)] * meg_j, \tag{4.6}$$

The chosen functional form is consistent with Moore's Law, which observes exponential increase in the number of components integrated on a chip. Technologies are assumed to be firm specific and are represented by two parameters, $\kappa^0_{b_j}$ and $\kappa^1_{b_j}$, for all products produced by the same firm as product j. Moreover, marginal costs are proportional to resolution levels and are decreasing with an exponential time trend for all products. To limit the number of cost parameters, I allow technologies to differ among the top seven firms but restrict all other firms to share the same marginal cost function. Therefore, I have $7 \times 2 + 2 = 16$ parameters to estimate. Consistent and efficient estimates of supply parameters $\theta^s = \{\kappa^0_{b_j}, \kappa^1_{b_j}\}$ can be obtained by using the two-step GMM method discussed before with a rich set of appropriate instruments. The assumption of rational expectations of firms promises instruments rich enough to be used. In principle, all variables observed by firms before their decision making are valid instruments. Those used in the estimation here for the product j produced by firm f at time t are: (1) the residual demand in different income groups at time t (3 IVs); (2) the market shock (1 IV) at time $t-1$; (3) the total revenue of each top seven brands at time $t-1$(7 IVs); (4) the number of products at the same resolution level produced by firm f (1 IV) and by all rival firms (1 IV) at time t; (5) the total number of products at all other resolution levels produced by firm f (1 IV) and by rival firms (1 IV) at time t; (6) the cost of product j at time t (1 IV); (7) the average cost of all other top seven firms (1 IV); (8) the distance of product j's resolution level from the highest resolution level of firm f (1 IV). In total, there are 18 supply-side instruments that interact with the error term in the moment condition (2.5). The validity of these insturments are obvious: (1) to (3) capture the demand structure; (4) and (5) the crowdedness of product space and thus the intensity of competition, within a resolution level and across resolution levels; (6) and (7) the cost advantage of firm f, and (8) the relative quality of product j. All the information contained in these instruments is known to firms at the time of their decision making given the setting of the current framework.

5 Estimation Results and Discussion

Table 5.1 presents the demand estimates that have three portions. The top portion shows the parameters associated with the mean utility invariant across income groups. Consistent with the data observations, the top seven brands that dominate the digital camera market have significant brand effects. The coefficient of resolution has the natural positive sign and is also significant. The significant coefficient of log price at -1.660 corresponds to an average price elasticity at nearly -3.2 for low-income households, which supports the conjecture that this income group is considerably price-elastic.

The difference of price elasticities across income groups is demonstrated in the middle portion of Table 5.1. The coefficient of log price is reduced by 0.508 for median-income households and 1.082 for high-income households. The corresponding average price elasticities is thus lowered to -2.1 for median-income and -0.9 for high-income. This huge heterogeneity in price elasticities explains the diverse adoption patterns across income groups and implies the changing consumer mix of residual demand over time. The results in this portion also indicate the importance of unobserved household characteristics in determining the utility from a purchase, as the coefficient for the unobservable is significantly positive. To check the accuracy of these heterogeneity parameters, I compare the penetration rates across income groups that are predicted by the model and the estimated parameters with those observed in the micro data. Table 5.2 shows that the predictions are precise in general, with the difference appearing mostly at the third digit after the decimal point. Figure 5.1 indicates that model prediction is most accurate for the high-income group and least for the median-income.

The bottom portion of Table 5.1 reports the estimated market shock process. As mentioned in the previous section, the realized market shocks are estimated as the time fixed effects in the regression of mean utilities. The estimated values of market shocks are shown in Figure 5.2. Since the market shock path displays a slightly upward time trend and strong seasonality, I choose a linear functional form as below to represent the market shock process:

$$\psi_t = \lambda_1 + \lambda_2 \psi_{t-1} + \lambda_3 December_t + \varsigma_t, \text{ where } \varsigma_t \sim i.i.d.N(0, \sigma_\varsigma). \tag{5.1}$$

The results in Table 5.1 show that all the parameters involved are significant. According to the estimates, the national taste for the digital camera category was getting mildly stronger and the seasonality in demand was dramatic.

Table 5.1: Estimates of Demand Parameters

Variables		Coefficient Estimates	Standard Errors
Mean Utility			
Canon	(β_b^{canon})	2.499*	0.193
Fuji	(β_b^{fuji})	1.911*	0.191
Kodak	(β_b^{kodak})	2.050*	0.194
Nikon	(β_b^{nikon})	1.789*	0.191
Olympus	$(\beta_b^{olympus})$	2.722*	0.194
Sony	(β_b^{sony})	3.178*	0.193
HP	(β_b^{hp})	1.877*	0.191
resolution	(β_m)	0.49*	0.026
log(price)	(β_p)	-1.660*	0.013
Household Heterogeneity			
median	(β_p^1)	0.508*	0.014
high	(β_p^2)	1.082*	0.019
unobservable	(β_p^u)	0.986*	0.005
Market Shock Process			
constant	(λ_1)	7.548*	1.909
lag value	(λ_2)	0.626*	0.094
December	(λ_3)	1.235*	0.199

NOTES: Digital camera models marketed in 2001 to 2004 are grouped at brand/megapixel level. Prices are the group average prices. The dummy December is added into the market shock process to explain the seasonality of consumer preference, but this treatment excludes the possible effect of holiday season on firms' forward-looking behavior in all previous months. Reported standard errors do not include simulation errors. * indicates significance at 5% level.

Table 5.2: Model Predicted vs. Observed Penetration Rates

Year	Income	Penetration Rates (predicted)	Penetration Rates (observed)
	low	0.0853	0.0804
2001	median	0.1743	0.1605
	high	0.2594	0.2470
	low	0.1008	0.1052
2002	median	0.2247	0.2185
	high	0.3448	0.3445
	low	0.1280	0.1353
2003	median	0.2995	0.3190
	high	0.4441	0.4477
	low	0.1771	0.1688
2004	median	0.4075	0.3943
	high	0.5609	0.5634

Figure 5.1: Model Predicted vs. Observed Penetration Rates

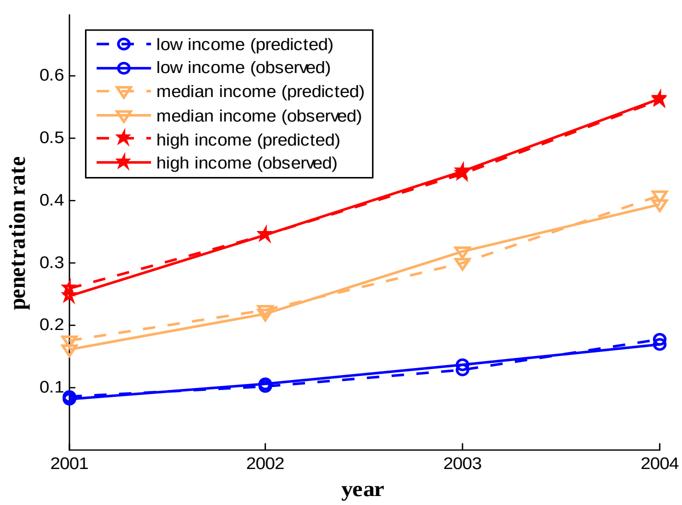
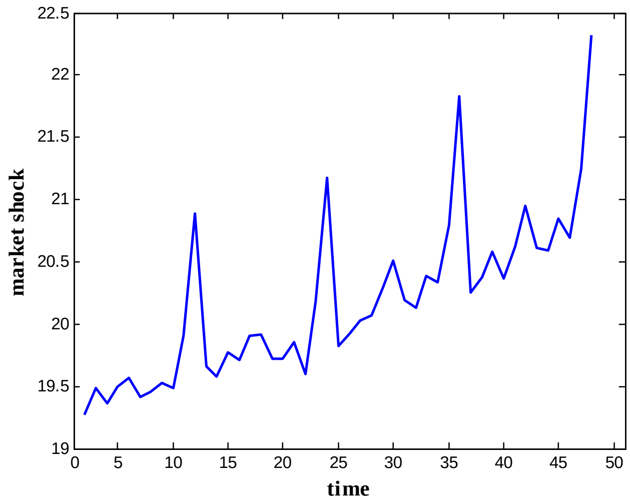


Figure 5.2: The Estimated Market Shock Path



The cost parameters estimated on the supply side are those in (4.6), where the production technology of each firm is characterized by two marginal cost parameters. I report the results in Table 5.3, in which cost parameters differ among the top seven firms but are shared by all the others. The coefficients of the constants in the marginal cost function are all significants, but the estimates of time trends are significant only for the biggest four firms. Figure 5.3 draws the marginal cost per megapixel of these four brands over the observation period. Olympus clearly produced the most costly digital cameras throughout this period. Sony started with a more expensive technology than Canon, but its technology advanced fast and it caught up with Canon at the end of 2003. Kodak was able to produce its products at the lower cost, but its technology was improving at the slowest speed.

The cost of each products and therefore the markups can be calculated given the estimated cost parameters. In order to illustrate the magnitude of the declines in markups relative to the declines in prices, I report in Table 5.4 the results from two descriptive regressions: the regression of prices and the regressions of markups in both level and percentage measures on brands and resolution levels with time trend. The time coefficients reveal that prices were decreasing by an average of \$8.58 per month while markups by \$2.81. This is to say that about one third of the price declines were attributable to the declines in markups. In terms of percentage markups, the observation period saw an average of monthly decrease of nearly two percent. Figure

Table 5.3: Estimates of Cost Parameters

Brands	Constant: κ^0	Time Trend: κ^1
Canon	4.761 (0.329)*	0.015 (0.0091)**
Fuji	4.712 (1.864)*	0.014 (0.0341)
Kodak	4.210 (0.390)*	0.012 (0.0093)***
Nikon	4.873 (1.545)*	0.017 (0.0117)
Olympus	5.020 (0.823)*	0.019 (0.0083)*
Sony	4.952 (0.337)*	0.020 (0.0107)**
HP	4.274 (0.760)*	0.013 (0.0212)
Others	4.177 (1.436)*	0.010 (0.0372)

NOTES: The top seven firms have different cost parameters but all others share the same. Standard errors are in parentheses. Simulation errors from the demand side are not included. * indicates significance at 5% level, ** 10% and *** 20%.

Figure 5.3: The Cost Evolution Over Time

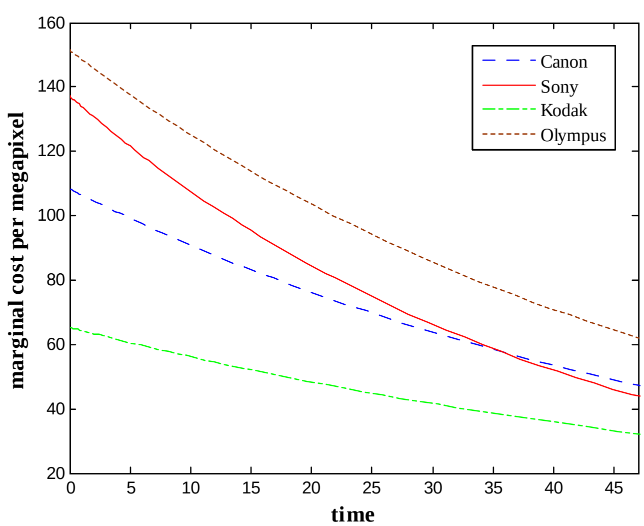


Table 5.4: Descriptive Price and Markup Regressions

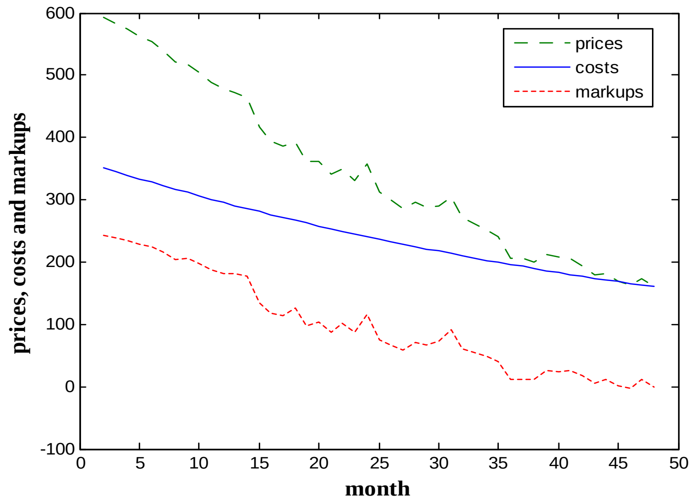
Variables	Price Regression		Markup Regression level		Markup Regression percentage	
Canon	104.843	(7.391)*	154.512	(7.665)*	0.626	(0.032)*
Fuji	83.174	(8.065)*	85.574	(7.671)*	0.423	(0.031)*
Kodak	-22.171	(7.482)*	16.557	(6.982)*	0.153	(0.029)*
Nikon	130.267	(7.431)*	118.287	(7.793)*	0.238	(0.033)*
Olympus	89.923	(7.053)*	88.289	(7.613)*	0.190	(0.031)*
Sony	99.936	(7.378)*	19.603	(7.842)*	0.105	(0.033)*
HP	-11.832	(7.883)*	-7.971	(10.673)	-0.159	(0.042)*
Resolution	105.138	(1.334)*	1.557	(0.901)**	0.006	(0.003)*
Time	-8.581	(0.151)*	-2.812	(0.654)*	-0.018	(0.006)*
Constant	95.955	(6.163)*	6.943	(10.036)	0.012	(0.022)
# Observations	2735		2735		2735	
R-squared	0.77		0.62		0.53	

NOTES: * indicates significance at 5% level, and ** 10%.

5.4 picks the most popular three megapixel digital cameras and graphs the paths of their average prices, costs and markups across the top four brands. It is even clearer that a significant proportion of the observed price declines resulted from the declines in markups.

The estimation results have not yet decomposed different sources of falling markups. Other than the interaction between demand and supply dynamics, intensifying competition may also give rise to the declines in markups. However, counterfactual analyses can be conducted to further evaluate how much the dynamic behavior contributes to the markup changes. The idea is simple: shutting down one or two of the dynamics generates new adoption patterns or new pricing policies, and the resulting new equilibrium price paths can be simulated by iterative procedures. To compare the magnitude of the generated price declines to what we observe in the real data will provide us an insight into the importance of the missing dynamics. Specifically, to evaluate the contribution of demand dynamics, households are assumed to be myopic and to make only multinomial discrete choices each period, without considering the improved market situation in the future. The adoption pattern can be recalculated for each household given the previous estimates of its preferences. This new demand structure serves as another input into firms' dynamic pricing problems and the prices are simulated until

Figure 5.4: The Average Prices, Costs and Markups of the Three Megapixel Products Produced by the Top Four Brands



both the demand and supply sides arrive in equilibrium. The scenario when firms are static, i.e. firms are maximizing only the current period profit, and the scenario when both dynamics are excluded can be investigated in similar ways.

6 Conclusion

This paper aims to address the reasons behind the rapid price declines typically observed in new durable goods markets. It develops an equilibrium model that separates price declines caused by cost reductions from those caused by declines in markups. The model distinguishes itself from the existing literature in terms of its incorporation of both consumers' forward-looking behavior and firms' dynamic pricing policies. The actual prices in the model thus represent the equilibrium market outcome consistent with both the demand and supply dynamics. The proposed estimation strategies are more tractable relative to those used in previous dynamic studies in two ways. First, the supply-side estimation is based on the optimality conditions for prices; it thus avoids computing equilibrium price paths and the resulting problem of multiple equilibria. Second, a simple market shock process fully characterizes the transition of firms' state space. The problem of the large dimensionality of state space that challenges most dynamic studies is thus solved.

The estimation of the model uses a newly collected dataset from the US digital camera market, in which household penetration data supplements the standard market level data to facilitate the estimation of consumer heterogeneity. The estimation results on the demand side corroborate significant differences in price elasticities across income groups and their diverse adoption patterns of the products.

More importantly, the supply-side estimates reveal that both costs and markups are declining rapidly over the observation period. Roughly speaking, cost reductions capture only two thirds of the corresponding price declines. The remaining one third of the price declines are attributed to the declines in markups. This finding is the first in the empirical literature that supports the long-existing theoretical argument – the interaction between demand and supply dynamics curtails the market power in durable goods markets.

With the estimated demand and cost structures, the model also enables further evaluation of the contribution of demand and supply dynamics to the declines in markups. The idea is to simulate new equilibrium price paths in counterfactual scenarios where one or both of the dynamics are turned off. Comparing these simulated price paths with those actually observed will help us decompose the sources of falling markup into either demand or supply dynamics, or other dynamics, such as intensifying competition. This is one of the directions to explore in future research.

Other extensions to the estimated model are also worth examining. On the demand side, adding consumer heterogeneity to the non-price product characteristics by introducing either random coefficients or interactions between non-price product attributes and household characteristics will complete the description of demand structure. Although incurring an extra computational burden, this exercise may give us a better understanding of the difference in price paths across brands and products. On the supply side, the current framework uses a simple deterministic marginal cost function and thus leaves out any stochastic or unobserved components in cost structures. Future experiments with more realistic cost specifications may provide better measures of cost reductions induced by advances in technologies. In addition, firms' non-price decisions, such as entry/exit and product innovations, are not formally examined yet in the model. Since these decisions are potentially informative about the intensity of competition and other sources that may contribute to the price declines, a practical treatment of these inherently dynamic and endogenous decisions will greatly enrich the model. This is another dimension that future research may explore.

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