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What difference does dynamics make? The case of digital cameras☆

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ABSTRACT

When the well-known BLP model is applied to products with rapid technological changes and declining prices it tends to yield implausible results. A sequence of increasingly sophisticated dynamic demand models, most recently Gowrisankaran and Rysman (2009, hereafter GR), have been developed to overcome these problems. We apply both models to new data on the US digital camera market. In addition, we demonstrate that the GR model can be specified as a BLP model plus an additional set of terms. This suggests that a dynamic model can be estimated as a BLP model plus a non-parametric function which is less computationally demanding. As a first step to implementing this semi-parametric approach we estimate a BLP model augmented with age as a proxy for the non-parametric component. We find that demand for digital cameras is more elastic when demand dynamics is accounted for in both the dynamic model and the BLP model with the age proxy. This suggests that the market is more competitive though the results are consistent with firms engaging in intertemporal price discrimination. Merger simulations predict the lowest price and quantity changes using the GR model.

1. Introduction

New products entering into and old products retiring from markets is a prevailing phenomenon. It is more noticeable in markets where there is rapid technological change and product prices fall steeply and persistently. Examples of such markets include consumer electronics like personal computers, television sets, mobile phones, digital camcorders and digital cameras. Although the static differentiated product demand model applied to products like cars yields satisfactory estimates and predictions (e.g., Berry et al., 1995, hereafter BLP), it has been observed that this model is likely to deliver counterintuitive estimates or predictions in markets with rapid product turnover and substantial price changes like consumer electronics (Gowrisankaran and Rysman, 2009; Melnikov, 2001). To address the problem, these researchers and other papers, such as Zhao (2007), Carranza (2010) and Conlon (2010), have introduced increasingly sophisticated and computationally demanding dynamic models of demand for differentiated durable goods.[1] In Gowrisankaran and Rysman (2009) (hereafter GR), for example, dynamics are included in the BLP framework by empirically modeling consumers as solving an optimal stopping problem when choosing among products. These papers have largely emphasized improving the methodology but the question, "How do our conclusions about durable goods oligopolies change when we introduce dynamics into econometric models?" remains.

In this paper we analyze what difference does introducing dynamics into empirical oligopoly models make by estimating both the BLP and GR models on a new dataset of the US digital camera industry. In addition, we propose a third, less computationally demanding, semi-parametric approach of estimating a dynamic demand model. We demonstrate that the GR model can be specified as a BLP model plus an additional set of terms and argue that under certain conditions a non-parametric function of a few variables can be used to represent the additional terms. As a first step to implementing this approach, in our third empirical model, we estimate a BLP model with product age as a proxy (hereafter BLPWP) for this non-parametric function.[2] The intuition for adopting product age as a proxy is that it is negatively correlated with the demand for a product regardless whether dynamics

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[1] See Aguirregabiria and Nevo (2011) for a general review.
[2] As we discuss in more detail below, Xiao (2008) independently used age as a control in a non-random coefficients model of demand for digital cameras. However, it is included without any specific interpretation beyond a standard control.

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arise from consumers expecting further technological change, future falling prices or just the depreciating effectiveness of advertising. We note that the proxy is only a partial solution and discuss how to handle resulting identification issues. Coefficients, elasticities and markups from all three models are compared. Furthermore, we also compare the results from simulating two mergers between Fujifilm and Nikon, and Canon and Sony.

We find that all three models yield plausible coefficients for the demand and pricing equations. In general the BLP and BLPWP results are more similar to each other than to the GR model. The estimated demand for digital cameras by the GR model and the BLPWP is more elastic, which is consistent with a more competitive market. This type of result is similar to that found by GR and Conlon (2010) and strikingly different to the results predicted by Chen et al. (2008) in their simulation analysis. In addition, all three models in the paper still feature declining markups over product lives, consistent with firms engaging in intertemporal price discrimination. In the merger simulations, the GR model predicts lower price increases following each merger. These results are important as they suggest that dynamic models imply a more competitive oligopoly of durable goods than static differentiated models. Introducing the age proxy does improve estimation in some respects in terms of expected adjustments to demand estimates.

The rest of the paper is organized as follows. The next section reviews the dynamic demand model of GR, compares it with the BLP model, and then proposes a semi-parametric approach to ease the computation burden of estimating the GR model. It further discusses estimation and identification. The data is described in Section 3 while estimation results and merger simulations are compiled in Section 4. The final section concludes the paper.

2. Model and estimation

In Gowrisankaran and Rysman (2009, GR), consumers may delay purchasing one of the available products because they believe technology will improve rapidly and they prefer to wait to purchase one of the improved products that they expect to come along. This section specifies the conditions under which the GR model can be simplified to the static demand model of BLP. These conditions suggest that it may be possible to extend the BLP model by introducing a non-parametric function to control for de facto competition from future purchases and still estimate the other parameters of the model. As a first step in this direction, we argue that product age could be used as a proxy to represent this non-parametric function. We conclude by describing the three sets of equations we estimate and also discuss identification and estimation issues.

2.1. Dynamic demand model of Gowrisankaran and Rysman

The main way the dynamic GR model differs from the static BLP model is that the demand for a product depends not only on its price and characteristics but also on the expected utility from purchasing new products offered in the future. Formally, suppose there are J_t distinct products marketed in period t. Each product, indexed by $j=1, 2, \ldots, J_t$, is infinitely durable. Suppose further that there are I_t consumers/households in market t and they have an infinite horizon, discounting the future utility with a common factor of ρ. Like GR we avoid complications associated with secondary markets by assuming that if a consumer already owns a product, it is effectively discarded upon purchase of a new product. In each period, the consumer decides whether to purchase one of the J_t products or make no purchase. In each period household i that purchases product j receives flow utility:

$$\delta^f_{ijt} \equiv \sum_{k=1}^{K} \beta_{ki} x_{jk} + \xi_{jt}, \tag{1}$$

where x_{jk} is the quality measure of observable characteristic k ($k=1, 2, \ldots, K$, including brand dummies) and ξ_{jt} is a product-specific characteristic observable to consumers but unobservable or immeasurable to researchers. The coefficients β_{ki} in Eq. (1) measure the marginal utility of characteristic k and are subscripted with i to allow for randomness in consumption utility.[3] The outside choice (i.e., no purchase) is denoted by $j=0$ with flow utility δ^f_{i0t}. If consumer i is not holding any product before period t, δ^f_{i0t} is normalized to zero. For those already owning a product, $\delta^f_{i0t}=\delta^f_{i\hat{j}\hat{t}}$, where $\hat{j}$ and $\hat{t}$ are the product and time of the most recent purchase. Thus, the net flow utility from purchase is:

$$u_{ijt} = \delta^f_{ijt} - \alpha_i \ln\left(p_{jt}\right) + \varepsilon_{ijt}, \tag{2}$$

where p_{jt} is the price of product j in period t and coefficient α_i measures the marginal disutility of price. The idiosyncratic shock to utility, ε_{ijt}, is assumed to have a type-I extreme value distribution. Except for being defined in terms of flow utility rather than lifetime utility, the utility function in Eq. (2) is very similar to that used in BLP.

For durable goods, each consumer's choice is influenced by their current state, described by state variables, and expectations about the future. In addition to the type of product initially held by the consumer there are two sets of state variables. The first set, denoted by $\varepsilon_{i.t}\equiv(\varepsilon_{i0t}, \ldots, \varepsilon_{iJ_t t})$, is the vector of idiosyncratic shocks for the J_t+1 goods (including the outside choice) the consumer decides over in period t. The second set of state variables is all attributes of current products and factors influencing future product attributes as denoted by Ω_t. Ω_t is assumed to evolve according to a Markov process. Hence the vector of state variables for consumer i at time t is $(\varepsilon_{i.t}, \delta^f_{i0t}, \Omega_t)$. Denote $V_i(\varepsilon_{i.t}, \delta^f_{i0t}, \Omega_t)$ as the value function and $EV_i(\delta^f_{i0t}, \Omega_t)=\int V_i(\varepsilon_{i.t}, \delta^f_{i0t}, \Omega_t) dP_\varepsilon$ as the expectation of the value function after integrating out $\varepsilon_{i.t}$. Hence, the Bellman equation for consumer i is:

$$V_i\left(\varepsilon_{i.t}, \delta^f_{i0t}, \Omega_t\right) = \max_{j=0,1,\ldots,J_t} \left\{u_{ijt} + \rho E\left[EV_i\left(\delta^f_{ijt}, \Omega_{t+1}\right) | \Omega_t\right]\right\}. \tag{3}$$

It is useful at this point to denote δ_{ijt} as the expected net utility from purchasing brand j conditional on consumer i's information at time t and δ_{i0t} as the conditional expected utility from not making a purchase at time t as follows:

$$\delta_{ijt} = \delta^f_{ijt} - \alpha_i \ln\left(p_{jt}\right) + \rho E\left[EV_i\left(\delta^f_{ijt}, \Omega_{t+1}\right) | \Omega_t\right] \tag{4}$$

$$\delta_{i0t} = \delta^f_{i0t} + \rho E\left[EV_i\left(\delta^f_{i0t}, \Omega_{it+1}\right) | \Omega_{it}\right]. \tag{5}$$

GR demonstrate that given the sufficient assumptions specified in their paper the state space can be reduced to two variables: the inclusive value and the flow utility from not purchasing, where the logit inclusive value for consumer i at time t is defined as:

$$\delta_{it} = \ln\left(\sum_{j=1,\ldots,J_t} \exp\left(\delta_{ijt}\right)\right). \tag{6}$$

Hence, the value function in Eqs. (3), (4) and (5) can be conditioned on δ^f_{i0t} and δ_{it} rather than δ^f_{i0t} and Ω_t. It is worth noting that the probabilities associated with future values of the inclusive value are not derived assuming rational expectations but rather the inclusive value is assumed to evolve as a Markov process.

[3] However, in practice the randomness of β_{ki} is often restricted to reduce computational burden and/or insure convergence. For instance, Melnikov (2001) and GR take β_{ki} as non-random constants across consumers.