# Brand Loyalty, Advertising and Demand for Personal Computer Processors: The *Intel Inside*® Effect*

Hugo Salgado†

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**Abstract**

In this paper I estimate the effect of the Intel brand and advertising expenditures on the demand for Personal Computer Central Processing Units (PC CPU). Two firms, INTEL and AMD, capture almost the entire market in this industry. Intel has followed a brand positioning strategy based on strong advertising and marketing activities, while AMD has centered its marketing strategy on lower prices. Even though the two companies offer products of similar quality, Intel has a dominant position in the industry, capturing more than 75% of the market share. I estimate random coefficient demand models, using

*This paper is a draft of the first chapter of my dissertation. In the second chapter I use the demand results to estimate a dynamic conduct parameter and in the third paper I estimate a dynamic cost function with learning-by-doing under a Markov Perfect Equilibrium. Please do not cite nor circulate. All comments are welcome.

†PhD. Candidate, Department of Agricultural and Resource Economics, University of California at Berkeley. e-mail: *salgado@berkeley.edu*

brand and advertising to explain the large observed differences in market share between AMD and INTEL. After controlling for quality and other unobserved product characteristics, I find that consumers are willing to pay a big premium for the Intel brand. Counterfactual experiments shows that in absence of advertising differences between the two firms, Intel's market share would have been between 35% and 70%, suggesting that strong advertising campaigns have allowed Intel to maintain a dominant position in the market. The results also suggest that advertising in the industry has increased the total sales of personal computers in about 25% and that advertising is combative working as a tool to redistribute market shares between firms.

## 1 Introduction

In the personal computer central processing unit (PC CPU[1]) market, two firms -Advanced Micro Devices (AMD) and Intel Corporation (INTEL)- capture more than 95% of the market, with INTEL capturing more than 75% of the market. Over the years many firms have tried to enter the market but AMD is the only that has become an important competitor to Intel. During the 1990s, AMD used a lower pricing strategy than Intel, and also created and introduced several new products that performed in a similar or better manner than those manufactured by Intel. Nevertheless, AMD products - even those similar in quality to Intel products- have not been successful in capturing a significantly higher market share.

Several arguments have been put forth to explain the inability of AMD to increase its market shares. Perhaps, the most important is that Intel has created a strong brand reputation among consumers. The *Intel Inside*® advertising campaign is one of the most important advertising efforts in the PC industry; it represented the first time than a PC component manufacturer directed advertising at final consumers. As a result of its advertising efforts, Intel has ranked fifth among the most important global brands since 2001, with an estimated brand value of over $30 billion in 2007.[2] In contrast, AMD does not place importance on brand positioning and advertising; rather, it concentrates its marketing strategy in low-prices, which has been shown to have a negative effect on brand reputation (Jedidi, Mela and Gupta, 1999).

[1]The CPU is the brain of personal computers that performs all the information processing tasks required for computing.

[2]The Best Global Brands 2007, Interbrand and Business Week, http://www.interbrand.com.

The Intel Inside program was launched in 1991, at a time when AMD was successfully producing and marketing clones of Intel 286 and 386 CPUs. To differentiate its products, Intel developed the *Intel Inside®* logo. It also developed a cooperative marketing program with PC manufacturers, under which it would provide a rebate to the manufacturer of up to 50% of PC manufacturer marketing expenditures if it included the Intel logo in its advertising. By the end of 1991, more than 300 PC manufacturers had joined the program. In 1994 Intel started its own TV advertising campaign and developed musical jingles to support the Intel Inside slogan. Since then, Intel has conducted strong advertising and brand loyalty campaigns, directed at both PC manufacturers and final consumers, in order to keep its brand reputation. By the end of the decade, more than 2,700 PC manufacturers were participating in the program, and more than $7 billion had been invested in advertising under the Intel Inside campaign. Just in 2001, more than 150 million Intel stickers were printed and Intel spent more than $1.5 billion on advertising under the cooperative program (Moon, 2005).

The marketing literature has recognized the effects of advertising on building brand preferences (Jedidi, Mela and Gupta, 1999), and the use of discrete choice models to measure the effects of advertising on demand is common (see for example Sriram, Chintagunta and Neelamegham, 2006). Bagwell (2007) presents a complete survey of the economic theory and empirical studies of advertising. The author divides the literature into the three different theories of the effects of advertising on demand: the persuasive view, the informative view and the complementary view. In the first view advertising induces consumers to buy the good and acts as a combative tool against competitors. From this point of view, advertising creates brand loyalty and results in greater market power for established firms; it might have a negative effect on welfare, and might be potentially excessive because it can only redistribute consumers among brands. The second view contends that advertising provides valuable information to consumers; therefore, it can be beneficial to consumers and facilitate entry of new firms into the market. From the second point of view, advertising is considered a cost associated with providing information to consumers and it could be under or over provided in the market. The third view posits that consumers see advertising as a complementary good to the product being advertised, and argues that the two goods can only be bought as a bundle. This could be the case when, for example, advertising provide "social prestige" to the product being consumed. From this third point of view, advertising might be undersupplied because of market incompleteness.

The empirical analysis of advertising is also diverse. Bagwell (2007) recognizes that there is no consensus on the effects of advertising; most effects are industry-specific and vary on a case-by-case basis. Two important aspects in empirical analysis are (1) considering the endogeneity of prices and advertising and (2) analyzing dynamic effects of advertising on consumer preferences. Villas-Boas and Winer (1999) discuss the effects of price endogeneity and the use of marketing variables in discrete choice models. Some authors find that advertising has long-lasting reputational effects over consumer demand, while other find that the effects of advertising on sales are largely depreciated within a year (Braithwaite 1928, Jastram 1955, Lambin 1976, Ashley, Granger and Schmalensee 1980, Boyd and Seldon 1990, Kwoka

1993, Leone 1995, among others). In terms of brand loyalty, Bagwell (20007) concludes that existing studies do not provide strong evidence that advertising increases brand loyalty or stabilizes market shares. In the PC industry, Goeree (2008) has analyzed the effects of advertising on the demand for PCs, and finds that advertising by PC manufacturers is an important component in explaining the high markups in the PC industry because it focuses the attention of uninformed consumers over a subset of the available products. I am not aware of any published paper that have analyzed the effect of the Intel brand on the demand for CPUs.

In this paper I estimate random coefficient demand models with aggregate data (following Berry 1994, Berry, Levinsohn and Pakes 1995, Nevo 2000). I incorporate brand and advertising effects to explain the high market shares of Intel products in the industry. I use a proprietary dataset containing quarterly sales and price data for 29 products manufactured by AMD and Intel from 1993 to 2004. After controlling for price, quality and other unobservable product characteristics of the products, I find that both the Intel brand and the advertising expenditures allow to explain consumer behavior and that consumers are willing to pay a high premium for Intel products -between 30% and 50% of Intel average selling price- and that if Intel had not employed strong advertising campaigns, its market shares would be significantly lower.

The rest of the paper is organized as follows. Section 2 presents the demand model and the estimation algorithm; Section 3 discusses the main characteristics of the market, the dataset and how advertising and brand effects are incorporated in the demand model; Section 4 presents the results and counterfactual simulations; Section 5 concludes and discusses the effects of the assumptions on the modeling results.

## 2 The Model of Demand and the Estimation Algorithm

This section presents the details of the random coefficient demand model and the estimation algorithm. Readers that are already familiar with the model and are interested largely in the application can proceed to the next section without missing anything fundamental.

Discrete choice models (DCM) of demand have a long tradition in the study of demand for differentiated products. DCM assume that consumers obtain welfare from product characteristics, including a random component unobserved by the researcher, and that based on those characteristics, consumers choose, from among the available products, the one that gives them the highest expected utility. The use of this framework to estimate demand for differentiated products is appealing because it focuses the analysis on the underlying utility function that determines the system of demand for the products, instead of trying to estimate demand for each alternative using a system of equations. The DCM structure greatly reduces the data requirements and the number of parameters that must be estimated, which makes it feasible to estimate a coherent system of demand for a large number of products and for markets with a different number of available products, as is the case in the PC CPU industry.

The study of demand for differentiated products allows us to estimate

DCM employing either individual purchases or aggregated, market level data. Several of these methods are analyzed in Berry (1994). Berry, Levinsohn and Pakes (1995) develop a method to estimate, through simulations, random coefficient DCM employing aggregated data and taking into consideration the endogeneity of prices in the demand system. This model of demand allows for heterogeneous preferences and permits the estimation of more reasonable substitution patterns among products, compared to other discrete choice models of demand. Nevo (2000) and Train (2008) present a deep treatment of this topic and of the algorithms required in estimation. Other well known applications of this method of demand include Petrin (2002), Goolsbee and Petrin (2004), Chintagunta, Dube and Goh (2005) and Train and Winston (2007) among many others.

### Demand

Following Nevo (2001) I present the main components of a random coefficient demand model for market data. We observe the market in $t = 1...T$ time periods[3], and in each period the market has $L$ consumers. We observe aggregate quantities, prices and a vector containing observable product characteristics ($X_{it}$) for each one of the $I_t$ products available in each period. The indirect utility by consumer $l$ from choosing product $i$ at time $t$ is given by

$$\begin{gathered} u_{lit} = \alpha_l(y_l - p_{it}) + \beta_l X_{it} + \xi_{it} + \varepsilon_{lit} \\ l = 1 \dots L, i = 1 \dots I_t, t = 1 \dots T \end{gathered} \tag{1}$$

[3]Alternative, these could be T different spatial markets in a given time period or a combination of both spatial markets and time periods.

where $y_l$ is the income of consumer $l$, $p_{it}$ is the price of product $i$ at time $t$, $X_{it}$ are observable product characteristics, $\xi_{it}$ represents product characteristics observed by the consumers but not by the researcher, $\varepsilon_{lit}$ is a random term with a Type I extreme value distribution, $\alpha_l$ is consumer $l$'s marginal utility of income, and $\beta_l$ is the vector of consumer $l$'s marginal utility from various product characteristics. To account for heterogeneous preferences, $(\alpha_l, \beta_l)$ are assumed to have a probability distribution $F(\alpha_l, \beta_l; \theta)$ over consumers whose parameters $\theta$ must be estimated. For example, as it will be assumed in this paper, these parameters could be independently distributed as normal or log-normal random variables, where $\theta$ denotes the mean and the variance of the related normal distributions.

The specification of the demand model also includes an outside good which capture the preferences of those consumers who decide not to buy any of the available products in the dataset. The indirect utility from this outside good, which is normalized to be zero, is:

$$u_{l0t} = \alpha_l y_l + \xi_{0t} + \varepsilon_{l0t} = 0 \tag{2}$$

The definition of the indirect utility function in (1) can also be written as:

$$\begin{aligned} u_{lit} &= \alpha_l y_l + \delta_{it}(p_{it}, X_{it}, \xi_{it}) + \mu_{lit}(p_{it}, X_{it}) + \varepsilon_{lit} && (3) \\ \delta_{it} &= f(X_{it}, p_{it}) + \xi_{it} && (4) \end{aligned}$$

In this reformulation $\mu_{lit}$ captures the portion of the utility from product

$i$ that differs among consumers. The term $\delta_{it}$ is common among consumers and is called the mean utility of product $i$ at time $t$. This term is assumed to be linear in the unobservable product characteristic, and it is usually linear in other parameters too. The distinction between the four terms of equation (3) is important for estimation. During estimation the last term $\varepsilon_{lit}$ is integrated out, giving rise to logit probabilities for each consumer; the individual specific part of utility ($\mu_{lit}$) is integrated over consumers to compute predicted market shares; and the mean utility ($\delta_{it}$) is estimated to make predicted market shares equal to observed market shares. The linearity of the mean utility in the unobserved product characteristic is exploited to construct moment conditions that account for endogeneity of prices. Endogeneity arises because equilibrium prices depend on product characteristics, in particular they depending on the unobserved characteristic $\xi_{it}$. The first term that involves income ($\alpha_l y_l$) does not affect the consumer's choice when comparing the alternatives and therefore disappears from the estimation problem.

Consumers are assumed to buy one unit of the good that give them the highest utility, which defines the set of consumers that choose product $i$ as

$$A_{it} = \{(\alpha_l, \beta_l, \varepsilon_{l0t}, ..., \varepsilon_{lJ_tt}) | u_{lit} \geq u_{lst} \forall s = 0, 1..J_t\} \tag{5}$$

The market share for good $i$ at time $t$ corresponds to the mass of individuals over the set $A_{it}$, which can be expressed as

$$s_{it}(p_t, X_t, \delta_t; \theta) = \int_{A_{it}} dF(\alpha_l, \beta_l, \varepsilon; \theta) \tag{6}$$

Where $F(\alpha_l, \beta_l, \varepsilon; \theta)$ is the distribution of these random terms among consumers. Assuming that $\varepsilon$ is distributed Type I Extreme value and is independent of $\alpha_l$ and $\beta_l$ , it is possible to integrate over these terms, resulting in the aggregated predicted shares:

$$s_{it}(p_t, X_t, \delta_t; \theta) = \int \frac{exp(\delta_{it} + \mu_{ilt})}{1 + \sum_{s=1}^{I_t} exp(\delta_{st} + \mu_{slt})} dF(\alpha_l, \beta_l; \theta) \tag{7}$$

The demand function for a set of parameters $\theta$ is given by

$$q_{it}(p_{it}, X_{it}; \theta) = s_{it}(p_t, X_t; \theta) \cdot M_t \tag{8}$$

where $M_t$ is the market size at time t.

## Estimation Algorithm

The estimation of the demand model uses the GMM procedure proposed by Berry (1994). The GMM function is constructed based on the orthogonality of the unobserved product characteristic error term ($\xi_{it}$) and a series of instruments to control for the endogeneity of price in the system of demand. To employ this approach, for a given value of the unknown parameters $\theta$, the corresponding error term $\xi_{it}(\theta)$ must be computed. Berry, Levinsohn and Pakes (1995) (BLP) develop a contraction mapping algorithm that performs this step. In this algorithm, for each trial value of $\theta$, a contraction mapping is employed to obtain the values of $\delta_{it}$ that make predicted market shares in equation (7) equal to observed market shares. Then, these values are used in the definition of $\delta_{it}$ to obtain an estimate of $\xi_{it}$. Since this contraction must be conducted at every point at which $\theta$ is evaluated, this method is computationally intensive and might present convergence problems either in the inner-loop (computation of $\delta$ for each evaluation of $\theta$) or in the outer-loop (computation of $\theta$ that minimizes the GMM function). Instead of the contraction mapping algorithm, I follow a Mathematical Programming with Equilibrium Constraints (MPEC) approach (Su and Judd 2008, Fox and Su 2008). This algorithm has several computational advantages over the traditional BLP approach and is discussed in detail in Fox and Su (2008).

The MPEC approach is based on a constrained optimization problem where the inner-loop of BLP is defined as a constraint to the GMM minimization problem. This approach is implemented in the AMPL optimization language[4], which uses a number of high-level optimization algorithms. Some of these algorithms allow the constraints to hold at the convergence point and not necessarily at every evaluation point of the parameters. Just this fact simplifies the estimation algorithm because it does not require to include the BLP inner-loop during the GMM optimization routine. Another advantage of using AMPL is that it uses automatic differentiation (AD)[5] so that computing explicit gradients and Hessians is not needed during the optimization routine. Instead, the gradient and Hessian are only computed once, at the convergence point to obtain estimates of the asymptotic standard errors of the parameters.

[4]AMPL: A Modeling Language for Mathematical Programming, for details see http://www.ampl.com and Fourer, Gay and Kernighan (2002).

[5]AD is a computational tool based on the way that computers evaluate functions. By dividing the objective function into a series of simple algebraic operations (for which the first and second derivatives are easy to compute) and employing the chain rule, the objective function is transformed to automatically provide the value of the objective function and its first and second derivatives. After the function has been transformed, the first and second derivatives are provided each time the objective function is evaluated at almost zero computational cost.

The estimation of the model requires: (a) the assumption of a family of probability distributions for the parameters that determine consumer preferences, (b) the specification of the numerical algorithm to compute the integral involved in the predicted shares of equation (7), and (c) the declaration of the objective function and the constraints of the GMM optimization problem. I present details for each one of these points below.

I start by assuming that the parameters $\alpha_l$ and $\beta_l$ are independently distributed following either a normal or log-normal distribution. [6] In both cases, the parameter $\theta$ corresponds to the mean and variance of the implied normal distribution.

Hence, for the normal distribution we have:

$$\alpha_l \sim N(\alpha, \sigma_\alpha^2) \quad (9)$$

$$\beta_l \sim N(\alpha, \sigma_\alpha^2) \quad (10)$$

and for the log-normal distribution:

$$\log(\alpha_l) \sim N(\alpha, \sigma_\alpha^2) \quad (11)$$

$$\log(\beta_l) \sim N(\beta, \sigma_\beta^2) \quad (12)$$

and for both cases:

$$\theta = (\alpha, \beta, \sigma_\alpha, \sigma_\beta) \quad (13)$$

[6] I discuss these two cases here because they are the one used in the estimation of the model.

To simulate the multidimensional integral in equation (7), I take draws from a standard normal distribution and given a set of parameters $\theta$, I transform the individual parameters as:

For the normal distribution:

$$\begin{aligned} \alpha_l &= \alpha + \sigma_\alpha \cdot v \\ \beta_l &= \beta + \sigma_\beta \cdot v \\ v &\sim N(0,1) \end{aligned} \tag{14}$$

and for the log-normal distribution:

$$\begin{aligned} \alpha_l &= exp(\alpha + \sigma_\alpha \cdot v) \\ \beta_l &= exp(\beta + \sigma_\beta \cdot v) \\ v &\sim N(0,1) \end{aligned} \tag{15}$$

Given L draws (one for each consumer) from the preference parameters $\{v^p_{ilt}, v^p_{ilt}\}^L_{l=1}$, I define $\delta_{it}$ and $\mu_{ilt}$ as follows.

For the normal distribution:

$$\begin{aligned} \delta_{it} &= -\alpha p_i t + \beta X_{it} + \xi_{it} \qquad (16) \\ \mu_{ilt} &= -\sigma_\alpha v^p_{ilt} p_i t + \sigma_\beta X_{it} v^X_{ilt} \end{aligned}$$

and for the log-normal distribution:

$$\delta_{it} = \xi_{it} \tag{17}$$

$$\mu_{ilt} \quad = \quad -exp(\alpha + \sigma_\alpha v^p_{ilt})p_it + exp(\beta + \sigma_\beta v^X_{ilt})X_{it}$$

Notice that when the normal distribution is assumed, the parameters $\alpha$ and $\beta$ enter just in $\delta_{it}$ and not in $\mu_{ilt}$, but if the log-Normal distribution is used all the parameters enter the individual specific part of the utility, $\mu_{ilt}$. Given that just the parameters that enter the individual specific part of the utility are involved in the non-linear inner-loop of the BLP approach, the log-Normal distribution has an important computational cost for the BLP approach but not for the MPEC approach.

Finally, using the draws over the consumer preferences density, we can compute an approximation to the integral involved in equation (7) to compute the predicted shares as:

$$s_{it}(p_t, X_t; \theta) = \sum_{l=1}^{L} \frac{exp(\delta_{it}(\theta) + \mu_{ilt}(\theta))}{1 + \sum_{s=1}^{I_t} exp(\delta_{st}(\theta) + \mu_{slt}(\theta))} \tag{18}$$

The GMM objective function is constructed using a quadratic form of the orthogonality condition between the vector of error terms ($\xi$) and a matrix of instruments ($Z$), weighted by the inverse of the square of the matrix of instruments, as presented below. In the MPEC approach the objective function is minimized with respect to three set of variables: the unknown parameters, the constants $\delta_{it}$ and the error terms $\epsilon_i t$. The GMM problem considers two set of constraints. The first set of constraints refers to the definition of $\delta_{it}$ that relates the error term $\xi_{it}$ to the product-specific constants. The second set of constraints imposes equality between observed market shares and predicted shares evaluated at a given vector $(\delta_{it}, \theta)$. Hence, the

MPEC GMM optimization problem is:

$$\underset{\theta,\delta,\xi}{Min}\, GMM(\theta) = \xi' Z(Z'Z)^{-1}Z'\xi \tag{19}$$

$$s.t. \quad \xi_{it} = f(\delta_{it}, \theta) \tag{20}$$

$$S_{it} = s_{it}(\delta, \theta) \tag{21}$$

Notice that the objective function just involves the variables $\xi$ and the instruments, which are related to the other variables through the constraints. The constraint in equation (20) relates the variable $\xi_{it}$ to the variable $\delta_{it}$, given the set of parameters $\theta$, which corresponds to the solution to the system of equations (16) or (17). The constraint in equation (21) correspond to the inner-loop in the traditional BLP procedure and imposes the requirement that at the convergence point, the predicted shares $s_{it}$ equal the observed market shares $S_{it}$, given the set of $\delta$ and the parameter vector $\theta$.

# 3 Application to the Personal Computer CPU Industry

### The Industry and the dataset

The history of the CPU market dates back to 1974. At this time, CPUs were invented to be used in electronic calculators. By 1978 Intel had introduced its first generation of a 16 bit CPU, the 8086, which was the basis for the x86 architecture currently used in personal computers. Since then, seven generations of CPUs have been introduced into the market, each one with a significant increase in performance and possibilities, expanding the potential use of computers from being simple calculators to machines that perform complex mathematical operations, manage enormous databases, and process digital sounds, images and movies.

The dominance of the CPU market by Intel and AMD began in 1982 when IBM chose Intel to provide the 286 processors for its new line of personal computers, the IBM PC/AT. IBM's policies required a secondary producer of the chips, and Intel had to sign an agreement with AMD in order to sell its chips to IBM. Some years later Compaq developed the first IBM PC clone, thus establishing a competitive market for IBM-compatible PCs. With this new source of demand, Intel tried to break its ties to AMD. Intel canceled the production agreement with AMD and refused to hand over technical specifications for its new chips. AMD challenged Intel's decision, and a long legal dispute ensued. In 1991, AMD was given the right to produce the Intel chips but in December 1994, the Carlifornia's Supreme Court denied AMD the right to use Intel codes. Later, AMD and Intel signed a cooperative agreement to share technological innovation, which allowed AMD to produce and sell CPUs based on the Intel 286, 386 and 486 technologies. Since then, AMD has developed its own chips architecture and has introduced the K5, K6 and K7 (Athlon) chips.

The most important characteristic of a CPU, and perhaps the only one that should matter to final consumers, is its capacity to perform a number of computing tasks in a short period of time. The performance of a CPU is usually associated with the clock speed of the processor, but this measure is not the only determinant of how quickly a CPU can perform. The clock speed only measures the number of cycles of instruction that are processed by the CPU in one second. There are several other characteristics that affects performance: for example, the amount of internal memory, the existence of a mathematical coprocessor, the front side bus speed (the speed at which the CPU communicates with other components) and other specific characteristics of the CPU design. Several benchmarks of performance that summarize the effects of these characteristics on product performance exist. One of the most widely used is the quality benchmark maintained by CPU Scorecard, which is the one I use in this paper to measure quality of the products.

The main data set used in this research was obtained from In-Stat, a research company that specializes in the CPU market[7]. It includes estimates of quarterly sales for CPUs, aggregated on 29 products for the period 1993-2004. Since there exist entry of new products and retirement of obsolete products, there is a total of 291 observations in the dataset[8]. The dataset also contains information on prices[9]. In-Stat obtains figures on list prices of Intel products and adjusts these prices for volume discounts offered to their major customers. Their main sources of information are Financial Statements reports and World Semiconductor Trade Statistics elaborated by the Semiconductor Industry Association (SIA). In-Stat uses this information to estimate unit shipments for each product by Intel and AMD, based on engineering relationships and capacity production of each fabrication plant

[7]This dataset is proprietary material belonging to In-Stat.

[8]A unit of observation is an individual product observed in a particular quarter

[9]Prices for AMD products are only available from 1999 to 2004, so the dataset was complemented with information from several other sources, including printed publications and on-line historical databases. The dataset contains 9 AMD products and 20 Intel products during the sample period.

(Aizcorbe, et.al. 2003). The In-Stat data set is complemented by data from two other sources. The first is firm-level advertising expenditures for each company; these data were obtained from the 10K and 10Q financial statements. The second extra source consists of information about CPU performance; it was obtained from The CPU Scorecard, a company that measures the performance of CPU products. The In-Stat database has been previously used by Song (2006, 2007) to estimate demand for differentiated products as well as to analyze welfare implications from investment in research and development in the CPU market. It has also been used by Gordon (2008) to estimate a demand model for durable goods.

Table 1 shows a summary of the dataset, including yearly quantities, average prices, average performance, and advertising expenditures from 1993 to 2004. The data show that Intel sales are more than three times AMD sales, and that Intel captures 83.49% of the total sales during this period. During most of this period, Intel's average prices were much higher than AMD's average prices, except in 2003 and 2004 where AMD prices are influenced by the sales of the more expensive Athlon 64 (the first 64-bit CPU). In terms of performance, Intel was a clear technological leader during the first part of the 1990's. Starting in 1999, with the introduction of the AMD Athlon, AMD closed the gap between its products and Intel's and in some years took the performance leadership with its products. The advertising data show the strong effort that Intel put on building brand reputation. In each year, Intel's advertising expenditures are between 4 and 8 times higher than AMD's advertising expenditures.

Table 1: Summary of Dataset

| Year | Quantities | | Prices | | Max. Performance | | Advertising | |
|---|---|---|---|---|---|---|---|---|
| | AMD | INTEL | AMD | INTEL | AMD | INTEL | AMD | INTEL |
| 1993 | 7100 | 29306 | 91 | 350 | 64 | 125 | 81 | 325 |
| 1994 | 8420 | 39144 | 93 | 356 | 102 | 199 | 114 | 459 |
| 1995 | 10900 | 55140 | 75 | 368 | 167 | 334 | 146 | 654 |
| 1996 | 8720 | 70788 | 50 | 299 | 274 | 502 | 153 | 974 |
| 1997 | 6960 | 84191 | 145 | 325 | 392 | 715 | 166 | 1200 |
| 1998 | 13500 | 84280 | 225 | 421 | 698 | 927 | 177 | 1300 |
| 1999 | 18111 | 98179 | 215 | 321 | 1717 | 1777 | 237 | 1700 |
| 2000 | 26400 | 138192 | 209 | 355 | 3030 | 2857 | 235 | 2000 |
| 2001 | 30500 | 120871 | 127 | 201 | 4142 | 3981 | 222 | 1600 |
| 2002 | 23100 | 122822 | 126 | 228 | 5753 | 6452 | 263 | 1700 |
| 2003 | 26000 | 116376 | 216 | 199 | 7691 | 7041 | 247 | 1800 |
| 2004 | 33000 | 116265 | 253 | 196 | 8604 | 8686 | 364 | 2100 |

Quantities are in millions of units, Prices are quantity-weighted averages in US dollars, Performance is a quantity-weighted average of the CPU Scorecard benchmark for each CPU, and Advertising is in millions of US dollars.

### Incorporating brand and advertising in the model of demand

I use the relative quality of each product, with respect to the maximum quality observed in the market each period, as the observable product characteristic. This defines the quality of the product as the distance of each CPU from what is considered to be the technological frontier in each period.

To measure the effects of the Intel brand and advertising expenditures on demand, I construct versions of static dynamic models of advertising. The static models of advertising consider that only current period advertising affect demand. For the dynamic models of advertising, I assume that demand is affected by accumulated advertising, which depreciate at a constant rate over time, defined as:

$$G_{jt} = A_{jt} + \sum_{\tau=1}^{T} \beta^{\tau} A_{jt-\tau} \tag{22}$$

Where $G_{jt}$ is the firms' goodwill that enters consumers demand, $A_{jt}$ is firms' $j$ advertising expenditure at time $t$ and $\beta$ is the goodwill depreciation factor.

## 4 Results

I present the estimation results for seven models of demand. The first five models consider static models of advertising assuming either a normal or a log-Normal preferences over price and quality, including a dummy for Intel brand or advertising expenditures. In the first two models I only include a dummy variable for Intel's products. This allows me to measure directly the premium that consumers are willing to pay for an Intel product, controlling for its quality. In the third and fourth model, I only use current advertising expenditures to test whether they can explain why consumers are willing to pay a premium for Intel products. I use the results of these models to conduct experiments about the effects of advertising on the two firms' market shares. In a fifth model, I explore the inclusion of both the dummy and the firms' advertising expenditures assuming a normal distribution of preferences[10].

The last two models explore the dynamic models of advertising using a normal distribution of preferences. In the sixth model, I estimate the dynamic advertising model without including a brand dummy and in the fifth model I include the dummy for Intel brand.

To control for endoeneity of prices in the system of demand, cost determinants are employed as instruments in the GMM estimation. The set of instruments consider product characteristics that affect costs as the number of transistors in a chip, the die size (size of the CPU) and production experience, which affect costs trough learning-by-doing.

Table 2 present the estimated coefficients and the corresponding asymptotic standard errors in parenthesis. In Models 1 through 4, all the coefficients are statistically significant at a 5% confidence level. The estimated normal distributions of the random coefficients indicate that an important proportion of consumers have a positive valuation of price (6.93% in Model 1 and 8.93% in Model 3) or dislike higher quality products (23.27% in Model 1 and 32.86% in Model 3). These results are not consistent with consumer

[10]Given that the results for models 5 to 7 are similar using either a normal or log-normal distribution and that they are not used in the conterfactual experiments, the results of the log-normal distribution are not reported.

theory but they are a consequence of the normal distribution having support over all the real line. The use of a log-normal distribution (Models 2 and 4) avoid these contra-intuitive results while maintaining the high dispersion in consumer valuations. Model 5 estimates the demand model using both an Intel dummy and current advertising level. We can observe that when both variables are included in the estimation most of the parameters are statistically insignificant. Model 6 estimates a dynamic model of advertising without including the Intel dummy and Model 7 add the Intel dummy to the estimation. In Models 6 and 7 the coefficient on advertising goodwill is not statistically significant and the depreciation rate of advertising is 0.02% per quarter, which seems very low. In what follows, I concentrate the analysis on the first four models.

In terms of valuing of the Intel brand, Model 1 implies that an average consumer is willing to pay \$170.78 more for an Intel product with the same performance as an AMD product. This correspond to 49.89% of the average Intel price in the sample. Model 2, which assumes a log-normal distribution, implies that the Intel premium is \$109.65 or 32.03% of the average Intel price.[11]

The estimated average own-price elasticities for the 29 products are presented in Table 3. The most important difference between the four models is that Model 3 predicts price elasticities that are lower than one (in absolute value) for 3 of the 29 products. This is not consistent with profit maximiza-

[11]To compute the Intel brand premium I divide the coefficient on Brand by the mean of the distribution on price coefficients. This is $\frac{\beta_I}{\beta_p}$ for the normal distribution and $\frac{\beta_I}{exp(\beta_p+\frac{\sigma_p^2}{2})}$ for the log-normal distribution.

Table 2: Results of Demand Estimation

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| Price | 19.6622 | 2.5067 | 11.6110 | 2.5350 | 6.6549 | 2.5352 | 14.6816 |
| | (4.1766) | (0.2676) | (2.0506) | (0.2160) | (4.8607) | (1.1924) | (3.1624) |
| Quality | 5.8358 | 1.1362 | 2.8331 | 1.1910 | 1.5392 | 0.9286 | 3.7272 |
| | (2.3671) | (0.2670) | (1.4869) | (0.2763) | (1.7769) | (0.6471) | (0.9478) |
| Brand | 3.3579 | 2.3411 | - | - | 0.8421 | - | 2.8377 |
| | (0.7899) | (0.4365) | | | (1.5713) | | (0.8849) |
| Advertising | - | - | 0.0070 | 0.0044 | -3.3224 | -0.0884 | 0.1701 |
| | | | (0.0013) | (0.0011) | (3.9083) | (0.2188) | (0.4155) |
| Adv. depreciation factor | - | - | - | - | - | 0.9998 | 0.9998 |
| | | | | | | (0.3091) | (0.2503) |
| sigma price | 13.2787 | 1.0530 | 8.6328 | 1.0403 | 7.5722 | 1.6755 | 7.8123 |
| | (3.1019) | (0.3188) | (2.2704) | (0.2837) | (3.2249) | (0.6908) | (1.7514) |
| sigma quality | 7.9928 | 0.8083 | 6.3851 | 0.8080 | 2.2777 | 3.7936 | 7.3055 |
| | (3.0003) | (0.2793) | (1.9343) | (0.2415) | (4.7667) | (0.6669) | (1.5049) |
| Distribution RC | Normal | Log-Normal | Normal | Log-Normal | Normal | Normal | Normal |
| % Positive Price Coefficient | 6.93% | 0.00% | 8.93% | 0.00% | 18.97% | 6.51% | 3.01% |
| % Negative Quality Coefficient | 23.27% | 0.00% | 32.86% | 0.00% | 24.96% | 40.33% | 30.50% |
| WTP for Intel Brand | 170.78 | 109.65 | - | - | 126.53 | - | 193.28 |

tion, because firms could increase price, generating a less-than-proportional reduction in demand, thereby increasing revenue. The firm will reduce their costs due to lower production, while at the same time increasing the sales of other products by the same firm. The combination of these effects will increase the firm's profits. [12] In all the other cases the firms price elasticities are higher than one in absolute value and seem reasonable.

To evaluate the effect of Intel advertising on demand, I conduct four experiments in which I change firms' advertising expenditures and simulate the resulting products demand. In the first experiment neither firm advertises; in the second experiment both firms advertise at the observed AMD levels; in the third experiment both firms advertise at the observed Intel advertising levels; and in the fourth experiment Intel advertising levels are increased by 10% while keeping AMD advertising levels unchanged. The results for the three first cases are similar in terms of relative market shares between firms. The results differ in the level of the outside share, with higher advertising increasing overall demand and reducing the outside product market share.

Figure 1 presents the shares of Intel sales as a proportion of both firms' total sales by quarter, for the four experiments using the results of Models 3 and 4. The change in Intel share is dramatic when both firms advertise in a similar way in the first three experiments (No Advertising, AMD Advertising level; and Intel Advertising level). In the first period, before 1999, a change in Intel advertising reduces Intel shares from around 90% to around 70%.

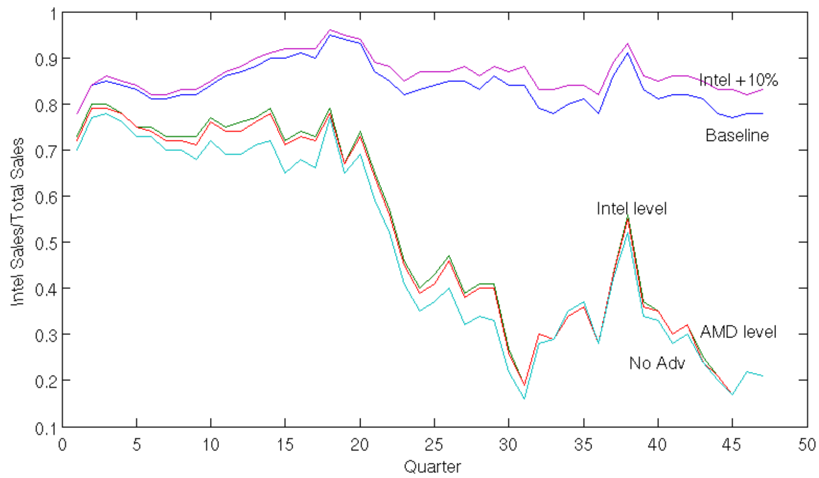
[12] One possible explanation to this is that due to the existence of learning-by-doing an increase in today prices reduces current period demand, reducing experience and increasing future periods production costs, which reduces future firm profits. A deeper analysis of this fact requires to analyze a dynamic model of firms behavior.

Table 3: Own Price Elasticities Different Models

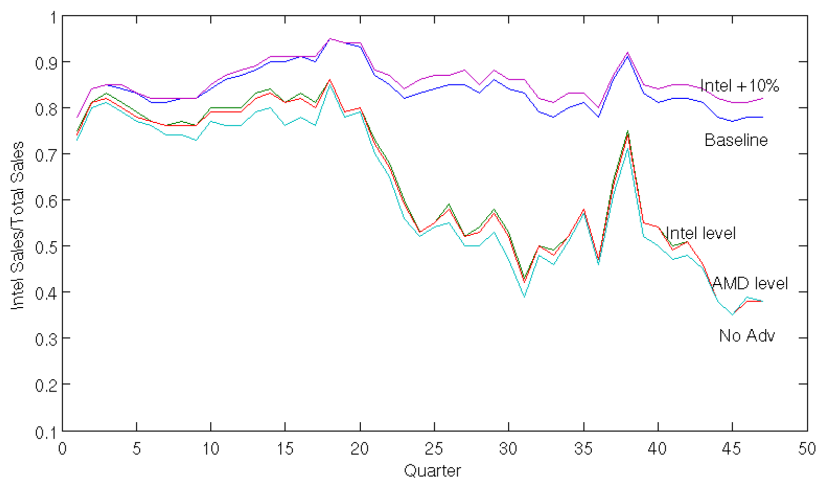
| Product | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Product 1 | -1.42 | -1.29 | -0.83 | -1.39 |
| Product 2 | -2.13 | -1.65 | -1.22 | -1.79 |
| Product 3 | -2.35 | -2.35 | -1.39 | -2.52 |
| Product 4 | -1.74 | -1.57 | -1.02 | -1.66 |
| Product 5 | -4.29 | -2.67 | -2.35 | -3.10 |
| Product 6 | -3.18 | -2.39 | -2.03 | -2.74 |
| Product 7 | -3.29 | -2.35 | -1.90 | -2.94 |
| Product 8 | -1.43 | -1.83 | -0.78 | -2.15 |
| Product 9 | -1.10 | -2.11 | -1.25 | -2.45 |
| Product 10 | -2.66 | -1.79 | -1.42 | -2.13 |
| Product 11 | -3.31 | -2.20 | -1.91 | -2.48 |
| Product 12 | -3.97 | -2.56 | -2.36 | -3.04 |
| Product 13 | -4.37 | -2.54 | -2.42 | -3.03 |
| Product 14 | -2.52 | -1.74 | -1.63 | -2.03 |
| Product 15 | -3.31 | -2.61 | -2.18 | -3.20 |
| Product 16 | -2.38 | -2.75 | -0.93 | -3.61 |
| Product 17 | -1.67 | -1.94 | -1.30 | -2.04 |
| Product 18 | -1.80 | -1.45 | -1.03 | -1.77 |
| Product 19 | -1.80 | -1.34 | -0.85 | -1.60 |
| Product 20 | -2.61 | -2.96 | -1.02 | -3.54 |
| Product 21 | -2.96 | -2.52 | -1.69 | -2.85 |
| Product 22 | -2.11 | -1.81 | -1.25 | -2.16 |
| Product 23 | -1.54 | -1.40 | -1.04 | -1.59 |
| Product 24 | -3.24 | -2.57 | -2.14 | -3.06 |
| Product 25 | -1.61 | -1.17 | -1.05 | -1.41 |
| Product 26 | -2.25 | -1.75 | -1.43 | -2.10 |
| Product 27 | -1.89 | -1.90 | -1.25 | -2.21 |
| Product 28 | -1.22 | -1.12 | -0.76 | -1.23 |
| Product 29 | -2.32 | -1.59 | -1.47 | -1.92 |
| Average | -2.43 | -2.00 | -1.44 | -2.34 |

After 1999, when Intel and AMD are closer in terms of product quality, the shares of Intel are reduced to levels around 40% in Model 3 and around 50% in Model 4. The relative shares between the two firms are almost the same if they advertise in a similar ammount, independent of the advertising level. Figure 2 presents the effect of advertising on total market demand, showing the inside goods' market share (one minus the outside good's market share). In the baseline case I assume that the observed market sales represent 80% of the market. We can observe that the effect of advertising in market demand is also very important. Advertising has an important impact on total sales, increasing the total demand for CPUs from levels around 70%, when no advertising is used, to over 85% of the potential market, when both firms use Intel's advertising levels. In the scenario in which Intel advertising is increased by 10%, the total demand increases by 1% on average, and Intel's relative share increases by more than 3%, thus reducing the demand for AMD products. These results suggest that advertising by Intel and AMD has succesfully increased the market size for PC and has allowed Intel to maintain a dominant position in the market.

These results assume that firms do not modify their pricing behavior, which could be unrealistic. Had Intel not been successful at creating a strong brand reputation, it could not have obtained a large premium for its products. These experiments intend to measure the impact of advertising on the demand for Intel, while controlling for prices, quality and other unobserved product characteristics. Analyzing the optimal pricing responses of Intel and AMD to a change in the other firms advertising level would require a model of the supply side of the market, which is outside the scope of this paper.

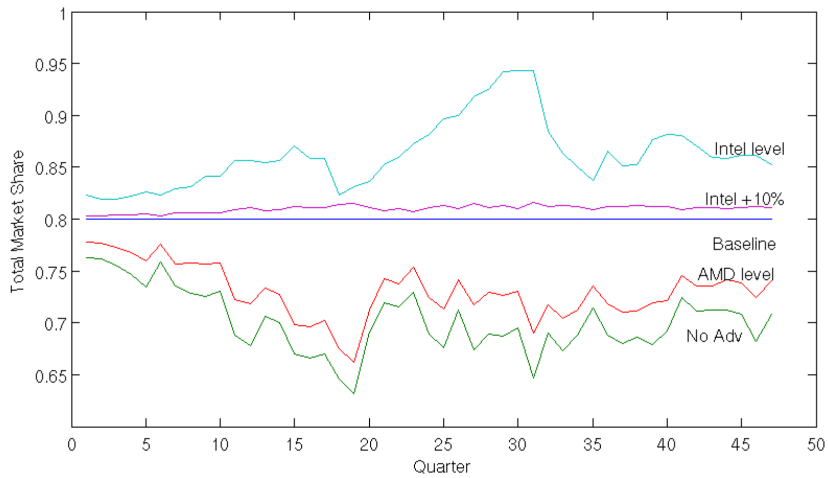



Model 3: Normal Distribution

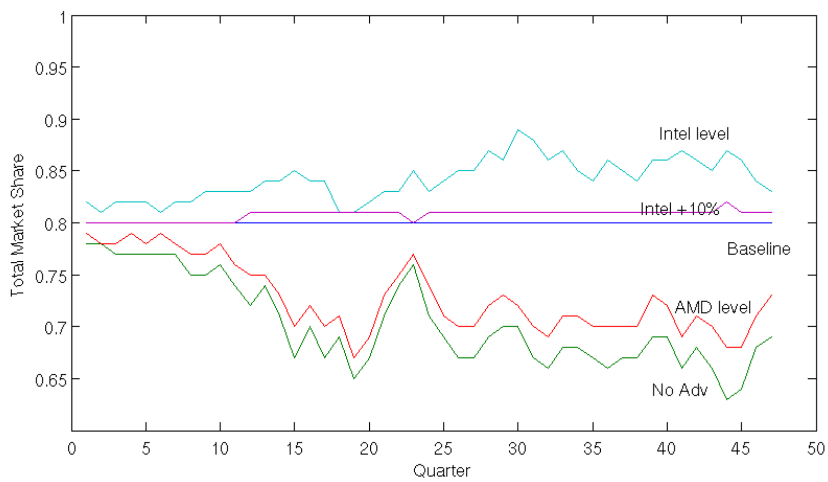



Model 4: Log-Normal Distribution

Figure 1: Effects of Advertising on Intel Market Shares



Model 3: Normal Distribution



Model 4: Log-Normal Distribution

Figure 2: Effects of Advertising on Market Demand

## 5 Discussion

In this paper I have applied a discrete choice model with random coefficients to the PC CPU Industry. The model uses an Intel brand dummy and advertising expenditures to capture the effect of the Intel brand on market share. The results suggest that consumers pay a high premium for the Intel brand; had Intel not invested in brand positioning, its market shares would have been much lower. An interesting question is why AMD does not make use of advertising and brand positioning as a marketing tool. In their financial reports, AMD usually claims that it has not been able to develop a financial basis to support extensive advertising campaigns. Also, some media interviews make it clear that AMD intends to let Intel take the leadership in advertising to final consumers trusting that the consequent increase in market size would benefit them[13]. Nevertheless, the results suggest that while advertising increases market size, it also helps intel to gain relative share over AMD.

The application of a discrete choice model of demand to the CPU market requires a number of assumptions. As in Song (2007), I assume that the behavior of direct buyers of CPUs, PC manufacturers, represent consumer preferences over products characteristics. I also assume that the valuation of the CPU in the demand for computers is separable from other computer components. These assumptions are reasonable because there is a one-to-one ratio of PCs to CPUs in the demand for computers, and the CPU is

[13]In a recent interview Stephen DiFranco, Vice President of Worldwide Sales and Marketing at AMD, said "I beg them publicly [refering to Intel], please advertise more. Create more demand. Some weeks in the United States there are more AMD desktops and notebooks sold than Intel.“

the main determinant of a PC system performance. The other components of the computer, like the size of the hard drive and other peripherals, are highly customizable. Additionally, there is anecdotal evidence that computer manufacturers represent consumer preferences; this has been cited as the reason that explain Intel decision of focus its advertising directly on final consumers (Moon, 2005).

In this paper I control for the endogeneity of prices using cost determinants. I assume that advertising expenditures, even when related to prices, are uncorrelated with unobserved product characteristics. This assumption is justified by the fact that advertising has been mainly directed at brand positioning in the market, rather than as a means of promoting particular products.

I do not study the supply side in this paper because I believe that supply is determined by dynamic considerations. There exists evidence that learning-by-doing is an important factor in this industry, which creates a dynamic game between the two firms. Today's pricing decisions affect all product sales, having an impact on production experience and on future unitary production costs. [14] In two additional papers, I evaluate market power in this industry with a dynamic conduct parameter (Salgado 2008a), and I estimate a dynamic cost function involving learning-by-doing (Salgado 2008b).

There are other characteristics of this market that I have ignored. One of them is that PC are durable goods; therefore, their demand might present

[14] This evidence is also sustained in the results. If I assume that firms behave in a static manner, the implicit marginal costs resulting from assuming this behavior are negative, which is consistent with learning-by-doing.

consumers with a dynamic decision. Gordon (2008) analyzes this case, but in order to solve the dynamic problem involving both sides of the market, supply and demand, he has to assume that only four products (two by firm) exist, instead of allowing for all the 29 products in the In-Stat database. Therefore, the realism gain by allowing a model that accounts for product durability is offset by the disadvantage of product aggregation, which also reduces the already small number of observations. I prefer to ignore these considerations in order to use a more disaggregated data and to be able to use the demand estimates to analyze (in separate papers) the dynamic supply side with learning-by-doing.

Another aspect of this market that I have ignored is firm's decisions to introduce or retire products, and to invest in research and development; a model of these decisions could be used to explain the interesting technology race among firms as well as to estimate firms' optimal decision of marketing expenditures.

## References

[1] Aizcorbe, A. (2006). "Why did Semiconductor Price Indexes Fall so Fast in the 1990s? A Decomposition", *Ecnomic Inquiry*, Vol. 44 (3), pp. 485-496.

[2] Ashley, R. Granger, C. and Schmalensee, R. (1980). "Advertising and Aggregate Consumption: An Analysis of Causality" Econometrica 48, pp. 1149-1168.

[3] Bagwell, K. (2007) “The Economic Analysis of Advertising” in Mark Armstrong and Robert Porter (Eds.), Handbook of Industrial Organization, Vol. 3, North-Holland: Amsterdam, pp. 1701-1844.

[4] Berry, S. (1994) “Estimating Discrete-Choice Models of Product Differentiation”, *RAND Journal of Economics* Vol. 25 (2), pp. 242-262.

[5] Berry, S., J. Levinsohn and A. Pakes (1995) “Automobile Prices in Market Equilibrium”, *Econometrica*, 63, 841-890.

[6] Boyd, R. and Seldon, B. (1990), “The Fleeting Effect of Advertising: Empirical Evidence from a Case Study”. Economic Letters 34, pp. 375-379.

[7] Braithwaite, D. (1928( “The Economic Effects of Advertisement”, Economic Journal 38, 16-37.

[8] Chintagunta, P., J. Dube and K. Goh (2005) “Beyond the endogeneity bias: The effect of unmeasured brand characteristics on household-level brand choice models”, *Management Science* Vol. 52, pp. 832-849.

[9] Fox, J., and C. Su (2008), “Improving the Numerical Performance of BLP Structural Demand Estimations” Unpublished working paper, CMS-EMS, Kellog School of Management, Northwestern University.

[10] Fourer, R., D. Gay and B. Kernighan (2002) “AMPL: A Modeling Language for Mathematical Programming”, Duxbury Press, 2nd Edition.

[11] Goeree, M. (2008) “Limited Information and Advertising in the US Personal Computer Industry”, Forthcoming in *Econometrica*.

[12] Gordon, Brett. (2008). "A Dynamic Model of Consumer Replacement Cycles in the PC Processor Industry" Unpublished working paper, Columbia Business School, January 2008.

[13] Jastram, R. (1955). "A Treatment of Distributed LAgs in the Theory of Advertising Expenditures" Journal of Marketing 20, pp. 36-46.

[14] Jedidi, K., C. Mela and S. Gupta (1999) "Managing Advertising and Promotion for Long-run Profitability" *Marketing Science* 18 (1), pp. 1-22.

[15] Kwoka, J. (1993) "The sales and competitive effects of styling and advertising practices in the U.S. auto industry". The Review of Economics and Statistics 75, pp. 649-656.

[16] Lambin, J. (1976) "Advertising, Competition and Market Conduct in Oligopoly over Time". North-Holland, Amsterdam.

[17] Leone, R. (1995) "Generalizing what is known about temporal aggregation adn advertising carryover", Marketing Science 14, 141-150.

[18] Moon, Y. (2005) "Inside Intel Inside" HBS California Research Center, Harvard Business School Publishing, Harvard University. Document 9-502-083.

[19] Nevo, A. (2000), "A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand", *Journal of Economics and Management Strategy*, Vol. 9, No.4, 513-548.

[20] Petrin, A. (2002), "Quantifying the Benefits of New Products: The Case of the Minivan" *Journal of Political Economy* Vol. 110 (4), pp. 705-729.

[21] Salgado, H. (2008a) "Dynamic Firms Conduct and Market Power: The Computer Processors Industry under Learning-by-Doing" Working Paper, University of California at Berkeley.

[22] Salgado, H. (2008b) "Estimating Learning-by-doing in the Personal Computer Processors Industry" Working Paper, University of California at Berkeley.

[23] Song, M. (2006) "A Dynamic Analysis of Cooperative Research in the Semiconductor Industry", Unpublished working paper, School of Economics, Georgia Institute of Technology.

[24] Song, M. (2007) "Measuring Consumer Welfare in the CPU Market: An Application of the Pure Characteristics Demand Model" *RAND Journal of Economics*, Vol. 38, pp. 429-446.

[25] Sriram, S., P. Chintagunta and R. Neelamegham (2006) "Effects of Brand Preference, Product Attributes, and Marketing Mix Variables in Technology Product Markets", *Marketing Science* Vol. 25 (5) pp. 440-456.

[26] Su, C. and K. Judd (2008), "Constrained Optimization Approaches to Estimation of Structural Models" Working paper presented in the Chicago-Argonne Institute of Computational Economics, July 2007.

[27] Train, K. and C. Winston (2007), "Vehicle Choice Behavior and the Declining Market Share of U.S. Automakers", *International Economic Review* Vol. 48, pp. 1469-1496.

[28] Train, K. (2008), "Discrete Choice Models with Simulation", Second Edition (Forthcoming), Cambridge University Press. (First edition (2003) available on-line at http://elsa.berkeley.edu/books/choice2.html)

[29] Villas-Boas, M. and R. Winer (1999), "Endogeneity in Brand Choice Models", *Management Science* Vol. 45, No.10, pp. 1324-1338.