Dynamic Firm Conduct and Market Power: The Computer Processor Market under Learning-by-Doing

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Abstract

In this paper I study the extent of competition in the computer CPU market in a dynamic structural model. Dynamics in the game are given by learning-by-doing in the production process, with future production costs being reduced with cumulative production. A behavioral parameter that nest three market structures -social welfare maximization, Nash behavior and joint profit maximization- is incorporated in the firms optimization problem. This parameters allows to identify the objective function of the firms that is consistent with a Markov Perfect Equilibrium of the game. The results suggest that firms behavior is close to a Nash Markov perfect equilibrium (MNPE) but slightly more competitive. A static model of firms behavior that does not consider the dynamic incentives of firms overestimate the extent of competition in the market. between firms.

Keywords: Dynamic Oligopoly, Market Power, Computers CPU Market.

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1 Introduction

Analyzing market power in the Personal Computer Processor industry is of central importance to any empirical analysis in this market. This is important, not only because the Central Processor Unit (CPU) is one of the most important components of a Personal Computer (PC)[1] but also because the market for CPUs is one of the most concentrated markets in the world. In this industry, just two firms –Intel Corporation (INTEL) and Advanced Micro Devices (AMD)– have historically captured more than 95% of the market share for IBM-Compatible PCs in the world and Intel has captured between 70% and 90% of the market. Because of the extent of this industry, market power could cause an important effect in the world economy; therefore, estimating the degree of imperfect competition in this industry is an important task.

The analysis of market power in this industry imposes an interesting challenge. Using static equilibrium techniques to analyze firms behavior in this market is not adequate because firms' decision-making process includes dynamic elements that should be incorporated into the modeling and estimation strategies. One of the most important and least studies source of dynamics in the CPU industry is the existence of learning-by-doing.

As many authors have pointed out, the traditional static measures of market power are misleading when firms play a dynamic game (Pindyck 1985, Corts 1999). This implies the necessity of using some econometric method that fully accounts for dynamics in firms behavior.

The empirical analysis of dynamic games has been characterized by an important computational burden associated to the available econometric

[1] The CPU has been called the *"single most important product of the 20th century"* (MIT 1999 Invention Index)

techniques. Most of the available methods use some form of fixed point iteration technique, which requires to compute equilibria many times, at a large number of points over the state space. It also requires to choose among possible many equilibria. These requirements impose an important computational burden restricting the classes of games that are possible to analyze to very simple ones. The technique I employ, by Bajari, Benkard and Levin (2007), avoids those obstacles by assuming that the observed firms behavior represents a Markov perfect equilibrium of the dynamic game, and use forward simulations to estimate unknown structural parameters, thus avoiding the need of computing equilibria even once.

I concentrate the source of dynamics in the market in learning-by-doing in the production process. It has been well documented that learning plays an important role in the semiconductor production process due to significant reduction of failure rates over the life-time of a product. When a product is first introduced, the proportion of units that pass quality and performance test (*yield*) could be as low as 10% of the output. Production experience and adjustments in the process decrease failure rates, increasing yield up to 90% (Irwin and Klenow, 1994). Becuase of the total cost involved on producing chips is independent of the yield, increases in yield reduce unitary production costs of working units.

The empirical studies of learning in the semiconductor industry have concentrated on computer memory manufacturing (Baldwin and Krugman 1988; Dick 1991; Irwin and Klenow 1994; Gruber 1996, 1998; Hatch and Mowery, 1999; Cabral and Leiblein, 2001; Macher and Mowery, 2003; Siebert, 2008), and even when memory and CPU production processes are subject to the same type of learning economies, no evidence exists of the importance of learning in CPU manufacturing. Even when most of the previous studies in the PC CPU industry recognize the existence of learning in the manufacturing process, they have focused on other characteristics of the market and ignored cost determinants and learning-by-doing as a key component of the industry (Aizcorbe 2006, 2006; Gordon 2008; Song 2007). There is no previous research that explores the extent of learning-by-doing in the computers CPU manufacturing process and its effects on firms conduct and market power.

The results suggest that firms' behavior is slightly more competitive than Nash behavior in the Markov perfect equilibrium (MPE), being closer to this form of competition than to social welfare maximization or joint profit maximization. Also, an static analysis largely overestimate the degree of competition, which implies that ignoring dynamics can lead to wrong conclusions in the analysis of market power in this industry.

The paper is organized as follows. Section 2 presents a review of the relevant literature on estimation of market power in dynamic models and on learning-by-doing in semiconductors. Section 3 describes the model and section 4 the econometric method. The results are discussed in section 5 and section 6 concludes.

2 Literature Review

Market Power in Dynamic Models

The estimation of market power in dynamic models is not new. Pindyck (1985) seems to be the first author on considering dynamics in the measurement of market power. His analysis focuses on monopoly market power, and propose the use of a dynamic version of the Lerner index. In order to compute this index the full marginal cost (FMC) needs to be computed, which includes not only current marginal cost but also the intertemporal effect of current decisions in future profits. The FMC function needs to be obtained for the social welfare maximizing solution of the problem and evaluated at firms observed behavior. The pindick index simply consist on replacing this FMC on the marginal cost of the traditional Lerner index.

A traditional method employed to measure market power in oligopoly models is the conduct parameter model (CPM). This method consist on using a parameter to nest the first order conditions of several market structures: social welfare maximization, nash behavior and collusion. The parameter is estimated using the nested first order conditions with the available data. Corts (1999) analyzes cases in which the use of these parameters is missleading and presents an example of tacit collusion sustained by repeated interaction among firms that a tratidional conduct parameter model is unable to discover. He suggest than in presence of dynamics incentives, the static CPM can largely overestimate the degree of competition.

Karp and Perloff (1989, 1993a, 1993b) have estimated dynamic versions of the CPM in the rice export and in the coffee export markets. They estimate a model for a homogeneous product with linear demand and cost of adjustment in quantities which generates dynamics in firms' choices. They estimate two versions of a dynamic CPM. In the first case, they use an open-loop model, in which firms choose a trajectory of output levels in an initial period. In the second case, they use a feedback model, in which firms choose rules that set output as function of state variables. They use a linear-quadratic model to simplify the estimation procedure, which allows them to obtain algebraic solutions for the equilibrium of the game. In both markets and models, they found that market is more competitive than Nash-Cournot. They also found that feedback strategy models imply less competitive output than open-loop models. In the Rice export market they found that behavior is closer to Nash equilibrium than to competition and in the Coffe export market they found that the behavior is relatively competitive.

The analysis of market power in the CPU market is by far more complex than previous studies because of a number of important characteristics of the market. First, AMD and INTEL produce several differentiated products for which a simple structure of demand is not possible; accounting for consumers heterogeneous preferences is crucial to understand the behavior of the demand (Salgado 2008a). Second, firms periodically introduce new, improved products, and retire obsolete products, which imposes additional challenges to demand estimation. Third, the dynamics I am interested on analyze are given by the existence of learning-by-doing in the production process which create non-linearities of the choice in the evolution of the game. For all these reasons, it is not feasible to analyze the market using a linear-quadratic model nor finding an expression for the equilibrium of the dynamic game that could be used in a traditional framework.

Learning-by-Doing

The learning-by-doing hypothesis states that in some manufacturing processes, cost are reduced as firms gain production experience. This hypothesis originated with Wright (1936), who observed that direct labor costs of airframe manufacturing fell by 20% with every doubling of cumulative output. Since then, many empirical studies have analyzed the existence of learning-by-doing in a variety of industrial settings, and a number of theoretical papers have analyzed implications of learning for endogenous growth, market concentration and firms' strategic interactions (Lee 1975, Spence 1981, Gilbert and Harris 1981, Fudenberg and Tirole 1983, Ghemawat and

Spence 1985, Ross 1986, Dasgupta and Stiglitz 1988, Mookherjee and Ray 1991,Habermeier 1992, Cabral and Riordan 1994, Cabral and Leiblein 2001).

Theoretical analyses have shown that learning-by-doing could create entry barriers and strategic advantages for existing firms (Lee 1975, Spence 1981, Ghemawat and Spence 1985, Ross 1986, Gilbert and Harris 1981) and facilitate oligopoly collusion (Mookherjee and Ray, 1991). Gruber (1992) presents a model in which learning-by-doing generate stability in market share over a sequence of product innovations, given the existence of leaders and followers in the market. Cabral and Riordan (1994) show that learning-by-doing creates equilibria with increasing dominance of one firm in the market and might generate predatory pricing behaviors from the leaders who use their cost advantages to prevent new firms from entering the market. Besanko, et.al. (2007) analyze a model of learning-by to explain the incentives that firms have to price strategically, showing that firms might price more aggressively to learn more quickly and gain dominance over competitors, as well as to prevent their competitors from learning.

The existence of learning-by-doing in semiconductor manufacturing has been widely analyzed. The source of learning has been attributed to the adjjustments that are necessary to obtain high productivity during fabrication. The semiconductor production process is based on hundreds of steps in which circuit patterns from photomasks are imprinted in silicon wafers and then washed and baked in several layers forming the millions of transistors that allow the chip to function as an information processing device. The steps involved on the fabrication of the chips, are required to happen in extremely precise conditions whose parameters need to be controlled and adjusted continuously. When a product is first transferred from the development labs to full production in the fabs, the number of unit that past control quality test (yield) is very small. Several fine-tuning steps need to be taken to obtain high yields and thus reduce the unitary production costs. It is the increase in the yield rates that generates a reduction in unitary production cost of the final products. Hatch and Mowery (1999) analyze detailed production data on unitary yields for a number of semiconductor chips and conclude that both cumulative production and engineering analysis of the production output are the source of improvements in yield rates over the lifetime of products.

Most of the empirical evidence of learning-by-doing in the semiconductor industry comes from memory chips manufacturing. This has been mainly because the market in the memory industry is more competitive, and data has been readily available since the 1980s. Based on new data availability for the CPU market, a more recent literature has studied different characteristics of the industry. Aizcorbe (2005) analyzes a vintage model of products introduction; Aizcorbe (2006) analyzes evolution of price indexes during the 1990s; Song (2007), Gordon (2008) and Salgado (2008a) analyze models of demand to measure consumer welfare, demand for durable products and effects of advertising and brand loyalty on demand, respectively. All of these papers have ignored the existence of learning-by-doing as a key component of the manufacturing process.

3 The Model

This section presents a structural econometric model that captures the most important characteristics of the CPU industry. There are two firms in the market, AMD (A) and INTEL (I), with n_{tA} and n_{tI} products available at period t. Products are differentiated in terms of their quality, which evolves stochastically over time. Products enter and exit the market exogenously to the firms pricing decision, it is common knowledge that product i enters the market in period t_{i0} and exit the market in time t_{iT}. Firms choose prices for each one of the available products and I_{jt} is the set of products available for firm j at time t.

In the remaining of this section I present the details of the components of the model: the demand, cost functions, the equilibrium concept of the dynamic game and the way in which the three different market structures are nested to identify firms dynamic conduct.

3.1 The model of demand

Demand is modeled using a random coefficient model with quality being the only relevant product characteristic. As in Salgado (2008a), I use a CPU performance benchmark that measures the speed at which each CPU can complete a number of tasks. Even though a more detailed characterization of the products is possible (using for example clock speed, amount of cache memory, front speed bus and other product characteristics)there exist a strong correlation between all these characteristics and the index of performance. I prefer to use a single characteristic to reduce the number of state variables and facilitate the estimation of the dynamic game.

Following Berry, Levinsohn and Pakes (1995) and Nevo (2000), I present the main components of a random coefficient demand model for the CPU industry. We observe the CPU market at $t = 1 \dots T$ time periods. The market has L potential consumers that must decide either buy one of the available products or not. We observe aggregate quantities, prices and a measure of quality (k_{it}) for each product. The indirect utility by consumer

l from choosing product i in time t is given by

$$u_{lit} = \alpha_l(y_l - p_{it}) + \beta_l k_{it} + \xi_{it} + \varepsilon_{lit} \qquad (1)$$
$$l = 1 \ldots L, i = 1 \ldots I_t, t = 1 \ldots T$$

where y_l is the income of consumer l, p_{it} is the price of product i at time t, k_{it} is the measure of quality of product i at time t, ξ_{it} is a product characteristic observed by the consumers and firms but unobserved by the researcher, ε_{lit} is a random term with a type I extreme value distribution, α_l is consumer l's marginal utility from income and β_l is consumer l's marginal utility from product quality. Additionally, we assume that the coefficients are independent and normally distributed among the population. Under this assumption, the preferences over income and quality of a randomly chosen consumer can be expresed as:

$$\begin{pmatrix} \alpha_l \\ \beta_l \end{pmatrix} = \begin{pmatrix} \alpha + \sigma_\alpha v_{\alpha l} \\ \beta + \sigma_\beta v_{\beta l} \end{pmatrix}$$

$$v_{\alpha l}, v_{\beta l} \sim N(0, 1)$$

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

$$u_{l0t} = \alpha_l y_l + \xi_{0t} + \varepsilon_{l0t} = 0 \qquad (2)$$

The indirect utility function in (1) can be written as

$$u_{lit} = \alpha_l y_l + \delta_{it}(p_{it}, k_{it}, \xi_{it}; \alpha, \beta) + \mu_{lit}(p_{it}, k_{it}, v_l; \sigma) + \varepsilon_{lit} \quad (3)$$

$$\delta_{it} \equiv \beta k_{it} - \alpha p_{it} + \xi_{it} \quad (4)$$

$$\mu_{lit} \equiv \sigma_\alpha v_{\alpha l} p_{it} + \sigma_\beta v_{\beta l} k_{it} \quad (5)$$

where δ_{it} is constant among consumers and is called the mean utility of product i at time t, and μ_{lit} captures the portion of the utility from product i that differs among consumers.

Consumers are assumed to buy one unit of the good that gives them the highest utility. This defines the set of characteristics of consumers that choose good i:

$$A_{it} = \{(v_l, \varepsilon_{l0t}, ..., \varepsilon_{lJ_tt}) | u_{lit} \geq u_{lst} \forall s = 0, 1..J_t\} \quad (6)$$

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

$$s_{it}(k_t, p_t, \delta_t; \sigma) = \int_{A_{it}} dP(v, \varepsilon) \quad (7)$$

Given the assumption over the distribution of ε, it is possible to integrate algebraically over ε, so we can rewrite equation (7) as:

$$s_{it}(k_t, p_t, \delta_t; \sigma) = \int \frac{exp(\delta_{it}(p_{it}, k_{it}, \xi_{it}; \alpha, \beta) + \mu_{ijt}(p_{it}, k_{it}, v_l; \sigma))}{1 + \sum_{s=1}^{J_t} exp(\delta_{st}(p_{it}, k_{it}, \xi_{it}; \alpha, \beta) + \mu_{ist}(p_{it}, k_{it}, v_l; \sigma))} dP(v_l)$$

The demand function for a set of parameters $\theta^d = (\alpha, \beta, \sigma_\alpha, \sigma_\beta)$ is given by

$$q_{it}(p_{it}, k_{it}; \theta^d) = s_{it}(k_t, p_t, \delta_t(\alpha, \beta); \sigma_\alpha, \sigma_\beta) M_t \quad (8)$$

where M_t is the potential market size at time t.

The estimation of the demand requires to use a GMM method to control for endogeneity of prices. For this, cost determinants like product characteristics that shift the supply but not the demand and that are uncorrelated with product quality (Die Size, Number of Transistors in the chip and production experience) are used. All the details of the estimation are given in Salgado (2008a).

3.2 Evolution of quality

The high rate of increase in quality is an important characteristic of the PC CPU market. Product quality increase over time due to the introduction of improvements to existing product and new characteristics that contribute to a higher performance. However, the main determinant of quality evolution in the market is the continuous introduction of new products over time. I model this characteristic of the market as described below.

There is a quality frontier $KF(t)$, which represents the maximum possible quality for a new product and that evolves exogenously over time. New products are introduced into the market at a quality level $(1-\alpha_n) * KF(t)$, where $\alpha_n \sim \text{Uniform}[\underline{\alpha_n}, \overline{\alpha_n}]$. For old products, there is a probability p_o that the product quality increases in a given period. If the product quality increases, it does so in a proportion α_o, being the new quality $k_t = (1+\alpha_o)k_{t-1}$, where $\log(\alpha_o) \sim N(\overline{\alpha_o}, \sigma_o)$. Table 1 summarize these processes.

It is assumed that both firms know the data generating process that generates the evolution of quality, and that they observe the quality of all the products currently available before making their pricing decisions, they do not know the realization of the random variables α_n, p_o, and α_o for future periods; therefore, when making decisions, they need to take expectations

Table 1: Characteristics of Quality Evolution

Quality Frontier	KF(t)
Distance from the frontier (%) of a new product	$0 < \alpha_n < 1$, α_n Uniform$[\underline{\alpha_n}, \overline{\alpha_n}]$
Probability that an old product increases its quality at time t	p_o
Increase in quality (%) if this is positive	$\alpha_o > 0$, $\log(\alpha_o) \sim N(\overline{\alpha_o}, \sigma_o)$

over future realizations of these variables.

3.3 Cost Function

Firms face learning-by-doing in the production process, and therefore the unitary cost reduces with production experience. I assume that learning is given entirely by the cumulative production of each product, and that learning spillovers do not exist.[2] Individual production cost differs accross products depending on two main characteristics, the die size (size of the surface of the chip in the wafer) and the number of transistors in the CPU. The cost function that captures these characteristics of the production process is the following, where i denotes an specific product:

$$\begin{aligned} c_{it} &= \theta_0^c + \theta_1^c DS_i + \theta_2^c TR_i + \theta_3^c \log(E_{it}) + \varepsilon_{it} \qquad (9) \\ \varepsilon_{it} &\sim N(0, \sigma_\varepsilon^2) \end{aligned}$$

In this specification DS_i is the die size and TR_i is the number of transistors in the Chip. For higher DS, fewer chips are produced by wafer; and for higher TR more complicated the production process is, and therefore

[2]Hatch and Mowery (1999) find that learning could be the result not only of cummulative production, but also of management efforts to analyze production data and discover the sources of failures.

the individual cost per chip is higher. These characteristics are fixed for a particular product. Given that I don't have data on production experience in the development facilities before the product is transfered to the fabs, I assume that for all products at the time of their introduction $E_{it_0} = 1$. Hence, the expected cost of production when a product is first introduced is $\theta^c_{0j} + \theta^c_1 DS_i + \theta^c_2 TR_i$, and it is reduced, at a decreasing rate, with production experience.

Production experience is given by cumulative production of each product and its equation of motion is given by

$$E_{it} = \sum_{\tau=t_{i0}}^{t-1} q_{i\tau}$$
$$E_{it+1} = E_{it} + q_{it}$$

3.4 Single Period profit function

The demand and cost functions previously presented define the per-period profit function for firm j as

$$\pi_{jt}(p_{jt}, p_{-jt}, \mathbf{s}_t) = \sum_{i \in I_{jt}} q_{it}(\mathbf{p}_{jt}, \mathbf{p}_{-jt}, \mathbf{k}_t)(p_{it} - c(E_{it}))$$

Where $\mathbf{p}_{jt}$ and $\mathbf{p}_{-jt}$ are the vector of prices for firm j and its competitor $(-j)$, $\mathbf{s}_t = [\mathbf{k}_t, \mathbf{E}_t]$ is the vector of profit-relevant state variables for firm j at time t, which is composed of the vector of quality for all products available in the market at time t ($\mathbf{k}_t$) and the vector of production experience ($\mathbf{E}_t$). Notice that the quality of each product in the market enters the demand function of every other product in a non-linear way through the random coefficient demand model, while experience enters only the cost function of the corresponding product.

3.5 Nesting Market Structures to Measure Firms Dynamic Conduct

To measure firms' dynamic conduct I nest three different market structures in the firm optimization problem. I estimate a single parameter that reflects whether firm behavior is consistent with the MPE in three possible scenarios: Perfect collusion or joint profit maximization (denoted by JPM), Nash behavior in the Markov perfect equilibrium (denoted by NMPE), and social welfare maximization (denoted by SWM). The parameter is included directly in the objective function of the firms, nesting the three leading cases, as will be explained below.

Identification of market power consist on identifying the function that is maximized by the firms when they take pricing decisions. If firms behave as dynamic Nash competitors, they maximize their own profits, taking as given the behavior of their competitors, as well as their competitor's responses to the evolution of the game. If they collude perfectly, we will observe that the equilibrium of the game maximizes joint profits. If they act as competive as social planners, we will observe that the equilibrium of the game maximizes social welfare, consisting on the sum of consumers' and producers' surplus).

To identify the objective function that firms maximize we define the following function for each firm j:

$$W_j(\mathbf{p}_j, \mathbf{p}_{-j}; \theta, \mathbf{s}) = \Pi_j(\mathbf{p}_j, \mathbf{p}_{-j}; \mathbf{s}) + (\lambda_1 + \lambda_2)\Pi_{-j}(\mathbf{p}_j, \mathbf{p}_{-j}; \mathbf{s}) + \lambda_2 \mathrm{CS}(\mathbf{p}_j, \mathbf{p}_{-j}; \mathbf{s}) \tag{10}$$

$$(\lambda_1, \lambda_2) = \begin{cases} (-\theta, 0) & \text{if } \theta \leq 0; \\ (0, \theta) & \text{if } \theta > 0. \end{cases}$$

$$\begin{aligned} \Pi_l &= \sum_{\tau=0}^{\infty} \sum_{i \in I_{lt}} \delta^\tau \pi_{lt}(p_\tau, s_\tau) \quad \text{, with } l = j, -j. \\ CS &= \sum_{\tau=0}^{\infty} \sum_{i \in I_\tau} \delta^\tau cs(p_\tau) \end{aligned}$$

Where Π_j represents the discounted value of firm j profits, Π_{-j} represents the discounted value of competitor's profits and CS represents the discounted value of the consumer surplus, $\mathbf{s}$ is a vector of state variables representing the current state of the game, I_τ represent the vector of available products at time τ, p_τ is the vector of prices of the products available at τ, and δ is the discount factor. The subindex i represents products, while a subindex j in the vectors I and p denotes the corresponding subvector with firm specific information.

The three leading cases (JPM, NMPE and SWM) are represented by the following values of θ and the corresponding values of λ_1 and λ_2:

Market Structure	θ	λ_1	λ_2
Joint Profit Maximization (JPM)	-1	1	0
Nash Markov Perfect Equilibrium (NMPE)	0	0	0
Social Welfare Maximization (SWM)	1	0	1

As θ moves from -1 to 0, λ_1 moves from 1 to 0, while keeping $\lambda_2 = 0$. This gives less weight in the objective function to the competitors' profits and the equilibrium moves from JPM to NMPE. As θ moves from 0 to 1, λ_2 moves from 0 to 1, while keeping $\lambda_1 = 0$. This gives more weight to the competitors' profit and to consumer surplus. This implies that the equilibrium moves from NMPE to SWM. Looking for the parameter θ that makes the observed choice consistent with an equilibrium of the game allows identification of the market structure that is closest to the observed behavior of firms.

3.6 The Game and the Equilibrium Concept

In every period firms choose simultaneously the price for each of their available products $i \in I_j$ to solve the game:

$$\max_{p_j} E[W_j(p_j, p_{-j}; s)]$$

where the expectation operator is applied over the realization of the present and future cost shocks and the evolution of quality for each product.

Given the constructed payoff function presented in the previous section, firms choose actions simultaneously in each period. Actions are prices for each of the available products.

Following Bajari, Benkard and Levin (2007) I focus the equilibrium analysis on pure strategy Markov perfect equilibrium (MPE). In an MPE each firm's equilibrium strategy depends only on profit-relevant state variables. A Markov strategy is defined as a function $\sigma_j : S \to A_j$ where S represents the state space and A_j represents the set of actions for firm j. A profile of s Markov strategy is a vector $\sigma = (\sigma_j(s), \sigma_{-j}(s))$.

If firm behavior is characterized by a Markov strategy profile σ, the maximized payoff function at a given state s can be written as

$$V_j(\mathbf{s};\sigma) = W_j(\sigma_j(s), \sigma_{-j}(s); s) \tag{11}$$

The strategy profile σ is a Markov Perfect Equilibrium if, given the opponent profile σ_{-j}, each firm does not have any other alternative Markov strategy σ'_j that increases the value of the game. That is, σ is an MPE if for all firms j, states $\mathbf{s}$ and Markov strategies σ'_j

$$V_j(\mathbf{s};\sigma_j,\sigma_{-j}) \geq V_j(\mathbf{s};\sigma'_j,\sigma_{-j}) \tag{12}$$

The estimation method consists of minimizing a loss function based on observations that violate the rationality constraint (12). I discuss the details of this method in the next section.

4 Estimation Method

For the estimation of the model I follow the econometric method by Bajari, Benkard and Levin 2007 (BBL). The authors propose the use of a two-step algorithm to estimate structural parameters of dynamic models of imperfect competition. In the first stage all the parameters that do not involve dynamics are estimated (the demand parameters, the evolution of quality and the policy function); and in the second stage, using the estimates of the first stage, the game is simulated to the future to obtain estimates of the value function. Then, the value function estimates are used to estimate the dynamic parameters. In this section I present details of these procedures.

4.1 Demand

The demand function is estimated using a random coefficient model of demand (Berry, Levinsohn and Pakes, 1995; Nevo 2000). The relative performance of a product compared to the fastest available product is used as a measure of quality and a dummy for the Intel brand is included to control for the high premium that consumers are willing to pay for Intel products. Cost determinants (die size, number of transistors and production experience) are used as instruments to control for endogeneity of prices and are employed in a GMM framework to obtain unbiased estimates of the parameters of the demand function. The estimation details are presented in Salgado (2008a).

4.2 Cost Functions

Using available data for three generations of products by Intel, I estimate the cost function presented in equation (9) using a GMM method. Given that the available data is a weighted average of the cost of the products within a generation, I need to conduct a non-linear estimation that search over individual cost parameters and use them to predict the average cost. Additionally, I need an estimate of the variance of the cost shocks to use in the forward simulation of the game, which we can also obtain from this estimation as is described below.

I observe aggregate cost data for three family of products.[3] The aggregation is given by:

$$c_{ft} = \frac{\sum_{i \in F_f} q_{it} c_{it}}{\sum_{i \in F_f} q_{it}} = \frac{\sum_{i \in F_f} q_{it} \left(\theta_0 + \theta_1 DS_i + \theta_2 TR_i + \theta_3 log(E_{it}) + \varepsilon_{it}\right)}{\sum_{i \in F_f} q_{it}} \tag{13}$$

In principle, I could estimate the following regression by non-linear least

[3] A family is an aggregation of products that share some important characteristics on design of the CPUs.

squares:

$$
\begin{aligned}
c_{jt} &= \theta_0 + \sum_{i \in F_j} \frac{q_{it}\left(\theta_1 DS_i + \theta_2 TR_i + \theta_3 log(E_{it})\right)}{\sum_{i \in F_j} q_{it}} + \epsilon_{jt} && (14) \\
\epsilon_{jt} &= \frac{\sum_{i \in F_j} q_{it}\varepsilon_{it}}{\sum_{i \in F_j} q_{it}} && (15)
\end{aligned}
$$

Given the *iid* assumption about ε_{it}, the error term ϵ_{jt} is heteroscedastic with variance

$$
\sigma^2_{\epsilon_{jt}} = \frac{\sum_{i \in F_j} q^2_{it}}{\left(\sum_{i \in F_j} q_{it}\right)^2} \sigma^2_{\varepsilon} \tag{16}
$$

I can weight every observation by $\lambda_{jt} = \frac{\sum_{i \in F_j} q_{jt}}{\sqrt{\sum_{i \in F_j} q^2_{it}}}$, creating a new error term $\epsilon^{'}_{jt} = \lambda_{jt}\epsilon_{jt}$ which is homoscedastic with variance σ^2_{ε}. From this estimation, I can obtain the cost parameters recover and an estimate of the variance of the cost shock, σ_{ε}.

4.3 The policy function

The policy function reflects the equilibrium behavior of the firms as a function of the state of the game. This function can be estimated from the data using observed prices and state variables. The exact functional form of the policy function is the result of the unknown (and possibly multiple) equilibrium of the game. As proposed by BBL, I assume that the observed prices at every state of the game reflects the equilibrium chosen by the firms.

I make two functional form assumption in order to estimate the policy function. First, I assume that the policy function is quadratic in the observed state variables. Second, I focus on a subset of the observed state variables. If I consider the profit relevant state variables to be the quality and production experience of all the products available in each period, the dimensionality of the state space changes over time as the number of available products changes. To avoid this problem I define three state variables that capture the effects of the main components of the model on the firms' equilibrium pricing decision. The variables considered are:

- The relative quality of each product with respect to the quality frontier (k_{it}), which affects the demand function.
- The production experience of the product i (E_{it}), which determines production cost, as previously defined. This variable captures the effect of learning on the pricing decision[4].
- The total experience of the firms' ($E_{-jt} = \sum_{k \in I_{-jt}} E_{kt}$). This variable captures the effect on a firm pricing decision when its competitor faces a lower production cost due to learning.

With these three variables I construct a quadratic approximation of the policy function as:

$$\hat{p}_{it} = p(k_{it}, E_{it}, E_{-jt}) + \varepsilon_{it}$$

This function is used in the computation of the expected discounted value of firms profits using a forward simulation of the game as proposed by BBL.

4.4 Forward Simulation of the Value Function.

The computation of the value functions requires the use of a forward simulation of the game. To estimate the dynamic cost parameters the method uses the MPE constraints in (12), which requires the evaluation of the value function at observed choices, and also at one-step deviations from observed

[4]I could have also included the die size and the number of transistors as state variables, but to simplify the analysis and to concentrate on the effects of learning on pricing decisions, I assume that equilibrium pricing does not depend on these variables.

choices. This needs to be done at any given value of the unknown dynamic conduct parameter (DCP).[5] The estimates of the demand, cost and policy functions have been previoiusly obtained. Given that the value function is linear in the DCP, which implies that neither firm profits nor consumer surplus change when the DCP changes, one can simulate the expected values of Π_j, Π_{-j} and CS and use these simulated values to compute the DCP that rationalizes firm behavior. To integrate over the random elements of the model, BBL proposes the use of a Monte Carlo integration, which requires to simulate the game taking random draws of the stochastic variables, and taking averages over the resulting discounted values. The same procedure is used to calculate the value function for the observed equilibrium policy and for small one-step deviations.

The computation of the expected value of Π_j, Π_{-j} and CS is performed using the following algorithm

1. Starting at time t, in which a value for the state s_0 is given, a value for each of the corresponding random variables (the cost shock ε and the quality shocks α_f and α_o) is drawn from its corresponding distribution.

2. In the first period (time t) the observed price (or a deviation) is taken as the choice. For the following periods ($\tau > t$) the equilibrium price is predicted using the estimated policy function.

3. Given vectors of prices and quality, the demand, cost of each available product, and the consumer surplus is predicted and the terms Π_j, Π_{-j} and CS are updated accordingly. Using the law of motion for each state variable, and the random draws from step (1), a new state for the next period, s_{t+1}, is determined.

[5]It suffices to assume that firms deviate in period t=0 and that they price using their policy functions in subsequent periods

4. In the following period, prices are predicted using the policy function and the updated value of the state variables (s_{t+1}). Steps (1) to (3) are repeated and the value of the v terms are updated. We keep moving forward, updating the value of the linear terms v for a large number of periods, until time T in which β^T is small enough so that the reminder of the infinite sum is approximately zero.

These steps generate a single path of the linear terms Π_j, Π_{-j} and CS, given a single realization of a series of random shocks over time. To compute the expected value over these shocks a Montecarlo method is used by repeating this procedure many times and taking the average over the results. For a given value of the unknown cost parameters, this procedure allows the evaluation of the value function at the observed choices and also at deviations from observed choice. Thus, I am able to estimate the terms $\hat{V}_{jt}(\sigma_1(s), \sigma_2(s))$ and $\hat{V}_{jt}(\sigma_1'(s), \sigma_2(s))$ involved in equation (12). Finally, I use the expected discounted value of the linear terms of the value function to estimate the unknown DCP parameters as explained below.

4.5 Estimating the Dynamic Conduct Parameter

Using the simulated expected values of Π_j, Π_{-j} and CS previously calculated the BBL procedure constructs a loss function from the MPE constraint in equation (12). This equilibrium condition requires that, if a strategy profile is an MPE then any one-step deviation, keeping its rival's strategy constant, must be unprofitable. This requirement is that for all j and all possible deviations $\sigma_j'(s)$:

$$V_j(\mathbf{s}; \sigma_j(s), \sigma_{-j}(s); \theta) \geq V_j(\mathbf{s}; \sigma_j'(s), \sigma_{-j}(s); \theta)$$

Define $g_j(\theta) \equiv V_j(\mathbf{s}; \sigma_j(s), \sigma_{-j}(s); \theta) - V_j(\mathbf{s}; \sigma'_j(s), \sigma_{-j}(s); \theta)$, then the previous condition can be written as

$$g_j(\theta) \geq 0 \tag{17}$$

Then, for a given value of θ and a sample of size n, define a quadratic loss function based on the observations that violate that condition

$$Q(\theta|n) = \frac{1}{n} \sum_{j=1}^{2} \sum_{k=1}^{n} \left(\min\{g_j^k(\theta), 0\} \right)^2 \tag{18}$$

Where k is an index for every observation in the sample. This quadratic function measures how far is the observed behavior from representing a Markov perfect equilibrium of the game at a given value of θ. To bring the observed behavior as close as possible to an MPE, we minimize the value of $Q_j(\theta|n)$. Therefore, the estimated value of the dynamic conduct parameter is given by

$$\hat{\theta} = \text{argmin}_\theta Q(\theta|n) \tag{19}$$

5 Data and Results

The main data set was obtained from In-Stat/MDR, a research company that specializes in the CPU market[6]. It includes estimates of quarterly sales for CPUs aggregated into 29 product categories for the period 1993-2004 (48 quarters) and due to entry and exit of products over time I have a total of 291 observations[7]. The dataset also contains information on prices[8]. In-Stat

[6] This dataset is proprietary material belonging to In-Stat/MDR.

[7] An observation is one product in a given time period.

[8] In the In-Stat/MDR dataset, prices for AMD products are available only for the period 1999 to 2004. Therefore, the dataset was complemented with several other sources, including printed publications and on-line historical databases. Also, it contains 9 AMD CPUs and 20 Intel CPUs in the sample period.

obtains figures on list prices of Intel products and adjusts them for volume discounts offered to their major customers. Their main sources are the 10K Financial Statements reports and the World Semiconductor Trade Statistics elaborated by the Semiconductor Industry Association (SIA). They use this information to estimate unit shipments for each product by Intel and AMD, based on engineering relationships and the production capacity of each plant. The In-Stat/MDR data set is complemented with two other sources. The first is firm-level advertising expenditures. These data have been obtained from the 10K and 10Q financial statements. The second supplementary source consists of information about CPU performance from *The CPU Scorecard*, a company that measures on a comparative basis the performance of different CPU products. The In-Stat database has been previously used by Song (2007) to estimate consumer welfare in the CPU market, and by Gordon (2008) to estimate a demand model for durable goods. In the remaining of this section I present the results. First, I show the results for four alternative specifications for demand, then I presents the estimated parameters for the evolution of quality, the policy function and the cost function. Finally, i show the estimated dynamic conduct parameters.

5.1 Demand estimation

The detailed demand estimation method is presented in Salgado (2008a). Table 2 shows the results for the four demand models employed in the simulations.

5.2 Cost Parameters

The estimated cost parameters are presented in Table 3. Neither DS nor TR are statistically significant but the variable of interest for the dynamic

Table 2: Results of Demand Estimation

	Model 1	Model 2	Model 3	Model 4
Price	19.6622	2.5067	11.6110	2.5350
	(4.1766)	(0.2676)	(2.0506)	(0.2160)
Quality	5.8358	1.1362	2.8331	1.1910
	(2.3671)	(0.2670)	(1.4869)	(0.2763)
Brand	3.3579	2.3411	-	-
	(0.7899)	(0.4365)	-	-
Advertising	-	-	0.0070	0.0044
	-	-	(0.0013)	(0.0011)
sigma price	13.2787	1.0530	8.6328	1.0403
	(3.1019)	(0.3188)	(2.2704)	(0.2837)
sigma quality	7.9928	0.8083	6.3851	0.8080
	(3.0003)	(0.2793)	(1.9343)	(0.2415)
Distribution RC	Normal	Log-Normal	Normal	Log-Normal
% Positive Price Coefficient	6.93%	0.00%	8.93%	0.00%
% Negative Quality Coefficient	23.27%	0.00%	32.86%	0.00%
Average Price Elasticity	-2.43	-2.00	-1.44	-2.34

estimation, production experience, is statistically significant[9]. This result reflects that learning plays an important role in explaining the available cost data.

Table 3: Estimated Cost Parameters

Var.	Coeff.	St. Error	t-value	p-value
Constant	162.3320	52.7957	3.0747	0.0034
DS	0.1231	0.1296	0.9501	0.3466
TR	0.0000	0.3604	0.0000	1.0000
log(E)	13.9067	4.3641	3.1866	0.0025

[9]I believe that the nonsignificance of these variables is a result of the aggregation during cost estimation and the small number of observations. In Salgado (2008b) I estimate the same specification of the cost function using the dynamic algorithm and explore differences in cost between the two firms. Estimating both, the cost function and the DCP implies non-linearities in the estimation method that generate an important computational burden for the estimation.

5.3 Evolution of Quality

I estimate the quality frontier using the follosing logistic curve:

$$FK(t) = \kappa_0 \frac{1 + \kappa_1 exp(-\kappa_2 t)}{1 + \kappa_3 exp(-\kappa_2 t)} \quad (20)$$

The frontier was estimated as the envolvent logistic function of the observed quality data. To estimate the quality frontier I compute the parameters of the logistic function that minimize the sum of the errors from the frontier to the observed data constraining the errors to be positive. The Table 4 shows the results from this estimation.

Table 4: Parameters of Quality Frontier

Parameter	Value
κ_0	11839
κ_1	7.4993
κ_2	0.1544
κ_3	321.1430

Recall that I assume that new products enter the market with quality $(1 - \alpha_n)FK(t)$ with α_n ~Uniform$[\underline{\alpha}_n, \overline{\alpha}_n]$. In the dataset I observe products that are introduced at a quality very close to the frontier and that are designated to compete in a high-performance segment; however, there are also some products that are destinated to a value-segment and they are introduced at a quality significantly below the quality frontier. For this reason I differentiate between frontier products, for which $\alpha_n^f \sim U(\underline{\alpha}_n^f, \overline{\alpha}_n^f)$ and non-frontier products, for which $\alpha_n^{nf} \sim U(\underline{\alpha}_n^{nf}, \overline{\alpha}_n^{nf})$. In sucessive periods following the introduction of a product, its quality increases with probability p_o, which I assume is common between frontier and non-frontier products. If a product increases its quality, it does so in a proportion α_o, so that $k_t = (1 + \alpha_o)k_{t-1}$, with $log(\alpha_o) \sim N(\mu_o, \sigma_o^2)$. The estimated parameters are presented in Table 5. Figure 1 presents the observed evolution of quality of the products in the dataset and the estimated quality frontier. The individuals colored lines show the obsreved index of quality for a given product over its life and the doted blue line shows the estimated logistic quality frontier.

Table 5: Parameters of Quality Evolution

Parameter	Value
$(\underline{\alpha}_n^f, \overline{\alpha}_n^f)$	(0.00,0.06)
$(\underline{\alpha}_n^{nf}, \overline{\alpha}_n^{nf})$	(0.13,0.71)
p_o	0.6770
μ_o	-2.8948
σ_o	0.7256

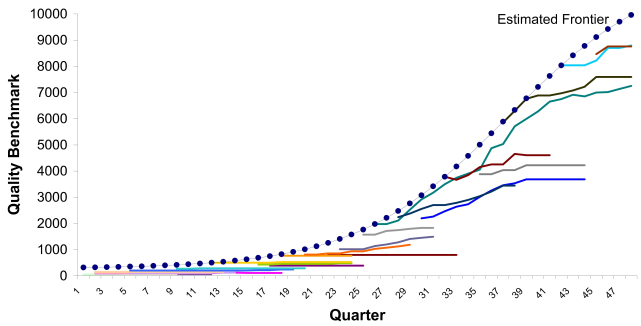

Figure 1: Evolution of Quality and Quality Frontier

5.4 Policy function

I estimate the policy function using a quadratic polynomial approximation. Prices are predicted using profit-relevant state variables as explanatory varialbes. The variables used to predict product prices are the relative quality of the good compared to the quality of the best product available in the market (which enters the demand function) the production experience (which determines production costs) and the total experience of the competitor (which captures the effect of a firm' choices over the competitor response in the MPE). Figure 2 shows the observed and predicted prices using the estimated quadratic approximation to the policy function. The differences between observed and predicted are assumed to be the realized cost shocks.

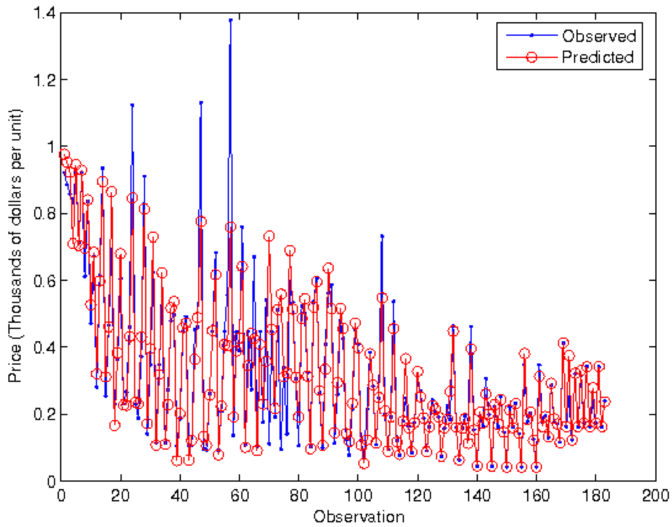

Figure 2: Policy Function

5.5 Dynamic Conduct Parameter

Table 6 shows the results of the estimation of the DCP using the dynamic algorithm for the four models of demand. All the estimates show that the equilibrium is closer to an MNPE than to the other two market structures. Models 1, 2 and 3 show firm behavior that is more competitive than MNPE, and Model 4 shows firm behavior that is consistent with MNPE. The last two columns show the classic measure of the traditional Static Conduct Parameter if we assume that firms don't take into account dynamics given by learning-by-doing. If dynamics given by learning are ignored, the equilibrium seems to be much more competitive and closer to competition than to Nash behavior.

Table 6: Results for the Conduct Parameter

	Dynamic Model		Static Model	
Model of Demand	Param	Std. Dev.	Param	Std. Dev.
Model 1	0.2021	0.0600	0.7254	0.0024
Model 2	0.0944	0.0071	0.8106	0.0026
Model 3	0.3160	0.0521	0.7283	0.0023
Model 4	0.0111	0.0488	0.8146	0.0026

6 Conclusions

In this paper I estimate a dynamic conduct parameter to analyze the degree of competition in the Personal Computer Processor market. There are two elements in this market that may generate incentives for firms to produce a quantity that is closer to a model of perfect competition. First, the existence of learning-by-doing. Under learning-by-doing firms have an incentive to produce a higher quantity of products during the initial periods of production, with the objective of reducing future production costs. Second, as analyzed by Siebert (2008), the existence of adjacent generations of products by the same firm may create a higher degree of competition in the market. Even when firms have few competitors, products competing with other products by the same firm can create more competitive results.

The results show that the market is more competitive than a Nash Markov Perfect Equilibrium but it is far from social welfare maximization. The results also show that ignoring dynamic incentives of firms, given by learning-by-doing, and assuming they behave in a static manner will generate a biased analysis and an overestimation of the degree of competition in the industry.

Several assumptions are necessary to simplify the model and allow me to estimate the behavioral parameters in the dynamic game. First, I assume that demand is static in the sense that people make buying decisions in every period without taking into account expectations of quality and prices of products that will be available in the future. I also assume that a discrete choice model of demand reflects consumers preferences and that PC manufacturers behavior, the main customers of AMD and INTEL, reflect consumers preferences. Finally, I also assume that the valuation of the CPU in the demand for computers is separable from other components of the computer. These assumption are reasonable because there is a one-to-one ratio of PC and CPU in the demand for computers and CPU is the main component determining system performance. The other components of the computer, like the size of the hard drive and other peripherals are highly customizable. Additionally, there is casual evidence that computer manufacturers represent consumer preferences. This was the original reason why Intel decided to advertise directly to consumers in its Intel Inside campaign (Moon, 2005).

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