Estimating Market Structure in a Dynamic Duopoly Model in the Personal Computer Processor Industry

Hugo H. Salgado *†

April, 2007

Abstract

In this paper I estimate a dynamic index of market structure to investigate the extent of competition in the personal computer processor industry. The dynamics of the game are given by the existence of learning-by-doing in the production process. Under learning-by-doing future production costs are reduced with cumulative production. A behavioral parameter that nest different market structures is incorporated in the objective function for each firm in the dynamic game and identified in a Markov perfect equilibrium. The results suggest that the biggest firm (Intel) behaves between Nash-Cournot and Perfect Collusion, and the smallest firm (AMD) behaves as a Nash-Cournot competitor. The estimated parameter fails to reject the existence of Nash-Cournot competition, while rejecting both social welfare maximization and perfect collusion between firms.

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

*I greatly appreciate the comments and suggestion for this research from Jeff Perloff, Larry Karp, Lanier Benkard, Ryan Kellog, Rocio Titiunik, Anin Aroonruengsawat, Rui Huang and Kristin Kiesel. All the remainder errors are my responsibility. Financial assistance from Jeff Perloff and the IBER Grant at UC Berkeley was fundamental to conduct this research.

†Department of Agricultural and Resource Economics, 307 Giannini Hall, University of California at Berkeley, e-mail: *salgado@berkeley.edu* and Departamento de Economia, Universidad de Concepcion, Chile.

1 Introduction

The CPU is the chip that processes data instructions -the brain of the personal computer- and it is therefore the most important component of a Personal Computer (PC). Given the importance that PC have for modern life, the way the CPU market is organized is of great importance for consumer welfare. The market for computer CPU is one of the most concentrated world markets. Two firms, Intel Corporation and Advanced Micro Devices (AMD), have historically had more than 95% of the market share in the whole planet[1]. Intel, the inventor of the PC CPU, has captured between 70% and 90% of the market. Because of the extent of this market the existence of market power could cause a big impact in the world economy and over consumer welfare. Estimating the degree of competitiveness and its effects over the market is therefore an important task.

Previous literature that have analyzed this market have assumed that firms behave in a Nash-Cournot equilibrium (Gordon 2006; Song 2006a, 2006b). In this proposal I analyze the validity of that assumption and explore the possibility that firms may have behaving more or less competitively than in a Nash-Cournot equilibrium.

The dynamic characteristics of the industry make non adequate to use traditional static equilibrium techniques to analyze competitiveness. As previous literature have shown (Pindick 1995, Corts 1999 and others) static measures of market power are misleading when firms play a dynamic game. In the PC CPU industry the firms' decision-making process includes sev-

[1] These market shares consider just CPUs for IBM compatible PCs and not CPUs for small electronic devices nor MAC computers.

eral dynamic elements that need to be incorporated into the modeling and estimation strategies to correctly measure the degree of market power.

One of the important sources of dynamics in this industry is the existence of learning-by-doing in the production process. It has been well documented that learning plays an important role in the semiconductor industry due to significant reduction in failure rates over the life cycle of a product. Production experience and adjustment in the process over time decreases failures rates which reduces future unitary production costs. This fact gives interesting dynamic considerations when firms decide production plans over time because increasing production effort in the present implies lower production cost in the future. Accounting for the effect of learning-by-doing on the firms' optimal choices will allow me to identify the market structure that best explains the observed data in a way that is consistent with the dynamics of this market.

The goal of estimating the degree of market power in a dynamic model imposes an interesting challenge. The previous literature that look at this kind of problems required to explicitly solve for the equilibrium of the game, or at least for the first order conditions, and to make strong assumptions on the type of strategies that players use, as for example open-loop assumptions, limiting the dynamics of the game. Based on Perloff, Karp and Golan (2007), this proposal explores the econometric technique by Bajari, Benkard and Levin (2006), which does not require to solve for the equilibrium of the game and allows to estimate the parameters under a close-loop in a Markov Perfect Equilibrium (MPE). An MPE imposes much weaker assumptions about the strategies that players use and how they incorporate their rival future responses to their current choices. Even though this methodology has been recently used by several authors to estimate firms primitive parameters of dynamic games (Rafique and Van Biesebroeck 2007, Ryan 2006, Ryan and Tucker 2007, Macieira 2006 and others), this is the first paper that uses this methodology to estimate an index of market power in a dynamic model. The remaining of this paper is organized as follows. First, in the next section I discuss the previous literature on estimation of the degree of market power under static and dynamic models, the literature that study the existence of learning-by-doing in the semiconductor industry and literature on methodologies to estimate dynamic games. Second, I present a theoretical model that describes the game that firms play in the industry. In this section I explain how the index of market structure is incorporated in the analysis. Third, I present and discuss the econometric technique by Bajari, Benkard and Levin (2006) that will be used to estimate the index of market structure in the industry. Fourth, I present a section that describe the sources of the data set and the main characteristics of the market. Fifth, I present and discuss the results. The results under this model suggest that firms are behaving in a Nash-Cournot way in the Markov perfect equilibrium of the game. A final section discuss the result and present possible extensions to this work.

2 Literature Review

2.1 Estimating Market Power

One of the most important research topic in the industrial organization literature is the measurement of the extent of competition in a market (Reiss and Wolak, 2005). The measurement of the degree of market power goes back to Lerner (1934) who presents the classic index based on the differences between price and marginal cost. Later in the 1970s, Iwata (1974) proposed a method to estimate a conjectural variation parameter and an statistical procedure to test for collusion. After that, a gigantic theoretical and empirical literature has being developed around the subject of estimating the degree of competition in a market.[2]

Until the end of the 1980s the analysis of market power was mainly static. The first in notice that static analysis was misleading when firms face a dynamic environment was Pindick (1985). He discusses why the Lerner's index can not be a good indicator in dynamic markets. Additionally, in a number cases it is not possible to compute Lerner's measure because marginal cost information is not available. More recently, Corts (1999) shows that a conduct parameter can be highly misleading in a dynamic oligopoly. He simulates a collusive market supported by repeated interaction and shows that an static conduct parameter may fail to detect any market power even if the price-cost margin are near the monopoly level. This calls for the necessity of explicitly model the dynamics of the market to measure market power in

[2]For a detailed review see Perloff, Karp and Golan (2007). Geroski, Phlips, and Ulph (1985), Bresnahan and Schmalensee (1987) and Bresnahan (1989) present surveys of the empirical literature in static models of competition.

a better way.

Under fundamental source of dynamics[3] the estimation of the extent of competition is challenging because one needs to model the optimal behavior of firms under different market structures. Price equal marginal cost is not necessarily the outcome that maximizes social welfare under a dynamic model. What is required for an optimal allocation is that marginal benefits equal full marginal cost, which is a function not only of the static production cost, but also of the shadow prices of the stock variables that are involved in the dynamic problem.

Karp and Perloff (1989, 1993a) have estimated dynamic oligopolies in the rice export and in the coffee export markets, respectively. They consider two models to estimate parameters that nest different market structures. In a first model, they use an open-loop assumption, in which firms choose a trajectory of output levels in the initial period. Under open-loop, it is assumed that firms consider just the direct effect of their actions over current rival decisions and not indirect effects trough the change on the state of the world that might induce changes in competitors behavior. In the second model, they use a feedback assumption, in which firms choose rules that set output as function of state variables. In both cases, they use a linear-quadratic model to simplify the estimation procedure. In both markets they found that the market is more competitive than Nash-Cournot. In the coffee market, they found that firms behavior is closer to price-taking than to collusion.

[3]The origin of dynamics in a model can be separated into *fundamental* and *strategic* reasons. In the first case, some dynamic element exists in the structure of the problem. This is the case, for example, when demand or cost functions have a dynamic structure. In the second case, the players could be looking forward because today's behavior can affect future behavior of the other players.

Perloff, Karp and Golan (2007) suggest the use of the econometric technique by Bajari, Benkard and Levin (2006) to estimate parameters that allows identification of the extent of competition under a Markov Perfect Equilibrium. This technique will be explored in this proposal to estimate competition in the computer CPU market.

2.2 Learning-by-doing in the semiconductor industry

The existence of learning-by-doing in the semiconductor industry has been well documented in the literature. Hatch (1996) provides an explanation of how this process works: *"It is the elimination of yield loses that results in substantial reductions in manufacturing costs. It is not uncommon for yields for new semiconductor processes to start as low as 10%. In such cases, the cost of scrapped output is initially very high but falls to low levels as yields rise to 90% or higher over time"*. Hatch and Reichelstein (1994) show that cumulative production and cumulative engineering analysis are the key determinants of learning-by-doing in the semiconductor industry.

The empirical application of learning-by-doing in the semiconductor industry have concentrated in the PC memory manufacturing (Aizcorbe, 2006). Even when the production of CPUs if far more complex than memory manufacturing, both processes share the characteristics that justify the existence of learning in the semiconductor industry, which is the reduction on failure rates trough adjustment in the production process during the life cycle of a product. A well accepted stylized fact is that the slope of the learning curve in the semiconductor industry is 28%, which means that unitary production cost fall in around 28% when cumulative output doubles. Applying different methods in the PC memory market a number of authors have obtained learning rates ranging from 16% to 51% (See for example Irwin and Klenow (1994), Siebert (2003) and Aizcorbe (2006))

Learning-by-doing generates dynamics incentives that affect the interpretation of traditional static measures of competition. Under learning firms have incentives to increase the rate of current production to decrease future production cost. A firm that enjoy market power needs to compare the current incentive to produce less, which increases prices, with the dynamic incentive to produce more, which reduces future costs. A dynamic social planner just have the incentive to produce more to reduce future cost, and therefore there should be a higher production and lower current price under the social planner than under monopoly. Hence, a firm with market power could not take full advantage of the learning-by-doing as would be socially desirable. For this reason, it is very important to investigate if firms are behaving in a collusive or competitive way, which will indicate if firms reach a sociable desirable outcome under this dynamic incentive.

2.3 Estimation of Structural Dynamic Oligopoly Models

The estimation of structural parameters in dynamic games can be highly simplified using an open-loop assumption. Under this assumption firms choose strategies as function of initial values of stock variables and time, and in the equilibrium they choose they complete path of actions taking as given the rival path of actions. If a symmetric equilibrium is also assumed, then the problem is therefore made strategically static. Perloff, Karp and Golan (2007) present two methodologies to estimate dynamic games under an open-loop assumption. The first method considers to solve the firms necessary conditions obtaining the Euler equation and estimate parameters on this equation by using an GMM method. The second method considers to estimate the parameters of the model using directly the dynamic programming equation and it is based on the fixed-point estimators developed by Rust (1987, 1994), Aguirregabiria and Mira (2002) and others.

The use of the open-loop assumption, although give simplicity to the estimation method, is very restrictive because it assumes that firms will not react to changes in the state of nature or adjust their behavior over time. A less restrictive assumption is the use of Markov strategies by firms and the Markov Perfect Equilibrium concept. This equilibrium concept was introduced by Maskin and Tirole (1987, 1988a, 1988b) and adapted for empirical applications by Pakes and McGuire (1994) and Ericson and Pakes (1995). When firms use Markov strategies, they take their decisions in every period as function of the value of state variables that have a direct effect on current profits. A number of recent papers have developed methods and estimated structural models of oligopolies using the Markov assumption (See for example Aguirregabiria, 2006; Aguirregabiria and Mira, 2004; Aguirregabiria and Mira, 2007; Bajari and Hong, 2005; Bajari, Benkard and Levin, 2006; Hotz and Miller, 1993; Hotz et al. 1994; Jenkis et al., 2004; Pakes, Ostrovsky and Berry, 2004; and Pesendorfer and Schmidt-Dengler, 2003).

In this paper I use the methodology proposed by Bajari, Benkard and

Levin (2006). This method is based in two stages of estimation. The first stage estimates the primitives involving no dynamics and the policy functions, which are the observed actions as function of observed state variables. The policy function explain how firms will behave in a given state of nature. Because the exact functional form of the policy function depends on the unknown solution to the game, it is estimated non parametrically. The first stage intends to explain what the firms do in the game and are used to simulate what they will do in the future. In a second stage the game is simulated to the future using the functions estimated in the first stage. This stage allows to estimate the structural dynamic parameters that make the observed equilibrium an optimal behavior. Jenkis, et.al (2004) working in a similar framework propose the use of a third stage, in which the estimation of the parameters of the first and second stage is improved. All the details of the estimation procedure are presented in section 4.

Other papers that have used the methodology by Bajari, Benkard and Levin (2006) to estimate parameters of dynamic games are Rafique and Van Biesebroeck (2007), Ryan (2006), Ryan and Tucker (2007) and Macieira (2006).

3 Model

The theoretical structural model in this paper considers a market with two firms (AMD and INTEL). Each firm choose in each time period the quantities to sell of each of its available products. Firms have at most two products available at each moment on time. It is assumed that the time in which a product enters and exits the market is exogenous and known by both firms. For the empirical application the different models of CPU are aggregated at the generation level so that just three products exists for each firm during the sample period. A generation of CPU shares the same technology of production and basic architecture of design. For this reason, learning-by-doing is present at this aggregation level.

Quality and quantity sold of the products are the most important determinants of the inverse demand. Quality is measured using an index of performance for each CPU. The performance index is a measure of the speed at which each CPU can perform a number of tasks [4]. The evolution of performance is assumed to follow a linear trend on time and it is known by both firms.

The inverse demand is modeled using a log-log functional form, where the price of each product is a function of the own quantity, the quantity of other products sold by the same firm, the quantity of other products sold by the competitor and the relative quality of each product. All products that are available in a given period are considered substitutes of each other.

The marginal cost of a CPU is constant and equal to average cost within each period; however, experience, which is measured by both cumulative production and time since the introduction of each product, reduces the average cost of future periods due to learning-by-doing. Learning generates a dynamic incentive because current production increases experience, reducing future marginal cost, which affects future optimal choices.

[4] Several of these indices exists. We use the only one that has a comparable measure for CPUs for all the time period in the dataset

The exact form of the game that firms are playing is assume to be unknown by the econometrician. An index of market structure form a linear combination of three possible equilibrium outcomes in the dynamic game: Social Welfare Maximization, Nash-Cournot and Perfect Collusion. The purpose of the paper is to identify the index of firm behavior as a linear combination of these known market structures.

In the remaining of this section I present the specific form of the demand function and the primitives of the supply side. I then present the way in which the index of market structure is introduced in the firms optimization problem. I finally present the equilibrium concept of the dynamic game. The next section presents the details of the econometric procedure used for the estimation of the parameters of the game.

3.1 Demand

The demand function is a single aggregate demand function for each differentiated product. The function to estimate has the following form [5]

$$p_{ijt} = p(q_{ijt}, q_{-ijt}, q_{-jt}, k_{ijt})$$

Where p_{ijt} is the price of the product, q_{ijt} is the quantity of the product, q_{-ijt} is the quantity of other products by the same firm, q_{-jt} is the quantity of other products by the other firm, k_{ijt} is the *relative* quality of the product

[5] I have tried several demand systems, including two and three stages nested logit and this aggregate demand form is what gave the best prediction for prices of each product and average markups for each firm. Nevertheless, I consider that this is one of the important parts of the research that need to be improved. Other approaches to demand estimation will be discussed in the final section of this proposal.

with respect to the average product in the market in the previous period. I discuss the construction of this index in the next section.

3.2 Definition and Evolution of Quality over Time

The measurement of quality relevant for the demand (k_{ijt}) is a relative measure which is formed with the ratio between the current quality level of the product (K_{ijt}) and the average quality of the products available in the last period (AK_t).

$$k_{ijt} = \frac{K_{ijt}}{AK_t}$$

The quality of each product (K_{ijt}) is assumed to follow an exogenous process over time so that just depends on the time since the introduction of the product (TSI_{ijt}) in a linear way. This functions are assumed to be known for both firms:

$$K_{ijt} = \kappa_{0ij} + \kappa_{1ij} \cdot TSI_{ijt}$$

The average quality (AK_t) of last period products is formed with a weighted average of the quantity sold of each product in the previous time period

$$AK_t = \frac{\sum_i \sum_j q_{i,j,t-1} K_{ij,t-1}}{\sum_i \sum_j q_{i,j,t-1}}$$

Notice that even when K_{ijt} is exogenous and can not be affected by firm production decisions, the firm can affect the average quality at each time period trough the quantity sold of each product. Therefore, k_{ijt} can be affected by the firm adding some dynamics to the demand side of the market. The effect of the state variables K_{ijt} and TSI_{ijt} on demand can be summarized in k_{ijt}. Is this variable, together with the information about products available at each moment of time, the only state variable (endogenous) that affects demand.

3.3 Cost Function

I assume that within each period average and marginal cost are equal and constant and they decrease over time due to learning-by-doing. I also assume that both firms face the same cost function and therefore the parameters do not depend on the firm. Nevertheless, every firm receive privately known cost shocks in each period for each product (ε_{ijt}). The cost shocks are assumed to be independent and identically normally distributed.

Due to learning by doing unitary costs are reduced with experience over time. I consider the two measures of experience that are commonly used in the learning-by-doing literature, time since the introduction of the product (TSI_{ijt}) and cumulative production (E_{ijt}). Hence, the cost function is

$$c_{ijt} = c(E_{ijt}, TSI_{ijt})$$

Where E_{ijt} represents the cumulative production of each product until time $t-1$ and TSI_{ijt} is the time since the introduction of each product. Due to learning-by-doing we expect cost to be decreasing in both E_{ijt} and TSI_{ijt}.

The state variables that affects costs are then E_{ijt} (endogenous) and TSI_{ijt} (exogenous).

3.4 Single Period profit function

The demand and cost functions previously defined allow me to define the per period profit function for each firm as

$$\pi_{jt}(q_{jt}, q_{-jt}, \mathbf{s}_{jt}) = \sum_i (p(q_{jt}, q_{-jt}, k_{ijt}) - c(E_{ijt}, TSI_{ijt})) \cdot q_{ijt} \tag{1}$$

Where $\mathbf{s}_{jt} = [\mathbf{k}_{jt}, \mathbf{E}_{jt}, \mathbf{TSI}_{jt}]$ is the vector of profit relevant state variables for the firm j at time t.

To estimate the market structure parameter I assume that the econometrician do not know the exact form of the payoff function of the game but the firms known exactly the game they are playing and therefore the exact form of the payoff function of the game. The profits from both firms and the consumer surplus will be nested using a market structure parameter to identify the payoff function in the Markov Perfect Equilibrium of the dynamic game. That will allow us to identify the market structure that is closest to the observed behavior in the MPE of the dynamic game.

3.5 Market Structure Parameter

Following Perloff, Karp and Golan (2007), I want to nest three different market structures in the MPE of the game. The identification of the market structure is done using a single parameter which moves the market between three leading cases: Perfect Collusion (PC) , Nash-Cournot (NC) and Social Welfare Maximization (SWM). These market structures are conditional on all the elements that have been assumed exogenous in the model as the number of firms in the industry, the number and speed of introduction of products, etc. In this application I am not interested in how the different market structures may have affected these characteristics of the market and therefore those effects can not be captured by the model. All that the model can capture is if, conditional on all those elements, the behavior of firms in choosing quantities is more competitive or collusive than the Nash-Cournot assumption.

The identification of this *conditional* market structure relies on the form of the problem that firms solve under the three leading cases. In the NC equilibrium firms maximize the expected discounted value of own profits, taking into account the current and future responses of their competitor. In the PC equilibrium firms maximize the expected discounted value of joint profits. In the SWM equilibrium the behavior of firms implies the maximization of the sum of both firms profits and consumer surplus. The identification of the market structure consist therefore in the identification of the function that has being maximized by the firms when they made their production decisions (for a more detailed discussion of this dynamic index of market power, see Perloff, Karp and Golan 2007, chapter 7).

To identify the objective function that firms have maximized in the dynamic game we define the following payoff function for firm j (time index has been suppressed to simplify notation), where $\theta \in [-1, 1]$ is the index of market structure:

$$W_j(\mathbf{q}_j, \mathbf{q}_{-j}; \theta) = \Pi_j(\mathbf{q}_j, \mathbf{q}_{-j}) + (\lambda_1(\theta) + \lambda_2(\theta)) \cdot \Pi_{-j}(\mathbf{q}_j, \mathbf{q}_{-j}) + \lambda_2(\theta) \cdot CS(\mathbf{q}_j, \mathbf{q}_{-j})$$

where:

$$(\lambda_1(\theta), \lambda_2(\theta)) = \begin{cases} (-\theta, 0) & \text{if } -1 \leq \theta \leq 0; \\ (0, \theta) & \text{if } 0 < \theta \leq 1. \end{cases}$$

Where $(\mathbf{q}_j, \mathbf{q}_{-j})$ represent the infinite sequence of quantities vectors over time by both firms, Π_j represents the expected discounted value of firm j profits, Π_{-j} represents the expected discounted value of profits of the other firm and CS represent the expected discounted value of the consumers surplus. Expectation is applied over current and future actions and random shocks over demand and cost functions. That is:

$$\begin{aligned} \Pi_j(\mathbf{q}_j, \mathbf{q}_{-j}) &= E\left[\sum_{\tau=t}^{\infty} \sum_i \beta^{\tau-t} \pi_{ij\tau}(\mathbf{q}_{ij\tau}, \mathbf{q}_{i-j\tau})\right] \\ \Pi_{-j}(\mathbf{q}_j, \mathbf{q}_{-j}) &= E\left[\sum_{\tau=t}^{\infty} \sum_i \beta^{\tau-t} \pi_{i-j\tau}(\mathbf{q}_{ij\tau}, \mathbf{q}_{i-j\tau})\right] \\ CS(\mathbf{q}_j, \mathbf{q}_{-j}) &= E\left[\sum_{\tau=t}^{\infty} \sum_i \sum_j \beta^{\tau-t} CS(\mathbf{q}_{ij\tau})\right] \end{aligned}$$

The three leading cases are represented by the following values of $\theta, \lambda_1, \lambda_2$:

Market Structure	θ	λ_1	λ_2
Perfect Collusion (PC)	-1	1	0
Nash-Cournot (NC)	0	0	0
Social Welfare Maximization (SWM)	1	0	1

As θ moves from -1 to 0, λ_1 moves from 1 to 0, keeping $\lambda_2 = 0$, giving less weight in the objective function to the other firm profits, which implies that the market moves from PC to a NC equilibrium. As θ moves from 0 to 1, λ_2 moves from 0 to 1 keeping $\lambda_1 = 0$ giving more weight to the competitors profits and to the consumer surplus. This implies that the equilibrium moves from NC to SWM. Looking for the parameter θ that makes the observed choice consistent with an MPE of the game will allows us to identify the market structure that is closest to the observed behavior of the firms.

3.6 The Game and the Equilibrium Concept

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

Following Benkard, Bajari and Levin (2006) I focus the equilibrium analysis on pure strategy Markov perfect equilibria (MPE). In a MPE each firm's equilibrium strategies depends only on the current period profit relevant state variables. A Markov strategy is defined as a function $\sigma_j : S \to Q_j$ where S represent the state space and Q_j represent the set of actions for firm j. A profile of Markov strategy is a vector $\sigma = (\sigma_1, \sigma_2)$.

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

$$V_j(\mathbf{s};\sigma) = E[W_j(\sigma(\mathbf{s}),\mathbf{s}) + \beta V_j(s';\sigma)|\mathbf{s}]$$

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 increase the value of the game. This is, σ is a MPE if for all firms j, states $\mathbf{s}$ and Markov strategies σ'_j

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

The empirical methodology will make use of this condition to identify the value of the structural parameters assuming that the observed behavior is part of a Markov Perfect Equilibrium.

4 Econometric Technique

The empirical strategy considers the estimation of the market structure parameter based on the algorithm proposed by Bajari, Benkard and Levin (2006). In this section I will present the main elements of the methodology.

The algorithm has two stages. In the first stage the non-dynamic elements and parameters of the models are estimated. In this application this stage requires the estimation of the demand curve, the cost function, performance evolution, the equilibrium policy function as a function of current value of state variables and the observed points of the value function. The second stage of the algorithm consists on the estimation of the parameter θ which identify the market structure.

4.1 First Stage Estimates

The first step in this stage is the identification of demand and cost parameters. Both functions are estimated using traditional IV methods. I estimate the demand using the state variables that affect unitary costs (TSI_{ijk}, E_{ijk}) as instruments for the endogenous quantities. The cost function is estimated using available data for average production cost for each product. All the details are presented in the section of Results.

The other important task is the estimation of the policy functions. Given that the exact functional form of the policy function depends on the unknown functional form of the value function, the best one can expect to do in this stage is to estimate the policy function non-parametrically (Jenkis, et al. 2004).

The Markov strategy assumption indicates that the only relevant variables for the policy function are current period profit relevant state variables. The assumption that the observed behavior is part of the equilibrium allows me to estimate the policy function using observed choices and state variables.

Bajari, Benkard and Levin (2006) propose the estimation of this relationship using multivariate local linear regression as presented by Fan and Gijbels (1996). In this method, for predicting the value of the optimal choice at a given point in the state space, the observations located within a certain distance of this point are considered. Then, these observation are used to estimate a weighted linear regression. For the weight a kernel function is used, giving more weight to the points that are closest to the point that want to be predicted [6]. The size of the interval used for the local points is adaptative, adjusting the size until obtain a predetermined number of closest neighbors. The number of neighbors is determined optimally by cross-validation. This methodology minimizes the sum of the squared errors from predicting the points in the sample, without including in the explanatory set the point that want to be predicted.

4.1.1 Value Functions

Given the assumption that the observed choices are an optimal solution to the game, the "observed" value of the payoff function correspond to the relevant observation of the value function. In our game the payoff function of each firm is unknown by the econometrician, because it depends on the value of the market structure parameter θ which is what we want to identify. Therefore, instead of calculating the value function, all I can do is to estimate what the expected discounted value of firms profits and consumer surplus where on each period. These terms do not depend on θ. These components will then be used to estimate the value of θ that makes the observed choice an MPE equilibrium of the game.

The value function for firm j is given by

[6] The Kernel function utilized is the Epanechnikov which gives to each point at a normalized distance $u \leq 1$ the value $\frac{3}{4}(1-u^2)$ and zero to the values of $u > 1$. For more details, see Fan and Gijbels (1996), chapters 3 and 7).

$$V_j(\mathbf{s};\sigma_j(s),\sigma_{-j}(s),\theta) \quad = \quad \Pi_j(\sigma(s),\mathbf{s}) + (\lambda_1(\theta)+\lambda_2(\theta))\cdot\Pi_{-j}(\sigma(s),\mathbf{s}) + \lambda_2(\theta)\cdot CS(\sigma(s),\mathbf{s})$$

Notice that because this function is separable on θ and σ_s, changes in θ will not change $\Pi_j(\sigma(s))$, $\Pi_{-j}(\sigma(s))$ and $CS(\sigma(s))$. I will estimate the values of these three terms assuming that the observed choice is part of the optimal strategy for each firm and then, I will use these objects to estimate the unknown parameter θ.

For doing so, we need to estimate the value of $\Pi_j(\cdot), \Pi_{-j}(\cdot)$ and $CS(\cdot)$ for observed choices and for one-step deviations from the observed choices in each period. Using the first stage estimation of demand, cost and policy functions, the methodology employs a forward simulation procedure that can be summarized as follows:

1. Starting at a time t=0, in which a value for the state s_0 is given, a value for ε_{ijt} (the cost shock) and η_{ijt} (the demand shock) is drawn from the distribution of the residuals of the first stage.

2. For t=0, the observed choice (or the deviation) is taken as the first period choice. For $t > 0$ the optimal choice is predicted using the non-parametric estimation of the policy function. In this case, the prediction error in the quantity is also incorporated in this stage taking a random value of the distribution of the residuals in the first stage of the policy function estimation. With all this information on prices, quantities and costs, I predict profits for both firms and consumer surplus for period t.

3. Using the law of motion for each state variable a new state for the next period, s_1, is determined.

4. In the next period, new values for the random shocks are drawn (cost, demand and production). Steps (1) to (3) are repeated and we move to the future calculating the predicted value of profits for both firms and consumer surplus in each period. We keep going forward for a large number of periods, until a time T in which β^T is small enough so that the reminder of the infinite sum can be approximately zero.

These steps generate a single path of profits and consumer surplus and we can calculate the discounted value of that path. But we need to calculate the expected value and not a single random observation of the discounted value of profits. Notice that what give randomness to the simulation is the fact that we are getting different demand, cost and production random shocks each time we repeat the simulation. By repeating this procedure many times and taking the average over them we obtain a simulated expected discounted value for the profits of each firm and also for the consumer surplus. This procedure allows us to calculate the value function for the observed choice and also for deviations from the observed choice, so we are able to estimate the following terms:

- $\Pi_j(\sigma(s))$, $\Pi_{-j}(\sigma(s))$, $CS(\sigma(s))$, with $q_j = \sigma_j(s)$.

- $\Pi_j(\sigma'_j(s), \sigma_{-j}(s))$, $\Pi_{-j}(\sigma'_j(s), \sigma_{-j}(s))$, $CS(\sigma'_j(s), \sigma_{-j}(s))$ for one-step deviations $q'_j = \sigma'_j(s)$.

We will use these objects in the second stage to identify the value of the market structure parameter that makes the observed behavior of firm the closest possible to a MPE of the game.

4.2 Second Stage Estimates

The second stage estimation procedure is based on the equilibrium condition for the MPE of the game which requires that if a strategy profile is an MPE then any one-step deviation for both firms, keeping its rival strategies constant, will be unprofitable. This requirement is that for all j and all possible deviations $\sigma_j'(s)$:

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

Let 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

$$g_j(\theta) \geq 0 \tag{2}$$

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

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

Where k is an index for every observation in the sample. This quadratic function measures how far is the observed behavior of representing a Markov perfect equilibrium of the game at a given value of θ. If we want the observed behavior as closest as possible of a MPE of the game we want to minimize the value of $Q_j(\theta|n)$. The estimator for θ is then:

$$\hat{\theta} := \arg\min_{\theta} Q_j(\theta) \tag{3}$$

As previously explained, some terms of the value function can be estimated independently of θ. Once these terms have been estimated the value of $Q_j(\theta)$ can be easily computed and therefore, the finding of $\hat{\theta}$ becomes an standard minimization problem in the sample.

5 Overview of the Market and Dataset

This section describes the CPU market, focusing on the existence of imperfect competition in the market. First, I will present some characteristics of the market under analysis. Then, I will present some data on prices and cost estimates to discuss the existence of imperfect competition in the industry.

The main data set has been acquired from In-Stat, a research company that specializes in the CPU market[7]. It includes estimates of quarterly shipments (sales) for each CPU model from 1993 to 2004 and historical prices for AMD and Intel processors. It also includes unitary cost estimates for the different families of Intel CPUs. In-Stat 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 Semicon-

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

ductor Industry Association (SIA). They use this information to estimate unit shipments for each product by Intel, based on engineering relationships and capacity production of each Intel plant (Aizcorbe, et.al. 2003). The In-Stat data set is complemented with two other sources: the first is firm-level marketing expenditures and cost of sales for each company. These data have been obtained from the 10K financial statements. The second extra source consists of information about CPU performance which is used as measure of quality. It has been acquired from The CPU Scorecard, a company that measures in a comparative basis and keep track of the performance of the different CPU products. The In-Stat database has been previously used by Song (2006a, 2006b) to estimate demand for differentiated products and welfare implications from investment in research and development in the CPU market. It has also been used by Gordon (2006) to estimate a demand model for durable goods.

With respect to the cost information, the main analyst of this data at In-Stat reports that: *"The cost model is derived from an analysis of the individual dies relative to the manufacturing process used to fabricate them. The primary factors influencing the product cost include wafer size, die size, manufacturing process node (include the number of metal layers), process maturity, anticipated yields, and package type."* (Jim McGregor, Personal communication). It can be inferred that the way in which this unitary cost is estimated is consistent with the learning-by-doing process in which yield is increased with time and production experience.

5.1 A Short History of the CPU Market

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 introduced the first generation of a 16 bit CPU, the 8086, which was the basis for the x86 architecture currently used in computer CPU. In the following years a technological race for faster CPU started between these two firms. Since then, seven generations of CPUs have been introduced into the market, each one with an incredible increase in performance and possibilities, expanding the potential use of computers from being simple calculators to managing gigantic databases, digital sound, images and movies.

Intel and AMD dominance of the CPU market began when IBM chose Intel's processor to be part of its new line of personal computers. As a part of IBM policies, they required a secondary producer of the chips and Intel had to sign an agreement with another company to be able to sell its chips to IBM. They choose as their secondary provider Advanced Micro Design (AMD). Some years later, a new market for IBM PC clones was developed and Intel tried to finish its tie to AMD. Intel canceled the agreement with AMD and refused to hand over technical specifications of its new chips. AMD challenged Intel's decision, and a long legal dispute started. The legal fight finished in 1991, giving AMD the right to produce the Intel chips. However, in December 1994, the Supreme Court of California denied to 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 CPU based on the Intel 286, 386 and 486 technologies. After that, AMD have been developing its own architecture introducing the K5, K6 and K7 generations of chips.

The large number of differentiated products in the Computer CPU market can be grouped in generations and families. A generation of products share the same basic production technology and design. Over the lifetime of a generation several improvements are introduced which give rise to the introduction of new families of product. When an important improvement is introduced, a new "family" of products within that generation is created. Within each family, several products are fabricated which are differentiated on the basis of several characteristics such as the clock speed (measured in Mhz), the amount of cache memory on the CPU and other elements that affect the performance of each product. This allows firms to differentiate products and to cover different needs of the wide range of users.

The most important characteristic of a CPU from a consumer's point of view is it capacity to perform different tasks in a short period of time. Performance is usually associated with the clock speed of the processor, but that is not the only determinant of how quick a CPU can be. The clock speed measures the number of cycles of instruction that are processed by the CPU in one second. There are several other characteristics of a CPU that affects performance as for example the amount of cache memory, the speed of the mathematical coprocessor or the front side bus speed which measure how faster the CPU can communicate with other components of the system.

When a new generation is introduced to the market, the new production technology implies an important increase in performance and therefore in product quality. This performance is continuously increased within each generation when new families and different products with faster clock speeds are introduced into the market. Figure 1 shows the average performance of the last four AMD and INTEL generations. The most important fact is the continuous improvement and different trend in performance that these products have over time.

5.2 A First Look to Competition in the CPU Market

If fast technological advancement is one of the main characteristics of the CPU market, other crucial characteristics are the high concentration and the high dominance of Intel in terms of market share. During the period of my data set Intel had an increasing share of the market from around 75% in 1993 up to 95% in 1997. With the introduction of the AMD K6 generation, Intel lost some participation in the market going back to levels around 80%-85%.

Another traditional static indicator of the existence of market power is the existence of high differences between prices and marginal costs. Figure 2 shows the average selling price of CPUs for Intel and AMD between 1998 and 2003. It also shows In-Stat average unitary cost estimates for both companies.

There are at least two interesting facts on this graph. First, Intel's average prices are far higher to AMD's average prices. Second, cost estimates of AMD and Intel seems to be of a similar order of magnitude, but Intel's average prices approximately double AMD's average prices. This can be explained because Intel sells similar products at higher prices than AMD, but also because a higher proportion of AMD sales are low quality products.

These observations might suggest that Intel is taking better advantage of its high market share and enjoying a higher degree of market power. Nevertheless, as previously stated, the simple observation of this static measure of market power could be misleading and the estimation of a measure that considers the dynamic elements of the industry is needed to draw a better conclusion.

6 Results

In this section I present the result of the empirical implementation of the econometric technique in the computer CPU market. I first present the result of the demand and cost estimation. Next, I present the observed and predicted markups and the estimation of quality evolution. Then, I show the results of the nonparametric estimation of the policy functions in the sample. Finally, I present the estimates of the parameter that identifies the market structure.

For the empirical model products are aggregated at the generation level. To calculate prices and quality of the aggregated products, I use the weighted average, using quantities sold as weights. Given limited data availability for the first two generations in the data set (particularly Amd486 and K5) and because they are similar products in comparison with the other generations, they have been aggregated in one single product. Therefore, the model considers three products for each firm. I call these products AMD1, AMD2, AMD3, INTEL1, INTEL2 and INTEL3. Even when some small firms were present in the market, mainly at the beginning of the data period, I ignore them and assume that the relevant market is a duopoly between AMD and INTEL.

6.1 Demand Estimation

The specific functional form of demand is the following:

$$\log(p_{ijt}) = \alpha_0+\alpha_1 \log(q_{ijt})+\alpha_2 \log(q_{-ijt})(1-dnp)+\alpha_3 \log(q_{-jt})+\alpha_4 k_{ijt}+\alpha_5 Intel+\alpha_6 dnp+\eta_{ijt}$$

Where p_{ijt} is the price of the product, q_{ijt} is the quantity of the product, q_{-ijt} is the quantity of other products by the same firm, q_{-jt} is the quantity of other products by the other firm, *dnp* is a dummy that takes the value 1 when the firm is producing just one product ($q_{-ijt} = 0$). The variable *dnp* control for situations in which log(0) is not defined, so that I can define $0 \cdot log(0) = 0$. The parameter α_6 will control for changes on demand when this happen. k_{ijt} is the relative quality of the product with respect to the average product in the market in the previous period and *Intel* is a dummy for the biggest firm.

Endogeneity of quantity is solved by using as instrumental variables the state variables that affect cost, experience and time since introduction, and additionally, the experience of the previous generation and experience of the generation following the product under analysis. These instruments are the variables that determine choice of quantities in the supply side in the Markov Perfect Equilibrium of the game and should be uncorrelated with uncontrolled determinants of price. A Wu-Hausman endogeneity test has an $F-value$ of 3.63 and a $p-value$ of 0.0598 which allows us to reject the null of exogeneity of price at a confidence level of 10%.

Table 1 presents a summary of the data set for the demand estimation. For this estimation I have 59 total observations for AMD products and 75 total observations for INTEL products. Nevertheless, given that price is just observed since 1995 for Intel and since 1999 for AMD that gave us a total of 95 observations for the demand estimation. Table 2 presents the estimation results for the inverse demand function.

The residuals from the demand estimation allows us to estimate the distribution of the demand shocks. They are assumed to have a normal distribution with mean zero and a empirical standard deviation of 0.21.

6.2 Cost Function Estimation

Given that detailed cost data is just available for Intel, that the production process between companies is similar and that average unitary cost seems to be similar between firms, I will assume that both firms present a similar learning-by-doing process in their production technology and the same cost functions for a product of the same generation.

The functional form for the cost function is the following:

$$c_{ijt} = \beta_{i0} + \beta_{i1}\log(E_{ijt}) + \beta_{i2}TSI_{ijt} + \varepsilon_{ijt}$$

Where E_{ijt} represents the cumulative production of each product until time $t-1$ and TSI_{ijt} is the time since the introduction of each product. Due to learning-by-doing we expect both β_{i1} and β_{i2} to be negative.

A dummy for the second and third product is used to capture difference in the cost of producing the first unit. The rate of learning is assumed to be the same between generations. The estimated parameters are presented in Table 3.

The results suggest that the unitary cost of a unit of the fifth generation (INTEL1 and AMD1) when 1 unit has been produced (log(1)=0) and it is in the first quarter of production (timesinceint=0) is around \$107. With every quarter, the cost is reduced in \$3.5. The unitary cost is also reduced in a non-linear way with cumulative production. AMD2 and INTEL2 products present a cost that is higher by \$59 to the cost of AMD1 and INTEL1, when introduced. AMD3 and INTEL3 products present a cost higher by \$15 to the first generation in the data. The regression presents high significance globally and individually for all the parameters.

The residuals from the estimation allow us to estimate the shock in costs which will be used in the forward simulation in the second stage. We assume that residuals are distributed normal with mean zero and with the empirical standard deviation of 18.58.

6.3 Predicted Markup

Using the demand and cost functions previously estimated and the observed production by firm, I am able to predict the markup for both firms for the whole period of the data set. I compared this prediction with average markup for each firm presented by In-Stat for some time periods. Figure 3 shows the predicted average markup and the markup presented by In-Stat/MDR for some time periods. Even when the cost function is estimated using just INTEL cost data at the product level, the estimated equations predict relatively well the markup for each firm, except at the beginning of the sample, where no data on price exists, where it predicts negative markups for AMD. I consider that the predicted markup has the main observed characteristics that are required to estimate the market structure parameter in the second stage of the algorithm.

6.4 Quality Evolution

For the forward simulation that allows us to estimate the value functions, I have assumed that quality follows an exogenous linear path over time and that it is known by both firms. I have estimated the parameters of a linear function that will predict the quality of each product, depending on the time since its introduction and its generation. The estimated parameters of the performance function are presented on Table 4.

6.5 Policy Functions

As previously presented, the Markov perfect assumption implies that the optimal choice in each period is a function of the current period state variables that affect current payoff. Table 5 shows that all the state variables considered have high statistical power to explain quantity choices. The sign of all coefficients agree with what is expected and are all statistically significant. One interesting point is the sign of the state variables that control for the experience of the past and the next generation. The experience of the next generation has a negative coefficient which controls for the fact that firms reduce the quantity of the old generation when they introduce a new generation. A similar interpretation is given to the positive sign of the parameter related to experience of the previous generation.

Even though a linear regression predicts relatively well the observed behavior of firms, as mentioned before, the method that will be used is non parametric local linear regression. The estimation procedure considers a linear regression in a neighborhood around each point to be evaluated. The neighborhood is chosen optimally using cross-validation. The optimally determined neighborhood size includes the 15 closest neighbors in each local estimation relevant state variables. In this case, these are variables that affect production costs (experience), state variables that affect demand (performance) and the set of products available in each period. Based on that, the variables used in this application are: performance of each product, cumulative production of each product, time since the introduction of each product, cumulative production of the product of the previous generation by the same firm and cumulative production of the product of the next generation by the same firm. Figure 4 presents a plot of the predicted choice using the local linear regression and the observed choice in the sample.

6.6 Value Functions

This step consist on the estimation of $\Pi_j(\mathbf{s}, \sigma(s))$, $\Pi_{-j}(\mathbf{s}, \sigma(s))$, and $CS(\mathbf{s}, \sigma(s))$ for all the observed choice in the data set and also $\Pi_j(\mathbf{s}, \sigma'_j(s), \sigma_{-j}(s))$, $\Pi_{-j}(\mathbf{s}, \sigma'_j(s), \sigma_{-j}(s))$, and $CS(\mathbf{s}, \sigma'_j(s), \sigma_{-j}(s))$ for different one-step deviations in the first period.

All these expected values are calculated using the forward simulation technique and will be used in the next section to estimate the value of θ that allows us to identify the market structure.

Figure 5 shows a plot of the estimated components of the value functions for the observed choices. This consists on each firm's expected discounted value of profits and expected present value of the consumer surplus, for the period of the data.

6.7 Market Structure Parameter estimation

To estimate the market structure parameter (θ) the following steps are taken. First, in every period, the expected present value of the profits are estimated for the observed choice and for one-step deviations from the observed choices. To calculate the expected value of profits, in every period a path of profits is simulated for a large number of periods and one value for the discounted present value of the profits is calculated. The same procedure is repeated

100 times and the mean is calculated to obtain the *expected* discounted value of the profits in each period. This is repeated for both firms in all the 48 time periods for which data is available. The procedure is repeated starting with the observed choice in every period, and also for one-step deviations of +/- 5%, +/-10% and +/-15% from the observed choice. After that, the differential profit between the deviations and the observed choice is calculated. Then, for a given value of θ, the value of the loss function is calculated by adding over the deviations that increase the value of the objective function. The parameter that minimize the loss function is chosen.

Table 6 presents the estimated market structure parameter. This parameter is presented for two cases. In the first case, it is assumed that the objective function that each firm solves is different. This gave one market structure parameter for each firm: θ^{AMD} and θ^{Intel}. The second case assumes that the objective function for both firms is the same, and therefore a common market structure parameter is estimated using the information for both firms. This parameter is called $\theta^{Industry}$.

The result suggest that the market structure is very close to the Nash-Cournot equilibrium of the game for AMD and for the Industry as a whole, obtaining point estimates for $\theta^{AMD} = -0.0176$, and $\theta^{Industry} = 0.0000$. The results for Intel suggest a market structure that is between Nash-Cournot and Collusion with $\theta^{Intel} = -0.4363$. Bootstrapped parameters gave a mean of $\theta^{AMD} = -0.0012, \theta^{Intel} = -0.2116$ and $\theta^{Industry} = -0.0548$. The standard deviation based on the bootstrapped parameters gave values of $\sigma_\theta = 0.0835$ for AMD, $\sigma_\theta = 0.1944$ for Intel and $\sigma_\theta = 0.0728$ for the Industry.

The point estimate and the bootstrapping allows us to estimate t-values to test for the different market structures. These t-values are presented in Table 7. If we use the point estimates, we can reject the existence of collusion and social welfare maximization for the three market structure parameters. We fail to reject the existence of a Nash-Cournot equilibrium in the game for AMD and the industry as a whole. If we use the mean of the bootstrapped parameters, we confirm the previous result for AMD and the industry ; additionally we fail to reject the existence of a Nash-Cournot equilibrium and reject the existence of collusion for Intel.

These result suggest that the observed behavior of firms is closest to a Nash Equilibrium of the game and allows us to reject the existence of perfect collusion and of social welfare maximization.

7 Conclusions

In this paper, the estimation of an index of market structure in a dynamic structural model has been applied to the computer CPU market. Two elements exist in this market that may generate incentives to firms to produce a quantity that is closer to static perfect competition. The first of them is the existence of learning-by-doing. Under learning-by-doing firms have incentives to produce higher quantity of products during the first periods of introduction of a product, with the objective of reducing future production costs. Additionally, as proposed by Siebert (2003), the existence of adjacent generations of products by the same firm may create a higher degree of competition in the market. When firms produce several products, even when firms have few competitors, the fact that products compete with other products by the same firm could create a more competitive results.

The observation of prices minus unitary cost markup suggests that Intel is taking advantage of its higher market share, obtaining a much higher markup and profit than its competitor, AMD. Nevertheless, the estimation of parameters in a dynamic model suggest that both firms are obtaining a result that is closest to a Nash-Cournot behavior in the Markov Perfect Equilibrium of the dynamic game, rejecting the existence of both competitive (welfare maximizing) and collusive behaviors.

Several assumptions have been necessary to simplify the model and have allowed me to estimate the behavioral parameter in the dynamic game. First, I have grouped products at the generation level. This might hide some of the variability of the data at the product and family level. Even when the available data could have allowed analysis at the product level for Intel products, the available data not fully disaggregated for AMD, which makes hard to estimate the model at that level for both firms. Probably, the existence of more competitive products may have generated a more competitive result, nevertheless, it is not clear how that compares to a social welfare maximization result under that model. Second, I have assumed that demand is static and that people take buying decisions in every period without taking in account expectations of quality and prices of products that will be available in the future. I have also ignored the fact that CPU are elements of durable goods. Incorporating these elements into the modeling strategy is very difficult and creates a two-side game between buyers and sellers. Third, being the computer CPU one component of a digital computer system, the demand of CPU is a derived demand from computer producers. This fact has been also ignored in the estimation procedure and the inverse demand function has been estimated using an aggregated demand. Incorporating other modeling strategies in the demand estimation is one of the possible extensions of this paper. Fourth, technical progress and the development of new products have been considered exogenous and the only control value for firm has been assumed to be the quantity of each product. Incorporating a more general model is another possible extension. Finally, the estimation of the market power parameters in a two-stage procedure, in which in the first stage the demand and cost functions are estimated and in a second stage the market power parameters are identified could generate a loss of efficiency. Other ways of improving the estimation can be explored and proposed in future work.

References

[1] Aguirregabiria, Victor and Pedro Mira. 2002. "Swapping the Nested Fixed Point Algorithm: a Class of Estimators for Discrete Markov Decision Models." Econometrica 70:1519-43.

[2] Aguirregabiria, Victor, and Pedro Mira. 2007. "Sequential Estimation of Dynamic Discrete Games." Econometrica, Vol. 75, No. 1: 153

[3] Aizcorbe, An a, Carol Corrado and Mark Doms. 2003. "Constructing Price and Quantity Indexes for High Technology Goods" Working Paper No14 in Aplied Economic Theory. Federal Reserve Bank of San Francisco.

[4] Aizcorbe, Ana. 2006. “Why did semiconductor price indexes fall so fast in the 1990s? A decomposition”. Economic Inquiry 2006 44(3):485-496.

[5] Bajari Patrick and Han Hong, 2005. “Semiparametric Estimation of a Dynamic Game of Incomplete Information.” Unpublished working paper.

[6] Bajari Patrick, Leniard Benkard and Jonathan Levin. 2006 “Estimating Dynamic Models of Imperfect Competition”, forthcoming Econometrica.

[7] Bresnahan, Timothy 1989. ”Studies of Industries with Market Power.” In Richard Schmalensee and Robert D. Willig, eds., The Handbook of Industrial Organization. Amsterdam: North-Holland.

[8] Bresnahan, Timothy and Richard Schmalensee. 1987. ”The Empirical Renaissance in Industrial Economics: An Overview.” Journal of Industrial Economics 35:371-77.

[9] Corts, Keneth. 1999, “Conduct Parameters and the Measurement of Market Power” Journal of Econometrics 88: 227-250.

[10] Ericson, Richard and Ariel Pakes. 1995. “Markov-Perfect Industry Dynamics: A Framework for Empirical Work.” The Review of Economic Studies, Vol. 62, No. 1: 53-82.

[11] Fan, Jaigjin and I. Gijbels. 1996. “Local Polynomial Modelling and Its Applications”, London: Chapman and Hall.

[12] Fundenberg, D. and J. Tirole. 1983. “Learning by doing and Market Performance” Bell Journal of Economics, 14: 522-530.

[13] Geroski, P., L. Phlips, and A. Ulph. 1985. "Oligopoly, Competition and Welfare: Some Recent Developments" Journal of Industrial Economics 33:369-87.

[14] Gordon, Brett. 2006. "Dynamic Demand and the Replacement of Durable Goods: An Application to the PC Processor Industry" Mimeo, Carnegie Mellon University, January 2006.

[15] Hashmi, Amir and Johannes Van Biesebroeck. 2007. "Market Structure and Innovation: A Dynamic Analyis of the Glboal Automobile Industry." Unpublished Working Paper.

[16] Hatch, Nile and Reichelstein. 1994. "Learning effects in semiconductor fabrication". Competitive Semiconductor Manufacturing Program Report CSM-33, University of California at Berkeley.

[17] Hatch, Nile. 1996. "Enhancing the Rate of Learning by Doing Through Human Resource Management". In THE COMPETITIVE SEMICONDUCTOR MANUFACTURING HUMAN RESOURCES PROJECT: Second Interim Report CSM-32. Clair Brown, Editor. Institute of Industrial Relations, University of California at Berkeley.

[18] Hatch, Nile and David Mowery. 1998. "Process Innovation and learning-by-doing in Semiconductor Manufacturing". Management Science, Vol 44, N. 11.

[19] Hotz, Joseph and Robert Miller. 1993. "Conditional Choice Probabilities and the Estimation of Dynamic Models." The Review of Economic Studies, Vol. 60, No. 3: 497-529.

[20] Hotz, Joseph, Robert Miller, Seth Sanders and Jeffrey Smith. 1994. "A Simulation Estimator for Dynamic Models of Discrete Choice." The Review of Economic Studies, Vol. 61, No. 2: 265-289.

[21] Irwin, Douglas and Peter Klenow. 1994. "Learning-by-Doing Spillovers in the Semiconductor Industry". The Journal of Political Economy 102 No6, 1200-1227.

[22] Iwata, Gyoichi. 1974. "Measurement of Conjectural Variations in Oligopoly". Econometrica, Vol. 42, No. 5: 947-966.

[23] Jenkins, Mark, Paul Liu, Rosa Matzkin and Daniel McFadden. 2004. "The Browser War Econometric Analysis of Markov Perfect Equilibrium in Markets with Network Effects." Posted at http://emlab.berkeley.edu/ mcfadden.

[24] Kim, Donghun. 2005. "Measuring Market Power in a Dynamic Oligopoly Model: An Empirical Analysis". Proceedings of the Australian Conference of Economists, 2005 [ISBN 0734026080]

[25] Karp, Larry and Jeffrey Perloff. 1989. "Dynamic Oligopoly in the Rice Export Market" The Review of Economics and Statistics, Vol LXXI, No3: 462-470.

[26] Karp, Larry and Jeffrey Perloff. 1993. "Open-Loop and Feedback Models of Dynamic Oligooly". International Journal of Industrial Organization, Vol. 11:369-389.

[27] Karp, Larry and Jeffrey Perloff. 1993a. "A Dynamic Model of Oligopoly in the Coffee Export Market" Amercian Journal of Agricultural Economics 75: 448-457.

[28] Lerner, Abba. 1934. "The Concept of Monopoly and the Measurement of Monopoly Power" Review of Economic Studies 3: 157-175.

[29] Macieira, Joao. 2006. "Extending the Frontier: A Structural Model of Investment and Technological Competition in the Supercomputer Industry." Unpublished Working Paper.

[30] Macher, Jeffrey and David Mowery. 2003. "'Managing' Learning by Doing: An Empirical Study in Semiconductor Manufacturing". Journal of Product Innovation Management 20:391-410.

[31] Maskin, Eric and Jean Tirole. 1987."A Theory of Dynamic Oligopoly, III: Cournot Competition." European Economic Review 31: 947-968.

[32] Maskin, Eric and Jean Tirole. 1988a. "A Theory of Dynamic Oligopoly, I: Overview and Quantity Competition with Large Fixed" Econometrica, Vol. 56, No. 3: 549-69.

[33] Maskin, Eric and Jean Tirole. 1988b. "A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles." Econometrica, Vol. 56, No. 3:571-99.

[34] Pakes Ariel, and Paul McGuire. 1994. "Computing Markov-Perfect Nash Equilibria: Numerical Implications of a Dynamic Differentiated Product Model". Rand Journal of Economics 25:555-89.

[35] Pakes Ariel, Michael Ostrovsky And Steve Berry. 2004. "Simple Estimators for the Parameters of Discrete Dynamic Games (with Entry/Exit Examples)." Harvard Institute of Economic Research Discussion Paper Number 2036.

[36] Perloff, Jeffrey, Larry Karp, and Amos Golan. 2007. "Estimating Market Power and Strategies". Cambridge University Press.

[37] Pesendorfer, Martin and Philipp Schmidt-Dengler. 2003. "Identification and Estimation of Dynamic Games." NBER Working Paper 9726.

[38] Pindyck, Robert. 1985. "The Measurement of Monopoly Power in Dynamic Markets". Journal of Law and Economics, Vol. 28, No. 1: 193-222.

[39] Reiss, Peter and Frank Wolak. 2005. " Structural Econometric Modeling: Rationales and Examples from Industrial Organization" Forthcoming in Handbook of Econometrics Volume 6. Accessed at ftp://zia.stanford.edu/pub/papers/reisswolak.pdf.

[40] Rust, John. 1987. "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher" Econometrica 87: 999-1033.

[41] Rust, John. 1994. "Structural Estimation of Markov Decision Processes." in Daniel L. McFadden, ed., Handbook of Econometrics, vol. 4, Elsevier Science, Amsterdam.

[42] Ryan, Stephen. 2006. "The Costs of Environmental Regulation in a Concentrated Industry." Unpublished working paper.

[43] Ryan, Stephen and Catherine Tucker. 2007. "Heterogeneity and the Dynamics of Technology Adoption." Unpublished Working Paper.

[44] Siebert, Ralph. 2003. "Learning by Doing and Multiproduction Effects Over the Life Cycle: Evidence from the Semiconductor Industry", CEPR Discussion Papers 3734, C.E.P.R. Discussion Papers.

[45] Song, Minjae. 2006a. "Measuring Consumer Welfare in the CPU Market: An Application of the Pure Characteristics Demand Model " Forthcoming RAND Journal of Economics.

[46] Song, Minjae. 2006b "A Dynamic Analysis of Cooperative Research in the Semiconductor Industry" Working paper, available at http://www.prism.gatech.edu/ ms433/papers.html

Table 1: Summary Statistics for the Demand Estimation

AMD					
Variable	Obs	Mean	Std. Dev.	Min	Max
price	29	100.79	50.17	64.00	250.00
prod	59	1476.67	2396.35	0.00	8800.00
prodi	59	2953.33	2783.76	0.00	8800.00
prodj	59	23136.29	9103.36	5967.00	36404.00
perf	59	0.39	0.55	0.00	2.43
INTEL					
Variable	Obs	Mean	Std. Dev.	Min	Max
price	66	245.03	133.65	84.00	787.00
prod	75	7712.10	10945.02	0.00	36404.00
prodi	75	15424.19	12141.55	0.00	36404.00
prodj	75	4430.00	2453.67	1200.00	8800.00
perf	75	0.63	0.66	0.00	2.38

Table 2: Inverse Demand Estimation.

Number of obs		=	95			
F(6, 88)		=	94.65			
$Prob > F$		=	0			
R-squared		=	0.8673			

lprice	Coef.	Std. Err.	t	$P > \|t\|$	[95% Conf.	Interval]
lprod	-0.0497	0.0323	-1.5400	0.1270	-0.1138	0.0145
lprodi*(1-dnp)	-0.0252	0.0261	-0.9700	0.3360	-0.0770	0.0266
lprodj	-0.0314	0.0486	-0.6500	0.5200	-0.1279	0.0652
perf	0.8810	0.0656	13.4300	0.0000	0.7506	1.0114
brand	0.7578	0.1251	6.0600	0.0000	0.5092	1.0063
dnp	-0.1834	0.1976	-0.9300	0.3560	-0.5761	0.2093
cons	4.4860	0.6454	6.9500	0.0000	3.2034	5.7685

Instrumented: lprod
Instruments: prodidummy lprodj perf brand dnp exp expnext expprev tsint

Table 3: Cost Function Estimation

Number of obs		=	67			
F(4, 62)		=	59.5			
Prob > *F*		=	0.0000			
R-squared		=	0.79			

uncost	Coef.	Std. Err.	t	$P > \|t\|$	[95% Conf.	Interval]
Logcumprod	-3.1779	1.2952	-2.4500	0.0170	-5.7671	-0.5888
Timesinceint	-3.5414	0.5040	-7.0300	0.0000	-4.5489	-2.5340
Gen6	59.3758	6.9280	8.5700	0.0000	45.5269	73.2247
Gen7	14.9099	6.6912	2.2300	0.0290	1.5344	28.2853
Constant	106.9539	11.4915	9.3100	0.0000	83.9827	129.9251

Table 4: Evolution of Quality

Number of obs		=	134			
F(7, 126)		=	991.79			
Prob > *F*		=	0.0000			
R-squared		=	0.98			

perf	Coef.	Std.Error	t	$P > \|t\|$	[95% Conf.	Interval]
tsint	27.2314	6.8364	3.9800	0.0000	13.7023	40.7606
tsig5	63.2453	8.2072	7.7100	0.0000	47.0036	79.4870
tsig6	225.9784	10.4767	21.5700	0.0000	205.2453	246.7116
firm	110.5089	67.7011	1.6300	0.1050	-23.4696	244.4873
firm6	2260.1620	119.6085	18.9000	0.0000	2023.4600	2496.8630
dg5	210.0696	113.4538	1.8500	0.0660	-14.4522	434.5914
dg6	1434.4910	139.5289	10.2800	0.0000	1158.3670	1710.6140
cons	-142.0165	89.1696	-1.5900	0.1140	-318.4805	34.4475

Table 5: OLS Regression of Quantity on State Variables

Number of obs		=	134			
F(5, 128)		=	71.89			
Prob > *F*		=	0.0000			
R-squared		=	0.74			

q	Coef.	Std. Err.	t	$P > \|t\|$	[95% Conf.	Interval]
perf	-3830.3	1462.7	-2.6200	0.0100	-6724.4	-936.15
exp	0.0453	0.0059	7.6700	0.0000	0.0336	0.0570
expprev	0.0214	0.0036	5.9900	0.0000	0.0143	0.0284
expnext	-0.2842	0.0237	-12.0000	0.0000	-0.3311	-0.2374
intel	5436.6	1442.6	3.7700	0.0000	2582.1	8291.2
cons	5951.5	1637.4	3.6300	0.0000	2711.7	9191.2

Table 6: Estimated Market Structure Parameters

	θ^{AMD}	θ^{INTEL}	$\theta^{Industry}$
$\hat{\theta}$	-0.0176	-0.4363	0.0000
Mean bootstraping	-0.0012	-0.2116	-0.0548
Std.Dev. Bootstraping	(0.0835)	(0.1944)	(0.0728)

Table 7: Hypothesis Tests for Market Structure (t-values)

Market Structure	Parameter Value	AMD	INTEL	Industry
Using Point Estimates				
Collusion	$\theta = -1$	11.7653	2.8997	13.7363
Nash-Cournot	$\theta = 0$	-0.2108(*)	-2.2443	0.0000(*)
Social Welfare Maximization	$\theta = 1$	-12.1868	-7.3884	-13.7363
Using Mean of Bootstrapped Distribution				
Collusion	$\theta = -1$	11.9617	4.0556	12.9835
Nash-Cournot	$\theta = 0$	-0.0144(*)	-1.0885(*)	-0.7527(*)
Social Welfare Maximization	$\theta = 1$	-11.9904	-6.2325	-14.4890

(*) Fail to Reject the null.

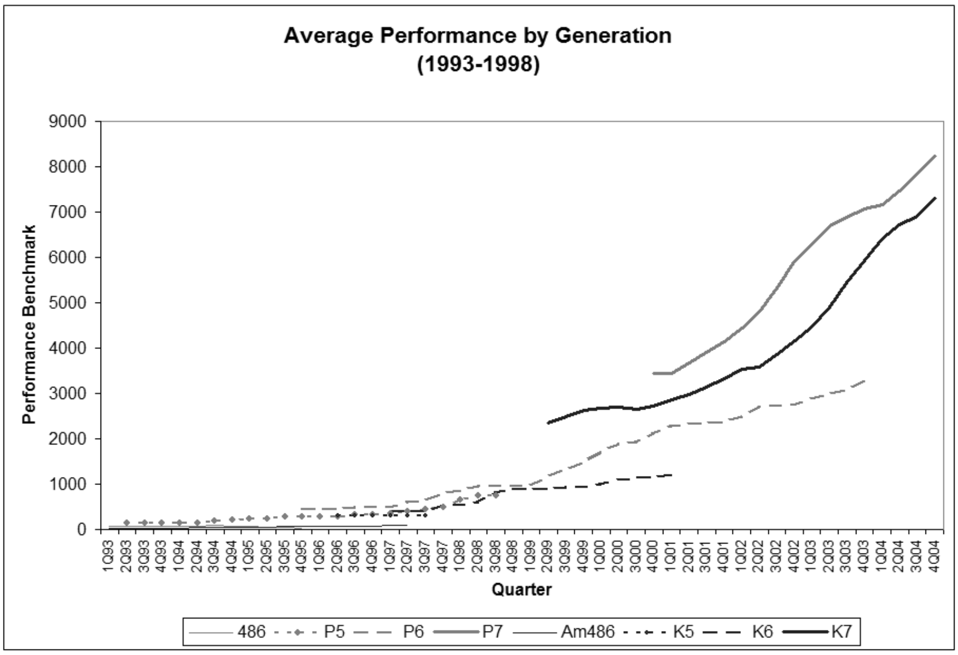

Figure 1: Average Performance (Quality) for each generation of products

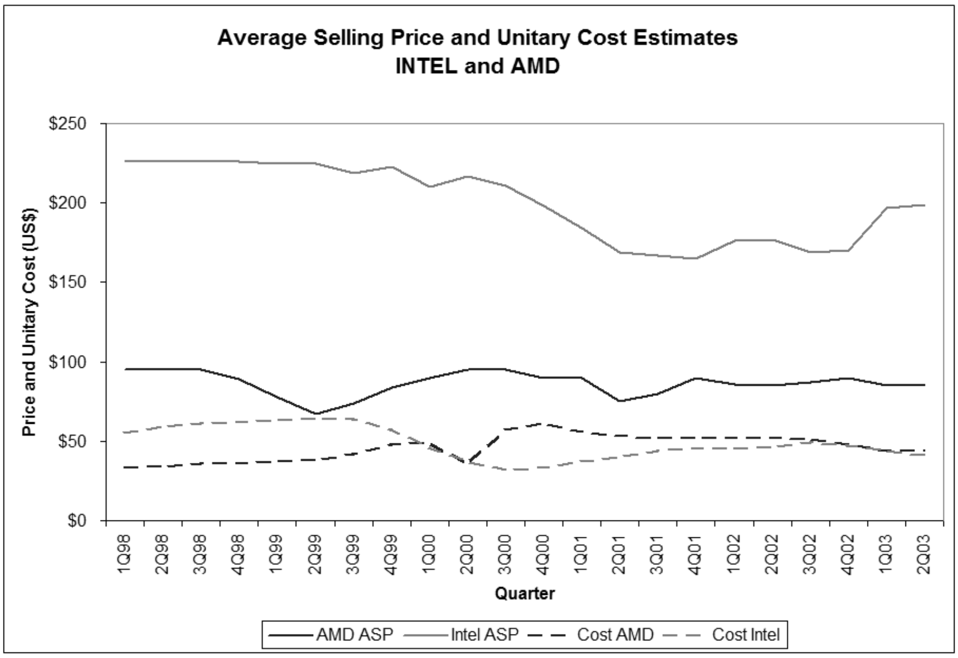

Figure 2: Average Selling Price and Unitary Cost by Firm

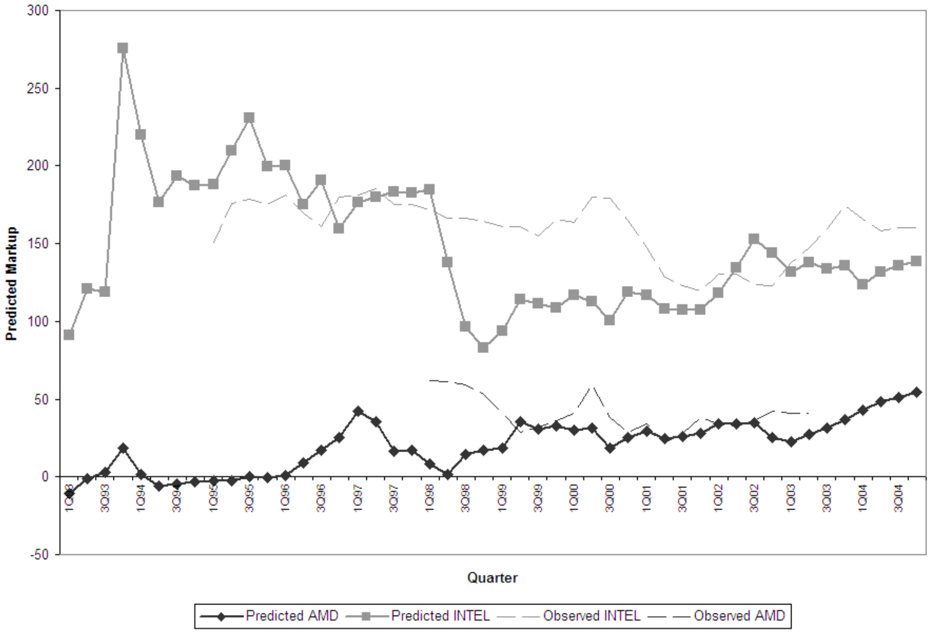

Figure 3: Estimated and Observed Markup for each firm

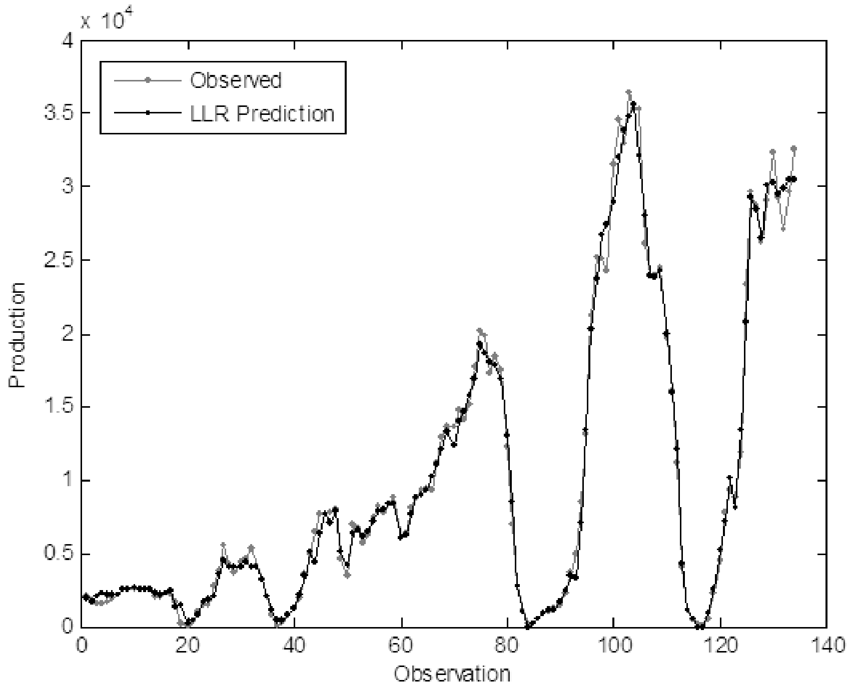

Figure 4: Estimated policy functions and observed choice

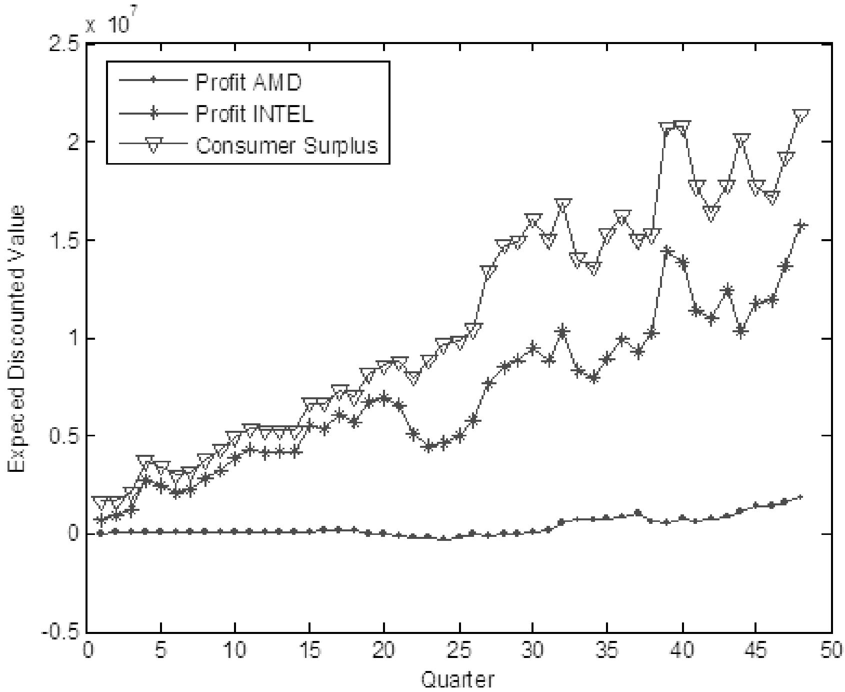

Figure 5: Estimated Components of the Value Functions