# Upstream Innovation and Product Variety in the U.S. Home PC Market*

Alon Eizenberg†
*Department of Economics*
*Yale University*

JOB MARKET PAPER

This Version: December 24, 2008

**Abstract**

This paper asks whether the rapid innovation in Central Processing Units (CPU) results in inefficient elimination of basic Personal Computer (PC) configurations. I estimate a model in which PC makers choose first which CPU options to offer with their products, and then set prices. I contribute to the literature on vertical product choices by relaxing assumptions which guarantee a unique equilibrium outcome, by allowing for a large product space, and by developing techniques which alleviate the burden associated with predicting counterfactual outcomes. My estimates imply that the demand for PCs is highly segmented. Using the model in counterfactual analysis, I find that Intel's Pentium M chip boosted notebook sales by 10.9%-18.9% and raised the average notebook price by $32 to $44 in 2004Q2. It also increased total consumer surplus by 3.3%-5.1%. This innovation led to a significant re-alignment of PC makers' product offerings, and, in particular, crowded out notebooks with Intel's older Pentium III chips. A traditional model with fixed product offerings does not capture this effect and, as a consequence, significantly understates the impact of the Pentium M on the market share of the Pentium III. I find that the elimination of the Pentium III was socially inefficient, although the magnitude of the lost welfare appears modest. Moreover, the impact of the innovation on the welfare of *all* segments of consumer demand was positive.

*I am grateful to my advisors, Steven Berry and Philip Haile, for their continued advice and encouragement. I also thank Donald Andrews, Eduardo Faingold, Josh Lustig, and participants at the Prospectus I.O. Workshop at Yale for many useful comments. I am grateful to IDC and to Mr. Steven Clough for making data available. All errors are mine. Financial support from the Carl Arvid Anderson Prize Fellowship, Cowles Foundation, is gratefully acknowledged.

†Comments welcome at alon.eizenberg@yale.edu.

# 1 Introduction

Innovation in Personal Computer (PC) technology plays a key role in fostering growth in many economic sectors. A salient feature of this process is a rapid elimination of existing products.[1] The goal of this paper is to ask whether this process results in *inefficient product elimination*. This question is motivated by consumer heterogeneity: while some consumers have a high willingness to pay for the most advanced technology available, others primarily perform basic tasks (e.g. Web browsing) which require modest computing power. This latter group of consumers could be hurt when basic PC configurations exit the market.

To address this question, I estimate a model of supply and demand in which the set of PC configurations offered to consumers is endogenously determined. I then perform counterfactual analysis to determine the impact of innovation on the portfolio of technologies offered to consumers, to determine whether products are inefficiently eliminated, and to quantify the impact of innovation on various consumer types. The answers to these questions depend on primitives: the distribution of consumer preferences, the variable and fixed costs incurred by PC makers, and the nature of the supply-side game.

I focus on innovation in the Central Processing Unit (CPU), a crucial PC component which is responsible for all calculations. CPU innovation plays a central role in the PC industry: in addition to directly improving PC performance, faster chips also increase the marginal value of complementary innovations in both software and hardware. The CPU market is controlled by two main vendors: Intel, and its smaller competitor Advanced Micro Devices (AMD). Downstream PC makers (e.g. Dell, Hewlett-Packard (HP), Gateway) purchase these chips and install them in their various PC products.

I model a two-stage game played by PC makers: in the first stage, they face a discrete menu of vertically differentiated CPUs, and simultaneously choose which CPU options to offer with their PC products. While consumer heterogeneity provides incentives to offer vertically differentiated PC configurations, offering each such configuration results in fixed costs. In the second stage,

[1] Pakes [2003] cites an average annual attrition rate of 85 percent.

the chosen configurations are sold to consumers in a simultaneous price-setting game. CPU innovation expands the menu of CPU options, and I use the model to predict the impact of this expansion on both product choices and prices in the PC market.

I use data on PC prices, characteristics and sales to estimate demand and marginal costs for PC products. These estimates reveal producers' variable-profit benefits from offering PC configurations. I also use the observed variation in product offerings to make inference on fixed cost parameters. For example, an observed decision to offer a certain PC configuration implies an upper bound on the fixed costs associated with it. Having estimated both the benefits and the costs which accrue to PC makers from offering PC configurations, I simulate equilibria of the two-stage game to study the impact of innovation.

My estimates imply that the demand for PCs is highly segmented. In particular, strong consumer heterogeneity is detected in price sensitivity, as well as in the degree to which consumer utility from any fixed bundle of PC characteristics falls over time. I find that the *average* willingness to pay for a fixed product falls by $257 every year. I interpret this as evidence that innovation in software drives the average consumer toward being more of an "advanced PC user" over time.[2] Consumers also display a considerable willingness to pay for PC brands, suggesting that product choices by some PC makers can have an important impact on the map from upstream CPU innovation to consumer welfare.

I use the estimated model in counterfactual analysis to study the impact of Intel's introduction of its Pentium M chip, which is considered a landmark in mobile computing. I find that, in the second quarter of 2004, the presence of the Pentium M contributed significantly to the growth of the mobile segment of the PC market. In particular, it boosted notebook sales by 10.9%-18.9% and increased the average notebook price by $32 to $44.

The presence of the Pentium M also led to a significant re-alignment of PC makers' product offerings; while PC configurations based on Intel's Pentium III (and some very fast Pentium 4 chips) were crowded out, other configurations (mostly based on Intel's Celeron and slow Pentium

[2] As discussed below, my sample period was not characterized by significant hardware upgrades driven by a new operating system from Microsoft, so other innovation (e.g. Web applications) is likely to have been the driving force behind this process.

4 chips) were added. The presence of the Pentium M decreased the market share of the Pentium III in the notebook segment from 13.6%-17.6% to merely 2%. Since the bulk of this decrease was due to product elimination, a restricted model which treats only prices (and not product choices) as endogenous significantly understates this effect, underscoring the value of a model with endogenous product choices.

I find that a social planner could improve welfare by adding Pentium III-based configurations to the market, in the sense that the added fixed costs would have been outweighed by the contributions to consumer surplus and to PC makers' variable profit. This suggests that the elimination of the Pentium III was inefficient. On the other hand, the magnitude of this inefficiency appears to be modest, and should be viewed in perspective; the overall effect of the Pentium M was clearly welfare-enhancing, and, in particular, it increased total consumer surplus by 3.3%-5.1%. Moreover, even though it crowded out certain technologies, the impact of the Pentium M on *all* segments of consumer demand was positive. As explained below, certain robustness checks for these results are necessary

**An important caveat: complementary innovation.** While my estimates capture the process by which consumers' utility from a fixed bundle of hardware characteristics falls over time, my framework does not account for the crucial role played by CPU innovation in fostering complementary innovation in software, which fuels this shift in consumer preferences.[3]

My analysis, therefore, does not account for some long-term contributions of CPU innovation to welfare. For example, some basic users may not benefit from the introduction of an advanced chip in 2004. If, however, this innovation facilitates the emergence of new software applications, these basic users may become more advanced users, and benefit substantially from that CPU innovation by, say, 2006. This motivates future quantitative research of dynamic complementarities in innovative activities.[4]

[3]Gawer and Cusumano [2002] describe the manner by which Intel acts to coordinate standards used by hardware and software developers in order to foster complementary innovation, which, in turn, increases the demand for new chips.

[4]See Rosenberg [1979] for a seminal discussion of this issue.

**Multiple equilibria, partial identification, and sample selection.** The paper offers a couple of methodological contributions. First, in contrast to previous work with vertical differentiation (e.g. Mazzeo [2002]), I relax assumptions which guarantee a unique equilibrium outcome. This results in partial identification of fixed costs. Following recent literature, I exploit necessary equilibrium conditions to estimate bounds on the partially-identified parameters.

Second, I allow for a large, discrete product space, which provides a detailed picture of PC product variety. This exacerbates the computational burden associated with simulating sets of counterfactual equilibria, as allowing for $n$ product choices yields $2^n$ feasible vectors of product offerings.[5] I develop techniques which alleviate this burden. The intuition behind these techniques is that, if a firm can profitably deviate by offering an additional product at a given situation, it would have the same profitable deviation when facing fewer competing products.

A difficult challenge tackled in this paper is sample selection, which arises since firms are explicitly assumed to have chosen the set of products observed in the data. This may bias familiar estimators of parameters governing variable profits. I impose a point-identifying assumption, according to which firms commit to product choices before they observe realizations of cost and demand shocks. In an appendix, I consider relaxing this assumption, and show that the selection mechanism itself can be used to generate moment inequalities which provide partially-identifying information on variable profit parameters. Since I have not yet implemented this alternative approach in practical estimation, its discussion should be viewed as preliminary.

**Related literature.** Spence [1976] argues that fixed costs restrict the number and variety of products offered in equilibrium, and that the set of products offered by firms may fail to be socially optimal. The potential for such market failures depends on market-specific parameters, motivating empirical research on the determinants of product variety in specific industries.

Song [2006, 2007], Gordon [2008], and Goettler and Gordon [2008] study the upstream CPU market. These papers assume that the CPU serves as a perfect proxy for the PC. The current

[5] As explained in Section 6, the partial identification implies that I cannot compute the actual set of counterfactual equilibria. Instead, I compute a set of outcomes that cannot be ruled out as equilibria of the game.

paper addresses a different set of questions (i.e., PC product variety), and, as a consequence, develops a very different framework.

A vast industrial organization literature considers estimation of partially-identified models (e.g. Haile and Tamer [2003], Pakes, Porter, Ho and Ishii [2006], Berry and Tamer [2006], Ciliberto and Tamer [2007]). Ishii [2006] estimates a model in which banks choose an integer number of ATM locations. The discreteness of this choice leads to multiple equilibria and partial identification, similarly as in my framework. My focus on product variety, however, implies that I am interested not only in the total number of PC configurations offered by a firm, but also in their type. As a consequence, I consider a vector of product-choice binary indicators for each firm.

Trajtenberg [1989] and Petrin [2002] study the welfare benefits associated with new goods. My work adds to this literature by explicitly modeling the impact of innovation on the entire portfolio of products offered, thus taking into account the lost welfare from eliminated technologies.

The rest of the paper is organized as follows: Section 2 describes the industry and the data used. Section 3 presents the model, and Section 4 discusses identification and estimation. Section 5 reports structural estimation results, while Section 6 addresses the economic question of interest via counterfactual analysis. Concluding remarks are offered in Section 7.

## 2 Data and Industry

The data used in this research come from a number of sources. PC market data is from IDC's Quarterly PC Tracker database. I observe three years of quarterly data (2001Q3-2004Q2) from the U.S. market, including the number of units sold and total dollar value by quarter (e.g. 2002Q3), segment (e.g. Home), vendor (e.g. Dell), brand (e.g. Inspiron), form factor (e.g. Portables), CPU vendor (e.g. Intel), CPU brand (e.g. Pentium 4) and CPU speed range (e.g., 1.0-1.49 GHz) combinations.

As discussed below, the demand model employed in this work assumes that a consumer buys at most one unit of some PC product in a quarter. This is a reasonable assumption for households, but not for commercial PC consumers.[6] I therefore use only the portion of the data which pertains to the Home segment of the market, and, following previous work (e.g. Goeree [2008]), define the size of the market as the number of U.S. households in a quarter, as reported by the U.S. Census Bureau.[7] Since PC makers typically target the Home and Commercial segments with *different product lines*, it is reasonable to study product choices in the Home market separately.[8]

For each observation, I compute the average price by dividing total value by total sales. I convert values to constant dollars using the Consumer Price Index (CPI), reported by the Bureau of Labor Statistics (BLS). I define a product as a unique combination of observed characteristics.[9] After removing observations with negligible market shares (defined as selling less than 100 units in the quarter), I obtain 2,287 observations, each of which is a quarter-product pair.

**The Home PC market**. The sample period corresponds to the early years of Microsoft's Windows XP operating system. Due to modest system requirements, the launch of Windows XP did not prompt widespread hardware upgrades by consumers. This makes the sample period appropriate for the estimation of a model in which the distribution of consumers' willingness to pay for computing power plays an important role.

Sales in the Home segment accounted for about 38% of total U.S. PC sales during the studied period. While many firms operate in this competitive market, some vendors (most notably Dell and HP) enjoy sizable market shares, as reported in Table 1 (see appendix C for all tables and figures). The top 5 vendors together accounted for a 60%-70% share of the market. A similar concentration level is reported by Goeree [2008] for the late 1990s.

The upstream market for CPUs is, by contrast, significantly more concentrated. Table 2 shows that more than 70% of the PCs sold in the Home market had an Intel CPU installed, while slightly over 20% had a CPU from AMD. IBM had a small market share by virtue of making the CPUs

[6] Purchases of the latter were studied by Hendel [1999].

[7] I interpolate linearly between the 2000 and 2004 household totals to obtain quarter-by-quarter figures.

[8] Some overlap exists between these markets, since some "Home" consumers purchase PC products designed for commercial users. I discuss below the steps I take to insulate the analysis of the Home market from such spillover effects.

[9] These definitions follow Goeree [2008]. The data used in that paper has a somewhat similar structure to that used in this paper, in that it also consists of 12 quarters, and has similar observed product characteristics.

used in Apple's computers. I exclude Apple products from the empirical analysis since I do not have processor speed information for them (Apple's market share during the sample period hovered about 3%).

Evidence for the rapid innovation in CPU technology is offered in Figure 1, which depicts the share of various CPU clock speed ranges in the three years of the sample. The market share of CPUs with clock speeds in the 2-2.99 GHz range jumped from merely 5% in the first year of the sample to almost 60% by the second year. In parallel, the share of slower CPUs fell sharply over time.[10] A fundamental force behind CPU innovation has been the ability of manufacturers to double the number of transistors on an integrated circuit every 18-24 months, a regularity known as "Moore's law".[11] As a consequence, chips become smaller, faster, less power-consuming, and cheaper to produce. Lower levels of power consumption played a key role in the growth of the mobile PC segment, while lower CPU production costs contributed (among other forces) to a rapid decline in average PC prices. Both these PC market trends are underscored in Figure 2.

**PC product lines and CPU technologies.** This paper is interested in the portfolio of CPU options offered with PC product lines. I define PC *product lines* as combinations of PC vendor, brand and form factor (e.g. "Dell-Inspiron-Portables"). I define a *CPU technology* as a combination of CPU brand and speed range (e.g., Intel's Pentium 4 1.5-1.99 GHz). Typically, multiple configurations of each product line are observed in the data, each with a different CPU technology installed.

Table 3a reports the rate of adoption of Intel's CPU technologies in Desktop PC product lines.[12] The columns of the table correspond to CPU technologies, and the entries report the fraction of PC product lines in which these technologies were offered. The first column, for

[10] Note, however, that clock speed alone is a poor indicator of CPU performance. CPUs of advanced generations (e.g. Intel's Pentium 4) are differentiated from their predecessors along dimensions other than raw clock speed: they may have more cache memory on board the chip, have better designs, or use more sophisticated algorithms. It is, therefore, important to control for both CPU brand and clock speed to adequately capture CPU performance, and I do so in the empirical application.

[11] The prediction by Intel's Gordon Moore was that the number of transistors on a chip would double and costs would fall by 50% every 18 months (Walters [2001], p.22).

[12] The analysis in this paper is restricted to PC makers' decisions to install Intel's CPUs. An analysis of the variety of AMD chips offered in PCs would be an interesting extension, but would require some careful attention given the asymmetry between the two chip makers.

example, reports the fraction of product lines to adopt Celeron processors with CPU speed in the 0.5-0.99 GHz range. These CPUs were utilized in 89% of product lines in the first quarter, but were rapidly phased out, in parallel to increased adoption of new CPU technologies. Table 3b reports such information for portable PC product lines.

Tables 3a and 3b convey significant variation, in that most CPU technologies are only adopted in a subset of product lines at a given point in time. A substantial amount of this variation, however, is somewhat artificial; first, certain CPUs could not be installed in certain PC product lines due to technical constraints. Second, some PCs with obsolete CPU technologies may be sold in a given quarter, in small amounts, simply because some firm still has them in stock. I describe below how I take such issues into account when defining the feasible set of CPU technologies.

# 3 Model

The primitives of the model are consumer demand for PCs, PC makers' marginal and fixed costs, and the Subgame Perfect Nash Equilibrium (SPNE) concept of a game played by the oligopoly of PC makers. I now describe the model in detail.

## 3.1 Household Demand

Following Berry, Levinsohn, and Pakes [1995] (BLP), and Goeree [2008], the demand for PCs is modeled by a random-coefficient-logit specification. A set $J_t$ of PC products is available for purchase in quarter $t$. Each household chooses at most one of the products in $J_t$, or chooses the outside option of not purchasing any of the PCs offered. The latter option may include buying a used PC, or buying an Apple computer.[13] The household makes the discrete choice that maximizes the following indirect utility function, describing the utility derived by household $i$ from PC product $j$ at time $t$:

[13] Gordon [2008] models the consumer replacement cycle with respect to CPU products. In order to keep the analysis of product variety tractable, my framework abstracts from durable good aspects of the PC. Incorporating such aspects is an important extension.

$$u_{ijt}(\zeta_{it}, x_j, p_{jt}, \xi_{jt}; \theta^d) = \underbrace{x_j\beta + \xi_{jt}}_{\delta_{jt}} + \underbrace{[-\alpha_i \times p_{jt}] + \sum_{k=1}^{K} \sigma^k x_j^k v_i^k}_{\mu_{ijt}} + \epsilon_{ijt} \tag{1}$$

The following notation is used: $x_j$ is a $K$-vector of PC product characteristics observed by the econometrician. In the empirical application, these include a constant term, a laptop dummy variable, and dummy variables for PC brands, CPU brands, and CPU speed ranges. I also include a time trend, which captures the degree to which the utility from fixed PC characteristics changes (falls) over time. $\xi_{jt}$ is a quarter-specific demand shock which is unobserved by the econometrician. The product's price is $p_{jt}$, and $\zeta_{it} \equiv (v_i, \{\epsilon_{ijt}\}_{j \in J_t})$ are household-specific variables: $v_i$ is a $(K+1)$-vector of standard-normal variables (assumed IID across households, as well as across the $(K+1)$ product characteristics, one of which is price), and $\epsilon_{ijt}$ are IID (across households and products) Type-I Extreme Value taste shifters.

I define $\alpha_i \equiv exp(\alpha + \sigma^p v_i^p)$, so that the price sensitivity is log-normal with parameters $(\alpha, \sigma^p)$. The demand parameters are $\theta^d = (\beta', \alpha, \sigma')'$. Note that utility is separated into a mean-utility component $\delta_{jt}$, and a household-specific deviation $\mu_{ijt} + \epsilon_{ijt}$. I further define $\theta_2 \equiv (\alpha, \sigma')'$, and, conditioning on $\delta$, I can write the utility function as $u_{ijt}(\zeta_{it}, x_j, p_{jt}, \delta_{jt}; \theta_2)$.

This specification allows households' taste toward a characteristic $k \in \{1, 2, ..., K\}$ to shift about its mean, $\beta^k$, with the heterogeneous term $\sigma^k v_i^k$. For computational reasons, I restrict many of the $\sigma^k$ to equal zero in the empirical application. I do allow for heterogeneity in price sensitivity, in the taste for portability, in the taste for the outside option, and in the degree to which that taste changes over time. Heterogeneity along these dimensions governs firms' incentives to provide product variety. I define the utility from the outside option by:

$$u_{i0t} = \epsilon_{i0t} \tag{2}$$

The model-predicted market share of product $j \in J_t$ is given by:

$$s_{jt}(x,p,\delta,v;\theta_2) = \int \frac{exp[\delta_{jt} + \mu_{ijt}(x_j,p_{jt},v_i;\theta_2)]}{1+\sum_{m\in J_t} exp[\delta_{mt} + \mu_{imt}(x_m,p_{mt},v_i;\theta_2)]} dP_v(v_i) \tag{3}$$

Where $P_v(\cdot)$ is the joint distribution of the taste shifters $v_i$.

### 3.2 Supply

I assume that, in each quarter, each PC maker is endowed with a pre-determined set of PC product lines. This assumption is justified by the fact that product lines (e.g. "Dell Inspiron Notebook") are typically well-established brands that do not frequently enter or exit the market. PC makers also face a menu of CPU technologies which they can offer with their various product lines. The timeline for a two-stage game, played by PC makers in each quarter, is:

1. PC makers simultaneously choose which CPU technologies to offer with each product line; they incur fixed costs for each such offered configuration.
2. For each PC configuration chosen in Stage 1, PC makers observe realizations of demand and marginal cost shocks that are unobserved by the econometrician; they then simultaneously set PC prices for these configurations.

As discussed below, the assumption that firms learn the realizations of the error terms only after committing to product choices is key to overcoming a sample selection problem. Since I control for brand-specific intercepts (for most brands), these errors should not capture any systematic brand effects that the firms are likely to know prior to committing to their configuration choices.

I now turn to a formal description of the game, beginning with some notation. Denote by $D$ the set of active PC vendors (quarter indices suppressed), and define $S_d$ as the set of product lines for firm $d \in D$. Let $H$ represent the menu of feasible CPU technologies (defined in Section 2 above). Denote by $L_{dm} \subseteq H$ the set of CPU technologies that firm $d$ chooses to offer with product line $m$.[14]

[14] For instance, if $d$ = "$Dell''$", $m \in S_d$ is Dell's "Inspiron" notebook product line, and $L_{dm} = \{$Pentium 4 1-1.49 GHz, Pentium 4 1.5-1.99 GHz$\}$, then Dell has chosen to sell two Inspiron configurations, based on Intel's Pentium 4 CPUs with the specified speed ranges.

**Stage 1**: In this stage, each firm $d \in D$ determines the sets $L_{dm}$ for each product line $m \in S_d$. These decisions are made simultaneously. Collecting all these sets yields the set $J = \{L_{dm}\}_{d \in D,\ m \in S_d}$ of all PC products that would be offered to consumers in the quarter.

Firm $d$ incurs a fixed cost for each offered configuration. These costs may include the fixed costs associated with the physical production of product configurations, the inventory management costs necessary to ensure that the product configuration is in stock, as well as administrative, sales and marketing costs. I assume that the total fixed costs incurred by firm $d$ are given by:

$$F_d = V_d \lambda \times \sum_{m \in S_d} |L_{dm}| \tag{4}$$

where $V_d$ is a vector of firm characteristics, and $\lambda$ is a parameter vector to be estimated. This assumption implies that firm $d$ incurs a constant fixed cost of magnitude $V_d \lambda$ for each configuration, such that its total fixed costs are proportional to the total number of configurations offered. This assumption could be relaxed to capture economies (or diseconomies) of scope. $V$ may include a constant and PC maker dummies (which capture systematic firm heterogeneity in fixed costs). The results reported in this paper are based on a simple specification for $V$ which includes a constant, and a dummy variable which receives the value 1 for major producers.

**Stage 2.** I let the log of marginal costs for a PC product $j \in J$ depend linearly on observed cost shifters, $\mathrm{w}_j$, and on an additive error term $\omega_j$:[15]

$$log(mc_j) = \mathrm{w}_j \gamma + \omega_j \tag{5}$$

In the beginning of Stage 2, firms observe realizations of $e_j = (\xi_j, \omega_j)'$ for each $j \in J$, i.e., for each configuration chosen for production in Stage 1 (to re-iterate, these are demand and marginal cost shocks that are unobserved by the econometrician, and appear in (1) and (5) above).

[15]In the empirical application I set $\mathrm{w}_j = x_j$, i.e., I let the same observed characteristics shift both utility and marginal cost. Note that the CPU price, charged by Intel or AMD, is a component of PC marginal costs. As a consequence, the $\gamma$ coefficients on CPU brand and speed provide reduced-form evidence with respect to the manner in which CPU prices vary with such attributes.

After observing these shocks, firms simultaneously set prices for products $j \in J$ to maximize profits. Firm $d$'s profits are given by:

$$\pi_d = \sum_{m \in S_d} \sum_{\ell \in L_{dm}} [p_{m\ell} - mc_{m\ell}] s_{m\ell}(p) \times M - F_d \tag{6}$$

where $p_{m\ell}, s_{m\ell}$, and $mc_{m\ell}$ are the price, market share and the (assumed constant) marginal cost associated with configuration $\ell$ of product line $m \in S_d$. $M$ is market size, $p$ is a $|J|$-vector of prices, and $F_d$ is firm $d$'s total fixed cost, specified in (4) above.

I assume that, given any Stage 1 history (and any parameter values), Stage 2 prices are uniquely determined in a pure-strategy, interior Nash-Bertrand price equilibrium.[16] Arranging products in a $|J|$-dimensional vector, equilibrium prices satisfy a vector of first-order conditions:

$$p - mc = (T * \Delta(p; \theta_2))^{-1} s(p) \tag{7}$$

where $T$ is a $|J| \times |J|$ PC product ownership matrix (i.e., $T_{i,j}$=1 if $i, j$ are produced by the same PC vendor, and is equal to zero otherwise), $\Delta_{i,j}$ is the derivative of the market share of product $j$ with respect to the price of product $i$, and * represents element-by-element multiplication. It is easy to show that the share derivatives depend on the non-linear demand parameters $\theta_2$.

**Solution Concept and Multiple Equilibria**. A Subgame Perfect Nash Equilibrium consists of product choices and prices $(J, p(J))$ which constitute a Nash equilibrium in every subgame. As explained above, I assume that Stage 2 prices $p(J)$ are set in a unique Nash-Bertrand equilibrium. In addition, I assume the *existence* of a pure-strategy SPNE for the two-stage game. I do not, however, assume *uniqueness* of the SPNE.

To gain intuition regarding the potential for multiple equilibria, consider the following simple example: suppose we have only two heterogeneous PC makers, each with a single product line. We may have one equilibrium in which only firm A caters to the value segment of the market by

[16] This is a standard assumption (e.g. Nevo [2001]). The results of Caplin and Nalebuff [1991] guarantee a unique price equilibrium under stronger restrictions than those imposed here.

offering a PC configuration with a slow CPU installed, and a second equilibrium, in which only firm B chooses to do so.

Finally, recall that even though period indices were suppressed for convenience, the two-stage game is assumed to be played in every quarter. This frequency is justified by the rapid entry and exit of products in the PC market.

## 4 Identification and Estimation

The parameters to be estimated are the demand parameters $\theta^d = (\beta', \alpha, \sigma')'$, the marginal cost parameters $\gamma$, and the fixed cost parameters $\lambda$.

Let $\theta = (\theta_d', \gamma')'$. The estimation strategy employed obtains an estimate of $\theta$ first, revealing information on variable profits associated with product configurations. Given the estimate $\hat{\theta}$, necessary equilibrium conditions are used to estimate bounds on the fixed cost parameters $\lambda$. These tasks are taken in turn in sub-sections 4.1 and 4.2 below.

### 4.1 Identification and Estimation of $\theta = (\beta', \alpha, \sigma', \gamma')'$

Intuitively, the demand parameters are identified from the joint distribution of prices, sales, and observed PC characteristics. Marginal cost parameters $\gamma$ are identified as follows: the pricing FOCs in (7) identify markups, allowing us to identify marginal costs as the difference between observed prices and these markups. The co-movement of these identified marginal costs with PC characteristics identifies $\gamma$.

Identification of $\theta$ is jeopardized, however, by sample selection, as the set $J$ of product configurations offered to consumers was selected by firms. The econometrician, therefore, does not observe a random sample from the underlying distribution of product characteristics. In this section, I describe a standard approach which allows point-identification of $\theta$. It also allows me to consistently estimate $\theta$ following the BLP method, and these estimates are reported in Section 5 below. In Appendix B I describe an alternative approach which relaxes the point-identifying assumptions for $\theta$.

The intuition for the point-identification approach is that, under the assumption that firms do not observe the error terms $e_j = (\xi_j, \omega_j)'$ until after they have selected their products, the selection does not depend on unobservables, and is therefore "ignorable".[17] Stating the point-identifying conditions requires a bit more notation. Let us collect all firms' product lines in the set $P = \{S_d\}_{d \in D}$. Denote by $\mathbf{J}$ the set of all $|H| \times |P|$ *potential* product configurations. It is from this set that firms pick, in Stage 1, the subset $J \subseteq \mathbf{J}$ actually offered to consumers. Let $X$ denote a $|\mathbf{J}| \times K$ matrix of product characteristics for all potential products, and let $F$ denote the fixed costs of all PC makers. I make the following assumption:

**Assumption 1.** $E[e_j|X, F] = 0$ *for each* $j \in \boldsymbol{J}$

Assumption 1 is very similar to the mean-independence assumption made by BLP, except that the relevant population here is that of all potential PC configurations, rather than the sub-population of products actually offered to consumers.

For each potential product configuration $j \in \mathbf{J}$, I define a selection indicator, $q_j(X, F)$, equal to 1 if $j$ was chosen for production, and equal to zero otherwise. This indicator does not depend on the error terms $e_j$ because firms do not know these values when making their Stage 1 product choices. This allows for a standard identification approach: let $z_j(X)$ be a $1 \times L$ vector of instrument functions pertaining to product $j$, where $L \geq dim(\theta)$. By application of the Law of Iterated Expectations, and using Assumption 1, we obtain:

$$E\big[q_j(X, F)e_j z_{j\ell}(X)\big] = 0 \text{ for } \ \ell = 1, ..., L \tag{8}$$

BLP show that a generic value for the parameter $\theta$ implies a unique solution $e_j(\theta)$ for each observed product $j \in J$. As a consequence, as long as $Pr[q_j = 1] > 0$, condition (8) implies:

$$E\big[e_j(\theta_0) z_{j\ell}(X)\big|q_j = 1\big] = 0 \text{ for } \ \ell = 1, ..., L \tag{9}$$

where $\theta_0$ is the true parameter value. Equation (9) defines $L$ moment conditions that provide

[17] See Wooldridge [2000], ch. 17, for a general discussion of the implications of selection mechanisms which depend on variables observed by the econometrician.

point identification of $\theta$.[18] Notice that we overcome the selection problem by obtaining a moment condition that is defined over observed products only. GMM estimation of $\theta$ using the moment conditions (9) follows the BLP method. Additional details regarding this estimation procedure are provided in Appendix A.1.

Since firms observe the errors $e$ before setting prices, it is necessary to account for price endogeneity. In choosing the instruments $z_j(X)$, I follow Berry [1994] and BLP by using variables that should be correlated with markups, and, therefore, with prices. In addition to the $x_j$ vector of PC characteristics, I use the number of product lines for both the vendor and competitors in various data cells (e.g., formfactor-speed cells), the number of competitors' Celeron-based configurations, the squared time trend, and the ratio of average rivals' speed to vendor's average speed.[19] I also use interactions of observed PC characteristics (laptop, Pentium and Celeron dummy variables) with a time trend to obtain additional instruments. These terms can be viewed as cost shifters excluded from the demand side, since they capture the decrease in the marginal costs of providing these PC characteristics over time.

Finally, note that this identification strategy for $\theta$ relies heavily on the assumption that firms observe the errors $e_j$ only after committing to product choices. In the absence of this assumption, the selection indicator $q_j(\cdot)$ would depend on these errors, and, as a consequence, condition (8) could fail. Appendix B offers the details of an alternative identification strategy which relaxes this assumption. I show that, given a parameter value $\theta$, bounds can be placed on the $e_j$ error terms associated with products that firms chose *not to offer*. This allows me to construct moment inequalities that are defined over the entire set $\mathbf{J}$ of *potential* products. This alternative strategy should be viewed as preliminary as I have not implemented it yet in practical estimation.

### 4.2 Identification and Estimation of the Fixed Cost Parameters $\lambda$

Given the point estimate $\hat{\theta}$ obtained in section 4.1, a set estimate can be obtained for $\lambda$. I assume that the product choices and prices observed in the data constitute an SPNE of the two-stage

[18] Additional regularity conditions are necessary for a formal identification argument.
[19] For the purpose of constructing this instrument I compute speed as the middle of the relevant speed range.

game. A necessary equilibrium condition is, then, that no firm could increase its expected profit by unilaterally altering its first-stage product choices, taking into account the impact of that deviation on second-stage prices (the simultaneous-move nature of the first stage implies that the firm need not consider an impact of its deviation on rivals' *product choices*). Such conditions imply bounds on expressions involving fixed cost parameters.[20] For example, to ensure that a deviation which eliminates a product is not profitable, the firm's savings of fixed costs must not exceed its expected losses of variable profit.

I let the vector $A_d$ denote firm $d$'s observed product choices. Each entry in this vector is a binary variable, which takes the value 1 if the relevant product configuration is chosen for production. Since firm $d$ may have more than one product line (i.e. the set $S_d$ may not be a singleton), the typical form of this vector is:

$$A_d = \Big\{ \underbrace{0\ 1\ 1\ 0\ 1}_{\text{Product Line 1}} \ , \ \underbrace{1\ 1\ 0\ 1\ 1}_{\text{Product Line 2}} \ , \ \ldots \Big\}$$

I define the sets $A_d^1 = \{k : A_d(k) = 1\}$ and $A_d^0 = \{k : A_d(k) = 0\}$, which collect the indices in $A_d$ corresponding to products offered and not offered in the observed sample, respectively.

**Upper and lower bounds on $V_d\lambda$.** Recalling that firm $d$'s per-configuration fixed costs are given by $V_d\lambda$, upper bounds can be placed on this quantity at the true parameter values:

$$V_d\lambda_0 \le E_{(e|\theta_0)}\Big[VP_d(A_d; e, \theta_0) - VP_d(A_d - \mathbf{1}_d^k; e, \theta_0)\Big] \equiv U_{d,k}(\theta_0), \qquad \forall k \in A_d^1 \tag{10}$$

where $\mathbf{1}_d^k$ denotes a vector of the same length as $A_d$ which $k^{th}$ entry is equal to 1, and all its other entries are equal to zero. $VP_d(\cdot)$ denotes the variable profit firm $d$ garners as a consequence of choosing various product portfolios (taking into account the impact of such portfolios on second-stage prices). $E_{(e|\theta_0)}$ denotes the firm's expectation over the true joint distribution of the error terms associated with all products. This notation reflects the fact that this distribution is

[20] See cf. Berry and Tamer for a discussion of the use of necessary equilibrium conditions in the context of partially-identified entry models.

indexed by the parameter $\theta$ (see Appendix A.2).

In words, condition (10) states that a deviation by firm $d$ which eliminates one of its observed products must not be profitable. To ensure that, firm $d$'s savings in fixed costs cannot exceed the expected drop in its variable profit.

An analogous argument generates lower bounds by considering deviations in which the firm adds a product configuration. In this case, the necessary equilibrium condition requires that the added fixed costs must exceed the expected variable profit gains:

$$V_d\lambda_0 \geq E_{(e|\theta_0)}\Big[VP_d(A_d + \mathbf{1}_d^j; e, \theta_0) - VP_d(A_d; e, \theta_0)\Big] \equiv L_{d,j}(\theta_0), \qquad \forall j \in A_d^0 \tag{11}$$

**Using the bounds on $V_d\lambda$ to estimate $\lambda$.** Following Haile and Tamer [2003], it is possible to apply the techniques of Manski and Tamer [2002] and estimate the fixed cost parameters $\lambda$ by means of minimizing a random criterion function which penalizes violations of the bounds on $V_d\lambda$ generated in (10) and (11):

$$\begin{aligned} Q_{|\mathbf{J}|}(\lambda) = \sum_{d \in D}\Bigg[ & \sum_{k \in A_d^1} (V_d\lambda - \hat{U}_{d,k}(\hat{\theta}))^2 \mathbf{1}\{V_d\lambda > \hat{U}_{d,k}(\hat{\theta})\} \\ & + \sum_{j \in A_d^0} (\hat{L}_{d,j}(\hat{\theta}) - V_d\lambda)^2 \mathbf{1}\{\hat{L}_{d,j}(\hat{\theta}) > V_d\lambda\}\Bigg] \end{aligned} \tag{12}$$

where $\mathbf{1}$ is the indicator function, and $\hat{L}_{d,j}(\hat{\theta})$ and $\hat{U}_{d,k}(\hat{\theta})$ are estimates of the bounds $L_{d,j}(\theta_0)$ and $U_{d,k}(\theta_0)$. The computational details associated with estimating these quantities are provided in Appendix A.2 (this estimation requires simulating the expectations which appear in (10) and (11) by drawing from an empirical distribution of $e$ given $\hat{\theta}$, and, at each such draw, computing price equilibria which would prevail under the observed action, and under the deviation). As explained in cf. Haile and Tamer, to improve the finite-sample properties of this procedure, one should obtain a set estimate of $\lambda$ by considering all values of these parameters which minimize

$Q_{|\mathbf{J}|}(\lambda)$ up to a tuning parameter which converges to zero as the sample size increases.[21]

Finally, note that the estimation results for $\lambda$ currently reported in Section 5 below were not obtained by minimizing the objective in (12) but by following a simple, heuristic approach: I searched for the values of $\lambda$ which made the condition $V_d\lambda \leq \hat{U}_{d,k}(\hat{\theta})$ hold on average across all $d \in D,\ k \in A_d^1$, and at the same time made the condition $V_d\lambda \geq \hat{L}_{d,j}(\hat{\theta})$ hold on average across all $d \in D,\ j \in A_d^0$. In words, the estimated set for $\lambda$ consists of the parameter values which make $V_d\lambda$ respect both the upper bounds and the lower bounds *on average*.

**Additional restrictions implied by the model.** Necessary equilibrium conditions could be used to obtain additional information on the model's parameters. The results reported in Section 5 below *do not* make use of such additional information. First, additional bounds on $V_d\lambda$ can be generated by considering more complex deviations. For example, a deviation in which two observed products are eliminated, and one unobserved product is introduced would provide an upper bound on $V_d\lambda$.

Second, additional information on $\theta$ (on top of the point-identifying information described in sub-section 4.1 above) can be obtained by considering a deviation in which the firm eliminates an observed product located at $k$ and launches an unobserved product located at $j$ instead. This deviation does not alter total fixed costs (see (4) above). Requiring that such deviations are not profitable yields the following conditions:[22]

$$E_{(e|\theta_0)}\left[VP_d(A_d; e, \theta_0) - VP_d(A_d + \mathbf{1}_d^j - \mathbf{1}_d^k; e, \theta_0)\right] \geq 0, \quad \forall d \in D,\ j \in A_d^0,\ k \in A_d^1 \qquad (13)$$

[21] Working out the properties of this estimator in the current context is a work-in-progress.

[22] In Appendix B I show that a similar condition to (13) facilitates partial identification of $\theta$ even if we relax the assumption that firms observe the shocks $e$ only after committing to product choices.

# 5 Estimation Results

Section 5.1 below reports estimation results for $\theta$, beginning with descriptive results based on the simple logit demand model, and continuing with BLP estimation results for the full model described in Section 3. Section 5.2 provides estimated bounds on fixed cost parameters.[23]

## 5.1 Estimation Results: Demand and Marginal Cost Parameters $\theta$

It is instructive to begin with a simple, descriptive outlook on the demand system. Table 4 reports demand estimation results based on the simple logit model, which is obtained from the demand model described in Section 3.1 by setting all the $\sigma$ coefficients to zero, so that consumer heterogeneity is only allowed via the additive IID $\epsilon_{ijt}$ term. Estimation is performed via linear regressions following Berry [1994]. The first column provides OLS estimates of the mean utility parameters $\beta$, while the second column employs 2SLS to account for the endogeneity of price using the instruments described in Section 4.1 above.

These results demonstrate the importance of correcting for price endogeneity. While demand is downward-sloping in both specifications, the price sensitivity coefficient is much larger (in absolute value) in the IV case. The results suggest that households value CPU speed as well as high-end CPU brands (the omitted CPU brand is Intel's Celeron). The taste for portability appears negative and insignificant, a point to which I return below. The negative sign on the time trend reflects the fact that a fixed bundle of characteristics becomes obsolete over time, most likely due to the emergence of advanced software applications which require better hardware.

**BLP estimation results for $\theta$.** By contrast to the simple logit model, the random-coefficient demand model described in Section 3 allows for more realistic substitution patterns (see the discussion in BLP), and captures consumer heterogeneity along important dimensions. Tables 5a and 5b provide estimation results for $\theta$ obtained by following the BLP estimation procedure.

[23]Some robustness checks are still needed with respect to the results reported. First, somewhat (but not dramatically) different estimates obtain for different starting values. Second, potential measurement error could stem from the fact that, in some cases, observations pertaining to the same PC vendor and quarter report identical unit sales.

Table 5a reports the estimated coefficients on main PC characteristics, while Table 5b reports estimated coefficients on a large number of dummy variables for PC vendors and brands. Economic implications of these estimates are offered in Table 6. The estimated parameters include mean utility parameters ($\beta$), parameters which capture heterogeneity in household tastes ($\sigma$), marginal cost parameters ($\gamma$), and the parameters of the distribution of price sensitivity.

The results in Table 5a reveal precise estimates of both the mean ($\alpha$) and the variance ($\sigma^p$) parameters of the log-normal price sensitivity. As in the simple logit results, households value CPU speed, as well as CPU brands, and these effects are very precisely estimated. The mean taste for laptop products is negative and imprecisely estimated, but significant heterogeneity in this taste is captured by the precisely-estimated $\sigma$ coefficient on the laptop dummy. Heterogeneity along this dimension is to be expected.

As in the simple logit results, the negative $\beta$ coefficient on the time trend implies that a fixed bundle of characteristics is becoming obsolete over time. The random-coefficient model allows me to precisely estimate, in addition, the degree of household heterogeneity in this important effect. I return to this issue below in the discussion of the quantitative economic implications of the estimated coefficients.

The marginal cost coefficients $\gamma$ are all very precisely estimated and economically reasonable. Producing a laptop is found to be 31.2% more expensive than producing a Desktop. Installing an Intel Pentium 4 instead of a Celeron CPU drives PC marginal costs up by a similar magnitude of 30.5%. The negative coefficient on the time trend implies that PC marginal costs fell at a rate of 9% per quarter. This is consistent with the sharp decline in PC prices depicted in Figure 2.

Table 5b reports a large number of estimated coefficients on dummy variables for PC vendors (e.g. Dell) and their various brands (e.g. Inspiron). Importantly, the coefficient on a given vendor dummy captures the effect of brands of that vendor which were not included, and not an "overall" vendor effect. Most of the effects are very precisely estimated. Controlling for brand and vendor information is useful, as these should be strongly correlated with unobserved quality. Moreover, had I not controlled for these brand effects, they would have showed up in the error terms $e_j$. This would have made it less reasonable to assume that firms do not observe these errors until after they have committed to their configuration choices.[24]

Table 6 offers an insight into some important economic implications of the estimated coefficients. Panel A of this table reports the willingness of the average household to pay for various product characteristics. The average household is willing to pay up to \$150.1 to upgrade from CPU speed in the 2-2.99 GHz range to the next speed range, 3-3.99 GHz. It is also willing to pay up to \$171.5 for an upgrade from the Intel Celeron to the Intel Pentium 4 brand, and up to \$447.3 for an upgrade to Intel's Pentium M.

These are considerable amounts, suggesting that CPU characteristics are important to the average PC consumer. Recall also that an entire distribution of these figures was actually estimated. One would expect some consumers (e.g. gamers, engineers) to be willing to pay much more than the average consumer for a better CPU. Figure 3 plots the estimated distribution of households' willingness to pay for an upgrade from Intel's Celeron to its Pentium M brand and reveals significant heterogeneity along this dimension.

Households are also willing to pay considerable amounts for a familiar PC brand name. The average household is willing to pay \$107.8 to upgrade from a non-branded notebook computer to Dell's Inspiron brand, and \$462.1 for IBM's ThinkPad A series. These results indicate that downstream PC makers possess powerful brand names, suggesting that their product choices may have an important impact on welfare.

An important aspect of PC demand is the pace at which households' utility from a fixed bundle of PC characteristics drops over time, as captured by the taste parameters associated with the time trend. Table 6 reports that the average household is "willing to pay" a negative amount of \$(-257) for a passing of one year. This means that, *holding everything else equal*, the average household's willingness to pay for fixed hardware drops by this amount every year, presumably since new software applications require better hardware over time. A sizable household heterogeneity along this dimension is displayed in Figure 4. Such heterogeneity is to be expected (for

[24] I do not, however, control for every brand, but rather for a large number of them.

example, a gamer's utility from a fixed PC product may drop much faster than that of a basic user).

To summarize, a key finding stemming from the estimated demand parameters is that households display strong heterogeneity in price sensitivity, as well as in the rate at which products become obsolete from their point of view. This heterogeneity affects both PC makers' incentives to offer vertically-differentiated product configurations, and the welfare implications of such product choices.

Panel B provides some additional economic implications of the BLP estimates for $\theta$. The median markup for a PC manufacturer is \$76.4, and the median price-cost margin (markup as a percentage of price) is 7.8%. As expected, markups are positively and strongly correlated with prices. Another intuitive finding is the positive correlation between the estimated demand and cost-side errors, $\xi_j(\hat{\theta})$ and $\omega_j(\hat{\theta})$.

### 5.2 Estimation Results: Fixed Cost Parameters $\lambda$

Bounds on fixed cost parameters were estimated as explained in section 4.2 above.[25] The results below are based on constructing bounds on fixed costs associated with offering product configurations of portable product lines in the last quarter of my sample (2004Q2). The estimated fixed costs should, therefore, be interpreted as associated with offering notebook PC configurations in that quarter.[26]

As a first step, it is necessary to determine the set $H$ of CPU technologies available in 2004Q2. As reported in Table 3b, many CPU technologies were installed in PCs sold in this quarter. Some of these, however, were highly obsolete technologies that accounted for very modest sales. Such technologies probably recorded positive sales due to dynamic inventory issues (e.g., some retailer clearing a small stock of obsolete PCs). While data limitations prohibit me from directly addressing such issues, I do not want my fixed cost estimates to be biased by such scenarios, and I therefore include in the set $H$ only CPU technologies that appear to have been installed in a

[25] Recall from that discussion that the results reported are based, at this point, on the heuristic approach which requires the various upper and lower bounds on the per-configuration fixed costs to hold *on average*.

[26] As explained in Section 6 below, the counterfactual analysis focuses on notebook product offerings in the same quarter.

significant number of PC products, and have generated significant sales:[27]

$$H = \left\{ \mathbf{C}\_1.5{-}1.99,\ \mathbf{C}\_2{-}2.99,\ \mathbf{P4}\_1.5{-}1.99,\ \mathbf{P4}\_2{-}2.99,\ \mathbf{P4}\_3{-}3.99,\ \mathbf{Pm}\_1{-}1.49,\ \mathbf{Pm}\_1.5{-}1.99 \right\}$$

where **C, P4** and **Pm** stand for Intel's Celeron, Pentium 4 and Pentium M brands, respectively, and the number ranges pertain to clock speed (e.g., **C**_1.5-1.99 are Celeron chips with clock speed between 1.5-1.99 GHz). I also applied some refinements to the set of portable product lines considered for generating bounds on fixed costs. I excluded some product lines that either primarily targeted the commercial PC market, or could not install certain CPU technologies due to technical constraints, in cases where I was aware of such issues.[28]

I report the estimation results for $\lambda$ in Table 7. Specification (a) includes only a constant term, and specification (b) allows for both a constant, and a dummy variable for manufacturers which produce a large volume of notebooks. Including only a constant in $V$ amounts to assuming that the per-configuration fixed costs are the same for all firms, and the estimated set for these costs is the interval $[1,165,999,\ 1,506,040]$ (\$). Specification (b) implies that this cost is in the $[1,170,000,\ 2,270,000]$ interval for major notebook producers and in the $[980,000,\ 1,500,000]$ interval for other notebook producers.

# 6 Using the Estimated Model: Counterfactual Analysis

In this section I analyze the impact of Intel's introduction of its Pentium M processor, which is considered a major innovation in mobile computing. Sub-section 6.1 provides some background and a description of the counterfactual experiment, while sub-section 6.2 provides the empirical results. Some important robustness checks for these results are needed.[29]

[27]Robustness checks and further refinement of these judgment calls are necessary.

[28]The judgment calls I made in this respect require some additional refinement. An additional issue is that, as explained above, I exclude products which sold less than 100 units in a quarter from the sample due to computational reasons, and I also consider such a product as "not offered" for the purpose of constructing bounds.

[29]In particular, updating the heuristic estimation results for the fixed cost parameters by minimizing the objective function in (12) is likely to impact the results of the counterfactual analysis.

## 6.1 The Impact of Intel's Pentium M: Background and Explanation of the Counterfactual Analysis

Rather than offering a further increase in clock speed, Intel's Pentium M chip introduced major improvements in chip design that allowed chips to achieve top performance at modest clock speeds. This resulted in a substantial reduction in power consumption and in longer notebook battery life.[30] Pentium M-based notebooks appear in the sample for the first time in the first quarter of 2003 (see Table 3b). The goal of my analysis is to answer the following questions: (1) what was the impact of the Pentium M's presence on product choices and prices in the notebook segment? (2) what was the impact of this innovation on various consumer types? and (3) did the Pentium M crowd out PC configurations based on older technologies, and, if so, was the elimination of such technologies socially efficient?

Looking at the data, one can observe that the introduction of the Pentium M was accompanied by a gradual exit of older Intel mobile CPUs such as the Pentium III. In the last sample period, i.e., the second quarter of 2004, only 2% of notebooks sold were Pentium III-based.[31] Among the five top-selling notebook product lines (i.e., notebook brands) in that quarter, only one recorded positive sales of a Pentium III-based configuration.[32] In the quarter immediately preceding the Pentium M's introduction, however, Pentium-III based notebooks enjoyed a market share of 14.1%, and were offered by the two top-selling brands. While this could suggest that the Pentium M played a key role in the elimination of the Pentium III, a more careful analysis is required in order to isolate the effect of the Pentium M's presence from the many other forces that operated in the market between 2003Q1 and 2004Q2.

To identify the effect of the Pentium M on product offerings and prices in the PC market, I perform the following counterfactual analysis for the 2004Q2 period: I remove the Pentium M chips from the set $H$ of CPU technologies available for installation. Then, I use the estimated model to compute the set of PC configurations, and PC prices, that would have prevailed in the

[30] "Bigger Notebooks Still Using Older Mobile Chips", Tom Krazit, IDG News Service September 28, 2004.

[31] Excluding Apple products, PCs with CPUs not made by Intel or AMD, and products with negligible sales.

[32] That configuration had very small sales, and it is possible that it recorded positive sales simply because a small remaining stock was cleared.

market in the absence of the Pentium M. Comparing these predictions to the observed outcomes provides a measure of the Pentium M's effect. Since I am especially interested in the effect of the Pentium M on the Pentium III, I include in the set $H$ a Pentium III option with speed in the 1.5-1.99 GHz range.[33] This allows me to ask how many Pentium III-based PC configurations would have been offered *in the absence of the Pentium M.*

For computational reasons, I focus my analysis on configuration choices by the five top-selling notebook brands in 2004Q2. This means that I only allow product configuration choices that pertain to these notebook brands to vary in the experiment. At the same time, *all* PC products (notebooks and desktops) are included in the experiment and their prices are treated as endogenous.[34]

Importantly, the Pentium M's market share in the notebook segment reached 31.8% by 2004Q2. This makes its analysis interesting at that point in time; an earlier analysis, at a point when this chip was making more modest sales, would have been of limited interest.

**Computing "potential equilibria".** We are interested in the set of SPNE outcomes of the two-stage game under the "no Pentium M" scenario. No equilibrium selection mechanism is imposed. Instead, I would like to compute the set of counterfactual equilibria, and use this set to place bounds on welfare predictions. What I actually compute, however, is the set of outcomes *that cannot be ruled out* as equilibria of the game. The reason for this approach is the partial identification of the fixed costs, which implies that it is not always possible to unambiguously rule out a particular outcome as an equilibrium.

Recall that $A_d$ was used to denote a vector of binary indicators describing the observed product choices of firm $d \in D$. I will now use this notation more generally to describe product choices by firm $d$ (not necessarily the observed ones). Let $A = \{A_d\}_{d \in D}$ be a long vector which describes product choices by all firms, and let $\mathbf{A}$ be the set of all such vectors. The set $\mathbf{A}$ has $2^{|A|}$ elements.

[33] This is the fastest Pentium III chip observed in a mobile PC in the sample. It was actually offered in a handful of PC product lines only. To clarify: the set $H$ in this experiment is obtained from that described in Section 5.2 above by removing the Pentium M technologies and adding the Pentium III 1.5-1.99 GHz technology.

[34] The brands with respect to which I allow configuration choices to vary accounted for 73% of notebook sales in the quarter.

I define the subset $A^e \subseteq \mathbf{A}$ as the collection of product choice vectors that can be supported in an SPNE of the two-stage game.

In order for a vector $A$ to be an element of $A^e$, it must be the case that no firm has a unilateral, profitable deviation from $A$. Fixed costs, however, are only partially-identified, and so is the profitability of deviations. As a consequence, it may not be possible to unambiguously determine whether $A \in A^e$. To deal with this issue, I define a set $A^{pe} \supseteq A^e$ which contains all elements $A \in \mathbf{A}$ that cannot be unambiguously ruled out as elements of $A^e$. Once the set $A^{pe}$ is computed, I can compute welfare measures at each of its elements, and use this information to place bounds on the counterfactual welfare predictions.

Computation of the set $A^{pe}$, which I refer to as the set of "potential equilibria," is a very difficult computational task: in principle, one has to check for profitable deviations from each of the $2^{|A|}$ vectors in $\mathbf{A}$. I allow for six CPU options and five PC product lines, and so $|A| = 30$. I reduce this number to 24 by requiring that a firm which owns two of the five brands makes the same configuration portfolio choice on both. This leaves me with the task of evaluating $2^{24}$ vectors (with each such evaluation requiring computation of the price equilibria that prevail under the various product-choice deviations). I was able to significantly reduce the computational burden by application of the following conjecture:

**Conjecture 1.** *(Strategic Substitutes): The increase in firm $d$'s variable profit from adding a product configuration at $A = (A_d, A_{-d})$ is at least as large as at $(A_d, A^*_{-d})$ where $A^*_{-d} \geq A_{-d}$*

where $A_{-d}$ denotes product choices by firm $d$'s competitors, and $A^*_{-d} \geq A_{-d}$ implies element-by-element inequality. Conjecture 1 is very intuitive: it suggests that the benefit from adding a product configuration is lower when the firm faces more competing products.[35] The usefulness of this conjecture is in that, once a certain element of $\mathbf{A}$ is ruled out as a "potential equilibrium," many other vectors can be automatically ruled out as well. This allowed me, in practice, to evaluate $16,384$ vectors rather than $2^{24} = 16,777,216$, resulting in an immense reduction in

[35]This conjecture is difficult to prove. I did, however, test it directly in more than 20,000 simulations, and found that it was validated in each of them.

computation time.[36]

The results reported below were obtained by setting the shocks to mean utilities and marginal costs $e_j$ at their mean of zero when evaluating the profitability of deviations. In fact, to be consistent with the model, I should have simulated firms' expected variable profits by drawing from the distribution of the error terms, as I did in the estimation of the fixed costs. The results reported below should, therefore, be viewed as preliminary and I plan to improve on this in future versions.

### 6.2 Counterfactual results

I now report the results obtained from the counterfactual experiment which, as explained in subsection 6.1 above, evaluates the impact of the presence of the Pentium M in 2004Q2 by removing it from the market, computing the counterfactual market outcomes, and then comparing these to the observed outcomes. I answer, in turn, the three questions stated above: what was the Pentium M's impact on product choices and prices? What was its impact on various consumer types? and finally, did it prompt an inefficient elimination of products?

**1. The Pentium M's impact on product offerings and prices**. Table 8 reports that the presence of the Pentium M boosted total notebook sales by 10.9% to 18.9%. Some of this growth came at the expense of Desktop sales, which were depressed by 1.6% to 2.6%. This high-quality chip also increased the sales-weighted average notebook price by \$32 to \$44. These findings reveal that the Pentium M made a significant contribution to the growth of the mobile market segment.

Table 8 continues to report the impact of the presence of the Pentium M on the product configurations offered by the five top-selling notebook product lines. The Pentium M "crowded out" between 2 and 4 such configurations based on Intel's Pentium III with speed in the 1.5-1.99 GHz range, and between 1 and 3 configurations based on Intel's Pentium 4 in the 3-3.99 GHz

[36] Total run time for the Matlab code was about 13 hours on a Desktop PC with an Intel Quad Core processor.

range. The latter technology was a rather direct competitor for the Pentium M in the high-end notebook market. This product elimination was also accompanied by more intense offerings of PC configurations based on Intel's Celeron and slower Pentium 4 chips. The presence of the Pentium M, therefore, has led to a major re-alignment of PC makers' product offerings.

The presence of the Pentium M decreased the total market share of Pentium III chips in the notebook segment from 13.6%-17.6% to merely 2%.[37] The bottom panel of Table 8, therefore, reports that the Pentium M decreased the Pentium III's share by 11.6 to 15.6 percentage points. The analysis, therefore, reveals that the Pentium M played a key role in the elimination of the Pentium III technology.

Since most of the effect of the Pentium M on the Pentium III's share was due to product elimination, a more traditional model which treats only prices - and not product choices - as endogenous would have significantly understated this effect. To see this, I predicted the counterfactual share of the Pentium III using a restricted analysis, which simply removes Pentium M-based PCs from the sample, and calculates a counterfactual price equilibrium. This restricted analysis finds that, in the absence of the Pentium M, the Pentium III's share would have been only 3.3%, which would imply that the Pentium M's effect on the Pentium III's share was only (-1.2) percentage points - a much more modest prediction than the (-11.6) to (-15.6) percentage points reported by the full model. This stark difference in predictions demonstrates the importance of accounting for endogenous product choices.

**2. The Pentium M's impact on various consumer types**. Table 9 reports that the Pentium M made a significant contribution to total consumer surplus, boosting it by 3.3% to 5.1%. These benefits were not evenly distributed among different consumer types: the vast majority of the benefits were garnered by the 20% least price sensitive consumers.

Since some basic PC configurations were crowded out by the Pentium M, we may wonder if some consumers were actually hurt by this innovation. The table reveals, however, that no such

[37] This includes all Pentium III chips, and not just those at the 1.5-1.99 GHz range.

effect is observed: the effect of the Pentium M on the surplus garnered by households in *each* of the quantiles of price sensitivity was positive. This could be explained by the fact that the new technology induced a competitive pressure that acted to decrease the prices of notebooks carrying other technologies (as well as by the finding that the Pentium M actually "crowded in" some basic notebook configurations, e.g. those with slow Pentium 4 chips, as explained above). Moreover, recall from the introduction that some long-run benefits to consumers from CPU innovations, namely, those associated with complementary software innovations, are not taken into account in the analysis provided.

**3. Was the elimination of the Pentium III efficient?** Having established that the Pentium M played a key role in the crowding out of the Pentium III, we may ask if it was actually efficient for the latter technology to leave the market. To investigate whether the absence of the Pentium III from the product lines of the major notebook producers in 2004Q2 reflected a market failure, I consider a hypothetical action by a social planner: adding to the market Pentium III-based configurations (with 1.5-1.99 GHz) of the five top-selling notebook brands.

The results of this analysis are presented in Table 10. Adding the Pentium III-based notebooks to the market would have increased total consumer surplus by \$8.68 million, or by 1%. It would have also increased total producer variable profit by \$2.36 million. On the other hand, producers (and hence society) would have also incurred additional fixed costs ranging between \$5.66 million and \$10.58 million. Defining welfare as the sum of consumer and producer surplus, the total welfare impact is positive, and bounded between \$0.46 million and \$5.38 million.[38] This suggests that a social planner could improve upon the market outcome by adding the older technology to the market, although the magnitude of the improvement appears somewhat modest.

These results provide an intuitive interpretation for the suggested wedge between the incentives of the social planner and those of the oligopoly of PC makers. Offering the Pentium III-based notebooks would increase the industry's total fixed costs by more than it would increase its

[38] It is worth noting that a more complete welfare analysis would also take into account the impact on the profits of upstream firms such as Intel and Microsoft.

variable profit. So, at least in this aggregate sense, it is unprofitable for the oligopoly of PC makers to offer such products. The social planner, in contrast, takes into account not only the implications for industry profits, but also the contribution to consumer welfare. Since the benefit to consumers outweighs the decrease in industry profits, the social planner would choose to add these products to the market.

**Summary: what was the impact of the Pentium M?** To summarize the findings of this section, I find that the Pentium M contributed significantly to the growth of the mobile segment of the market, as well as to consumer welfare. It also led to a major re-alignment of product offerings in this segment, crowding certain technologies out of the market while helping other technologies. Even though notebooks with the older Pentium III technology were crowded out by the Pentium M, the effect of this innovation on households belonging to all quantiles of price sensitivity was positive (with the least price sensitive consumers enjoying the lion's share of the benefits). Finally, some evidence was provided that the absence of the Pentium III from the product lines of top notebook manufacturers reflected a market failure, although the welfare loss appears modest.

As mentioned above, the results reported here are preliminary at this point as some important robustness checks are necessary. An important robustness analysis would involve altering counterfactual marginal costs; in the absence of the Pentium M, Intel might have charged a higher price for its other chips, which would have increased the marginal costs associated with some PC configurations. Adjusting the analysis to account for that is a work-in-progress. The reduced-form evidence on systematic differences in CPU prices available from the estimated marginal costs of PC makers provide a useful source of information in this context.

# 7 Concluding Remarks

This paper asks whether CPU innovation leads to an inefficient elimination of existing PC products. To address this question, I estimate a model in which PC makers endogenously choose which CPU options to offer with their PC product lines. I relax strong assumptions which guarantee a unique equilibrium outcome, and exploit necessary equilibrium conditions to tackle the resulting partial identification of fixed costs.

I provide a rich analysis of PC product variety by allowing for a large product space, which requires me to develop computational techniques which alleviate the burden associated with predicting counterfactual outcomes. I overcome a sample selection problem by imposing a point-identifying assumption, and provide the details of an alternative approach, which would allow one to relax this assumption and obtain partial identification of variable profit parameters.

I find that the demand for PCs is highly segmented, such that households differ considerably in their price sensitivity, and in the pace at which their utility from a fixed bundle of hardware characteristics falls over time. I find that the *average* household's willingness to pay for fixed hardware falls substantially over time, consistent with a scenario according to which software innovations create incentives for hardware upgrades.

I use the estimated model to evaluate the impact of Intel's introduction of the Pentium M chip. I find that this technology had a major impact on the notebook segment of the PC market. In addition to boosting sales and average prices, this innovation also led to a significant re-alignment of PC makers' product offerings. In particular, it crowded out Pentium III-based notebook configurations. A traditional model with fixed product choices fails to account for this product elimination, and, as a consequence, substantially understates the effect of the Pentium M on the market share of the Pentium III.

I also find that the introduction of the Pentium M contributed significantly to consumer surplus. The vast majority of these benefits were enjoyed by the least price sensitive segment of consumer demand. At the same time, even though some technologies were crowded out by the Pentium M, all segments of demand were positively affected by this innovation.

The Pentium M, therefore, made a substantial contribution to the growth of the mobile PC segment, as well as to consumer welfare. At the same time, some evidence was provided that the elimination of the Pentium III technology (in which the Pentium M's presence played a key role) was inefficient, in the sense that a social planner could have increased total welfare by adding to the market Pentium III-based notebooks. This happens since the additional fixed costs are outweighed by the increases to consumer surplus and to PC makers' variable profits. The magnitude of the lost welfare associated with the absence of the Pentium III, however, does not appear to be large. Moreover, as explained above, some important robustness checks are required with respect to the results reported.

A couple of interesting issues are left for future research. While I do not impose an equilibrium selection mechanism, my framework could be used to investigate it. Ciliberto and Tamer [2007] test (and reject) the hypothesis that firms coordinate on the equilibrium outcome which maximizes total industry profits in their study of the airline industry. An interesting exercise in the current framework could be to compute the set of potential equilibria in a given quarter, and then ask what was special about the equilibrium that was actually played by firms.

An important aspect of CPU innovation is that it fosters complementary innovation in software and hardware. Such complementary innovation prompts households to use more advanced applications, which, in turn, increases the demand for advanced CPUs. A quantitative, dynamic analysis of this "positive feedback loop" is likely to improve our understanding of the singular contribution of CPU innovations to growth in the $21^{st}$ century economy.

## References

Andrews, D. W. K., and P. Guggenberger (2009): "Validity of Subsampling and 'Plug-in Asymptotic' Inference for Parameters Defined by Moment Inequalities," forthcoming *Econometric Theory*

Berry, S. (1994): "Estimating Discrete-Choice Models of Product Differentiation," *RAND Journal of Economics*, 25(2): 242-262

Berry, S., Levinsohn, J., and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63(4): 841-90

Berry, S., and E. Tamer (2006): "Identification in Models of Oligopoly Entry," in *Advances in Economics and Econometrics: Theory and Applications*, Ninth World Congress, vol. 2, R. Blundell, W.K. Newey and T. Persson, eds., Cambridge Univ. Press

Caplin, A., and B. Nalebuff (1991): "Aggregation and Imperfect Competition: On the Existence of Equilibrium," *Econometrica*, 59(1): 25-59

Chernozhukov, V., Hong, H., and E. Tamer (2007): "Estimation and Confidence Regions for Parameter Sets in Econometric Models," *Econometrica*, 75(5): 1243 - 1284

Ciliberto, F., and E. Tamer (2007): "Market Structure and Multiple Equilibria in Airline Markets," *mimeo*, Northwestern University

Gawer A., and M.A. Cusumano (2002): "Platform Leadership: How Intel, Microsoft, and Cisco Drive Industry Innovation," *Harvard Business School Press*

Goeree, M. S. (2008): "Limited Information and Advertising in the US Personal Computer Industry," forthcoming *Econometrica*

Goettler, R., and B. Gordon (2008): "Durable Goods Oligopoly with Innovation: Theory and Empirics"

Gordon, B. (2008): "A Dynamic Model of Consumer Replacement Cycles in the PC Processor Industry," Forthcoming *Marketing Science*

Haile, P.A., and E. Tamer (2003): "Inference with an Incomplete Model of English Auctions," *Journal of Political Economy*, University of Chicago Press, 111(1): 1-51

Heckman, J. (1976): "The common structure of statistical models of truncation, sample selection, and limited dependent variables and a simple estimator for such models," *Annals of Economic and Social Measurement 5*, 475-592

Hendel, I. (1999): "Estimating Multiple-Discrete Choice Models: An Application to Computerization Returns," *Review of Economic Studies*, 66(2): 423-446

Ishii, J. (2006): "Interconnection Pricing, Compatibility, and Investment in Network Industries: ATM Networks in the Banking Industry," *mimeo* Stanford University

Manski, C.F. and E. Tamer (2002): "Inference on Regressions with Interval Data on a Regressor or Outcome," *Econometrica* 70: 519-546

Mazzeo, M.J. (2002): "Product Choice and Oligopoly Market Structure," *RAND Journal of Economics*, 33(2): 221-242

Nevo, A. (2000): "A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand," *Journal of Economics and Management Strategy*, 9: 513-548

Nevo, A. (2001): "Measuring Market Power in the Ready-To-Eat Cereal Industry," *Econometrica*, 69(2): 307-342

Pakes, A. (2003): "A Reconsideration of Hedonic Price Indexes with an Application to PC's," *American Economic Review*, 93(5): 1578-1596

Pakes, A., J. Porter, K. Ho, and J. Ishii (2006): "Moment Inequalities and their Application," *mimeo*, Harvard University

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

Rosenberg, N. (1979): "Technological Interdependence in the American Economy," *Technology and Culture*, 20: 25-50

Song, M. (2006): "A Dynamic Analysis of Cooperative Research in the Semiconductor Industry"

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

Spence, M. (1976): "Product Selection, Fixed Costs, and Monopolistic Competition," *The Review of Economic Studies*, 43(2): 217-235

Train, K. (2003): "Discrete Choice Methods with Simulation", *Cambridge University Press*

Trajtenberg, M. (1989): "The Welfare Analysis of Product Innovations, with an Application to Computed Tomography Scanners," *Journal of Political Economy* 97: 444-479

Walters, G.E. (2001): "The Essential Guide to Computing," *Prentice Hall PTR*

Wooldridge, J.M. (2002): "Econometric Analysis of Cross Section and Panel Data," *The MIT Press*, Cambridge, Massachusetts

# A Details Concerning the Estimation Procedure

## A.1 Estimation of $\theta$: Computational Details

Estimating $\theta$ following the BLP method requires one to compute the errors $e_j(\theta) = (\xi_j(\theta), \omega_j(\theta))'$ for any generic value of the parameter $\theta$. The integral in (3) is approximated via simulation; I draw the $v_i$ household-specific taste shifters for $ns = 3000$ households. To reduce the error induced by simulation, I use antithetic draws.[39] I then obtain the market share predicted by the model for product $j$ (quarter indices suppressed) as follows:

$$s_j(x, p, \delta, P_{ns}; \theta_2) = \frac{1}{ns} \sum_{i=1}^{ns} \frac{exp(\delta_j + \mu_{ij})}{1 + \sum_{m \in J} exp(\delta_m + \mu_{im})} \tag{14}$$

where $P_{ns}$ is the distribution of the simulation draws. The market share equation, which should hold exactly at $\theta_0$, is given in vector form:

$$s(x, p, \delta, P_{ns}; \theta_2) = S \tag{15}$$

where $S$ denotes *observed* market shares. Given a fixed value for $\theta_2$, we invert this equation to retrieve a vector of mean utility levels, $\delta(\theta_2)$, using the BLP contraction mapping:

$$\delta^{h+1} = \delta^h + ln(S) - ln[s(x, p, \delta^h, P_{ns}; \theta_2)] \tag{16}$$

The vector of demand-side unobservables $\xi$ can now be computed by:

$$\xi(\theta^d) = \delta(\theta_2) - x\beta \tag{17}$$

where $x$ is a covariate matrix for the products observed in the sample. Marginal cost unobservables are computed from (7):

$$\omega(\theta) = log[p - (T * \Delta(\theta_2))^{-1}s] - x\gamma \tag{18}$$

Next, I define the GMM objective function. Recall that $z_j(X)$ is a $1 \times L$ vector, and define:

$$Z_j = \begin{bmatrix} z_j & 0 \\ 0 & z_j \end{bmatrix}_{2 \times 2L}, \qquad g_j(\theta) = Z_j' e_j(\theta)$$

Letting $N$ denote the total number of products in the sample, the objective function is given by:

[39]See Train [2003]. Antithetic draws are used in Goeree's [2008] analysis.

$$Q_N(\theta) = \left[\sum_{j=1}^{N} g_j(\theta)\right]' \Phi^{-1} \left[\sum_{j=1}^{N} g_j(\theta)\right] \tag{19}$$

where $\Phi^{-1}$ is a $2L \times 2L$ PD weight matrix. The initial choice for this matrix is $[\sum_{j=1}^{N} Z_j' Z_j]^{-1}$. With an initial estimate for $\theta$ at hand, denoted $\hat{\theta}^1$, I estimate the *optimal weight matrix* by $[\sum_{j=1}^{N} g_j(\hat{\theta}^1) g_j(\hat{\theta}^1)']^{-1}$. Re-estimating $\theta$ using the updated matrix yields the estimates reported in Tables 5a-5b.

### A.2 Set Estimation of Fixed Cost Parameters $\lambda$: Computational Details

Estimation of the quantities $U_{d,k}(\theta_0)$ and $L_{d,j}(\theta_0)$ which appear on the RHS of (10) and (11), respectively, is performed as follows. The BLP estimate $\hat{\theta}$ implies empirical values $e_j(\hat{\theta})$ for all products observed in the sample (a total of 2,287) using equations (17) and (18) above. From this empirical distribution, I draw 500 vectors of error terms $e$ for all products that need to be considered (in the current case, observed and potential products in 2004Q2). Note that we draw from the *joint distribution* of $(\xi, \omega)$.

At each such error vector, I simulate price equilibria under $(A_d)$ and $(A_d - 1_d^k)$, and compute the variable profit figures which appear in (10). Averaging over the variable profit differences yields the estimate of $U_{d,k}(\theta_0)$. An analogous procedure yields estimates for $L_{d,j}(\theta_0)$. Price equilibria are simulated by iterating on the first-order conditions (7) until convergence, which typically takes a few seconds of computation time.

## B Relaxing Point Identifying Assumptions for Variable Profit Parameters $\theta$

Relaxing the assumption that firms only observe the error terms $e$ after making their product choices implies that the selection indicator would now depend on unobservables, i.e., it would be written as $q_j(X, F, e)$. Correcting the resulting selection bias with traditional, point-identifying approaches (such as those in Heckman [1976]) is not possible, since that would require specifying a simple model for $q_j(\cdot)$, whereas this object actually depends in a very complex fashion on the observed and unobserved features of *all products*, and is not even uniquely determined in equilibrium.

I describe here an alternative approach that seeks *partial identification* of $\theta$. I have not pursued actual estimation of $\theta$ following this strategy, and it is likely to involve a substantial computational burden.

Under the assumptions specified below, I show that given a generic value for $\theta$, necessary equilibrium conditions can be used to obtain upper (lower) bounds on the $\xi$ ($\omega$) error terms associated with products that are *unobserved by the econometrician*. In addition, equations (17) and (18) above show how to compute exact values for these errors for observed products. The resulting partial information on the distribution of these error terms is translated into a partial identification argument for $\theta$ via moment inequalities. These inequalities would reduce to BLP's moment equalities if all products were observed.

I now provide the details of the identification argument. A formal proof of identification is outside the scope of this paper. I maintain Assumption 1, which stated the mean-independence of $e$ from $X$ in the population of all *potential products* $\mathbf{J}$ (see Section 4.1). I also add the following assumption:

**Assumption 2.** *The support of the marginal distribution of $\omega$ has an upper bound, $\omega^U$. The support of the marginal distribution of $\xi$ has a lower bound, $\xi^L$.*

I now show that Assumptions 1 and 2 yield moment inequalities involving $\theta$ if the support bounds $\omega^U$, $\xi^L$ are known. Since they are not likely to be known to the econometrician, I return below to the issue of identifying these support bounds. This latter task would require additional assumptions.

For observed products $j \in J$, equations (17)-(18) imply an exact value $e_j(\theta) = (\xi_j(\theta), \omega_j(\theta))'$. For *unobserved* products $j \in \mathbf{J} \backslash J$, I compute, for each guess of $\theta$, an upper bound $\overline{\xi}_j(\theta)$ and a lower bound $\underline{\omega}_j(\theta)$.

Without loss of generality, assume that the unobserved product $j \in \mathbf{J} \backslash J$ belongs to firm $d$, and, with a slight abuse of notation, let $j \in A_d^0$. Consider any $k \in A_d^1$, i.e., any observed product offered by this firm (I assume that this set is not empty, i.e., the firm offers at least one product). Using necessary equilibrium conditions, the bounds $\overline{\xi}_j(\theta)$ and $\underline{\omega}_j(\theta)$ are defined as the implicit solutions to the following equations:

$$VP_d(A_d + \mathbf{1}_d^j - \mathbf{1}_d^k; \theta, \omega_j = \omega^U, \xi_j = \overline{\xi}_j) - VP_d(A_d; \theta) = 0 \qquad (20)$$

$$VP_d(A_d + \mathbf{1}_d^j - \mathbf{1}_d^k; \theta, \xi_j = \xi^L, \omega_j = \underline{\omega}_j) - VP_d(A_d; \theta) = 0 \qquad (21)$$

In words, we consider a deviation in which the firm eliminates the observed product located at $k$ and introduces product $j$ instead. This deviation does not alter total fixed costs, and so its profitability hinges entirely on its variable profit implications. The idea underlying (20) is that, all else equal, the higher is the demand shifter $\xi_j$, the more profitable is the deviation. An upper bound on $\xi_j$, therefore, is the value at which the firm is indifferent about performing this deviation. The profitability of the deviation also depends on the unknown $\omega_j$ value, but fixing it at the upper bound of its support yields a valid upper bound on $\xi_j$. An analogous argument, specified in (21), places a lower bound on the $\omega_j$ value.

I now set up moment inequalities as follows: define $|\mathbf{J}|$-vectors $\tilde{\xi}$ and $\hat{\xi}$, which $j^{th}$ elements are given by:

$$\tilde{\xi}_j(\theta) = \begin{cases} \xi_j(\theta) & j \in J \\ \overline{\xi}_j(\theta) & j \in \mathbf{J} \backslash J \end{cases} \qquad \hat{\xi}_j(\theta) = \begin{cases} \xi_j(\theta) & j \in J \\ \xi^L & j \in \mathbf{J} \backslash J \end{cases}$$

At the true parameter value $\theta_0$, we have $\hat{\xi}_j(\theta_0) \leq \xi_j \leq \tilde{\xi}_j(\theta_0)$ for each $j \in \mathbf{J}$. For each product $j$, let $z_j : R^{|\mathbf{J}| \times K} \to R^L_+$ be a nonnegative vector-valued function of instruments. We get:

$$E[\hat{\xi}_j(\theta_0) z_j(X) | j \in \mathbf{J}] \leq E[\xi_j z_j(X) | j \in \mathbf{J}] \leq E[\tilde{\xi}_j(\theta_0) z_j(X) | j \in \mathbf{J}] \tag{22}$$

By Assumption 1 and the Law of iterated expectations, $E[\xi_j z_j(X) | j \in \mathbf{J}] = 0$, implying a set of moment inequality conditions involving $\theta$:

$$E[\hat{\xi}_j(\theta_0) z_j(X) | j \in \mathbf{J}] \leq 0 \leq E[\tilde{\xi}_j(\theta_0) z_j(X) | j \in \mathbf{J}] \tag{23}$$

Note that, if all products are observed, i.e., $J = \mathbf{J}$, the selection problem disappears, and (23) is reduced to the BLP moment equalities. Intuitively, the more severe is the selection problem, the further away from point identification we get. Sets of "supply-side" moment inequality conditions can be analogously obtained. Define the $|\mathbf{J}|$-vectors $\tilde{\omega}, \hat{\omega}$ by their $j^{th}$ elements:

$$\tilde{\omega}_j(\theta) = \begin{cases} \omega_j(\theta) & j \in J \\ \underline{\omega}_j(\theta) & j \in \mathbf{J} \backslash J \end{cases} \qquad \hat{\omega}_j(\theta) = \begin{cases} \omega_j(\theta) & j \in J \\ \omega^U & j \in \mathbf{J} \backslash J \end{cases}$$

Which yields:

$$E[\tilde{\omega}_j(\theta_0) z_j(X) | j \in \mathbf{J}] \leq 0 \leq E[\hat{\omega}_j(\theta_0) z_j(X) | j \in \mathbf{J}] \tag{24}$$

**Identifying the support bounds.** Throughout the discussion above I made reference to the support bounds $\xi^L$ and $\omega^U$ without specifying how one may learn their values. One possible avenue to do that is to define a subset of products which introduction is assumed to be predetermined to the game. Observe in Table 3a that, at each point in time, at least one CPU option was offered in the vast majority of product lines (e.g. **P3**_0.5-0.99 in 2001Q3). Such a CPU option may be viewed as an "industry standard" option, offered by most firms (and virtually all major firms). This motivates the following assumption:

**Assumption 3.** *A subset $J^P \subset \boldsymbol{J}$ of the potential products is offered in a manner that is pre-determined to the two-stage game. In addition, $E[e_j|X, j \in J^P] = 0$ holds, and the distributions of $\xi_j$ and $\omega_j$ conditional on $j \in J^P$ have the same support bounds as those of the unconditional distributions.*

The idea behind this assumption is that, since the products in $J^p$ are not selected on account of unobservables, the mean-independence condition should not be violated within this sub-population. Assumption 3 yields *moment equalities*: since $J^p \subset J$, i.e., all the pre-determined products are observed, a generic value for $\theta$ implies exact values $e_j(\theta)$ for each $j \in J^p$ using (17) and (18) above, and we get:

$$E[e_j(\theta_0)z_j(X)|j \in J^p] = 0 \tag{25}$$

These moment conditions point-identify a subset of the elements of $\theta$, denoted $\theta^P$, while providing no information on other elements. In addition, exact values $e_j(\theta^P)$ are implied for each $j \in J^P$ by using (17)-(18) once again. The support bounds are then identified by $\xi^L = \inf_{j\in J^p} \xi_j(\theta^P)$, $\omega^U = \sup_{j\in J^p} \omega_j(\theta^P)$.

**Discussion**. An unattractive feature of the identification strategy above is that it relied on the assumption of a pre-determined set of products. This may be more reasonable in some applications than in others. Coming up with an alternative approach for pinning down the support bounds, therefore, would be desirable.

Finally, actual estimation of $\theta$ following this approach would require constructing the sample analogs of the moments in (23)-(25). While efficient estimation would use all these conditions simultaneously, the computational burden would be significantly alleviated if one uses (25) first to obtain a point estimate of $\theta^P \subset \theta$, and then obtains set estimates of the remaining parameters using (23)-(24), holding the point estimates fixed. This is still likely to be computationally expensive, so that a parsimonious specification for utility and marginal cost is likely to be necessary.

# C Tables

Table 1: Top Vendors' Market Shares, US Home PC Market

| Year 1 | | Year 2 | | Year 3 | |
|---|---|---|---|---|---|
| Vendor | Market Share | Vendor | Market Share | Vendor | Market Share |
| Dell | 0.190 | Dell | 0.263 | Dell | 0.279 |
| HP* | 0.185 | HP | 0.234 | HP | 0.258 |
| Compaq* | 0.092 | eMachines | 0.076 | eMachines* | 0.070 |
| Gateway | 0.091 | Gateway | 0.070 | Gateway* | 0.053 |
| eMachines | 0.060 | Toshiba | 0.042 | Toshiba | 0.043 |
| Top 5 vendors | 0.618 | Top 5 vendors | 0.685 | Top 5 vendors | 0.704 |

Years: 01Q3-02Q2, 02Q3-03Q2, 03Q3-04Q2. *Compaq and HP merge in Year 1, eMachines and Gateway merge in Year 3.

Table 2: CPU Vendor Shares

| Vendor | Market Shares | | |
|---|---|---|---|
| | Year 1 | Year 2 | Year 3 |
| Intel | 0.71843 | 0.72246 | 0.74496 |
| AMD | 0.24429 | 0.23643 | 0.22032 |
| IBM | 0.03230 | 0.03450 | 0.03048 |
| Others | 0.00477 | 0.00524 | 0.00323 |
| Transmeta | 0.00022 | 0.00135 | 0.00097 |
| Via | 0.00000 | 0.00002 | 0.00005 |

Years: 01Q3-02Q2, 02Q3-03Q2, 03Q3-04Q2, U.S. Home market.

## Table 3a: Fraction of Desktop Product Lines to Install Intel's CPUs

| Quarter | **C**_0.5-0.99 | **C**_1-1.49 | **C**_1.5-1.99 | **C**_2-2.99 | **P3**_0.5-0.99 | **P3**_1-1.49 |
|---|---|---|---|---|---|---|
| 2001Q3 | 0.89 | 0.00 | 0.00 | 0.00 | 0.93 | 0.67 |
| 2001Q4 | 0.46 | 0.42 | 0.00 | 0.00 | 0.46 | 0.50 |
| 2002Q1 | 0.35 | 0.58 | 0.00 | 0.00 | 0.31 | 0.31 |
| 2002Q2 | 0.13 | 0.57 | 0.00 | 0.00 | 0.17 | 0.13 |
| 2002Q3 | 0.09 | 0.39 | 0.48 | 0.13 | 0.13 | 0.13 |
| 2002Q4 | 0.07 | 0.04 | 0.44 | 0.41 | 0.11 | 0.04 |
| 2003Q1 | 0.04 | 0.04 | 0.41 | 0.41 | 0.04 | 0.00 |
| 2003Q2 | 0.04 | 0.04 | 0.37 | 0.41 | 0.04 | 0.00 |
| 2003Q3 | 0.04 | 0.04 | 0.24 | 0.48 | 0.04 | 0.00 |
| 2003Q4 | 0.04 | 0.04 | 0.20 | 0.52 | 0.04 | 0.00 |
| 2004Q1 | 0.00 | 0.04 | 0.15 | 0.54 | 0.00 | 0.00 |
| 2004Q2 | 0.00 | 0.00 | 0.17 | 0.54 | 0.00 | 0.00 |

| Quarter | **P4**_1-1.49 | **P4**_1.5-1.99 | **P4**_2-2.99 | **P4**_3-3.99 |
|---|---|---|---|---|
| 2001Q3 | 0.48 | 0.26 | 0.00 | 0.00 |
| 2001Q4 | 0.65 | 0.65 | 0.12 | 0.00 |
| 2002Q1 | 0.58 | 0.73 | 0.50 | 0.00 |
| 2002Q2 | 0.43 | 0.70 | 0.65 | 0.00 |
| 2002Q3 | 0.26 | 0.74 | 0.70 | 0.00 |
| 2002Q4 | 0.11 | 0.37 | 0.81 | 0.00 |
| 2003Q1 | 0.11 | 0.44 | 0.81 | 0.15 |
| 2003Q2 | 0.11 | 0.44 | 0.81 | 0.15 |
| 2003Q3 | 0.08 | 0.28 | 0.92 | 0.60 |
| 2003Q4 | 0.12 | 0.28 | 0.92 | 0.60 |
| 2004Q1 | 0.08 | 0.19 | 0.92 | 0.65 |
| 2004Q2 | 0.08 | 0.17 | 0.92 | 0.63 |

Calculations pertain to the Home market and exclude vendors identified as "Others", Apple products, and PC products which sold under 100 units in a quarter. C,P3, and P4 stand for Intel's Celeron, Pentium III and the Pentium 4 brands, repsectively. **P3**_0.5-0.99 implies Pentium III with clock speed range between 0.5 and 0.99 GHz.

Table 3b: Fraction of Portable Product Lines to Install Intel's CPUs

| Quarter | **C**_0.5-0.99 | **C**_1-1.49 | **C**_1.5-1.99 | **C**_2-2.99 | **P3**_0.5-0.99 | **P3**_1-1.49 |
|---|---|---|---|---|---|---|
| 2001Q3 | 0.81 | 0.00 | 0.00 | 0.00 | 1.00 | 0.15 |
| 2001Q4 | 0.59 | 0.21 | 0.00 | 0.00 | 0.79 | 0.72 |
| 2002Q1 | 0.36 | 0.25 | 0.00 | 0.00 | 0.64 | 0.86 |
| 2002Q2 | 0.12 | 0.31 | 0.00 | 0.00 | 0.54 | 0.62 |
| 2002Q3 | 0.11 | 0.21 | 0.07 | 0.00 | 0.18 | 0.64 |
| 2002Q4 | 0.10 | 0.03 | 0.23 | 0.10 | 0.16 | 0.42 |
| 2003Q1 | 0.03 | 0.06 | 0.26 | 0.13 | 0.19 | 0.39 |
| 2003Q2 | 0.03 | 0.03 | 0.21 | 0.12 | 0.15 | 0.42 |
| 2003Q3 | 0.03 | 0.00 | 0.25 | 0.13 | 0.16 | 0.34 |
| 2003Q4 | 0.03 | 0.03 | 0.22 | 0.13 | 0.13 | 0.28 |
| 2004Q1 | 0.00 | 0.03 | 0.18 | 0.18 | 0.03 | 0.18 |
| 2004Q2 | 0.00 | 0.03 | 0.19 | 0.19 | 0.03 | 0.19 |

| Quarter | **P4**_1-1.49 | **P4**_1.5-1.99 | **P4**_2-2.99 | **P4**_3-3.99 | **Pm**_1-1.49 | **Pm**_1.5-1.99 |
|---|---|---|---|---|---|---|
| 2001Q3 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2001Q4 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2002Q1 | 0.07 | 0.18 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2002Q2 | 0.19 | 0.38 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2002Q3 | 0.14 | 0.46 | 0.32 | 0.00 | 0.00 | 0.00 |
| 2002Q4 | 0.10 | 0.52 | 0.58 | 0.00 | 0.00 | 0.00 |
| 2003Q1 | 0.13 | 0.52 | 0.58 | 0.00 | 0.10 | 0.06 |
| 2003Q2 | 0.12 | 0.48 | 0.55 | 0.00 | 0.09 | 0.09 |
| 2003Q3 | 0.09 | 0.53 | 0.59 | 0.06 | 0.22 | 0.19 |
| 2003Q4 | 0.13 | 0.50 | 0.50 | 0.09 | 0.31 | 0.25 |
| 2004Q1 | 0.12 | 0.42 | 0.52 | 0.12 | 0.21 | 0.48 |
| 2004Q2 | 0.06 | 0.44 | 0.50 | 0.13 | 0.28 | 0.56 |

See notes for Table 3a. Pm stands for Intel's Pentium M brand. CPU technologies with very small installation rates excluded.

# Table 4: Descriptive Results, logit Demand

| $\beta$ | Logit_OLS | Logit_IV |
|---|---|---|
| Price (00$) | -0.0395*** | -0.157** |
| | (0.0135) | (0.0649) |
| Laptop dummy | -0.616*** | -0.298 |
| | (0.0999) | (0.199) |
| Trend | -0.0398** | -0.138** |
| | (0.0171) | (0.0567) |
| **CPU Speed Range Dummies** | | |
| 1-1.49 GHz | 0.200* | 0.385** |
| | (0.107) | (0.152) |
| 1.5-1.99 GHz | 0.383*** | 0.660*** |
| | (0.138) | (0.208) |
| 2-2.99 GHz | 0.752*** | 1.223*** |
| | (0.156) | (0.303) |
| 3-3.99 GHz | 0.779*** | 1.586*** |
| | (0.253) | (0.508) |
| **CPU Brand Dummies** | | |
| AMD Duron | 0.694*** | 0.544** |
| | (0.208) | (0.254) |
| AMD Athlon | 0.691*** | 0.695*** |
| | (0.115) | (0.133) |
| Intel Pentium III | 0.227** | 0.507*** |
| | (0.116) | (0.189) |
| Intel Pentium 4 | 0.359*** | 0.629*** |
| | (0.103) | (0.176) |
| Intel Pentium M | 0.724*** | 1.554*** |
| | (0.215) | (0.489) |
| Constant | -10.66*** | -9.441*** |
| | (0.183) | (0.699) |
| Observations | 2287 | 2287 |
| R-squared | 0.491 | 0.473 |

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Dummy variables for PC vendors and brands included, not reported

## Table 5a: BLP Estimates for $\theta$, Main PC Characteristics

| | $\beta$ | SE | $\sigma$ | SE | $\gamma$ | SE |
|---|---|---|---|---|---|---|
| Constant | 4.479 | 3.108 | 1.546 | 1.933 | 6.759 | 0.020 |
| Laptop Dummy | -0.690 | 1.158 | 3.785 | 0.518 | 0.312 | 0.013 |
| Trend | -1.444 | 0.263 | 0.430 | 0.081 | -0.090 | 0.002 |
| **CPU Speed Range Dummies** | | | | | | |
| 1-1.49 GHz | 2.390 | 0.386 | | | 0.156 | 0.013 |
| 1.5-1.99 GHz | 3.621 | 0.521 | | | 0.232 | 0.016 |
| 2-2.99 GHz | 6.212 | 0.809 | | | 0.412 | 0.017 |
| 3-3.99 GHz | 9.584 | 1.374 | | | 0.709 | 0.030 |
| **CPU Brand Dummies** | | | | | | |
| AMD Duron | -0.915 | 0.443 | | | -0.120 | 0.023 |
| AMD Athlon | 0.912 | 0.217 | | | 0.031 | 0.013 |
| Intel Pentium III | 3.517 | 0.484 | | | 0.272 | 0.014 |
| Intel Pentium 4 | 3.855 | 0.487 | | | 0.305 | 0.010 |
| Intel Pentium M | 10.051 | 1.361 | | | 0.741 | 0.032 |
| **Price sensitivity** | $\alpha$ | SE | $\sigma^p$ | SE | | |
| | 0.810 | 0.179 | 0.301 | 0.060 | | |

Obs: 2287. Dummies for PC vendor, brands included, reported in 5b. Standard errors do not take into account simulation error, which is mitigated via antithetic draws.

## Table 5b: BLP Estimates for $\theta$, PC Vendor & Brand Dummies

| | $\beta$ | SE | $\gamma$ | SE | | $\beta$ | SE | $\gamma$ | SE |
|---|---|---|---|---|---|---|---|---|---|
| **Dell** | 12.332 | 2.603 | 0.774 | 0.062 | **Toshiba** | 7.933 | 1.684 | 0.479 | 0.050 |
| dimension | -10.426 | 2.813 | -0.915 | 0.065 | portege | 0.593 | 1.018 | 0.093 | 0.059 |
| inspiron | -9.908 | 2.732 | -0.838 | 0.064 | port_tablet | 2.855 | 1.303 | 0.218 | 0.085 |
| Latitude | -7.529 | 2.137 | -0.488 | 0.071 | satellite | -5.405 | 1.752 | -0.517 | 0.055 |
| OptiPlex | -13.509 | 2.819 | -0.903 | 0.064 | satpro | -2.628 | 1.141 | -0.132 | 0.053 |
| **HP** | -0.976 | 0.334 | -0.049 | 0.021 | **Sony** | 5.684 | 0.821 | 0.306 | 0.037 |
| evoipaq | -1.651 | 0.519 | -0.174 | 0.030 | VAIO_DS | -3.909 | 0.871 | -0.265 | 0.043 |
| media | 7.568 | 0.870 | 0.424 | 0.029 | VAIO_R | 0.500 | 0.824 | 0.205 | 0.052 |
| pavilion | 2.625 | 0.385 | -0.015 | 0.024 | VAIO_W | 3.163 | 0.979 | 0.283 | 0.059 |
| presario | 2.593 | 0.355 | 0.026 | 0.020 | VAIO_505 | 1.288 | 0.963 | -0.007 | 0.061 |
| cmpq_ntbk | 1.841 | 0.653 | 0.175 | 0.033 | VAIO_FX | 0.951 | 0.734 | 0.053 | 0.053 |
| cmpq_ultprtbl | 10.945 | 2.221 | 0.741 | 0.080 | **IBM** | 2.037 | 1.217 | 0.208 | 0.083 |
| **Gateway** | 0.309 | 0.399 | 0.068 | 0.025 | IBM_netvista | -3.868 | 1.307 | -0.244 | 0.087 |
| Gateway3 | -2.619 | 0.730 | -0.408 | 0.035 | IBM_thinkCentre | 0.419 | 1.301 | 0.040 | 0.095 |
| Gateway5 | 1.755 | 0.865 | -0.030 | 0.048 | IBM_thinkpadA | 8.348 | 2.084 | 0.452 | 0.097 |
| Gateway7 | 2.159 | 0.690 | 0.077 | 0.035 | IBM_thinkpadT | 1.253 | 1.366 | -0.016 | 0.092 |
| essential | 2.124 | 0.458 | -0.098 | 0.030 | IBM_thinkpadR | -3.304 | 1.291 | -0.233 | 0.085 |
| performance | 1.751 | 0.530 | 0.039 | 0.034 | **Acer_veriton** | -2.120 | 0.382 | -0.120 | 0.016 |
| media | 4.960 | 0.828 | 0.365 | 0.035 | **Averatec** | 1.131 | 0.688 | -0.034 | 0.048 |
| Gateway4 | -1.320 | 0.510 | -0.139 | 0.031 | **Fujitsu** | -1.090 | 0.354 | -0.018 | 0.023 |
| Gateway6 | 4.725 | 1.077 | 0.173 | 0.051 | **MicroElectronics** | -1.585 | 0.236 | -0.009 | 0.017 |
| solo | 0.185 | 0.868 | -0.106 | 0.050 | | | | | |
| **eMachines** | 0.389 | 0.602 | -0.325 | 0.050 | | | | | |

See notes for Table 5a. The coefficients on vendors (e.g. Dell) **do not** capture an "overall" vendor effect, but rather the effect of omitted brands of that vendor (see text).

## Table 6: Economic Implications of BLP Estimates

| A. Willingness to pay | |
|---|---|
| | Average Consumer WTP ($) |
| 1-1.49 GHz → 1.5-1.99 GHz | 54.8 |
| 1.5-1.99 GHz → 2-2.99 GHz | 115.3 |
| 2-2.99 GHz → 3-3.99 GHz | 150.1 |
| Celeron → Pentium III | 156.5 |
| Celeron → Pentium 4 | 171.5 |
| Celeron → Pentium M | 447.3 |
| HP (Compaq) Presario | 71.9 |
| Dell Inspiron | 107.8 |
| Sony VAIO R | 275.2 |
| IBM Thinkpad A | 462.1 |
| 1 year forward* | -257.0 |
| B. Additional Information | |
| Median Markup ($) | 76.4 |
| Median (p-mc)/p | 0.078 |
| Corr(markup, price) | 0.912 |
| Corr($\xi, \omega$) | 0.820 |

*Change in willingness to pay over one year, see text

## Table 7: Fixed Cost Parameters $\lambda$

| | (a) | | (b) | |
|---|---|---|---|---|
| Parameter | Lower Bound | Upper Bound | Lower Bound | Upper Bound |
| Constant | 1,165,999 | 1,506,040 | 980,000 | 1,500,000 |
| Big Notebook Producer | | | 0 | 1,290,000 |
| **Per-configuration fixed cost ($V_d\lambda$) $** | | | | |
| Big Producers | | | 1,170,000 | 2,270,000 |
| Other Producers | | | 980,000 | 1,500,000 |

Confidence intervals not yet provided. Results obtained using information from notebook product offerings in 2004Q2 (see text).

## Table 8: The Effect of Intel's Pentium M on 2004Q2 Outcomes

| | Lower bound | Upper bound |
|---|---|---|
| Total Notebook Sales | +10.9% | +18.9% |
| Total Desktop Sales | -2.6% | -1.6% |
| Mean Notebook price* ($) | +32 | +44 |
| **Impact on number of PC configurations (top 5 brands)**** | | |
| # P3_1.5-1.99 | -4 | -2 |
| # C_1.5-1.99 | +1 | +3 |
| # C_2-2.99 | +1 | +1 |
| # P4_1.5-1.99 | +2 | +2 |
| # P4_2-2.99 | -1 | +2 |
| # P4_3-3.99 | -3 | -1 |
| **Impact on Pentium III's share of total Portables sales** | | |
| Share P3 (percentage points) | -0.156 | -0.116 |

Entries with a positive (negative) sign imply that the presence of the Pentium M has increased (decreased) the relevant quantitity by the reported amount. For instance, the Pentium M increased total notebook sales by 10.9% to 18.9%.

* Sales-weighted average

** These entries describe the impact of the Pentium M on the number of configurations offered by the five top-selling notebook brands. For example, between 2 and 4 configurations of these top-selling brands with Intel's Pentium III chip (1.5-1.99 GHz) were crowded out. **C**, **P3**, and **P4** stand for Intel's Celeron, Pentium III and Pentium 4 brands, respectively.

## Table 9: The Effect of Intel's Pentium M on Consumers

| | **Absolute Effect ($ million)** | | **% Change** | |
|---|---|---|---|---|
| | Lower bound | Upper bound | Lower bound | Upper bound |
| Total Consumer Surplus | +27.92 | +41.87 | +3.3% | +5.1% |
| **Price Sensitivity Quantiles** | | | | |
| 0-20% Price sensitive | +25.90 | +38.19 | +3.80% | +5.70% |
| 20%-40% Sensitive | +1.24 | +2.52 | +1.39% | +2.87% |
| 40%-60% Sensitive | +0.53 | +1.04 | +0.99% | +1.96% |
| 60%-80% Sensitive | +0.06 | +0.09 | +0.77% | +1.20% |
| 80%-100% Sensitive | +0.01 | +0.03 | +1.65% | +4.95% |

See text.

## Table 10: Effect on Welfare of Adding Pentium III-based Products

| | |
|---|---|
| Effect on consumer surplus: | +8.68 |
| Effect on PC makers' variable profits: | +2.36 |
| Effect on PC makers' fixed costs: | [+5.66, +10.58] |
| Total welfare effect: | [+0.46, +5.38] |

All quantities in $ million. Total welfare is the sum of consumer and producer surplus. See text for more details.

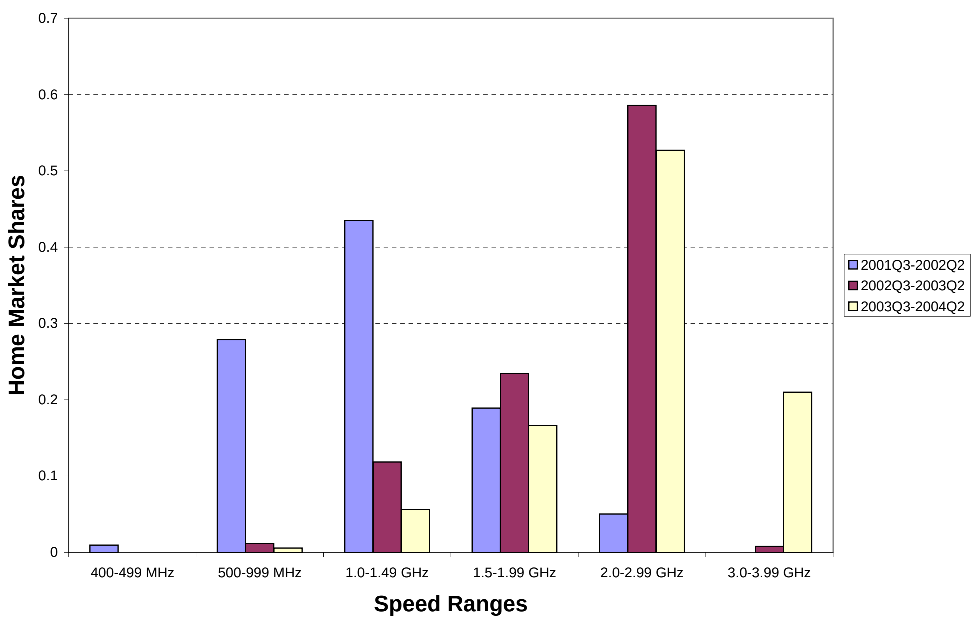


Figure 1: CPU speed range shares, U.S. Home Market, over the three sample years

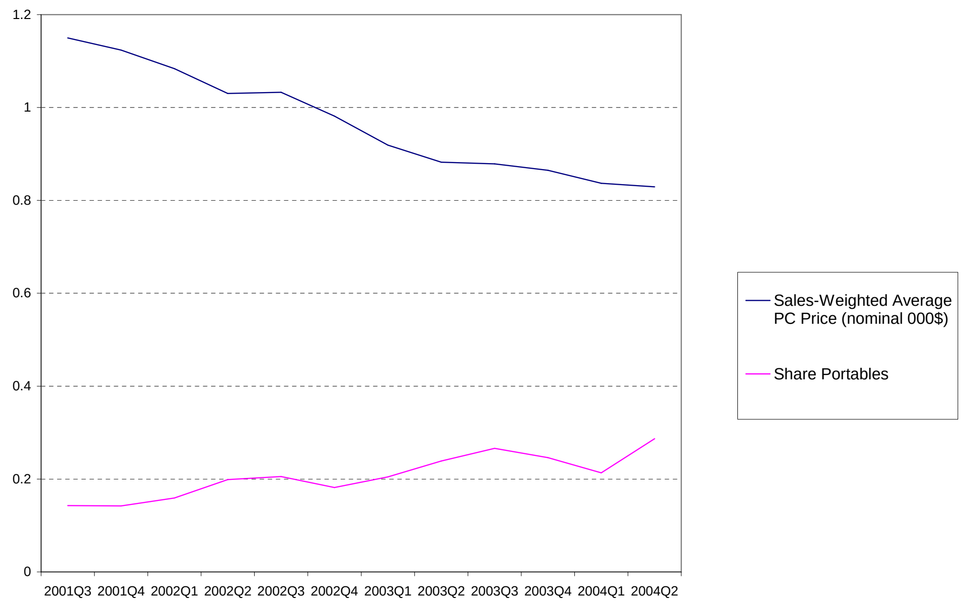


Figure 2: Sales-weighted average prices ($1000's) and share portables, U.S. Home PC Market

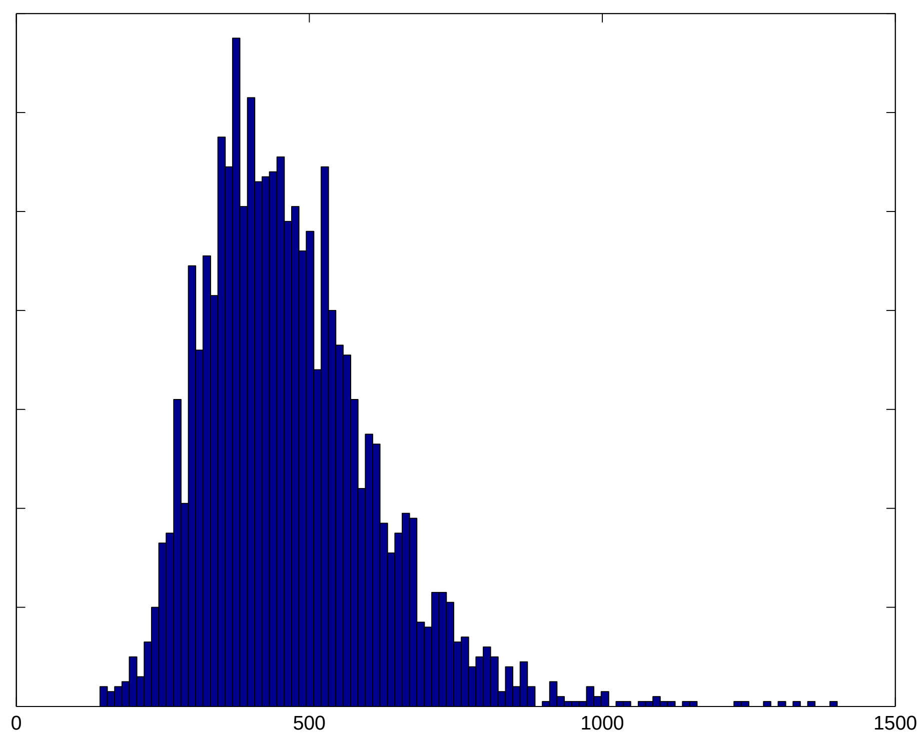


Figure 3: Willingness-to-pay for an upgrade from Intel's Celeron to its Pentium M processor ($)

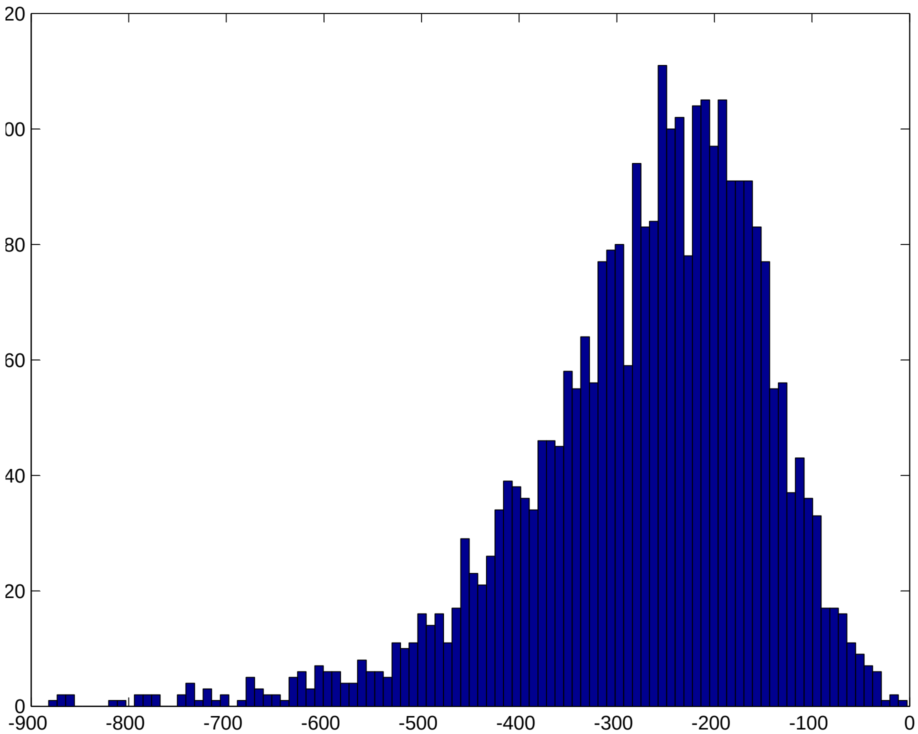


Figure 4: Willingness-to-pay for “1 year forward”($) (see text)