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

ALON EIZENBERG

Department of Economics, Hebrew University of Jerusalem

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This article investigates the welfare implications of the rapid innovation in central processing units (CPUs), and asks whether it results in inefficient elimination of basic personal computer (PC) products. I analyse a game in which firms make multiple discrete product choices, and tackle challenges such as partial identification and sample selection. Estimation results demonstrate that the demand for PCs is highly segmented, and that fixed costs consume a substantial portion of the per-unit producer profit. The estimated model implies that Intel's introduction of its Pentium M chip contributed significantly to the growth of the mobile PC segment and to consumer welfare. The lion's share of the benefits to consumers was enjoyed by the 20% least price-sensitive consumers. I also find that the Pentium M crowded out the Pentium III and Pentium 4 technologies, and that the benefits to consumers from keeping those older products on the shelf would have been comparable to the added fixed costs. While *total welfare* cannot be increased by keeping older technologies on the shelf, such a policy would have allowed the benefits from innovation to "trickle down" to price-sensitive households, improving their access to mobile computing.

Key words: Product variety, Personal computers, CPU, Innovation, Endogenous product choices, Discrete product choices, Multiple equilibria, Partial identification, Sample selection.

JEL Codes: L10, L11, L13, L15

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 the rapid elimination of existing products. The goal of this work 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 or word processing), which require modest computing power.

When basic PC configurations disappear, consumers who would have optimally chosen to purchase them end up buying stronger machines, or do not purchase a PC at all. A policy that would keep basic configurations on the shelf could contribute to the welfare of such consumers. From the point of view of a social planner, however, these consumer benefits must be weighed against the impact on producer profit, and, specifically, the additional fixed costs associated with keeping basic configurations on the shelf. If these costs are not too large, the planner may prefer to keep those products on the shelf, implying that their elimination was inefficient.

Theoretical analyses (Spence, 1976; Mankiw and Whinston, 1986) demonstrate that equilibrium product variety may indeed be socially inefficient. Two types of externalities drive such failures: a firm that introduces an additional product variant provides a *positive* externality, since it cannot privately capture the full surplus from this product. On the other hand, it also imposes a *negative* externality on its rivals. Either insufficient or excessive product introductions may, therefore, obtain. It is necessary to learn the values of market-specific cost and demand parameters to determine the existence, nature, and magnitude of such market failures.

Motivated by this question, I estimate a model of supply and demand in which both the set of offered PCs, and their prices, are endogenously determined. I then perform counterfactual analyses to study the impact of innovation on the portfolio of offered configurations, 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, variable and fixed PC costs, 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 software and hardware. The CPU market is controlled by Intel, and its smaller competitor Advanced Micro Devices (AMD). Downstream PC makers (*e.g.* Dell, Hewlett-Packard (HP)) purchase those 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 of these CPUs to offer with their PC products. While consumer heterogeneity provides incentives to offer multiple configurations, offering each such configuration results in fixed costs. In the second stage, the chosen configurations are sold to consumers in a simultaneous price-setting game. CPU innovation expands the menu of feasible 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, revealing producers' variable-profit benefits from offering different configuration portfolios. I also use the observed variation in product offerings to make inference on fixed costs. For example, an observed decision to offer a certain configuration implies an upper bound on its cost. Having estimated both the benefits and the costs which accrue to PC makers from offering configuration portfolios, I simulate outcomes of the two-stage game to study the impact of innovation.

Findings: My estimates reveal strong consumer heterogeneity in price sensitivity, in the taste for portability, and in the degree to which the utility from a 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, reflecting the rapid pace of innovation. I also find that fixed costs consume a substantial portion of PC makers' per-unit variable profit. Institutional details provide support to the presence of substantial fixed costs.

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 artificially remove this technology from the market, and compute the set of potential equilibria under this "no Pentium M" scenario.[1] Comparing these outcomes to outcomes in the observed equilibrium (*i.e.* in the presence of the Pentium M) provides a measure of the Pentium M's effect.

I find that, in the second quarter of 2004, the presence of the Pentium M made a substantial contribution to the growth of the mobile PC segment, and that some of this growth came at the expense of Desktop sales. The presence of the Pentium M increased the total consumer surplus by 3.2%–6.3%. This innovation also crowded out notebook configurations based on Intel's older

1. As explained below, the term "potential equilibria" pertains to outcomes that cannot be ruled out as equilibria of the game. The need to work with this concept stems from the partial identification of fixed costs, also to be discussed below.

Pentium III and Pentium 4 chips. I document substantial heterogeneity in the impact of innovation on different consumer types: the 20% least price-sensitive consumers enjoy the bulk of the benefits from innovation, while other consumer segments are virtually unaffected.

I use the model to ask whether a social planner could improve welfare by adding back to the 2004Q2 market notebook PCs based on the eliminated technologies. I find that the gains in variable profit and consumer surplus would have been largely offset by the added fixed costs, and so *total welfare* cannot be improved. Keeping basic PCs on the shelf, however, still has important welfare implications: it allows the benefits from innovation to "trickle down" to the 80% of households who do not benefit from it in equilibrium. This happens since the presence of the innovative configurations exerts a downward pressure on the equilibrium prices of basic configurations. In equilibrium, this channel is shut down, since the basic configurations disappear.

Being "allowed" to remain on the shelf, the basic configurations form a category of affordable laptops that was absent from the actual 2004Q2 market: expected equilibrium prices for these basic configurations range between \$707 and \$740, compared to an expected \$905 average price given the observed set of products. Price-sensitive consumers respond to this opportunity: their notebook purchase probabilities substantially rise. Keeping basic technologies on the shelf, therefore, improves their access to mobile computing. My framework makes it possible to elicit these findings since it combines a study of endogenous product portfolios and prices with a detailed analysis of cost and demand.

Discussion and some caveats: CPU offerings by Intel and AMD determine the feasible menu from which PC makers can choose their configuration portfolios. Since my counterfactual analysis focuses on the variety of configurations offered by leading notebook producers, I treat desktop product offerings as exogenous (though the *prices* of all products, desktops and notebooks, are treated as endogenous). Two of the three leading notebook producers (Dell and Toshiba) did not use AMD chips during the sample period, and this lack of variation does not allow me to identify the cost of offering AMD-based notebooks. I, therefore, take the offerings of AMD-based notebooks as given. In my model, notebook manufacturers face a menu of Intel CPUs, and decide which subset of those to install in their product lines.

I treat the menu offered by Intel as exogenous. Intel expands this menu by launching innovative chips, a process which can be reasonably viewed as exogenous given that the pace of innovation is largely driven by Moore's Law. Intel also removes old chips from this menu, and my analysis takes this into account. The assumption that PC makers' decisions do not affect Intel's offered menu is a simplifying one, and can be justified by Intel's clear role as an industry leader. I leave a more nuanced analysis of Intel's relationship with its clients for future work.[2]

I employ a static model, thereby ignoring PC durability and forward-looking behaviour by consumers and firms. This simplification is motivated by tractability: estimating a dynamic model that allows for a large variety of products, systematic consumer heterogeneity via random coefficients, and endogenous product portfolios *and* prices is well outside the scope of this article.[3] My paper, therefore, joins a tradition of static empirical models that study the value of

2. In the last couple of decades, Intel has taken a clear leadership position in coordinating industry standards (Gawer and Cusumano, 2002). Intel likely enjoys substantial bargaining power versus the thin-margin PC makers: for example, it subsidizes the advertising budgets of leading PC makers via its "Intel Inside" program (Lee *et al*., 2013).

3. While recent literature has made substantial progress in estimating complex models of demand and supply, I am not aware of empirical dynamic analyses that incorporate all the above features. For example, Gowrisankaran and Rysman (2012) estimate a dynamic demand system with many products and systematic consumer heterogeneity via random coefficients, but do not formally model the supply side. Goettler and Gordon's (2011) dynamic study of the CPU market models endogenous innovation and pricing decisions. They, however, treat Intel and AMD as single-product firms, and do not allow systematic consumer heterogeneity. These are very useful restrictions given their research questions, but my focus on product variety calls for a different approach.

new product introductions (*e.g*. Trajtenberg, 1989; Hausman, 1996; Petrin, 2002). I contribute to this literature by modelling the endogenous elimination of older technologies, and the resulting heterogeneous impact of innovation on different consumer types.

While I do not formally model durability and dynamics, the outside option in my demand model captures the value of a used PC that consumers already own, and the inclusion of a time trend allows the mean quality of this outside option to improve over time. This helps me address an issue pointed out by Aizcorbe (2005): while quality increases and prices fall over time, later periods have lower-valuation consumers "remaining" in the market, and a model that does not account for this may overstate the consumer welfare growth. The time trend controls for this issue, albeit in a simple, reduced-form fashion. Random coefficients allow me to capture another realistic aspect: the heterogeneous valuation of the outside option, reflecting, among other things, ownership of different used machines by different consumer types.

I, therefore, view the static model as a useful step toward a better understanding of the issue of equilibrium product variety in this market. Just the same, it clearly prohibits me from analyzing some very important aspects of the research question. A dynamic model would imply that different consumer types not only purchase different PCs, but make their purchases *at different times*, and firms are likely to take this into account. Moreover, my framework does not account for the crucial role played by CPU innovation in fostering complementary innovation in software. My analysis, therefore, does not account for some long-term welfare contributions of CPU innovation. I return to these issues in the concluding section.

My welfare calculations define "producer profit" as the profit of PC makers only. My framework does not, therefore, consider the effect of PC makers' decisions on the profit of upstream firms like Intel or Microsoft. The strong segmentation of consumer demand, however, implies that keeping basic PC configurations on the shelf should not cannibalize sales of Intel's new chips to a large extent. Moreover, the counterfactual changes to product offerings that I consider (*i.e*. adding or removing a particular configuration of a downstream notebook PC product line) should have a much more important impact on the thin-margin PC makers than on Intel.

Finally, my framework does not explicitly address the secondary market for used and refurbished PCs. In principle, this market could provide an ideal solution to the problem addressed in the article.[4] This secondary market, however, has not yet developed sufficiently to perform this role. The IDC estimated in 2008 that of the 70 million PCs sold in the U.S. every year, about 3.5 million (or, 5%) are fixed up and resold. The biggest buyers of these refurbished machines are non-profit organizations and schools, suggesting a very small impact on the consumer segment that I study.[5] It is difficult to estimate the total size of the market for used PCs, but an indirect analysis shows that the data I use are not likely to miss a substantial volume of such transactions.[6] It does not appear, therefore, that I have ignored a substantial secondary market in my analysis. The limited

4. This possibility is articulated by TDX Tech, an IT company: "From a marketing standpoint, computers will become obsolete as soon as they are bought because there is always something newer available. But when it comes to usability, people are increasingly realizing that this is no longer the case. A refurbished computer made 5 years ago will run Microsoft Office and other mainstream applications and browse the internet as well as the latest piece of technology." Source: the company's website: http://www.tdxtech.com.

5. "Microsoft: Reused PCs Need Windows, Too", Businessweek.com, November 2008.

6. Using the Consumer Expenditure Survey of the US Bureau of Labor Statistics (BLS), I calculated that the average per-person annual spending on "Computers and computer hardware (for) nonbusiness use" was $57.92 in 2003. In correspondence, the BLS confirmed that this figure pertains to *the combined spending on new and used computers*, since the BLS does not separate spending on new and used PCs in its survey (I am very grateful to Steven Henderson and Nicholas Zwileneff at the BLS, and especially to my research assistant Kostia Kofman.). Dividing the total value of 2003 transactions that I observe in my data by total U.S. population, I obtain a figure that is even larger: $60.88. While these are crude calculations, they do suggest that my data provide very good coverage of the universe of PC purchases. Additional details are available from the author upon request.

role played by the secondary market is probably associated with information asymmetries, and by the high incidence of technical problems in used PCs.

Methods and related literature: The framework proposed in this article has two main methodological aspects. The first is the estimated model, that has the following features: (i) firms make multiple-discrete product choices, such that both the number and the identity of offered products are treated as endogenous, (ii) a detailed model of differentiated-product cost and demand systems is incorporated, and (iii) the model allows for product-specific structural errors, and formally deals with the resulting selection bias issue. A second methodological aspect is the counterfactual analysis: I go beyond the estimation of a partially-identified model, and use this estimated model to simulate sets of "potential equilibrium" predictions.

This article belongs in a growing literature that treats product choices as endogenous (see Crawford (2012) for a recent survey). To provide some examples, Ishii (2006) treats the number, but not the identity, of ATMs offered by banks as endogenous. Draganska *et al*. (2009) treat both the variety and prices of ice cream products as endogenous. My framework differs from theirs in several respects: first, they do not address the problem of selection on unobservables, and instead assume that this issue is sufficiently controlled for by observed product characteristics. Second, they assume that fixed costs are private information, allowing them to compute a unique equilibrium outcome. In contrast, I assume full-information and explicitly deal with multiple equilibria in both the estimation, and in the counterfactual analysis.[7]

The discrete nature of the product choices implies that a unique equilibrium is not guaranteed, leading to the partial identification of fixed costs (Tamer, 2003). Recent literature (Ciliberto and Tamer, 2009; Pakes, Porter, Ho, and Ishii [PPHI] (2011), Ho and Pakes, 2012) exploits necessary equilibrium conditions to place bounds on partially identified parameters. Most of these applications employ a reduced-form profit function, whereas I derive this function from a detailed model of cost and demand. I extend the necessary conditions approach to a multiproduct setup, and estimate bounds on the fixed costs of leading notebook manufacturers.

A sample selection problem arises since firms are explicitly assumed to have selected the set of products observed in the data. Such selection problems in discrete games are discussed extensively by PPHI who propose several possible solutions. In my framework, structural errors are incorporated into both the fixed and the variable components of the profit function, creating a potential bias in the estimation of both variable profits and fixed costs. The decision to launch a particular product may depend on the errors of all other products, making this a very difficult problem to solve. I formally address these issues. First, the selection on variable profit unobservables is handled via a standard assumption that is familiar from the literature: firms only observe the realizations of these errors after committing to product choices.

Second, to address the selection on fixed cost errors, I propose a strategy that builds on a partial-identification approach: under suitable assumptions, I estimate support bounds for fixed costs, and substitute them for non-randomly missing bounds to obtain moment inequalities that do not condition on observed choices.[8] Since I assume that different configurations of the same

7. Additional examples include Crawford *et al*. (2011) who treat the number and quality of products as endogenous. They model continuous quality choices, and therefore rely on very different methods than mine. Berry *et al*. (2013) treat the number and type of radio stations as endogenous. They, however, assume single-product firms, do not formally incorporate selection into the estimated model, focus on the *number* of stations of each type as the endogenous variable, and do not use the model to solve for counterfactual sets of equilibrium predictions. Finally, Nosko (2011) adopts elements of the framework that was introduced in this article.

8. This strategy, introduced in this article, has recently been adopted by Nursky and Verboven (2013) who estimate bounds on the fixed costs of car dealerships. This approach is related to Manski's (2003) strategy for bounding the mean of a random variable when some observations are non-randomly missing. Notice that the fixed cost parameters are only partially identified because of two separate reasons: the non-uniqueness of equilibrium, and sample selection.

product line have different structural errors, the errors cannot be differenced out as suggested by one of PPHI's strategies. My approach is closest in spirit to another PPHI strategy (see their Example 3) since it obtains moment inequalities that do not condition on observed choices. My strategy for constructing such moments, however, is different than theirs.

Simulating sets of counterfactual predictions requires me to consider many feasible product-choice vectors and to search for profitable deviations from each of them. I develop a concept of "potential equilibria" since, given the partial identification of fixed costs, it is not always possible to unambiguously determine whether a deviation is profitable. Focusing the counterfactual analysis on the mobile segment allows me to restrict the space of such cumbersome computations without sacrificing much of the economic content. The remaining problem is still quite challenging computationally, but I demonstrate that such challenges can be overcome.

Finally, this article also contributes to the literature on the CPU market. Song (2007, 2010), Gordon (2009), and Goettler and Gordon (2011) study this market using dynamic models, assuming that the CPU serves as a perfect proxy for the PC. The current study addresses a different set of questions (*i.e.* product variety), and therefore develops a very different framework.

The rest of this article 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 questions 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.[9] 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 (Home), vendor (Dell), brand (Inspiron), form factor (Portables), CPU vendor (Intel), CPU brand (Pentium 4), and CPU speed range (1.0–1.49 GHz) combinations.[10] 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. I define a product as a unique combination of observed characteristics.[11]

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 consumers.[12] I therefore use only the portion of the data which pertains to the Home segment of the market, and, following previous work (Sovinsky Goeree, 2008), I define the size of the market as the number of U.S. households in a quarter, as reported by the U.S. Census Bureau.[13] 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.

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

9. http://www.IDC.com/.

10. In some cases, slightly less-disaggregated information is available in that sales are split evenly among observations pertaining to the same vendor-quarter cell. This issue is not likely to cause a problem since the implied average prices appear very reasonable.

11. These definitions follow Sovinsky Goeree (2008). The data used in that paper have a somewhat similar structure to those used in this article, in that they also consist of 12 quarters, and have similar observed product characteristics.

12. Purchases of the latter were studied by Hendel (1999).

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

TABLE 1
Top vendors' market shares, U.S Home PC market

Year 1		Year 2		Year 3	
Vendor	Share	Vendor	Share	Vendor	Share
Dell	0.190	Dell	0.263	Dell	0.279
HP[a]	0.185	HP	0.234	HP	0.258
Compaq[a]	0.092	eMachines	0.076	eMachines[a]	0.070
Gateway	0.091	Gateway	0.070	Gateway[a]	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

Note: Years: 01Q3-02Q2, 02Q3-03Q2, 03Q3-04Q2. [a]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

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

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. The top 5 vendors together accounted for a 60%–70% share of the market. 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 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%).[14]

Evidence for the rapid innovation in CPUs is offered in Figure 1, depicting 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.[15]

14. After removing Apple products, observations with negligible market shares (defined as selling less than 100 units in the quarter), observations with a dollar value of zero, and observations with missing speed information, I obtain 2287 quarter-product observations.

15. It is worth noting 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, have better designs, or use more sophisticated algorithms. In the empirical application I control for both CPU brand and clock speed, which together adequately capture CPU performance. Alternatively, one

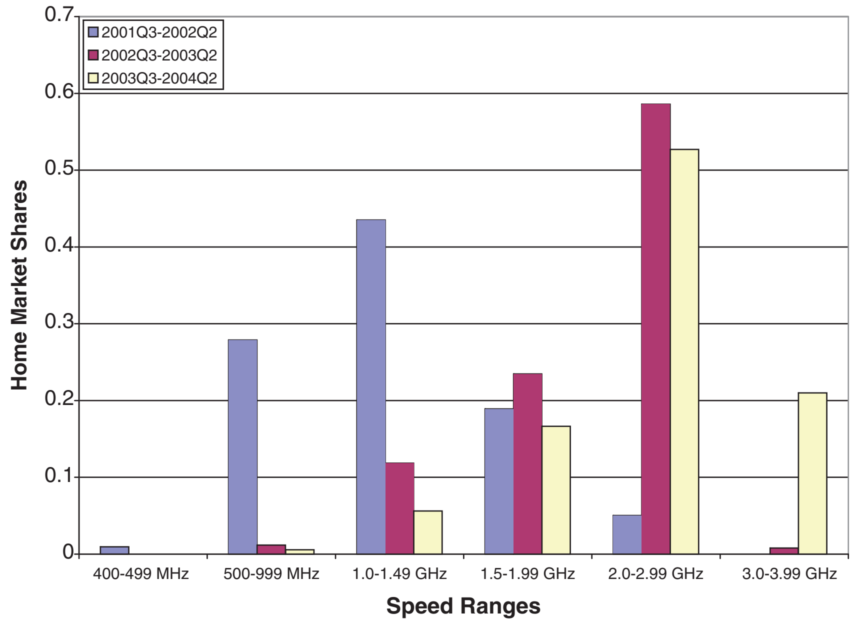


FIGURE 1

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

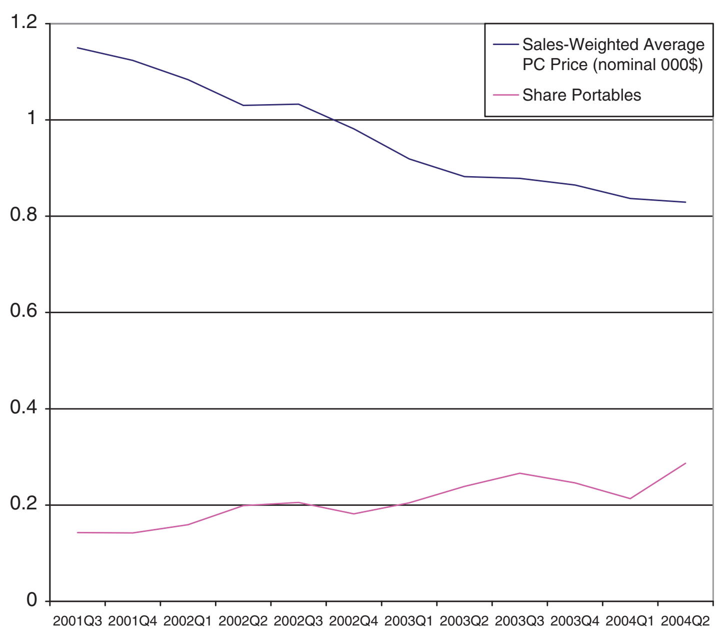


FIGURE 2

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

A fundamental force behind CPU innovation has been the ability to double the number of transistors on an integrated circuit every 18–24 months ("Moore's law"). As a consequence, chips become smaller, faster, less power-consuming, and cheaper to produce. Lower power consumption contributed to the growth of the mobile PC segment, while lower production costs contributed to a rapid decline in PC prices. Both these trends are underscored in Figure 2.

PC product lines and CPU technologies: This article studies 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 *CPU technologies* as combinations 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. 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 example, reports the fraction of product lines that adopt Celeron processors with CPU speed in the 0.5–0.99 GHz range. These CPUs were utilized in 89% of the product lines in the first quarter, but were rapidly phased out, in parallel to increased adoption of new CPU technologies. Note that the "adoption rate" of a technology is different than its market share.[16] Table 3b reports adoption rates for portable PC product lines.

Table 3a and b convey significant variation, in that most CPU technologies are only adopted in a subset of product lines at a given point in time. This variation is instrumental in identifying the cost of offering PC configurations. Some of this variation, however, is 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. In such cases, it is likely that Intel has already phased out the relevant technology, and it would therefore be misleading to include it in the menu of CPU technologies that PC makers can feasibly install. I describe below how I take such issues into account in defining the feasible set of CPU technologies.

Another insight is that some "old" CPUs can still be found on the market even after most PC makers have abandoned them. The PC consumer described in this article, however, cares not only about the CPU but also about the PC in which it is installed. Imagine a consumer who appreciates the Toshiba notebook brand, but has only modest computing-power needs. This consumer may optimally choose a Pentium III-based Toshiba notebook. If this product is eliminated, this consumer may not view a cheap notebook brand with the Pentium III installed as an attractive substitute to the Toshiba-Pentium III combination. This motivates characterizing product variety in this market in terms of PC-CPU combinations.

Product configurations and fixed costs: Different configurations of a PC product line may differ not only in the CPU installed, but also in other dimensions that I do not observe: for example, they may need different motherboards, since different CPUs are not always "pin compatible". They may also be sold with different disk drives or memory chips. This motivates me to include configuration-specific errors in the utility, marginal cost, and fixed cost specifications.

I assume that each additional configuration of a PC product line is associated with fixed costs. My estimation results suggest that those are of a sizable magnitude. Why should we expect such substantial fixed costs? Fixed production costs increase in the number of configurations for several reasons. First, offering a wider array of configurations leads to smaller production

could use one of the various "CPU benchmarks" created by users to rate processors. Conditioning on both the brand and the speed, however, should provide most of the information contained in those (somewhat arbitrary) ratings.

16. To demonstrate via the Celeron 0.5–0.99 example, there were 28 desktop product lines in 2001Q3, 25 of which offered this CPU technology, implying an adoption rate of $25/28 = 0.89$.

TABLE 3

Adoption rates of CPU technologies

(a) Desktop product lines

Quarter	C_0.5-0.99	C_1-1.49	C_1.5-1.99	C_2-2.99	P3_0.5-0.99
2001Q3	0.89	0.00	0.00	0.00	0.93
2001Q4	0.46	0.42	0.00	0.00	0.46
2002Q1	0.35	0.58	0.00	0.00	0.31
2002Q2	0.13	0.57	0.00	0.00	0.17
2002Q3	0.09	0.39	0.48	0.13	0.13
2002Q4	0.07	0.04	0.44	0.41	0.11
2003Q1	0.04	0.04	0.41	0.41	0.04
2003Q2	0.04	0.04	0.37	0.41	0.04
2003Q3	0.04	0.04	0.24	0.48	0.04
2003Q4	0.04	0.04	0.20	0.52	0.04
2004Q1	0.00	0.04	0.15	0.54	0.00
2004Q2	0.00	0.00	0.17	0.54	0.00

Quarter	P3_1-1.49	P4_1-1.49	P4_1.5-1.99	P4_2-2.99	P4_3-3.99
2001Q3	0.67	0.48	0.26	0.00	0.00
2001Q4	0.50	0.65	0.65	0.12	0.00
2002Q1	0.31	0.58	0.73	0.50	0.00
2002Q2	0.13	0.43	0.70	0.65	0.00
2002Q3	0.13	0.26	0.74	0.70	0.00
2002Q4	0.04	0.11	0.37	0.81	0.00
2003Q1	0.00	0.11	0.44	0.81	0.15
2003Q2	0.00	0.11	0.44	0.81	0.15
2003Q3	0.00	0.08	0.28	0.92	0.60
2003Q4	0.00	0.12	0.28	0.92	0.60
2004Q1	0.00	0.08	0.19	0.92	0.65
2004Q2	0.00	0.08	0.17	0.92	0.63

(b) Portable product lines

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

Notes: Home market, Intel technologies. Excluding vendors identified as "Others", Apple products, and products with sales smaller than 100 units in a quarter. C=Celeron, P3=Pentium III, P4=Pentium 4 and Pm=Pentium M. P3_0.5–0.99=Pentium III with speed between 0.5 and 0.99 GHz. As explained in the text, the "adoption rate" of a technology is different than its market share. To demonstrate this concept, consider the C_0.5–0.99 example: there were 28 desktop product lines in 2001Q3, 25 of which offered this CPU technology, implying an adoption rate of $25/28 = 0.89$. CPU technologies with very small installation rates excluded in panel (b).

batches and lower economies of scale. Second, inventory management costs may substantially increase due to the need to use different hardware components (CPU, motherboard) in different configurations. PC makers normally order such components from upstream suppliers, who may be capacity constrained, leading to production delays.

Upon receiving such components from the supplier, the PC maker subjects them to quality control testing. If the shipment fails this test, it may take several weeks to overcome the setback.[17] Timely assembly and shipment of multiple configurations may, therefore, involve costly challenges.[18] Additional costs result from labeling and packaging each offered configuration.

Selling additional configurations in a particular quarter also increases the firm's sales and marketing costs. For example, ads often include a detailed description of multiple configurations (Sovinsky Goeree, 2008), and so extra ad space may be needed to inform consumers of additional configurations. Distribution fixed costs may also increase due to the need to place a wider array of products on physical and virtual shelves.

Consistent with these institutional details, I model fixed costs as being associated with offering the configuration in a particular quarter, allowing these costs to be subject to shocks at the configuration-quarter level. In principle, there could be additional "set-up" costs, that are paid once at the first time in which the configuration is offered. Unlike the launching of a new PC product line (*e.g.* the IBM ThinkPad), however, launching a new configuration of an existing product line is not likely to involve substantial learning or development costs. Installing a new CPU in an existing PC product mostly requires the use of a compatible and appropriately-configured motherboard. Given the limited scope of set-up costs, I do not model them and instead focus on the costs of selling the configuration in a given quarter.[19]

3. MODEL

The primitives of the model are consumer demand for PCs, PC 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 *et al.* (1995) (BLP), and Sovinsky Goeree (2008), PC demand is modeled by a random-coefficient-logit specification. A set J_t of PC products is offered in quarter t. Each household chooses at most one of these products, or chooses the outside option of not purchasing any of them. The latter option may include buying or continuing to own a used PC, or buying an Apple computer. Households maximize the following indirect utility function, describing the

17. An example of a failed quality control test for a component purchased from an upstream supplier, and its implications, is described in "Building the Perfect Laptop", *Bloomberg Businessweek*, 14 February 2008.

18. Dell's FY09 10-K filing comments that: "Our financial success is partly due to our... ability to achieve rapid inventory turns. Because we maintain minimal levels of component and product inventories, a disruption in component or product availability could harm our financial performance...We require a high volume of quality products and components from third party vendors... Our increasing reliance on these vendors subjects us to a greater risk of shortages, and reduced control over delivery schedules of components and products...*as well as a greater risk of increases in product and component costs*...In addition, defective parts and products from these vendors could reduce product reliability and harm our reputation." (*emphasis* added).

19. My static model assumes that offering a configuration at time t does not affect the cost of offering the configuration in future quarters. While this is a simplifying assumption, the fact that firms strive to keep low inventories implies that it is a reasonable one.

utility derived by household i from PC product j at time t:

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

where x_{jt} is a K-vector of PC characteristics that are observed by the econometrician, including 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 that captures the change over time in the valuation of the outside option. The variable ξ_{jt} is a demand shifter that is unobserved by the econometrician. Price is denoted 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 ϵ_{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 (α,σ^p).[20] The demand parameters are $\theta^d=(\beta',\alpha,\sigma')'$. Note that utility is separated into a mean-utility component δ_{jt}, and a household-specific deviation $\mu_{ijt}+\epsilon_{ijt}$. I further define $\theta_2\equiv(\alpha,\sigma')'$.

This specification allows households' taste towards a characteristic $k\in\{1,2,...,K\}$ to shift about its mean, β^k, with the heterogeneous term $\sigma^k v_i^k$. For computational reasons, I restrict many of the σ^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 (via a random coefficient on the constant term), and in the degree to which that taste changes over time (via a random coefficient on the time trend). 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:

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

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 predetermined 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:

20. The log-normal distribution helps in fitting the model to the data, presumably since it imposes that all simulated consumers have the correct sign for their price sensitivity. This functional form was used, for instance, in Song (2014) study of the PC industry.

1. PC makers observe realizations of shocks to fixed costs that are unobserved by the econometrician; they then simultaneously choose which CPU technologies to offer with each product line, and 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.

At stage 1, firms are assumed to know the distribution of shocks to demand and marginal cost, but they only observe their realizations at Stage 2, after having committed to their product choices. Since I control for detailed PC brands (for most brands) and for CPU brand and speed range, these errors should not capture systematic effects that firms are likely to know prior to committing to their configuration choices. I now turn to a formal description of the game.

Denote by D the set of active PC vendors (quarter indices suppressed), and let S_d denote the set of product lines for firm $d \in D$. Let H represent the menu of feasible CPU technologies. Denote by $L_{dm} \subseteq H$ the set of CPUs that firm d chooses to offer with product line m.[21]

Stage 1: In the beginning of this stage, firms observe realizations of shocks to fixed costs. Each potential PC configuration (*i.e.* CPU option) that firm d could feasibly offer is associated with fixed costs that would be incurred, should the firm choose to offer that configuration. Let $\mathcal{J}^d$ represent the set of all firm d's *potential* product configurations, *i.e.* both those configurations offered, and those which the firm chooses not to offer. This set has $|S_d| \times |H|$ elements. The following specification is chosen for the fixed cost associated with firm d's product $j \in \mathcal{J}^d$:

$$F_j = F^d + \nu_j, \quad \text{with } E\left[\nu_j \middle| j \in \mathcal{J}^d\right] = 0 \tag{4}$$

This specification implies that the fixed costs associated with firm d's products are given by adding together a mean, F^d, viewed as a parameter to be estimated, and a mean-zero error term. It allows for both heterogeneity in fixed costs across firms (via the mean), and for stochastic fluctuations about that mean across configurations (and time periods, recalling that quarter indices were suppressed). Fixed cost heterogeneity across configurations is to be expected: for example, they may raise different inventory management issues.

The additivity in fixed costs of different configurations does not allow for economies (or diseconomies) of scope. The same simplifying restriction has been used by Draganska *et al.* (2009). Institutional details suggest that economies of scope may arise from the relative ease of handling technologically similar configurations. Diseconomies may arise from the increased managerial attention needed to handle the inventory of multiple components. Such effects could be captured by adopting a more flexible specification, and I explore such an approach in Appendix A.3. As explained there, several reasons motivate me to favour the simpler specification described above. First, identification of the sign of the nonlinear effect (*i.e.* whether economies or diseconomies of scope obtain) would rely crucially on functional form assumptions. Second, estimating bounds on a single parameter (F^d) allows me to perform inference using rather simple methods.

Upon observing the shocks ν_j, firms proceed with simultaneous product configuration choices: each firm $d \in D$ determines the sets L_{dm} for each product line $m \in S_d$. Collecting these sets across all firms yields the set $J = \{L_{dm}\}_{d \in D,\ m \in S_d}$ of all PC products that would be offered in the quarter. Firms then pay the fixed costs F_j associated with each configuration they offer.

21. For instance, if $d =$ "*Dell*", $m \in S_d$ is Dell's "Inspiron" product line, and $L_{dm} = \{\text{P4 1-1.49 GHz, P4 1.5-1.99 GHz}\}$, then Dell has chosen to sell two Inspiron configurations, based on Intel's Pentium 4 CPUs with the specified speed ranges.

Restricting the set of PC product lines for which fixed costs are estimated: In order to reduce the computational burden, and focus on estimating parameters that would be useful for the welfare analysis, the empirical application estimates fixed costs for certain PC product lines only (demand and marginal cost parameters, however, are estimated for all products). Since the counterfactual analysis focuses on the notebook segment of the market, I only estimate notebook fixed costs. Moreover, since the aggregate market share of the leading four product lines exceeds 70% (with the fifth-largest line being substantially smaller than the leading four), fixed cost parameters were only estimated for the four top-selling notebook product lines.

These four leading notebook lines belong to the three leading notebook producers: Dell, HP and Toshiba, with HP owning two of those product lines. Given the technological similarity of the two HP product lines (and HP's tendency to make similar configuration choices for both), I impose that both of HP's product lines are characterized by the same mean (per configuration) fixed cost parameter F^{HP}. Together with F^{Dell} and $F^{Toshiba}$, this leaves me with three fixed cost parameters to estimate. Notice that F^{Dell}, F^{HP}, and $F^{Toshiba}$ are fixed cost parameters that are specific to particular notebook product lines of these manufacturers.

Determining the sets H in the empirical application: Importantly, Intel constantly phases out old chips in order to shift production toward more efficient production lines. Intel posts announcements of these decisions, known as PCNs (Product Change Notification), informing PC makers of the last date in which they can place an order for the discontinued chips.[22] This implies that I must restrict the set of CPUs that can be considered as "feasible" in a given quarter.

If I fail to eliminate chips that were not really available to PC makers, I may compute false lower bounds on fixed costs: as Section 4.2 explains, a lower bound on fixed costs is generated by any feasible product that was not offered. If the configuration was not really feasible, this bound would be misleading. Ideally, I would like to rely on Intel's PCNs to determine when to remove chips from the feasible set. Since I only observe CPU brand and speed range, while the PCNs pertain to very detailed CPU model specifications, this turns out to be very difficult in practice. As an alternative, I infer what the feasible set is from observed offerings, relying on the logic that if a chip is feasible, at least some of the many firms in the industry would offer it.

In particular, I include in this set, for a given quarter, Intel CPUs that satisfy the following criteria: (i) the CPU technology must sell at least 10,000 units, (ii) it must be offered by at least two firms, and (iii) it must be offered by at least one of the four leading notebook product lines mentioned above. CPUs that sell a very small quantity, or are offered in the product lines of a single PC maker are strongly suspect of being discontinued. It is very likely that they only register positive sales due to a small remaining stock that was cleared in the current quarter. A similar logic motivates ignoring chips that were not offered by a single one of the leading notebook brands, since it is smaller firms that are more likely to still be selling some outdated chips. Moreover, I am estimating the fixed costs of the four leading notebook product lines, and so the feasible set should include CPUs that are relevant for these leading lines (as opposed to some niche product line, such as an ultraportable that may admit special types of chips).

This strategy runs the risk of selecting information on observed outcomes. To address this concern, I report in Appendix A.3 robustness checks demonstrating that the estimates are not sensitive to dropping any one of the three restrictions. The sets H obtained by applying these criteria in the various quarters are reported in Table 4. As we move forward in time, the entire menu of CPUs is changing: new CPUs are being added, and older CPUs are dropped.[23]

22. For an example of such a notice, see https://qdms.intel.com/dm/d.aspx/6352D9B4-C564.../PCN110104-00.pdf

23. As Table 4 shows, Pentium 4 1.5–1.99 GHz chips entered the feasible set before their 1.0–1.49 GHz counterparts, and the Pentium M 1.5–1.99 GHz were available before their 1.0–1.49 GHz counterparts. Intel sometimes introduces a

TABLE 4
The sets H of feasible CPU technologies

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
P3_0.5-0.99	X	X	X									
P3_1.0-1.49		X	X	X	X	X	X	X	X	X		
C_0.5-0.99	X	X	X									
C_1.0-1.49		X	X	X	X							
C_1.5-1.99					X	X	X	X	X	X	X	X
C_2-2.99						X	X	X	X	X	X	X
P4_1.0-1.49				X	X	X	X					
P4_1.5-1.99			X	X	X	X	X	X	X	X	X	X
P4_2-2.99					X	X	X	X	X	X	X	X
P4_3-3.99										X	X	X
PM_1.0-1.49									X	X	X	X
PM_1.5-1.99								X	X	X	X	X

Notes: The table reports, for each of the 12 data quarters, the set H of feasible CPU technologies. See text for the three criteria which determine inclusion in this set.

Stage 2. I let the log of marginal costs for a PC product j depend linearly on observed cost shifters, w_j, and on an additive error term ω_j:

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

I set $\mathrm{w}_j = x_j$, *i.e.* the same observed characteristics shift both utility and marginal cost.

In the beginning of Stage 2, firms observe realizations of $e_j = (\xi_j, \omega_j)'$ 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). Firms then simultaneously set prices for products $j \in J$ to maximize profits. Firm d's profits are given by:

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

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 ℓ of product line $m \in S_d$. M is the market size, p is a $|J|$-vector of prices, and TF_d is firm d's total fixed cost.

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.[24] 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.

weakened version of an existing CPU for price discrimination reasons (Deneckere and McAfee, 1996). Also note that chips of a particular brand (*e.g.* Pentium M) differ not only in clock speed, but also in additional dimensions, such as the amount of cache memory. It is possible that the 1.0–1.49 GHz Pentium M is actually more advanced than the 1.5–1.99 GHz Pentium M. This is especially likely with chips introduced towards the end of the sample period, when clock speed started to become less important. Finally, robustness checks reported in Appendix A.3 change the feasible sets in ways that undo the pattern in which a slow chip may enter the feasible set after a fast one.

24. This is a standard assumption in the literature on differentiated product demand (*e.g.* Nevo, 2001). The results of Caplin and Nalebuff (1991) guarantee a unique price equilibrium under stronger restrictions than those imposed here.

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. 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, suppose we had only two heterogeneous PC makers, each with a single product line. We could have one equilibrium in which only firm A caters to the value segment of the market by offering a low-end PC configuration, and a second equilibrium, in which only firm B does 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 γ, and the fixed cost parameters F^{Dell}, F^{HP}, and $F^{Toshiba}$ capturing the mean, per-configuration, per-quarter fixed cost for those firms' leading notebook product lines. Let $\theta = (\theta_d', \gamma')'$. The estimation strategy obtains an estimate $\hat{\theta}$ first, revealing information on variable profits associated with product configurations. Necessary equilibrium conditions then place bounds on fixed cost parameters. These tasks are explained in turn in the subsections below, and involve overcoming sample selection issues.

4.1. *Estimating the variable profit parameters* $\theta = (\beta', \alpha, \sigma', \gamma')'$

Intuitively, the demand parameters are identified from the joint distribution of prices, sales, and observed PC characteristics. Marginal cost parameters γ 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 γ.

Identification of θ is jeopardized, however, by sample selection, as the set J of offered configurations was selected by firms. The econometrician, therefore, does not observe a random sample from the underlying distribution of product characteristics. I address this issue using a standard approach: the timing assumptions of the model imply that θ is still point-identified, and can be consistently estimated following the BLP method. The intuition is that, under the assumption that firms do not observe the error terms until after they have selected their products, the selection does not depend on these unobservables. Selection on e can, therefore, be ignored. This has the familiar flavor of a "selection on observables" argument (see Wooldridge, 2002, ch. 17, for a general discussion).

A referee pointed out that merely assuming that the firm does not observe the realizations of e until it has committed to its product choices is not necessarily sufficient to overcome the selection problem: if marketing research allows the firm to obtain some forecast of e, its product choices would be correlated with e. While firms are indeed able to forecast demand, as long as they are mostly able to forecast the systematic effects for which I control (PC and processor brand, form factor, processor speed), the assumption that they cannot forecast e (except for knowing its distribution) can be viewed as a reasonable (though imperfect) simplification.

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 $\mathcal{J}$ the set of all $|H| \times |P|$ *potential* product configurations. It is from this set that firms pick, in Stage 1, the subset $J \subseteq \mathcal{J}$ actually offered to consumers. Let X denote a $|\mathcal{J}| \times K$ matrix of product characteristics for all the 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* $j\in\mathcal{J}$

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 $j\in\mathcal{J}$, I define a selection indicator, $q_j(X,F)$, which is equal to 1 if j was chosen for production, and is 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:

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

BLP show that a generic value for the parameter θ 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:

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

where θ_0 is the true parameter value. Equation (9) defines L moment conditions that provide point identification of θ.[25] Notice that we overcome the selection problem by obtaining a moment condition that is defined over observed products only. GMM estimation of θ using the moment conditions (9) follows the BLP method. Additional details regarding this estimation procedure are provided in Appendix A.1.

Choice of instruments: Equation (9) shows that any function of the observed characteristics X is a valid instrument. Since prices are set in stage 2 after the firm observes the realized errors, they are endogenous. Choosing instruments that are correlated with prices allows one to address this price endogeneity issue. Following Berry (1994) and BLP, I choose 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 its competitors in various data cells (*e.g.* form factor-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.[26] I also use interactions of observed PC characteristics (laptop, Pentium, and Celeron dummy variables) with a time trend to obtain additional instruments. These 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.

4.2. *Estimating the fixed cost parameters F^d*

Given the point estimate $\hat{\theta}$ obtained in Section 4.1, set estimates can be obtained for the fixed cost parameters F^{Dell}, F^{HP}, and $F^{Toshiba}$ (also referred to as F^d parameters, see Section 3). Recall the definition of such parameters: F^{Dell} is the mean, per-configuration, per-quarter fixed cost for Dell's leading notebook product line.

Since there is no guarantee of a unique equilibrium, even if I specified a distribution for fixed costs, the probabilities of product-choice outcomes could not be pinned down, making it impossible to write down a well-defined likelihood function (Tamer, 2003). A unique equilibrium

25. Additional regularity conditions are necessary for a formal identification argument.

26. For the purpose of constructing this instrument I compute speed as the middle of the relevant speed range.

prediction for the number of offered products obtains if one assumes that products are homogenous (Bresnahan and Reiss, 1991), but this would clearly not allow me to study product variety. Berry (1992) and Mazzeo (2002) obtain a unique equilibrium by imposing an assumption on the order of moves in an entry game. Such an assumption, however, may not be attractive in a market in which several equally important sellers choose product portfolios. I, therefore, follow the strand of literature that does not impose a unique equilibrium, and instead obtains partial identification via necessary equilibrium conditions (*e.g.* PPHI; Ho and Pakes, 2012).[27]

I use information from product offerings in quarters 7 through 12 in estimating the F^d parameters. Not using information from quarters 1 through 6 saves on computation time, and allows me to focus on the latter part of the sample, which is more relevant for the counterfactual analysis.

The observed product choices and prices are assumed to support an SPNE of the two-stage game. A necessary equilibrium condition is, then, that no firm can 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 on rivals' *product choices*). Such conditions imply fixed cost bounds. In particular, an upper bound can be derived on the fixed cost associated with each offered product, and a lower bound is available for the costs associated with each product the firm does not offer. These bounds, in turn, are used to construct bounds on the F^d parameters.

Let the vector A_d denote firm d's observed product choices. Each entry in this vector corresponds to a potential product configuration the firm may offer, and is a binary variable, taking the value 1 if the relevant product configuration is offered, and zero if it is not offered. Also define the sets $A_d^1=\{k:A_d(k)=1\}$ and $A_d^0=\{k:A_d(k)=0\}$, which collect the indices corresponding to products offered and not offered, respectively.[28] The set of all the entries in A_d corresponds to $\mathcal{J}^d$, defined above as the set of all firm d's potential products.

Bounds on F_j: Consider configuration $j\in A_d^1$, *i.e.* firm d chose to offer this configuration. We obtain the following upper bound on F_j, the fixed costs associated with this configuration:

$$F_j \leq E_{(e|\theta_0)}\Big[VP_d(A_d;e,\theta_0)-VP_d(A_d-\mathbf{1}_d^j;e,\theta_0)\Big]\equiv\overline{F}_j(\theta_0),\qquad \forall j\in A_d^1 \tag{10}$$

where $\mathbf{1}_d^j$ denotes a vector of the same length as A_d which j^{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 indexed by the parameter θ (see Appendix A.1).

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. Analogously, if j was not offered, a lower bound on its fixed cost is available: a deviation that adds j to the firm's portfolio must not be profitable, implying

27. The literature offers several additional approaches. Following Bjorn and Vuong (1985), one may specify equilibrium-selection parameters, but this approach is not likely to work well in a large game as the one studied here. Seim (2006) assumes that profitability shocks are private information, which alleviates (but does not formally eliminate) the multiple equilibria issue.

28. A practical issue is that, as explained above, I exclude products that 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".

that the added fixed costs must exceed the expected variable profit gains:

$$F_j \geq E_{(e|\theta_0)}\Bigg[VP_d(A_d+\mathbf{1}_d^j;e,\theta_0)-VP_d(A_d;e,\theta_0)\Bigg]\equiv \underline{F}_j(\theta_0), \quad \forall j\in A_d^0 \tag{11}$$

Using the bounds on F_j to set-identify F_d: Recalling that $F_j=F^d+\nu_j$, and applying a conditional expectation to (10) implies:

$$F^d+E\big[\nu_j|j\in A_d^1\big]\leq E\big[\overline{F}_j(\theta_0)|j\in A_d^1\big]$$

The expectation on the RHS is identified. If we could assert that $E\big[\nu_j|j\in A_d^1\big]=0$, we would have identified an upper bound on F^d. However, this conditional expectation is not zero: unlike the error e_j, the error ν_j was known to the firm at the time it committed to its product choices. While its unconditional mean is zero, its mean *conditional* on the product being offered need not be zero. The term $E\big[\nu_j|j\in A_d^1\big]$, therefore, represents a selection bias.

To circumvent this problem, I proceed with a strategy that allows me to obtain bounds on F_j for every potential product $j\in\mathcal{J}^d$, which hold regardless of whether this product is offered or not. It is then possible to obtain inequalities which involve the unconditional mean of ν_j, which does equal zero. To that end, I impose a bounded-support condition on firm d's fixed costs:

Assumption 2. $\sup_{j\in\mathcal{J}^d}\{F_j\}=F_d^U<\infty$, $\inf_{j\in\mathcal{J}^d}\{F_j\}=F_d^L>-\infty$

This assumption suggests that fixed costs associated with firm d's products have a bounded support given by $[F_d^L,F_d^U]$. The assumption that fixed costs are bounded from below is clearly weak as they can be assumed to be non-negative. The assumption that they are bounded from above is also reasonable, since the potential products considered here are standard CPU options installed in standard notebook PC product lines (a point to which I return below).

The intuition for why a bounded support is helpful can be stated as follows: imagine (only for a moment) that the econometrician knew the support bound F_d^U. It would have then been possible to use F_d^U as an upper bound on F_j for every configuration j that is unobserved in the sample (while still using $\overline{F}_j$ computed from the necessary condition (10) as an upper bound for any configuration j that is observed). In this way, we can obtain upper bounds on fixed costs regardless of whether the product was actually introduced, circumventing the selection problem.

In practice, the support bounds F_d^L and F_d^U are not known to us. The next assumption, however, guarantees that we can identify an interval which contains this unknown support:

Assumption 3. $[F_d^L,F_d^U]\subset supp\big($*expected change in variable profit due to elimination or addition of a single product by firm d*$\big)$

This assumption states that the support of the fixed costs is contained within the support of the expected change in variable profit resulting from single-product changes to the firm's product portfolio. As indicated in (10) and (11) above, such expected changes in variable profit are identified, and, as a consequence, so is their support, denoted by $[V_d^L(\theta_0),V_d^U(\theta_0)]$.

The intuition underlying Assumption 3 is that adding or removing a "blockbuster" product configuration has a substantial impact on *variable profit*, while adding or removing a "niche" configuration has a minimal effect. The length of the support $[V_d^L(\theta_0),V_d^U(\theta_0)]$ should, therefore, be quite large. In contrast, the impact on *fixed costs* of adding or removing a product primarily involves the added (or saved) per-product inventory management costs, or sales and marketing costs, which support can be assumed to be shorter than the support of variable profit changes.

Bounding the support of fixed costs via Assumptions 2 and 3 may appear, at first, inconsistent with the very problem of selection that we wish to resolve: fundamentally, products that we do not observe might have been characterized by infinitely large fixed costs, whereas here we place a finite bound on such costs. Note, however, that the set of potential products in this application does not include *any* hypothetical PC configuration. Rather, it is a set of CPU options that are offered by the leading PC manufacturers at the relevant time period, and, therefore, consists of rather standard configurations. Using the highest variable profit difference (stemming from a removal or addition of one product) ever computed for this firm's leading notebook product line as an upper bound on the fixed cost of some specific configuration of this product line is, therefore, quite conservative.

I now construct the identified set. For each $j \in \mathcal{J}^d$, define the following random variables:

$$L_j(\theta_0) = \begin{cases} V_d^L(\theta_0) & j \in A_d^1 \\ \underline{F}_j(\theta_0) & j \in A_d^0 \end{cases} \qquad U_j(\theta_0) = \begin{cases} \overline{F}_j(\theta_0) & j \in A_d^1 \\ V_d^U(\theta_0) & j \in A_d^0 \end{cases}$$

The following bounds on F_j now apply to *any* potential product of firm d (*i.e.* without conditioning on whether the product is offered):

$$L_j(\theta_0) \leq F_j \leq U_j(\theta_0) \quad \forall j \in \mathcal{J}^d \tag{12}$$

One can now apply an *unconditional expectation* to obtain:

$$EL_j(\theta_0) \leq F^d \leq EU_j(\theta_0) \;\; \forall j \in \mathcal{J}^d \tag{13}$$

The inequalities in (13) define the identified set for the parameter F^d.

Estimation: Motivated by the identified set in (13), the estimated set is obtained by replacing the true variable-profit parameter vector θ_0 with its consistent BLP estimator $\hat{\theta}$, computing the variables $L_j(\hat{\theta})$ and $U_j(\hat{\theta})$ for each potential product j, and then computing the sample averages of these variables.[29] Computing $L_j(\hat{\theta})$ and $U_j(\hat{\theta})$ requires estimating the following quantities: $\underline{F}_j(\theta_0)$ for all $j \in A_d^0$ and $\overline{F}_j(\theta_0)$ for all $j \in A_d^1$, as well as the support bounds $V_d^L(\theta_0)$ and $V_d^U(\theta_0)$ of such expected changes in variable profits.

The upper bounds $\overline{F}_j(\theta_0)$ for all $j \in A_d^1$ and the lower bounds $\underline{F}_j(\theta_0)$ for all $j \in A_d^0$ are estimated by simulating the expected changes to variable profits associated with adding or dropping products from the firm's observed portfolio (see equations (10) and (11)). The simulation, described in detail in Appendix A.2, involves drawing from the estimated distribution of the variable profit errors e. To estimate the support bounds, we first collect all the estimated $\overline{F}_j(\hat{\theta})$ and $\underline{F}_j(\hat{\theta})$ in a vector V_d, which j-th element is given by:

$$V_d(j) = \begin{cases} \overline{F}_j(\hat{\theta}), \; j \in A_d^1 \\ \underline{F}_j(\hat{\theta}), \; j \in A_d^0 \end{cases}$$

A natural estimator for $V_d^L(\theta_0)$ is given by $\min_{j \in \mathcal{J}^d} \left\{ V_d(j) \right\}$, and an estimator for $V_d^U(\theta_0)$ is given by $\max_{j \in \mathcal{J}^d} \left\{ V_d(j) \right\}$. Such estimators, however, are likely to suffer from finite-sample

29. Plugging in the estimator $\hat{\theta}$ for θ_0 means that the confidence interval described below needs to be corrected to account for the error in estimating θ. While this can be performed via a computationally expensive bootstrap, the precision with which θ is estimated suggests that the results are not likely to change much. The interval, in principle, also needs to be adjusted for the simulation error in computing the quantities in (10) and (11). As discussed in Appendix A.2., such expensive computations are not performed and are not likely to affect the findings of the article.

bias. I apply a simple method of correcting this bias presented in Hall and Park (2002).[30] The results section below reports estimated sets with and without such an adjustment. Reassuringly, the impact of such adjustments is not large.[31]

Having explained how to compute L_j and U_j, the *estimated set* is given by $[\overline{\ell}_n^d(\hat{\theta}), \overline{u}_n^d(\hat{\theta})]$ where

$$\overline{\ell}_n^d(\hat{\theta}) = (1/n^d)\sum_{j=1}^{n^d} L_j(\hat{\theta}), \quad \overline{u}_n^d(\hat{\theta}) = (1/n^d)\sum_{j=1}^{n^d} U_j(\hat{\theta})$$

with $n^d = |\mathcal{J}^d|$ denoting the number of firm d's potential products. Following arguments in Imbens and Manski (2004), we can construct a $(1-\alpha)\times 100\%$ confidence interval for F^d by constructing appropriate one-sided intervals for the sample averages:

$$\left[\overline{\ell}_n^d(\hat{\theta}) - \frac{S_\ell(\hat{\theta})}{\sqrt{n^d}} z_{1-\alpha},\ \overline{u}_n^d(\hat{\theta}) + \frac{S_u(\hat{\theta})}{\sqrt{n^d}} z_{1-\alpha}\right] \tag{14}$$

where $S_\ell(\hat{\theta})$, $S_u(\hat{\theta})$ are estimators of the standard deviation of L_j and U_j, respectively.

Note that, while I only use six markets (Q7–Q12) to estimate F^d, the relevant sample size is not the number of markets, but the number of the product line's potential products. Table 4 shows that each product line has $n^d = 41$ such potential products (to clarify, the seventh quarter has six such products, and summing these numbers over Q7–Q12 yields 41). The expectations $E(L)$ and $E(U)$ from equation (13) are defined over the sequence of these potential products. For the purpose of estimating bounds on F^{Dell} and on $F^{Toshiba}$, the sample size has 41 observations, while for the purpose of estimating bounds on F^{HP} the sample size is 82, since I impose the restriction that both of HP's relevant product lines are characterized by the same fixed cost parameter. Additional details regarding this set estimation are available in Appendix A.2.

Alternative estimators: The literature (*e.g.* PPHI; Holmes, 2011) discusses alternative assumptions for the distribution of ν. In particular, one could assume that these shocks are not correlated with products choices (*e.g.* they could be viewed as mean-zero measurement errors or optimization errors by the firm). Alternatively, one could suppress the shocks to zero. Section 5.2 below discusses estimates obtained under the baseline specification, and under both of these alternatives. Appendix A.3 discusses additional moment conditions that could potentially be exploited: namely, those that consider additional deviations from the firm's observed portfolio, beyond the addition or removal of a single product at a time. As shown there, the selection problem does not allow such moments to contribute additional information.

30. Consider a random sample $(X_1, \ldots X_n)$ from the distribution of the random variable X, and order it as $X_{(1)}, \ldots X_{(n)}$ where $X_{(k)} > X_{(k-1)}$ for each $k \in \{2, \ldots, n\}$. A downward-biased estimator of the upper bound of the support of X is $X_{(n)}$. The following correction for this estimator is suggested:

$$X_{(n)} + \frac{\sum_{i=1}^m (X_{(n-i+1)} - X_{(n-i)}) K(i/m)}{\sum_{i=1}^m K(i/m)}$$

where $K(\cdot)$ is a Kernel function. Following Hall and Park, I set $K(u) = (15/16)(1-u^2)^2 I(|u| \le 1)$ and $m = n^{2/3}$.

31. A second source of bias has to do with the fact that we do not observe realizations of the actual random variable in which we are interested (that is, variable profit differences), but rather estimates of such quantities that contain sampling error. Estimates of the maximum (minimum) of such quantities suffer from an upward (downward) bias as discussed in Haile and Tamer (2003). However, this is an "outward" bias that does not invalidate the procedure, since all that is required is that the true quantities are contained within the boundaries. This bias does imply, however, that the set estimates for F^d would be conservative in the finite sample.

TABLE 5
Descriptive results, logit demand

β	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^2	0.491	0.473

Notes: Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Dummy variables for main PC vendors and brands included, not reported.

5. ESTIMATION RESULTS

5.1. *Estimation results: variable profit parameters θ*

It is instructive to begin with a simple, descriptive outlook on the demand system. Table 5 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 σ coefficients to zero. Estimation is performed via linear regressions following Berry (1994). The first column provides OLS estimates of the mean utility parameters β, while the second column employs 2SLS to account for the endogeneity of price using the instruments described in Section 4.1. 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.

Households value CPU speed as well as high-end CPU brands (the omitted 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 the value of the outside option is improving over time, consistent with ownership of better PCs by the household population.

Full-model (BLP) estimation results for θ: The random-coefficient demand model allows for more realistic substitution patterns than the simple logit, and captures consumer heterogeneity along important dimensions. Table 6a and b provide estimation results for θ obtained by

TABLE 6
BLP estimates for θ

(a) Main PC characteristics

	β	SE	σ	SE	γ	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	α	SE	σ^p	SE		
	0.810	0.179	0.301	0.060		

(b) PC vendor and brand dummies

	β	SE	γ	SE		β	SE	γ	SE
Dell	12.332	2.603	0.774	0.062	**eMachines**	0.389	0.602	−0.325	0.050
dimension	−10.426	2.813	−0.915	0.065	**Toshiba**	7.933	1.684	0.479	0.050
inspiron	−9.908	2.732	−0.838	0.064	portege	0.593	1.018	0.093	0.059
latitude	−7.529	2.137	−0.488	0.071	port_tablet	2.855	1.303	0.218	0.085
optiPlex	−13.509	2.819	−0.903	0.064	satellite	−5.405	1.752	−0.517	0.055
HP	−0.976	0.334	−0.049	0.021	satpro	−2.628	1.141	−0.132	0.053
evoipaq	−1.651	0.519	−0.174	0.030	**Sony**	5.684	0.821	0.306	0.037
media	7.568	0.870	0.424	0.029	vaio_ds	−3.909	0.871	−0.265	0.043
pavilion	2.625	0.385	−0.015	0.024	vaio_r	0.500	0.824	0.205	0.052
presario	2.593	0.355	0.026	0.020	vaio_w	3.163	0.979	0.283	0.059
cmpq_notebook	1.841	0.653	0.175	0.033	vaio_505	1.288	0.963	−0.007	0.061
cmpq_ultprtbl	10.945	2.221	0.741	0.080	vaio_fx	0.951	0.734	0.053	0.053
Gateway	0.309	0.399	0.068	0.025	**IBM**	2.037	1.217	0.208	0.083
gateway3	−2.619	0.730	−0.408	0.035	netvista	−3.868	1.307	−0.244	0.087
gateway5	1.755	0.865	−0.030	0.048	thinkCentre	0.419	1.301	0.040	0.095
gateway7	2.159	0.690	0.077	0.035	thinkpadA	8.348	2.084	0.452	0.097
essential	2.124	0.458	−0.098	0.030	thinkpadT	1.253	1.366	−0.016	0.092
performance	1.751	0.530	0.039	0.034	thinkpadR	−3.304	1.291	−0.233	0.085
media	4.960	0.828	0.365	0.035	**Acer_veriton**	−2.120	0.382	−0.120	0.016
gateway4	−1.320	0.510	−0.139	0.031	**Averatec**	1.131	0.688	−0.034	0.048
gateway6	4.725	1.077	0.173	0.051	**Fujitsu**	−1.090	0.354	−0.018	0.023
solo	0.185	0.868	−0.106	0.050	**MicroElectronics**	−1.585	0.236	−0.009	0.017

Notes: Obs: 2287. Standard errors are not corrected for simulation error, which is mitigated via antithetic draws. See text for additional discussion of these coefficients.

following the BLP estimation procedure. Table 6a reports the estimated coefficients on main PC characteristics, while Table 6b reports estimated coefficients on a large number of dummy variables for PC vendors and brands. The estimated parameters include mean utility parameters (β), parameters which capture heterogeneity in household tastes (σ), marginal cost parameters (γ), and the parameters of the distribution of price sensitivity.

Table 6a reveals precise estimates of both the mean (α) and the standard deviation (σ^p) of the log-normal price sensitivity. 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 σ coefficient on the laptop dummy. Heterogeneity along this dimension is to be expected. As in the logit results, the negative β coefficient on the time trend implies that the value of the outside option is increasing over time. The random coefficient on the trend allows me to precisely estimate, in addition, the degree of household heterogeneity in this effect.

The marginal cost coefficients γ 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 6b reports estimated coefficients on a large number of dummy variables for PC vendors (*e.g.* "Dell") and their various brands (*e.g.* Dell's "Inspiron"). Dummy variables were included for all major vendors and for their major brands, but not for some very small vendors, which products serve as the "base" category.[32] 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, making it less reasonable to assume that firms do not observe these errors at the time they choose their configurations.

Importantly, vendor coefficients in Table 6b capture the effect of the vendor's brands for which no dummy variable was included. For instance, the "Dell" utility effect of 12.332 captures the effect of Dell's "Precision Workstation" and "Precision Mobile Workstation" brands, for which no dummy was included. The large utility coefficient and the large marginal cost coefficient are consistent with the "Precision" machines being high-quality, expensive products that account for relatively small sales in the Home market.

To obtain the utility effect of the popular Dell "Inspiron" notebook brand, one must sum the Dell coefficient (12.332) together with the Inspiron coefficient (-9.908) to obtain a total effect of 2.423. The marginal cost effect is calculated similarly: 0.774–0.838=-0.064, implying that the "Inspiron"'s marginal cost is 6.4% lower than that of a laptop in the "base" category. These utility and cost advantages are consistent with the observed popularity of this brand. Calculating brand effects as in the "Inspiron" example, it is easy to verify that additional popular brands (HP Pavilion, HP Presario, and Toshiba Satellite) utility effects range between 1.617 and 2.528, while their marginal cost effects range between -0.063 and -0.023. Other laptops (*e.g.* Dell latitude, Gateway 6 Series, IBM ThinkPad A, Sony VAIO 505) have larger utility effects than the four popular brands mentioned above, but enjoy lower observed sales. The reason is that these laptops also have higher marginal costs, which translate into higher consumer prices.

Elasticities, markups, and consumer willingness to pay: I now discuss important economic implications of the raw θ coefficients. Reassuringly, all products are priced at the elastic portion of their demand curves. I follow Genakos (2004) and calculate, in each quarter, the percentage drop in the total market share of all PCs (*i.e.* all "inside goods" combined) in response to a 1% increase in the price of all PCs. Over the 12 quarters, this elasticity ranges between -3.6 and -6, with a median value of -4.7. Interestingly, Genakos finds the exact same elasticity for the Home segment of the market (see table 6 in that paper). The own-price elasticities are, therefore, reasonable and comparable to those found in the literature.

Table 7a reports a matrix of own-price and cross-price elasticities for a sample of 5 desktops and 5 laptops in 2004Q2 (all of which have a Pentium 4 processor at the 2–2.99 GHz speed range). Laptops' shares are typically much more sensitive to changes in prices of other laptops than to

32. This "base" category accounts for 24.3% of total PC sales. Almost all of these (23.6%) pertain to vendors identified in the data as "Others", and the remainder (0.7%) pertain to some other very small vendors.

TABLE 7a
Estimated demand elasticities for a sample of products

	Dell	HP	Gateway	Sony	IBM	Dell[a]	Gateway[a]	HP[a]	IBM[a]	Toshiba[a]
Dell Dimension	−9.07	**0.26**	**0.10**	**0.03**	**0.00**	0.05	0.00	0.02	0.00	0.04
HP Pavilion	**0.25**	−10.43	**0.14**	**0.05**	**0.01**	0.05	0.00	0.02	0.00	0.04
Gateway 5 Series	**0.17**	**0.25**	−11.96	**0.09**	**0.01**	0.04	0.00	0.02	0.00	0.04
Sony VAIO R	**0.10**	**0.20**	**0.20**	−13.22	**0.01**	0.03	0.00	0.02	0.00	0.03
IBM ThinkCentre	**0.17**	**0.25**	**0.17**	**0.09**	−12.10	0.04	0.00	0.02	0.00	0.04
Dell Inspiron[a]	0.07	0.07	0.03	0.01	0.00	−11.10	**0.02**	**0.18**	**0.01**	**0.45**
Gateway 4 Series[a]	0.06	0.07	0.04	0.01	0.00	**0.46**	−11.99	**0.18**	**0.01**	**0.41**
HP Presario[a]	0.06	0.07	0.04	0.02	0.00	**0.44**	**0.01**	−12.08	**0.01**	**0.39**
IBM ThinkPad T[a]	0.04	0.07	0.05	0.02	0.00	**0.35**	**0.01**	**0.16**	−12.97	**0.31**
Toshiba Satellite[a]	0.07	0.07	0.03	0.01	0.00	**0.51**	**0.02**	**0.18**	**0.01**	−11.15

Notes: All elasticities computed in the last quarter of the sample, 2004Q2. The (i,j) cell reports the percentage change in the market share of product *i* (row) given a one percent increase in the price of product *j* (column). All products (desktops and laptops) have a Pentium 4 processor at the 2-2.99 GHz speed range. [a]Indicates a laptop.

TABLE 7b
Markups and willingness to pay

Willingness to pay		Markups and additional information	
	Average consumer WTP (US$)		
1-1.49 GHz → 1.5-1.99 GHz	54.8	Median markup (US$)	76.4
1.5-1.99 GHz → 2-2.99 GHz	115.3	Median (p-mc)/p	0.078
2-2.99 GHz → 3-3.99 GHz	150.1	Corr(markup, price)	0.912
Celeron → Pentium III	156.5	Corr(ξ, ω)	0.820
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[a]	−257.0		

Notes: [a]Change in willingness to pay over one year, see text.

changes in desktop prices, and vice versa (this is emphasized in the table using bold type). The random coefficient on price creates, in addition, segmentation by price: an increase in the price of the IBM ThinkPad T Series laptop, a relatively expensive product, has a rather mild effect on the sales of the other laptops. These intuitive patterns are consistent across the sample.

The left-hand panel of Table 7b reports the willingness of the average household to pay for various product characteristics (notice that by "average household" I refer to the household with the mean price sensitivity in the general household population—not in the subpopulation of those who actually purchase a PC). 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 3–3.99 GHz range, and up to $447.3 to upgrade from Intel's Celeron to its Pentium M brand. CPU characteristics are, therefore, important to the average household. Figure 3 captures substantial heterogeneity in this willingness to pay.

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. This also suggests that it is important to take into account both CPU and PC characteristics when modelling demand in this market.

The negative time trend included in the utility from all "inside products" allows me to compute, in addition, that the mean valuation for a fixed bundle of characteristics falls at an impressive rate of

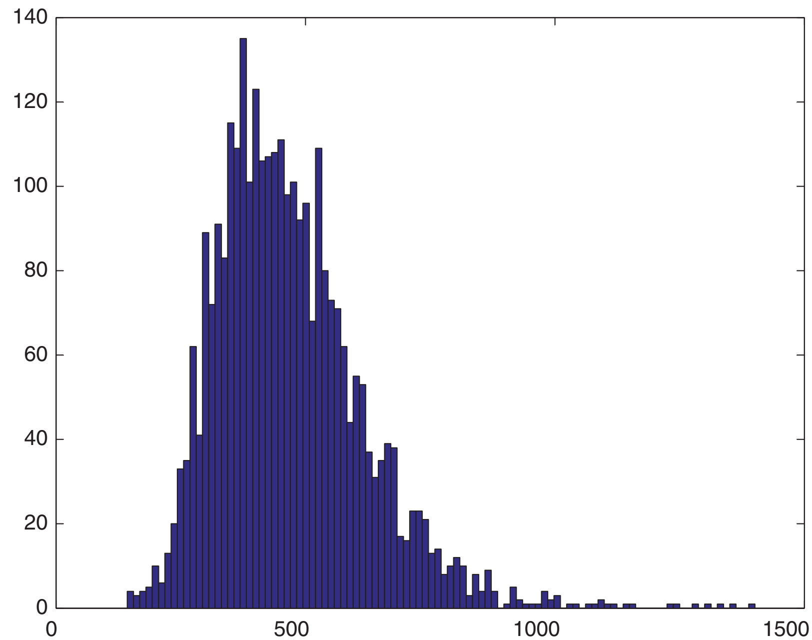


FIGURE 3

WTP for an upgrade from Intel's Celeron to its Pentium M chip ($)

$257 per year, consistent with the strong pace of innovation. This effect is strongly heterogeneous across different consumers, as shown in Figure 4. Clearly, the estimated demand parameters convey strong heterogeneity in preferences. This heterogeneity affects both PC makers' incentives to offer vertically differentiated configurations, and the welfare implications of such choices. Both of these issues are investigated in Section 6.

The right-hand panel of Table 7b provides some additional economic implications of the estimates for θ. 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 marginal cost errors, $\xi_j(\hat{\theta})$ and $\omega_j(\hat{\theta})$.

5.2. *Estimation results: fixed cost parameters F^d*

Table 8a reports set estimates computed with and without an adjustment to the estimated support bounds of variable profit differences. The adjustment widens the estimated sets, but only in a modest fashion. The estimated sets (in $ M) for F^{Dell} and $F^{Toshiba}$ appear similar: [2.353, 4.559] and [2.555, 4.119], respectively. In contrast, HP's mean, per-configuration per-quarter fixed cost F^{HP} appears lower, with an estimated set of [1.081, 2.795]. Clearly, I cannot reject the null hypothesis that all three parameters are equal. To gain perspective on magnitudes, let us focus on Dell's leading notebook product line in 2004Q2. The average fixed cost per notebook unit is estimated to be between $41 and $79.[33] The estimated average variable profit per such notebook

33. Dell offered six configurations of the relevant product line in 2004Q2. To compute per-unit costs, I set the shocks ν to zero, and obtain that the total fixed costs of the six configurations are bounded between $ 14.1 million (*i.e.* 2.353×6) and $ 27.4 million (4.559×6). Dividing by the number of units sold in 2004Q2 yields the $41 and $79 bounds.

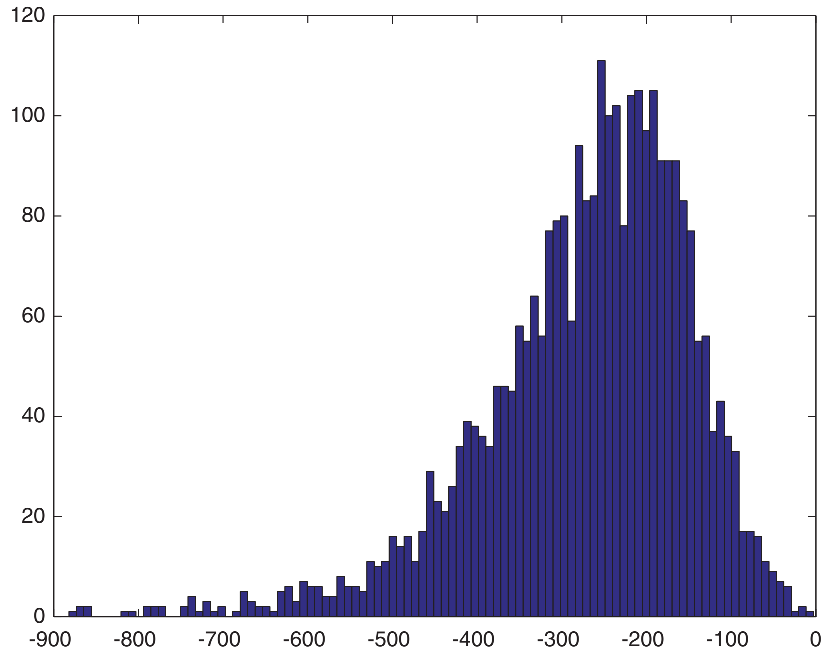


FIGURE 4
WTP for "1 year forward"($) (see text)

unit is \$88. These estimates imply that per-configuration fixed costs consume a substantial share of the per-unit profit.

The estimates in Table 8a indicate that fixed costs are important, and it is interesting to consider several possible explanations for this finding. First, since PC makers offer most of the feasible configurations (65% on average), it does not seem that these estimates are driven by a low rate of offered products. Second, an interesting role may be played by the choice of the demand model. Suppose that I used the Pure Characteristics model (Berry and Pakes, 2007), that shuts down the ϵ terms, instead of the Random Coefficient Logit. In this model, each product has only two substitutes: those "adjacent" to it in terms of perceived quality. The effect on fixed cost bounds is not clear: for instance, the lost variable profit from removing a product (and hence the upper bound on fixed cost) could be very big, or very small, depending on whether the adjacent products to the removed product are sold by the same firm, or by a competitor.[34]

Alternative specifications and estimators: If one assumes that ν are measurement or optimization errors that are uncorrelated with products choices (PPHI; Holmes, 2011), we obtain that $E[\nu_j|j\in A_d^1]=E[\nu_j|j\in A_d^0]=0$. Equations (10) and (11) then deliver:

$$E[\underline{F}_j(\theta_0)|j\in A_d^0]\leq F^d\leq E[\overline{F}_j(\theta_0)|j\in A_d^1]$$

Replacing the expectations by appropriate sample averages generates an estimated set for F^d. By construction, assuming away the selection issue shrinks the estimated sets: we no longer replace missing bounds by support bounds, and instead average only over the non-missing bounds. These narrower estimated sets are reported in Table 8b.

34. Note that Song (2014) estimates the Pure Characteristics Model in the Home PC market and finds that it produces far too low willingness-to-pay measures.

TABLE 8a

Bounds on fixed cost parameters F^d (\$ M)

	Estimated set	Estimated set (adjusted[a])	95% CI[b]
F^{Dell}	[2.427, 4.529]	[2.353, 4.559]	[2.309, 4.914]
F^{HP}	[1.094, 2.721]	[1.081, 2.795]	[0.983, 3.009]
$F^{Toshiba}$	[2.622, 4.069]	[2.555, 4.119]	[2.295, 4.453]

Notes: This estimation utilizes information on specific notebook product lines of these firms (see text). The number of potential products, n^d, is 41 for Dell and Toshiba and 82 for HP. [a]With adjustment for support bounds (see Section 4.2). [b]The confidence interval does not take into account the variance due to the estimation of θ and to the simulation of expected variable profits, see text.

TABLE 8b

Set estimation of F^d assuming uncorrelated ν errors

	Estimated set: baseline	Estimated set: uncorrelated errors
F^{Dell}	[2.427, 4.529]	[2.749, 4.213]
F^{HP}	[1.094, 2.721]	[1.495, 1.716]
$F^{Toshiba}$	[2.622, 4.069]	Bounds cross: lower=4.124, upper=3.509

The left column reproduces (from Table 8a) the estimated sets under the baseline specification, while the right column reports estimated sets under the assumption of zero correlation between ν and the product choices. This "shrinking" is smallest for F^{Dell}, and largest for $F^{Toshiba}$. In Toshiba's case, the bounds cross, which can be interpreted as either point identification, or as a rejection of the no correlation assumption (or of any other part of the model).

This alternative approach entails placing a restriction on the distribution of the fixed cost shocks ν: that these shocks are uncorrelated with product choices. My approach, in contrast, allows firms to condition their product choices on these shocks. My approach, however, places other restrictions on the distribution of ν: Assumptions 2 and 3, which impose a bounded support on fixed costs, and require this support to be contained inside an identified support of variable profit differences. Both approaches, therefore, combine the necessary equilibrium conditions with assumptions on the distribution of ν to deliver set identification. Neither one of these alternative strategies necessarily dominates the other. While the wider sets provide less information regarding the parameters of interest, they are robust to selection, and are still informative enough to generate interesting economic conclusions.

It is also worthwhile to consider the interpretation of the identified set in (13). This set does not contain information that violates the Nash conditions. Just the same, it does contain parameter values that are inconsistent with the true data generating process. To see this, consider first the "narrower" set obtained by assuming that ν are uncorrelated with product choices. Were we willing to specify the equilibrium selection mechanism, this set would shrink to a point. Since we do not specify this mechanism, we end up with an identified interval that contains points that are inconsistent with the true equilibrium selection mechanism. It does, however, contain the true parameter value. It therefore provides a useful way of placing bounds on this true value, while avoiding making an assumption about equilibrium selection. Relaxing the "uncorrelated errors" assumption, and adding Assumptions 2 and 3 instead, widens the identified interval even further. This highlights the tradeoff between different sets of assumptions that can be placed on the distribution of ν, on the one hand, and the amount of information that we obtain about the parameter F^d, on the other hand.[35]

35. Another potential assumption on the distribution of the ν shocks could suppress them to zero. In this case, every configuration the firm offers provides an upper bound on F^d, so that the tightest upper bound would be the smallest of

6. USING THE ESTIMATED MODEL: COUNTERFACTUAL ANALYSES

I analyse the impact of Intel's introduction of its Pentium M processor, which is considered a major innovation in mobile computing. Section 6.1 provides background and describes the questions of interest. Section 6.2 describes practical details, and Section 6.3 provides the results.

6.1. *The impact of Intel's Pentium M: background and questions of interest*

Rather than offering a further increase in clock speed, Intel's Pentium M chip introduced major improvements in chip design that allowed it to achieve top performance at modest clock speeds, resulting in reduced power consumption and longer notebook battery life.[36] Pentium M-based notebooks appear in the sample for the first time in the first quarter of 2003 (see Table 3b). My analysis asks 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 its impact 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?

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 (2004Q2), only 2% of notebooks sold were Pentium III based.[37] Among the five top-selling notebook product lines (*i.e.* notebook brands) in that quarter, only one recorded positive (and very low) sales of a Pentium III-based configuration. 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 Pentium M's effect from many other forces that operated in this market between 2003Q1 and 2004Q2.

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.

6.2. *Description of the counterfactual analysis*

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 absence of the Pentium M. Comparing these predictions to outcomes in the observed equilibrium provides a measure of the Pentium M's effect.[38] 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

these estimated upper bounds. Similarly, the largest of the lower bounds generated by non-offered configurations would provide the tightest lower bound on F^d. This approach runs into a serious practical issue: the bounds cross in a substantial fashion. These crossings should not come as a surprise: even if one suppresses the structural errors to zero, we would still expect there to be some measurement or sampling error in the computation of the bounds. The moment inequality approach averages such errors out, while here they lead to a systematic downward (upward) bias in estimating the tightest upper (lower) bound.

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

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

38. As explained below, I compare expected outcomes (*i.e.* expectations over the distribution of the error terms e) given the counterfactual and observed sets of products.

1.5–1.99 GHz range.[39] This allows me to ask how many Pentium III-based PC configurations would have been offered *in the absence of the Pentium M*.

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: due to the partial identification of fixed costs, 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 $\mathcal{A}$ be the set of all such vectors. Let the subset $A^e \subseteq \mathcal{A}$ collect all product choice vectors that can be supported in an SPNE.

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 $A \in \mathcal{A}$ 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.

It is worth noting that elements of A^{pe} that do not belong in A^e are not equilibria of the game. My approach is to identify qualitative findings that hold across all the outcomes in A^{pe}. By definition, since A^{pe} contains A^e, these qualitative findings (*e.g.* that the Pentium M crowds out the Pentium III) can be said to hold across all the elements of the set A^e. The set A^{pe} is also useful in placing bounds on quantitative findings. For example, I report below that, across all elements of A^{pe}, the Pentium M contributes between 3.2% and 6.3% to consumer surplus. This range contains the range that applies to the equilibria set A^e, and, therefore, provides a useful way of bounding the true welfare effects.[40]

Computation: Computation of the set A^{pe}, which I refer to as the set of "potential equilibria", is a cumbersome task: one has to check for necessarily profitable deviations from each of the $2^{|A|}$ vectors in $\mathcal{A}$. This requires evaluating expected variable profits at all these vectors, with each such evaluation being expensive: as in the estimation of fixed costs, expected variable profits are simulated by drawing from the distribution of the error terms e, computing a price equilibrium and variable profits at each such draw, and averaging over the simulated draws.

For this reason I impose several restrictions on the analysis. First, I fix all product choices except those made by the four top-selling notebook product lines, and only allow configuration

39. This is the fastest Pentium III chip observed in a mobile PC, and it was offered in a handful of product lines only. It was excluded from the feasible set in 2004Q1 and 2004Q2 on account of criterion (iii), since it was not offered by any of the four leading notebook product lines (see Appendix A.3). As Table A1 and the discussion in the appendix indicate, including this chip in the feasible set has a very minimal effect on the estimated parameters.

40. Had I adopted the "uncorrelated errors" assumption discussed in Section 5.2, the estimated sets for fixed cost parameters would shrink to those displayed in Table 8b. This should make the set A^{pe} smaller (in a weak sense), since it would then become easier to rule out outcomes as potential equilibria. Notice that the qualitative findings that I report would continue to hold, by definition, across all the outcomes in the smaller A^{pe} set, so all the qualitative findings of the article would still hold. I may be able to get tighter quantitative predictions by following this approach. These findings, however, would not be robust to the selection issue. Also note that even though the identified set from equation (13) can contain values that are inconsistent with the true data-generating process, as discussed above, it also contains the true parameter value. As a consequence, the set A^{pe} does contain the true set of equilibria A^e, making it possible to obtain valid qualitative and quantitative predictions as explained above.

choices of these four product lines to vary in the experiment. I refer to these as the "participating product lines" (or "participating brands"). At the same time, *all* PC products (notebooks and desktops) are included in the experiment and their prices are treated as endogenous.

Second, I restrict the set H of potential configurations by requiring that firms offer Pentium 4 configurations in the speed ranges 1.5–1.99 and 2–2.99 GHz. In the observed equilibrium, all the participating brands offer these configurations. Fixing these choices allows me to reduce the computational burden while still treating as endogenous the most interesting choices: those which pertain to offering low-end configurations such as the Pentium III or the Celeron, and to offering Pentium 4 chips with speed range above 3 GHz. The latter technology can be viewed as a competitor of the Pentium M in the high-end segment of the market.[41] These restrictions imply that the set of CPU technologies over which firms make endogenous choices is:

$$\left\{P3\_1.5\_1.99,\;\; C\_1.5\_1.99,\;\; C\_2\_2.99,\;\; P4\_3\_3.99\right\}$$

With these four CPU technologies, and the four participating notebook brands, we have that $|A|=16$, that is, 16 product choices are treated as endogenous. I reduce this number to 9 by imposing that firms must make a single "Celeron" choice (*i.e.* they can either offer both of the Celeron configurations, or none), and that HP, that owns two of the four participating brands, must make the same configuration choices for both its brands (HP makes very similar such choices for these brands in the observed sample). This leaves me with the task of evaluating $2^9=512$ vectors as candidates for potential equilibria.

In the counterfactual analysis, I set the structural errors ν_j in the specification for fixed costs to zero. The per-configuration fixed cost is, therefore, assumed to lie in the estimated interval for F^d, the firm's mean fixed cost. For example, Dell's per-configuration fixed cost is assumed to be between \$ 2.353 million and \$ 4.559 million (see Table 8a). Another potential approach, that would be more consistent with the assumption used to estimate the model, would be to simulate the fixed cost by drawing from the distribution of ν_j. Since F^d is only partially identified, however, it is not clear how to draw from the distribution.

This issue reflects an interesting tradeoff associated with partially-identified models. These models have the credibility advantage of avoiding strong point-identifying assumptions. But once we attempt to use the model for prediction purposes, this very advantage becomes a limitation: it is difficult to compute sets of counterfactual predictions, and it is not clear how to draw from the partially identified distributions. My pragmatic approach to this issue is to allow the ν_j shocks to be correlated with product choices in the estimation of the model, thus obtaining selection-robust estimates, but to set these shocks to zero in the counterfactual analysis. Future research can, hopefully, provide other solutions to this interesting tradeoff.[42]

Additional details on computation, including a complete description of the algorithm, are available in Appendix B. Out of the 512 feasible vectors, a total number of 30 vectors are found to be elements of A^{pe}. This means that, while fixed costs are only partially identified, I am able to rule out about 94% of the feasible product-choice vectors as equilibria of the game.

41. The Pentium M emerged as the winning technology since improving its performance did not require increased power consumption.

42. Yet another possible strategy would have used the bounds $\overline{F}_j$ and $\underline{F}_j$ (see equations (10) and (11)) for any configuration that "participates" in the counterfactual and for which such bounds were estimated in 2004Q2, and to use the bounds on F^d whenever $\overline{F}_j$ or $\underline{F}_j$ are not available. This, however, would have forced me to assume that fixed cost shocks to particular configurations are the same in the actual and counterfactual 2004Q2 markets.

6.3. *The impact of the Pentium M: results*

As explained above, the counterfactual experiment evaluates the impact of the presence of Intel's Pentium M in 2004Q2 by comparing outcomes in the observed equilibrium to counterfactual predictions for a hypothetical "no Pentium M" scenario. Since firms make product choices prior to observing the realizations of the demand and marginal cost errors e, I evaluate the welfare measures in both the counterfactual scenario, and in the observed equilibrium, as simulated expectations over the distribution of e.[43] 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 inefficient product elimination?

1. The Pentium M's impact on product offerings and prices: Table 9 reports the impact of the presence of the Pentium M on expected 2004Q2 outcomes. Given the set of products in the observed equilibrium, the expected total notebook sales (units) are 1.707 million. In the absence of the Pentium M, these sales are between 1.379 and 1.614 million.[44] This suggests that the Pentium M increases the expected total notebook sales by 5.8% to 23.8%. Some of this growth comes at the expense of expected Desktop sales, which are depressed by 0.9% to 3.1%. The expected sales-weighted average notebook price is between \$ 829 and \$ 872 in the absence of the Pentium M, compared to \$ 905 in its presence. These findings suggest that the Pentium M made a significant contribution to the growth of the mobile market segment.

Table 9 continues to report the Pentium M's impact on the product configurations offered by the four top-selling notebook product lines. In the presence of the Pentium M, none of these brands offered Pentium III configurations with speed in the 1.5–1.99 GHz range. In contrast, in the absence of the Pentium M, between one and four of these brands would have offered such a configuration. The Pentium M also crowds out configurations based on Intel's Pentium 4 in the 3–3.99 GHz range. The prediction for the Celeron-based products is ambiguous: some potential equilibria imply that they were crowded out, while others imply the opposite. The bottom panel of Table 9 reports that the presence of the Pentium M reduces the total expected share of the Pentium III in the notebook segment from 15.6%–23.9% to merely 7.7%, suggesting that the Pentium M played a key role in eliminating the Pentium III technology.[45]

2. The Pentium M's impact on various consumer types: Table 10 reports the impact of Intel's Pentium M on the expected consumer surplus. With the observed set of products, the expected total consumer surplus is \$ 1.21 billion, whereas in the absence of the Pentium M, it is between \$ 1.14 billion and \$ 1.18 billion. Expected consumer surplus is, therefore, boosted by 3.18% to 6.29% as a consequence of the Pentium M's presence. The table continues to report a breakdown of the expected benefits from the Pentium M's presence that accrue to different *quintiles* of price sensitivity. The vast majority of the benefits are garnered by the 20% least price-sensitive households, while the impact on other segments is minimal to non-existent. This is consistent with the strong heterogeneity in price sensitivity and with the relatively high price of laptops during the sample period: price-sensitive households were not affected much by developments in the mobile segment as it was relatively unlikely for them to buy a notebook.

3. Efficiency aspects of product elimination: Having established that the Pentium M crowded out older technologies, we may ask if it was actually efficient for such technologies to exit. To investigate whether the absence of the Pentium III from the product lines of the major notebook

43. To be clear, after computing the set of potential equilibria A^{pe} in the hypothetical scenario, I compute welfare measures at each such outcome, and then use these measures to place bounds on counterfactual welfare outcomes. These outcomes are then compared to the welfare outcomes which obtain given the observed sample, *i.e.* in the presence of the Pentium M. All the compared quantities are computed in terms of expectations over the distribution of the e error terms.

44. To clarify, these values represent the highest and lowest values recorded over the set of potential equilibria A^{pe}.

45. These shares pertain to all Pentium III chips, and not just those at the 1.5–1.99 GHz range.

TABLE 9
Effect of Intel's Pentium M on expected 2004Q2 outcomes

		"No Pentium M" counterfactual	
	Observed[a]	Lower bound[b]	Upper bound[b]
Total Notebook Sales (M)	1.707	1.379	1.614
Total Desktop Sales (M)	3.831	3.866	3.952
Mean Notebook price[c] ($)	905	829	872
Impact on number of PC configurations (top 4 brands)			
		"No Pentium M" counterfactual	
	Observed	Lower bound[b]	Upper bound[b]
# P3_1.5-1.99	0	1	4
# C_1.5-1.99	3	0	4
# C_2-2.99	3	0	4
# P4_3-3.99	1	2	4
Impact on Pentium III's share of total portables sales			
		"No Pentium M" counterfactual	
	Observed[a]	Lower bound[b]	Upper bound[b]
Share P3	0.077	0.156	0.239

[a]As explained in the text, these are not outcomes observed in the sample, but rather simulated expected outcomes computed at the set of products observed in the sample, which includes Pentium M-based notebooks. This does not pertain to the reported observed number of configurations, which is simply the observed sample quantity. [b]The bounds represent the largest and smallest values computed over the set of all potential counterfactual equilibria. [c]Sales-weighted average.

TABLE 10
The effect of Intel's Pentium M on consumers

		"No Pentium M" counterfactual	
	Observed[a]	Lower bound[b]	Upper bound[b]
Total expected consumer surplus	1213.7	1141.9	1176.3
Expected surplus for price-sensitivity quantiles (see text)			
0–20% price sensitive	992.7	932.6	955.1
20%–40% sensitive	130.3	123.1	129.9
40%–60% sensitive	76.5	73.2	76.8
60%–80% sensitive	12.6	11.9	12.8
80%–100% sensitive	1.6	1.1	1.7

Notes: All figures in M$. [a]As explained in the text, these are not outcomes observed in the sample, but rather simulated expected outcomes at the set of products observed in the sample. [b]The bounds represent the largest and smallest values computed over the set of all potential counterfactual equilibria.

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 four top-selling notebook brands. Similarly, I also calculate the impact of adding Pentium 4 configurations in the 3–3.99 GHz speed range (since one of the four brands had such a configuration in the observed sample, such configurations were added to the other three brands).

Panel A of Table 11 reports that adding the Pentium III-based notebooks to the market increases total expected consumer surplus by $9.368 million, or by 0.77%. It also increases total producer variable profit by $2.802 million. On the other hand, producers would have also incurred additional

TABLE 11
Expected welfare effects of adding products based on older CPUs

	Added configurations	
	P3_1.5-1.99	P4_3-3.99
A. Total welfare components (M$)		
Change to consumer surplus:	9.368	7.027
Change to PC maker variable profit:	2.802	1.705
Change to fixed costs:	[–14.267, –7.071]	[–10.149, –4.515]
Total effect:	[–2.097, 5.099]	[–1.417, 4.216]
B. Effect on different consumer segments' surplus (M$)		
Quantile of price sensitivity		
0–20% price sensitive	6.018	6.445
20%–40% sensitive	2.060	0.443
40%–60% sensitive	0.978	0.118
60%–80% sensitive	0.213	0.015
80%–100% sensitive	0.099	0.005
C. Prices, sales, and choice probabilities in the Pentium III counterfactual		
Price range for added configurations ($ US):	707–740	
Total sales (units) of added configurations:	141,988	
Increase in probability of buying a laptop, by consumer segment[a]:		
Quantile of price sensitivity		
0–20% price sensitive	27%	
20%–40% sensitive	18%	
40%–60% sensitive	24%	
60%–80% sensitive	27%	
80%–100% sensitive	6%	

Notes: Configurations based on Intel's Pentium III chips in the 1.5–1.99 GHz speed range were added to all four participating brands, while configurations based on its Pentium 4 chips with speed above 3 GHz were added to three (see text). All figures evaluated at expected 2004Q2 outcomes. [a]These are not percentage point increases, but rather percentage increases in these probabilities.

fixed costs ranging between \$7.071 million and \$14.267 million.[46] Defining welfare as the sum of consumer and producer surplus, the total expected impact on welfare ranges between a negative effect of \$ (−2.097) million, and a positive effect of \$5.099 million. We cannot affirmatively conclude, therefore, that the absence of the Pentium III-based notebooks reflects a market failure. A similar picture emerges when adding back Pentium 4-based PCs.

Panel B of Table 11, however, points out that the consumer benefits from adding Pentium III-based PCs to the market are enjoyed by consumer segments other than the 20% least price-sensitive. Panel C reveals the reason for this effect: the presence of the Pentium M exerts a downward pressure on the prices of Pentium III-based PCs. The prices of these basic PCs range between \$707 and \$740, compared to an expected sales-weighted average notebook price of \$905 given the observed set of products.

The experiment, therefore, creates a category of affordable laptops that were absent from the actual 2004Q2 market, and allows the benefits from the Pentium M's introduction to "trickle down" to the large masses of consumers who did not benefit at all from this innovation in the observed equilibrium. Price-sensitive consumers respond to this opportunity: laptop purchase probabilities increase by 18%, 24%, 27%, and 6% for households who are in the following

46. Evaluated using the boundaries of the estimated set for the relevant firms' mean fixed costs.

quintiles of the price-sensitivity distribution: 20%–40%, 40%–60%, 60%–80%, and 80%–100%, respectively. The added four notebooks enjoy substantial expected sales of 141,988 units (roughly 8% of the total expected sales given the observed set of products).

In market equilibrium, older configurations disappear, shutting this channel down. The intervention that keeps these products on the shelf, alongside the cutting-edge innovation, allows the benefits from innovation to be enjoyed by a much larger group of consumers.

Practical policy implications: Can (and should) the government intervene in firms' decisions regarding their product line offerings? Such an intervention would require a complex and time-sensitive analysis of a rapidly changing market. Moreover, given that total welfare cannot be improved, it is not clear that such an intervention is justified.[47] Ultimately, the goal of this paper is to present an interesting aspect of innovation that has not received much attention in the literature: while innovation is a remarkably important process with huge welfare benefits, these benefits may be strongly skewed, at least in the short run, in favour of a rather small consumer group due to the rapid elimination of non-frontier products.

7. CONCLUDING REMARKS

This article studies the consequences of rapid elimination of existing products brought about by the arrival of innovative products. I estimate a model that treats both product choices and prices as endogenous. I relax assumptions which guarantee a unique equilibrium outcome, and formally address selection bias issues. A detailed model of differentiated-product cost and demand allows me to perform a fine-grained analysis of the impact of innovation on the set of offered products, and of the resulting heterogeneous effects of innovation on different consumer types.

An important limitation of my work is the static framework, which prohibits me from considering the role played by product durability and the forward-looking behaviour of consumers and producers. Forward-looking behaviour by consumers would imply that different consumer types may not only purchase different PCs, but may also make their purchases at different times.

Suppose that the Pentium M technology is about to be launched, and that consumers believe that it would immediately crowd out Pentium III-based PCs. Given such expectations, "power-hungry" consumers should delay their purchase until the Pentium M has been introduced. Consumers with more modest computing needs, in contrast, may choose to purchase a Pentium III-based PC *before the Pentium M arrives* and crowds such configurations out of the market. If, on the other hand, consumers expect there to be a time window in which both the Pentium M and the Pentium III would be simultaneously available, low-valuation consumers may also delay their purchase until the Pentium M arrives, since they would expect its arrival to exert a strong downward pressure on the prices of Pentium III-based PCs.

My final counterfactual analysis, that adds Pentium III-based PCs to the 2004Q2 market, can be viewed as an artificial creation (or, extension) of such a time window. While I cannot analyse strategic timing decisions, this analysis does capture the fact that low-valuation consumers' laptop purchase probabilities substantially rise in such time windows. Rapid product elimination implies that these "windows of opportunity" are very short, prohibiting most consumers from reaping the benefits of CPU innovation (at least in the short run). My static analysis shows that firms strategically eliminate basic configurations, thus preventing the benefits from innovation from "trickling down" to the large mass of potential consumers.

Of course, generating these predictions from a static framework is an important limitation. In particular, this static framework does not allow me to analyse a very important aspect of the

47. Interestingly, this policy would not decrease total welfare, since the added fixed costs would be offset by the added benefits. It will merely reflect a transfer of benefits from firms to certain consumer groups.

research question: how do firms choose *paths* of product portfolios and prices to optimally control the dynamic evolution of PC ownership among different consumer segments?

In the static framework, there are two benefits to eliminating basic configurations: fixed cost savings, and the stirring of consumers towards buying high-markup advanced products. The downside of such product elimination is that it limits the firm's ability to cater to low-valuation consumers, such that many of these consumers end up not purchasing a laptop at all. In a dynamic setup, an additional consideration arises: eliminating basic configurations can shorten or eliminate the "windows of opportunity" in which basic and advanced configurations are both available, thus changing *the timing* in which particular consumer groups make purchases. While the elimination of such time windows prohibits some low-valuation consumers from purchasing a laptop at all, it also motivates some other low-valuation consumers to act fast and purchase a Pentium III-based PC before such configurations disappear. Solving for optimal paths of product portfolios and prices could allow one to study how firms balance these different considerations, thus improving our understanding of firms' incentives to offer different degrees of product variety.

Nair (2007) solves numerically for optimal pricing paths of Video-game monopolists facing an estimated demand system with forward-looking, heterogeneous consumers. It is difficult to solve such a problem because of the strategic interaction between forward-looking consumers and firms (*e.g.* high-valuation consumers may "pose" as low-valuation ones and wait for prices to fall). Solving for optimal paths of both prices and product portfolios of multi-product PC oligopolists is likely to be a much more difficult problem, which investigation must be left outside the scope of the current study. Estimating and solving such a dynamic model would allow us to obtain a deeper understanding of the equilibrium level of product variety in rapidly evolving markets, making it an attractive area for future research.

Another important issue left for future work is the role played by CPU innovation in fostering complementary software innovation.[48] Such a channel, which I cannot address with the static framework (except for controlling for it in a simple way using the time trend), could qualify my finding that most households do not benefit from CPU innovation: clearly, this finding applies to static, short-term benefits. Improvements in software have important spillovers that can benefit all consumer types in the long-run.

Moreover, such complementary innovation prompts households to use more advanced applications, which, in turn, increases the demand for advanced CPUs. A dynamic analysis of this "positive feedback loop" could provide a more complete picture of the singular contribution of CPU innovations to economic growth and welfare in the 21st-century economy.[49]

APPENDIX

A. ESTIMATION DETAILS

A.1. *Estimation details for the variable profit parameters θ*

Estimating θ 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 θ. 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.[50] I then obtain the market share predicted by the model for product j (quarter indices suppressed) as follows:

$$s_j(x,p,\delta,P_{ns};\theta_2)=\frac{1}{ns}\sum_{i=1}^{ns}\frac{exp(\delta_j+\mu_{ij})}{1+\sum_{m\in J}exp(\delta_m+\mu_{im})} \tag{A1}$$

48. 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.

49. See Rosenberg (1979) for a seminal discussion of such positive feedback loops.

50. See Train (2003). Antithetic draws are used in Sovinsky Goeree (2008).

where P_{ns} is the distribution of the simulation draws. The market share equation, which should hold exactly at θ_0, is given in vector form:

$$s(x,p,\delta,P_{ns};\theta_2)=S \tag{A2}$$

where S denotes *observed* market shares. Given a fixed value for θ_2, we invert this equation to retrieve a vector of mean utility levels, $\delta(\theta_2)$, using the BLP contraction mapping:

$$\delta^{h+1}=\delta^h+ln(S)-ln[s(x,p,\delta^h,P_{ns};\theta_2)]. \tag{A3}$$

The vector of demand-side unobservables ξ can now be computed by:

$$\xi(\theta^d)=\delta(\theta_2)-x\beta \tag{A4}$$

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

$$\omega(\theta)=log[p-(T*\Delta(\theta_2))^{-1}s]-x\gamma. \tag{A5}$$

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:

$$Q_N(\theta)=\left[\sum_{j=1}^{N} g_j(\theta)\right]' \Phi^{-1}\left[\sum_{j=1}^{N} g_j(\theta)\right] \tag{A6}$$

where Φ^{-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 θ 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 θ using the updated matrix yields the estimates reported in Table 6a and b.

A.2. *Estimation details for the fixed cost parameters F_d*

The upper bounds $\overline{F}_j(\theta_0)$ for all $j\in A_d^1$ are estimated as follows: the BLP estimate $\hat{\theta}$ implies empirical values $e_j(\hat{\theta})$ for all the products observed in the sample, a total of 2287 (see Appendix A.1). From this empirical distribution, I draw 1000 vectors of error terms e for all the potential products $j\in\mathcal{J}$ in the relevant quarter. Recalling that $e=(\xi,\omega)$, I am effectively drawing from the *joint distribution* of the shocks to demand and marginal cost, which reflects their positive correlation.

At each such simulated error vector, I compute price equilibria under (A_d) and $(A_d-1_d^j)$ (*i.e.* with and without product j), and compute the decrease in variable profit associated with eliminating product j that appears in (10).[51] Averaging over these simulated decreases in variable profit yields the estimate of $\overline{F}_j(\theta_0)$, denoted $\overline{F}_j(\hat{\theta})$. An analogous procedure yields estimates for $\underline{F}_j(\theta_0)$ for all $j\in A_d^0$, by simulating the expected increase in variable profit associated with adding product j to the firm's portfolio from (11). Such estimates are denoted by $\underline{F}_j(\hat{\theta})$.[52]

Note that the estimation approach for the fixed costs parameters is based on the sample average being a consistent, asymptotically normal estimator of the mean, which is guaranteed for IID sequences. Eizenberg (2009) provides conditions for consistency and asymptotic normality given dependence among the L_j (and U_j) variables for $j=1,...,n^d$.

Finally, note that the confidence intervals, in principle, need to be adjusted to account for the variance in the estimation of θ, as well as for the error due to the simulation of expected variable profits. These adjustments can be performed using a computationally expensive bootstrap approach. As the results sections indicate, performing this procedure would not change the findings of the article: it is sufficient to examine the estimated set of fixed costs to notice that one cannot reject the null hypothesis which argues that the elimination of basic product configurations is efficient. Using the confidence interval instead of the estimated set, whether adjusted or not, would not change this.

51. Price equilibria are simulated by iterating on the first-order conditions (7) until convergence, which typically takes a few seconds of computation time.

52. A feature of this procedure is that the empirical distribution of the error terms includes some favorable values (*e.g.* high utility shocks or low cost shocks). Since profits are non-linear functions of these error terms, the simulations can overstate products' variable profit potential. I performed several robustness checks (*e.g.* setting the errors to zero or imposing a finite-support condition on the joint distribution of the mean utility and marginal cost), and found that the qualitative findings of the article are robust to this issue.

TABLE A1

Robustness to dropping criteria for inclusion in the feasible set

A. Technologies added to the set when dropping each criterion[a]

Quarter	(i)	(ii)	(iii)
Q7	PM 1.0-1.49	PM 1.5-1.99	
Q8	P4 1.0-1.49, PM 1.0-1.49		
Q9	P4 1.0-1.49		
Q10	P4 1.0-1.49		
Q11	P3 1.0-1.49		P3 1.5-1.99
Q12	P3 1.0-1.49		P3 1.5-1.99

B. Estimated sets obtained by dropping inclusion criteria[b]

	Dropped criterion			
Parameter	None	(i)	(ii)	(iii)
F^{Dell}	[2.427, 4.529]	[2.449, 4.909]	[2.132, 4.443]	[2.482, 4.726]
F^{HP}	[1.094, 2.721]	[1.061, 2.779]	[1.094, 2.636]	[1.079, 2.586]
$F^{Toshiba}$	[2.622, 4.069]	[2.558, 3.999]	[2.417, 4.040]	[2.575, 4.187]

Notes: [a]The first, second and third columns show which technologies are added to the feasible set if we drop criterion (i), (ii), and (iii), respectively. [b]The first column shows the original estimated sets, reproduced from Table 8, when no criteria are dropped. The next columns show how the sets change as we drop each criterion.

A.3. *Robustness, additional moments, and economies of scope*

Robustness to changes in the definition of the feasible set: I present three robustness checks, each of which removes one of the three criteria for inclusion in the feasible set H. In this way, I can investigate whether any one of the three restrictions is driving the fixed cost estimates. The results of this approach are reported in Table A1.

Panel A of this table reports which technologies are added to the set, in each quarter, when we drop each of the inclusion criteria in turn. The feasible sets are most affected by dropping criterion (i), the one which requires that the relevant CPU technology sells at least 10,000 units in the quarter. Dropping this criterion adds one CPU to the set in every quarter, except Q8 where two chips are added. As the second column shows, dropping criterion (ii), which required that the chip would be offered by at least two firms, has a very minimal effect on the feasible sets: the feasible sets in all quarters but Q7 remain unaffected. A similar minimal effect is reflected in the third column: dropping the third criterion, which requires that the chip would be offered by at least one of the four leading product lines, only affects the feasible sets of Q11 and Q12. Panel A, therefore, shows that none of the criteria has a dramatic effect on the feasible set.

Panel B shows how the estimated sets for the parameters $F^{Dell}, F^{HP}, F^{Toshiba}$ are affected by dropping the three criteria. The first column to the left reproduces the original estimates, obtained when all three criteria are applied. The next three columns show how the sets change as we drop each criterion. As the table shows, the estimates do change, but are quite robust to dropping these criteria.[53]

Exploiting additional moments: There are additional deviations, beyond those in which the firm removes or adds a single product configuration, that could provide information on the estimated parameters. Let us consider first deviations that do not change the number of offered configurations. Suppose that a firm deviates from its observed choices by removing an observed product j, and offering instead some other product k, one that was not offered in the observed equilibrium. This deviation incurs an additional fixed cost of $F_k = F^d + \nu_k$, but saves the fixed cost $F_j = F^d + \nu_j$, so that it ends up "saving" a magnitude of $\nu_j - \nu_k$ (noting that these "savings" could be negative). The necessary condition that renders this deviation unprofitable implies:

$$\nu_j - \nu_k \leq E_{(e|\theta_0)}\left[VP_d(A_d; e, \theta_0) - VP_d(A_d - \mathbf{1}_d^j + \mathbf{1}_d^k; e, \theta_0)\right]$$

53. Note also that the exercise that drops criterion (i) adds the Pentium M chip with speed at the 1.0–1.49 range to the feasible set of Q7 and Q8. This removes the counter-intuitive pattern discussed in Section 3.2: now this chip is introduced to the feasible set before the Pentium M 1.5–1.99, rather than being introduced after it. The table then shows that this issue has a very minimal effect on the estimates.

Since the systematic component of fixed costs, F^d, cancels out, this inequality does not provide information about this parameter. Therefore, it cannot help us tighten the bounds on F^d. Such an inequality does provide partially identifying information on the variable-profit parameters θ. In particular, had I assumed that the errors are identical for products of the same firm, the left-hand side of the inequality would equal zero, and one would obtain an inequality that partially identifies θ. Note, however, that θ is already point-identified in my framework.

Deviations that change the number of offered configurations do provide information on F^d. The simplest such deviations (and the ones that I have used in this article) are those that either add, or remove a single product from the firm's portfolio. But additional deviations can be considered, for instance, deviations that remove *two* observed products, j and k. The fixed costs savings afforded by such a deviation must not exceed the expected loss of variable profit:

$$2F^d + \nu_j + \nu_k \leq E_{(e|\theta_0)}\left[VP_d(A_d; e, \theta_0) - VP_d(A_d - \mathbf{1}_d^j - \mathbf{1}_d^k; e, \theta_0)\right]$$

Denote the RHS of this inequality by $\overline{F}_{jk}$. The problem here is selection: we can only compute $\overline{F}_{jk}$ if both products, j and k, have been offered by the firm. To overcome this, we can pursue an approach similar to the one in the article. Suppose that there are n potential configurations, implying $n!/((n-2)! \cdot 2!)$ potential product pairs. For pairs (j,k) that were offered, we can bound the random variable $2F^d + \nu_j + \nu_k$ from above using $\overline{F}_{jk}$, as shown above. For pairs (j,k) such that at least one of the products was not offered, we can bound this quantity using the support of fixed costs: $2F^d + \nu_j + \nu_k = F_j + F_k \leq 2F_d^U \leq 2V_d^U$. Define a random variable U_{jk} such that $U_{jk} = \overline{F}_{jk}$ if both j and k are offered in the observed equilibrium, and $U_{jk} = 2V_d^U$ otherwise. The inequality $2F^d + \nu_j + \nu_k \leq U_{jk}$ then holds for *every* pair of feasible products (j,k), whether or not they are offered. Taking unconditional expectations on both sides, we get the following moment inequality that provides an upper bound on F^d: $F^d \leq E(U_{jk}/2)$, where the expectation is taken over all feasible pairs (j,k).

The table below shows the estimated upper bounds for $F^{Dell}, F^{HP}, F^{Toshiba}$ obtained by following this approach. The right column shows the bounds computed from this "new" approach, while the left column reproduces the bounds from the baseline specification (see Table 8a):

Parameter	Estimated upper bound ($m)	
	Original moments	"New" moments
F^{Dell}	4.529	4.945
F^{HP}	2.721	3.308
$F^{Toshiba}$	4.069	4.567

As the table shows, the "new" moments derived from considering deviations that remove two products at a time do not help us to tighten the upper bound on the F^d parameters. The intuition behind this is that, as we consider more sophisticated deviations, the selection problem becomes worse: that is, there are even more cases where we cannot compute an upper bound from a necessary equilibrium condition, and must use the support bound instead.

Additional deviations could consider removing three, four, five or more products at a time, or adding multiple products. More sophisticated deviations could add two products and eliminate a third product. However, for very similar reasons as above, none of these conditions should help tighten the bounds on F^d.

Economies of scope: The difficulty in introducing economies of scope is that the specification and estimation must address the difficult problem of selection on the ν errors. I present one such possible approach.[54] Consider product line d, and denote the number of its offered configurations by n. Consider some potential configuration j that the firm chose not to offer. I model the additional fixed cost that would be incurred if j is added to the portfolio by $F^d + \nu_j + F^{d2} \cdot n$. Analogously, considering any configuration k that the firm chose to offer, I model the fixed cost savings from eliminating k by $F^d + \nu_k + F^{d2} \cdot n$.

The difference from the baseline specification is the presence of the term $F^{d2} \cdot n$. If the parameter F^{d2} is positive (negative), it implies diseconomies (economies) of scope. Setting $F^{d2} = 0$ returns us to the article's baseline specification. The goal is to estimate the two parameters F^d, F^{d2}. Let n^j denote the observed number of offered configurations of the product line to which j belongs as a potential configuration. For a configuration j that was *offered* in the observed sample, we obtain the following bounds:

$$V_d^L(\theta_0) \leq F^d + F^{d2} \cdot n^j + \nu_j \leq \overline{F}_j(\theta_0)$$

54. PPHI allow similar non-linearities in a Monte Carlo analysis of their ATM application, but they only consider the number of ATMs, rather than their identity, and assume that all ATMs of the same bank have the same structural error.

where the upper bound $\overline{F}_j(\theta_0)$ is defined exactly as in equation (10), while $V_d^L(\theta_0)$ is the lower bound of the support of fixed costs.[55] Considering a configuration j that was *not offered* in the sample, we obtain:

$$\underline{F}_j(\theta_0) \le F^d + F^{d2} \cdot n^j + \nu_j \le V_d^U(\theta_0)$$

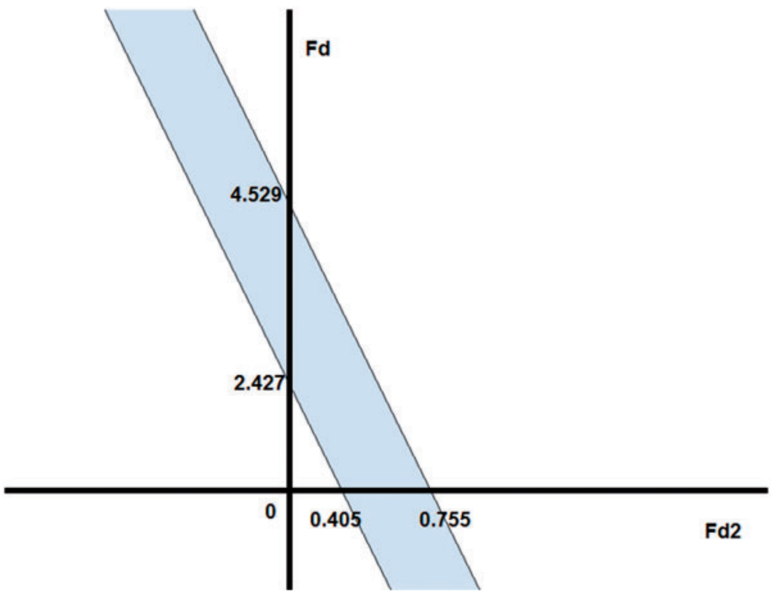
where the lower bound $\underline{F}_j(\theta_0)$ is defined as in equation (11), while $V_d^U(\theta_0)$ is the upper support bound. Defining the random variables L_j and U_j exactly as in Section 4.2, and taking unconditional expectations, we now obtain:

$$EL_j(\theta_0) \le F^d + F^{d2} \cdot En^j \le EU_j(\theta_0)$$

Replacing the expectations by sample averages, and the true variable profit parameters θ_0 by their BLP estimator $\hat{\theta}$, we obtain the estimated set. Denote by $\overline{\ell}_n^d(\hat{\theta}), \overline{u}_n^d(\hat{\theta}), \overline{n}^d$ the sample averages corresponding to EL_j, EU_j, En^j, respectively. We obtain the following inequalities:

$$\overline{\ell}_n^d(\hat{\theta}) \le F^d + F^{d2} \cdot \overline{n}^d \le \overline{u}_n^d(\hat{\theta})$$

We obtain two lines in the F^d, F^{d2} space that bound all parameter combinations that satisfy the moment inequalities: both lines have a slope of $-\overline{n}^d$, the line that bounds the estimated set from above has an intercept of $\overline{u}_n^d(\hat{\theta})$, and the one that bounds it from below has an intercept of $\overline{\ell}_n^d(\hat{\theta})$. This estimated set is shown below for Dell's case (note that the figure is not to scale):



The shaded rectangular area delineates the set of parameter values that satisfies the moment conditions. Notice that the line in this set which satisfies $F^{d2} = 0$ shows the baseline estimated set for F^{Dell}, [2.427, 4.529] (see Table 8a).

Unfortunately, and by construction, this estimated set does not help us sign the parameter F^{d2}, so we cannot determine if economies or diseconomies of scope obtain. This issue could be addressed by adding moment inequalities: using some set of instrumental variables that are orthogonal to the error ν, we could derive such additional moment conditions and place additional restrictions on the estimated set. It is not clear, however, that the application offers natural candidates for such instruments. More importantly, there is very little variation (sometimes, none) in the *number* of configurations offered by a firm over time. The identification of the sign of F^{d2} would, therefore, rely heavily on functional form. Finally, estimating bounds on a single parameter allows me to perform inference using the rather simple methods of Imbens and Manski (2004). Inference on a multidimensional parameter would require more demanding techniques (Chernozhukov *et al.*, 2007; Andrews and Jia, 2012).

55. A slight modification of the article's assumptions is then necessary: the relevant support is not that of a configuration's "inherent" fixed costs, but rather the support of changes to total fixed costs associated with adding or removing a single configuration. Via an assumption similar to Assumption 3, this support must be assumed to be contained in a wider support of variable profit changes $[V_d^L(\theta_0), V_d^U(\theta_0)]$. There is very little practical importance to this.

B. COMPUTING COUNTERFACTUAL POTENTIAL EQUILIBRIA: THE ALGORITHM

Denote by C_d the estimated interval for F^d, the firm's mean fixed cost. Evaluating a product-choice vector A to determine whether it is a potential equilibrium (*i.e.* a member of A^{pe}) requires computing, for each firm, an interval of its per-configuration fixed cost under which it does not have a profitable deviation from A. Denote this interval, pertaining to firm d, by I_d^A. If, for each firm d making endogenous product choices, this interval has a non-empty intersection with the estimated interval of its fixed costs, C_d, the vector A cannot be ruled out as supporting an equilibrium, and is deemed an element of A^{pe}. Also note that I_d^A itself may be empty, in which case A is clearly ruled out as a potential equilibrium.

Computing the interval I_d^A tends to be rather expensive, and, in many cases, unnecessary, since one can often quickly verify that a necessarily profitable deviation exists. For that reason, the actual algorithm used to compute the set of potential equilibria A^{pe} has the following three steps:

1. For each vector $A \in \mathcal{A}$, check whether any firm has a necessarily profitable single-product deviation from A.
2. For each of the vectors that were not ruled out in step 1, check whether any firm has a necessarily profitable multiproduct deviation.
3. For each vector A that survived step 2, compute I_d^A for each firm d. If, for every firm d, $I_d^A \cap C_d \neq \emptyset$, determine that $A \in A^{pe}$.

Given that steps 1 and 2 already examined each possible deviation and did not find any of them to be necessarily profitable, step 3 may seem redundant. However, it is possible that firm d's per-product fixed costs must lie in some interval, denoted $I1$, to prevent one deviation from being necessarily profitable, and must also be inside some other interval, $I2$, to guarantee that *another* deviation is not necessarily profitable. Suppose that both $I1$ and $I2$ have non-empty intersections with C_d, but that $I1 \cap I2 = \emptyset$. In this case, even though neither of these deviations is necessarily profitable individually, one of them must be profitable. Due to this subtle point, step 3 is necessary. Note that we could perform step 3 only—however, as explained above, performing steps 1 and 2 first saves computation time. In practice, out of 512 feasible product-choice vectors, 210, 69, and 30 vectors survived the first, second, and third steps, respectively. The size of the A^{pe} set is, therefore, 30.

I was able to 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.[56] The usefulness of this conjecture is in that, once a certain deviation is found to be necessarily profitable (unprofitable) at some vector A, it can be automatically considered to be profitable (unprofitable) at many other vectors. This made it possible to avoid a direct computation of expected variable profits in about 9% of the 512 vectors in $\mathcal{A}$. In an earlier draft of this article, which allowed for a much larger space of potential outcomes (but saved on computation time with a "shortcut" that set the $e = (\xi, \omega)$ error terms to zero, rather than repeatedly drawing from their estimated distribution as performed in this article), this conjecture allowed me to evaluate $16,384$ vectors rather than $2^{24} = 16,777,216$—an immense reduction in computation time.

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56. 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.

Supplementary Data

Supplementary materials are available at *Review of Economic Studies* online.

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