Technological Stagnation or Rising Market Power? Evidence from the Japanese Computer Hardware Industry

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Abstract

Technological innovation in computer hardware, often measured by rapid decline in the relative price of computer hardware, significantly boosted productivity growth in the past. The massive decline in these relative prices stopped during the last two decades globally. To disentangle the causes behind recent price increases, we structurally estimate supply and demand model using detailed Japanese computer product-level data from 2006 to 2015, and back out the marginal costs and markups. Our results indicate that price reductions in earlier sample period resulted from marginal cost decreases, while the price stabilization in later sample period reflects halted technological progress rather than increased market power. Recent PC market trends suggest genuine technological stagnation.

Keywords: Market Power, Markup, Computer Hardware, Demand Estimation

1 Introduction

Technological innovation is a fundamental driver of economic growth and a key determinant of economic welfare. Historically, significant technological advancements—especially those embodied in capital, from the innovations in power technologies to the contemporary introduction of personal computers and robotics—have consistently raised productivity levels and

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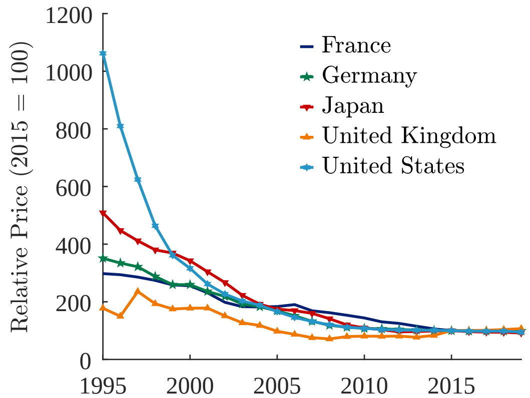

Figure 1: Relative Computer Hardware Prices

Notes: The prices of computer hardware investment goods are taken from EUKLEMS. Their relative prices are computed by deflating the investment prices using the aggregate inflation rates for each country.

enhanced societal welfare (Hulten (1992), Greenwood et al. (1997)). Among these technologies, personal computers, in particular, have served as general-purpose technologies, playing a central role in driving the IT revolution and significantly contributing to productivity growth since the 1990s.

However, over the past two decades, there have been signs of a slowdown in this particular technological innovation. Specifically, the rate of technological progress associated with personal computers—as typically measured by the relative price of investment goods in macroeconomics—began to decelerate in the last two decades. Figure 1 illustrates trends in computer hardware technological progress across advanced economies. As clearly indicated in the figure, this slowdown has been especially pronounced in the United States, a country previously characterized by rapid technological advances in this domain. During this period of technological stagnation, investment in personal computers has also weakened globally, suggesting that declining technological advancement has suppressed capital investment (Takahashi and Takayama (2023)).

Although this figure points toward possible stagnation in computer technology, other mechanisms remain plausible. In particular, recent literature has documented rising market power across numerous sectors, including in the US economy, as a contributing factor to increased prices (De Loecker et al. (2020))). It is therefore reasonable to hypothesize that heightened market power in the PC industry may partially account for the observed price increases and the associated investment decline.

Motivated by this observation, we analyze the PC market—a crucial sector driving technological progress—by structurally estimating supply and demand to identify and isolate the economic forces underlying significant shifts in time-series prices. To analyze this industry trend, we use detailed product-level data from the Japanese PC market. We specify a demand system that explicitly incorporates heterogeneous agents and assume that multiproduct computer hardware manufacturers engage in Nash-Bertrand competition. Our estimation approach leverages the detailed product-level information—including prices, quantities, market shares, and comprehensive product characteristics collected over time—in conjunction with micro-moments derived from household survey data. These micro-moments capture variations in consumer demographics and purchasing behavior across different income groups. Using the estimated demand parameters, we subsequently derive product-specific markups by imposing firms' first-order conditions for profit maximization.

Our primary findings are as follows. The price declines observed in the earlier half of our sample period were driven mainly by reductions in marginal costs, causing a corresponding drop in the average Lerner index. Around 2009, the downward trend in prices stalled, largely due to the cessation of marginal cost reductions, resulting in the Lerner index remaining stable thereafter. These results align with conclusions derived from relative prices, a common macroeconomic proxy for technological innovation. Specifically, falling prices in the PC market have historically indicated technological advances; hence, the recent stabilization of prices reflects a halt in technological progress.

2 Data

This section describes the data sources and presents basic descriptive information. There are mainly two datasets for our analysis. The first dataset is about computer hardware, and the second one is about households.

2.1 Computer Hardware Market Data

Our primary data source comprises point-of-sale information on retail prices and product characteristics of personal computers (PCs) sold in the Japanese retail market. This dataset, provided by BCN Inc., covers a significant portion of total PC sales in Japan, ensuring its representativeness of the Japanese retail PC market. It contains monthly observations of retail prices and detailed characteristics for both desktop and notebook PCs. All prices have been deflated to real terms using Japan's consumer price index with January 2010 as the baseline period to maintain consistency and comparability across time.

2.2 Consumer Choices and Demographics

We use confidential household-level microdata from the Household Consumption Survey to examine household PC purchase behavior. The survey provides monthly data at the household level, capturing detailed consumption patterns related to ICT goods, online shopping, and purchases of high-value, infrequently acquired goods and services. To mitigate noise and sampling issues associated with unitary households, we limit our sample to non-unitary households. Although the data are originally collected on a monthly basis, we aggregate them to a bimonthly frequency to ensure sufficient observations within each income bracket for analysis.

Our analysis examines the relationship between household income and PC purchases. The dataset reports income within discrete brackets, allowing us to assess whether a household purchased a PC and at what price relative to its income group. Prior to 2010, the survey classifies income into 12 brackets; after 2010, it adopts a more detailed classification with 14 brackets. To maintain consistency throughout the sample period, we harmonize all income data to conform to the pre-2010 structure.

This dataset allows us to systematically analyze the relationship between income levels and PC expenditures. We compute income distributions and the covariance between income and the prices of purchased PCs, which serve as micro-moments in our demand estimation. These moments capture income-driven heterogeneity in consumer behavior and price sensitivity, thereby facilitating the identification of deep parameters.

3 Model

Our framework builds on the differentiated product demand and oligopoly pricing model, which is widely used in the industrial organization literature. The demand side of our model closely follows Grigolon and Verboven (2014), whereas the supply side follows Berry et al. (1995).

3.1 Consumer Demand

There is a continuum of consumers, indexed by i. Market is defined as a national–level market at a monthly level, and indexed by t.The set of available products in market t is denoted by J_t. Consumer i's indirect utility from choosing product j in market t is given by

$$u_{ijt} = -\alpha_{it} p_{jt} + \beta' X_{jt} + \xi_{jt} + \theta_{f(j)} + \theta_{y(t)} + \theta_{m(t)} + \zeta_{ig(j)t} + (1-\rho)\epsilon_{ijt}, \tag{1}$$

whereas the utility from choosing the outside option ($j = 0$) is:

$$u_{i0t} = \zeta_{ig(j)t} + (1-\rho)\epsilon_{i0t}.$$

The key components of the utility function include price, denoted by p_{jt}, and a vector of observable product characteristics, denoted by X_{jt}. Specifically, our empirical specification of product characteristics X_{jt} considers HDD size, SSD size, RAM size, CPU speed (measured in MHz), the number of months passed since the product's initial release, and a dummy indicating laptop PCs. Unobservable product characteristics are captured by the term ξ_{jt}. Additionally, to control for fixed effects, we incorporate dummy variables representing firms, years, and months within years, denoted by $\theta_{f(j)}$, $\theta_{y(t)}$, and $\theta_{m(t)}$.

Idiosyncratic consumer preference heterogeneity are captured by the composite term, $\zeta_{ig(j)t} + (1-\rho)\epsilon_{ijt}$. Here, ϵ_{ijt} are independent and identically distributed random variables following the type 1 extreme value distribution. The term $\zeta_{ig(j)t}$ captures the preference heterogeneity within a group. Here, we group PCs as (1) desktop PCs, (2) laptop PCs, and (3) outside option. We construct the combined error term $\zeta_{ig(j)t} + (1-\rho)\epsilon_{ijt}$ continues to follow a type 1 extreme value distribution, as shown by Cardell (1997). The nesting parameter $\rho \in [0,1)$ measures the degree of correlation among consumer preferences within each group. At the boundary, $\rho = 0$ corresponds to the standard multinomial logit model, while as ρ approaches 1, taste shocks within each group become nearly perfectly correlated.

Following Berry et al. (1999), we allow consumer price sensitivity, α_{it}, to vary inversely with income. Specifically, we assume that the coefficient on the price α_{it} is given by

$$\alpha_{it} = \frac{\alpha}{y_{it}}, \tag{2}$$

where y_{it} represents consumer i's income in market t.

Incorporating equation (2), we can rewrite the indirect utility (1) as:

$$u_{ijt} = \begin{cases} \delta_{jt} + \mu_{ijt} + \zeta_{ig(j)t} + (1-\rho)\epsilon_{ijt}, & j = 1, \dots, J_t \\ \zeta_{ig(j)t} + (1-\rho)\epsilon_{i0t}, & j = 0 \end{cases},$$

where $\delta_{jt} = \beta' X_{jt} + \xi_{jt}$ captures the mean utility of product j, and $\mu_{ijt} = -\alpha_{it} p_{jt}$ represents the individual-specific deviation arising from the consumer's income and the product's price. We normalize the values of δ_{0t} and μ_{i0t} to zero.

It follows from demand structure of the random coefficient nested logit model that the probability that consumer i selects product j is

$$s_{ijt} = \frac{\exp\left(\frac{\delta_{jt}+\mu_{ijt}}{1-\rho}\right)}{\exp\left(\frac{I_{igt}}{1-\rho}\right)} \times \frac{\exp\left(I_{igt}\right)}{\exp\left(I_{it}\right)},$$

where the inclusive value terms I_{igt} and I_{it} are defined as:

$$I_{igt} = (1-\rho)\log\left[\sum_{j \in J_{gt}} \exp\left(\frac{\delta_{jt} + \mu_{ijt}}{1-\rho}\right)\right], \quad I_{it} = \log\left[\sum_{g} \exp\left(I_{igt}\right)\right],$$

where J_{gt} denotes a set of products that belongs to group g in market t.The aggregate market share of product j in market t, denoted by s_{jt}, is then obtained by integrating individual-level choice probabilities over the distribution of heterogeneous consumer tastes:

$$s_{jt} = \int s_{ijt} dF(\boldsymbol{\mu}_t),$$

where $F(\boldsymbol{\mu}_t)$ denotes the joint distribution of the individual-specific random components $\{\mu_{ijt}\}_{i,j}$ in the population.

3.2 Supply Side

On the supply side, we introduce a model of Bertrand competition among multiproduct PC manufacturers. Manufacturers are assumed to set prices simultaneously, maximizing their own profits, given the differentiated nature of their products.

Specifically, each manufacturer f produces a set of products $\mathbf{J}_{ft}$ in market t and competes by choosing the prices of these products. The profit function for manufacturer f in market t is given by:

$$\pi_{ft} = \sum_{j \in \mathbf{J}_{ft}} (p_{jt} - mc_{jt}) q_{jt}(\mathbf{p}_t),$$

where p_{jt} is the price of product j in market t and mc_{jt} represents its constant marginal cost in market t. Additionally, $q_{jt}(\mathbf{p}_t)$ denotes the quantity sold of product j given the vector of entire market prices, $\mathbf{p}_t = (p_{jt})_{j \in J_t}$. Following standard practice in the empirical industrial organization literature, marginal costs are assumed constant for simplicity and tractability.

Manufacturers set prices to maximize profits according to the Bertrand competition framework described above. This leads to the following system of first-order conditions (FOCs) for profit maximization:

$$q_{jt}(\mathbf{p}_t) + \sum_{l \in \mathbf{J}_{ft}} (p_{lt} - mc_{lt}) \frac{\partial q_{lt}}{\partial p_{jt}} = 0, \quad \forall j \in \mathbf{J}_{ft}.$$

Stacking these conditions for all products in market t, we express the equilibrium conditions in matrix notation:

$$\mathbf{q}_t(\mathbf{p}_t) - D_t(\mathbf{p}_t)(\mathbf{p}_t - \mathbf{mc}_t) = \mathbf{0}, \tag{3}$$

where $\mathbf{q}_t = (q_{1,t}, \ldots, q_{J_t,t})'$, $\mathbf{p}_t = (p_{1,t}, \ldots, p_{J_t,t})'$, and $\mathbf{mc}_t = (mc_{1,t}, \ldots, mc_{J_t,t})'$. Here, $D_t(\mathbf{p}_t)$ is a $J_t \times J_t$ matrix defined by the element-by-element multiplication of two matrices, specifically

$$D_t(\mathbf{p}_t) \equiv \Omega_t \odot S(\mathbf{p}_t),$$

where the operator $\odot$ represents the Hadamard (element-wise) multiplication. In the above definition, the matrix Ω_t represents the ownership structure among products in market t. Its (i, j)-th element equals 1 if products i and j belong to the same manufacturer, and 0 otherwise. The matrix $S(\mathbf{p}_t)$ is defined such that its (i, j)-th element is $-\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{it}}$, capturing how changes in the price of product i affect the demand for product j.

Given these equilibrium conditions, we can solve explicitly for the marginal costs as follows:

$$\mathbf{mc}_t = \mathbf{p}_t - D_t(\mathbf{p}_t)^{-1}\mathbf{q}_t(\mathbf{p}_t) \tag{4}$$

This expression allows us to infer marginal costs directly from observed prices and quantities, conditional on the demand estimates, $D_t\left(\mathbf{p}_t\right)^{-1}$.

4 Estimation and Results

In this section, we estimate the structural demand model described above and explore the underlying factors contributing to recent price trends in Japan's computer hardware industry.

4.1 Estimation of Consumer Demand

We estimate consumer demand parameters (α, β, ρ) following the approach developed by Berry et al. (1995). The key econometric challenge in identifying these parameters arises from potential endogeneity. Specifically, the price coefficient α is subject to endogeneity due to the correlation between prices p_{jt} and unobserved product qualities ξ_{jt}. Additionally, identification of the nesting parameter ρ is necessary to characterize the correlation structure of unobserved preferences within product groups.

To address these identification challenges, we construct moment conditions based on both macro-level and micro-level data. At the macro level, we impose mean independence restrictions,

$$\mathbb{E}[\xi_{jt} Z_{jt}^d] = 0$$
$$\mathbb{E}[\xi_{jt} X_{jt}] = 0,$$

where Z_{jt}^d denotes a vector of excluded instruments, and X_{jt} represents observable product characteristics. Following standard practice in the literature, we employ the so-called BLP instruments, defined by aggregating competitors' characteristics within and across firms. Specifically, the instruments include characteristics of other products offered by the same firm ($Z_{jt}^{BLP,other} = \sum_{k \in J_{ft} \setminus \{j\}} x_{kt}$) and characteristics of rival firms' products ($Z_{jt}^{BLP,rival} = \sum_{k \notin J_{ft}} x_{kt}$). Recall that there are four key product characteristics used in our analysis: CPU speed (MHz), RAM size, HDD size, and SSD size. Furthermore, we construct additional instruments that reflect market structure by counting the number of products offered by the same firm within the same product category (Desktop or Laptop) and the number offered by rival firms within the same category. These steps yield a total of ten excluded instruments to achieve credible identification.

To enhance identification through richer variation in the data, we incorporate micro-level moments derived from consumer-level observations. Specifically, we divide consumers into three income groups with roughly equal representation: a low-income group (annual income up to 4 million JPY), a middle-income group (annual income between 4 and 7 million JPY), and a high-income group (annual income above 7 million JPY). Using these income classifications, we match empirical moments related to two aspects of consumer behavior. First, we match observed probabilities of making a purchase conditional on belonging to a particular income group. Second, we match observed average purchase prices conditional on consumers' income group and conditional on having chosen an inside option (a specific PC product). Formally, we match conditional purchase probabilities, such as $\mathbb{E}[\mathbf{1}\{j \neq 0\} \mid y \in \mathcal{G}_g]$ for $g \in \{low, mid, high\}$, and conditional expected prices, such as $\mathbb{E}[p_{jt} \mid j \neq 0, y \in \mathcal{G}_g]$ for all $g \in \{low, mid, high\}$. While these moments could theoretically be matched year-by-year, we simplify by aggregating across the entire sample period to facilitate estimation.

The implementation of this structural estimation procedure is conducted using the PyBLP software package developed by Conlon and Gortmaker (2020) and Conlon and Gortmaker (2025), providing robust and efficient estimation capabilities consistent with best practices in empirical industrial organization.

4.2 Results

Table 1 reports the estimation results for the random coefficient nested logit demand model. All the characteristics of PCs positively affect demand. Households prefer purchasing recent models and notebooks.

Figure 2 summarizes our main findings. The average price sharply declined until 2010, and this decline reflects a corresponding decrease in marginal cost. The average markup has been roughly constant over the entire sample period. These findings indicate a near-complete pass-through of marginal costs to prices in *level*s.

To clarify when this result emerges, it is useful to examine a simpler setting. Consider a monopolistic firm producing a single product, with demand given by $q(p)$ and constant marginal cost mc. Following Bulow and Pfleiderer (1983), the relationship between price and marginal cost changes is expressed as:

$$p'(mc) = \frac{\varepsilon}{\varepsilon + \left(\frac{\partial p}{\partial \varepsilon}\frac{\partial \varepsilon}{p} + 1\right)},$$

Variables	Estimates	Standard Error
Product Characteristics β		
HDD size	1.971	0.161
SSD size	9.103	1.237
RAM size	0.465	0.038
CPU Speed (in MHz)	0.799	0.071
Months since release	-0.047	0.002
Dummy for Notebook	0.899	0.021
Demand Elasticity α	-46.594	3.933
Nesting Parameter ρ	0.564	0.017

Table 1: Demand Estimates

where $\varepsilon = \partial \ln q / \partial \ln p$ is the demand elasticity. Complete pass-through in levels ($p'(c) = 1$) occurs precisely when the super-elasticity of demand exactly equals one:

$$-\frac{\partial p}{\partial \varepsilon} \frac{\partial \varepsilon}{p} = 1.$$

Our empirical evidence indicates that the aggregate demand function roughly meets this criterion.

This near-complete pass-through is also documented in the existing literature. Nakamura and Zerom (2010) report a one-for-one relationship between retail coffee prices and coffee commodity prices measured in levels. In addition, recent evidence provided by Sangani (2024), who examines microdata for gasoline and food products, confirms the presence of complete pass-through.

Given this near-complete pass-through, studying markups in a conventional manner may not be particularly informative. Figure 3 plots the implied average Lerner index. As illustrated, the Lerner index steadily increased until 2010 but has since plateaued. A naive interpretation might suggest that firms experienced simultaneous technological improvements, reflected in declining marginal costs, and growing market power. However, such a conclusion warrants caution, as our analysis provides an alternative interpretation: the markup remained nearly constant due to specific properties of the demand function.

5 Final Remark

This paper provides a detailed empirical analysis of Japan's computer hardware industry, explicitly examining the factors underlying the price stabilization observed in recent decades.

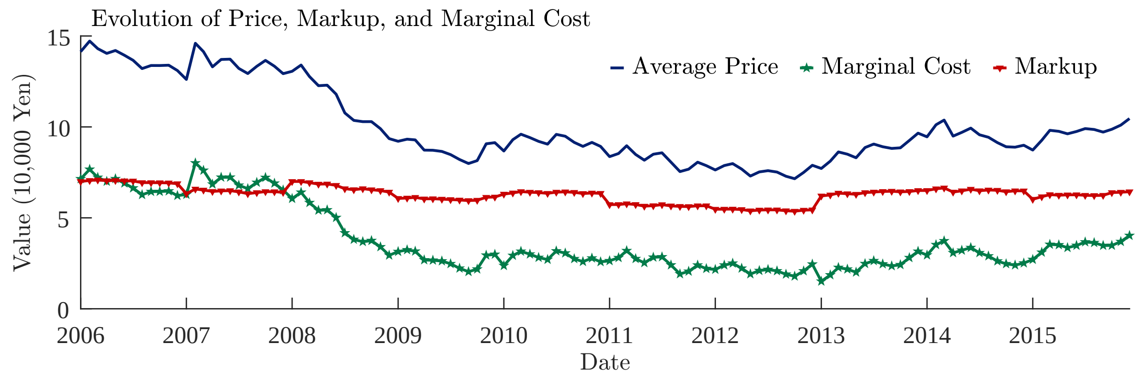

Figure 2: Evolution of Average Price, Markup, and Marginal Cost

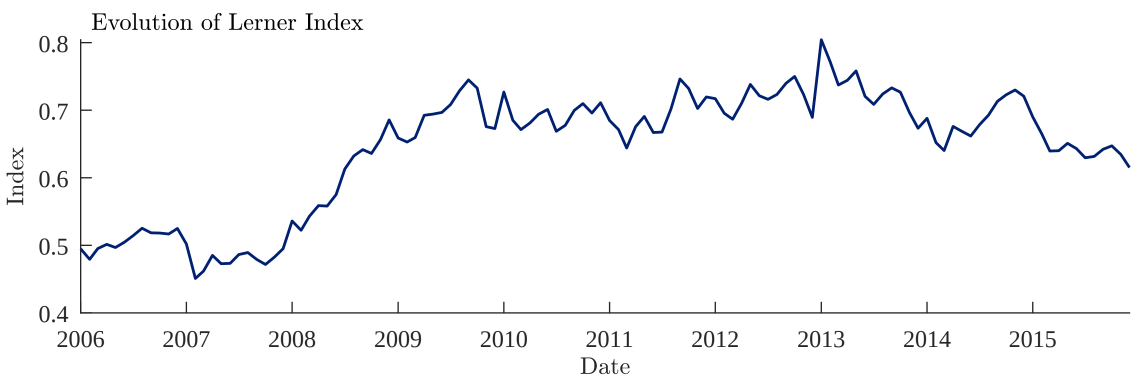

Figure 3: Evolution of Lerner Index

By structurally estimating consumer demand using comprehensive micro-level household data, we seek to identify why computer prices ceased declining around 2010.

Our analysis shows that the significant price reductions prior to 2010 resulted from persistent declines in marginal costs, reflecting substantial technological progress. However, the price stabilization observed after 2010 coincides precisely with the halt in marginal cost reductions, indicating genuine technological stagnation. In other words, our finding of nearly complete marginal cost pass-through to retail prices suggests that traditional markup-based explanations offer limited insight, underscoring the importance of understanding underlying technological and demand-side factors.

The Japanese case offers broader insights. Specifically, it suggests that the recent global slowdown in computer hardware price reductions—often interpreted as evidence of rising market power—may instead reflect fundamental technological stagnation. Given the crucial role of computers as general-purpose technologies, prolonged technological stagnation poses serious challenges to future economic growth and productivity gains. Future research should investigate the root causes of this technological slowdown, assess possible policy interventions, and explore whether similar patterns exist in other high-tech industries.

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