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# MEASURING THE ROLE OF TECHNOLOGY-PUSH AND DEMAND-PULL IN THE DYNAMIC DEVELOPMENT OF THE SEMICONDUCTOR INDUSTRY: THE CASE OF THE GLOBAL DRAM MARKET

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This paper reexamines and resolves the long dispute over the source of technological innovation by suggesting an integrated technology-push and demand-pull model. We derive an equilibrium model within the framework of differentiated product analysis and explain the dynamic interaction between these two sources of innovation. Based on the empirical analysis of the global DRAM market, we show that the relative importance of technology-push and demand-pull in technological innovation is described by an L-type curve which describes the phenomenon where technology-push is greater than demand-pull in the early stages and then decreases as demand-pull becomes greater. Our finding suggests that the role of supply and demand is different in inducing technological change and their relative importance changes with product development over the technological life cycle; the marginal prices of products are an important factor in determining the principal forces of technological innovation between these two sources.

*JEL classification codes*: O32, O31
*Key words*: sources of technological innovation, technology-push, demand-pull, Nash equilibrium of technological innovation, DRAM

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## I. Introduction

In this study, we reexamine and resolve the long dispute over the source of technological innovation by theoretically and empirically verifying the dynamic changes in the interaction between two sources of innovation, technology-push and demand-pull, in the development of the global semiconductor industry. The sources of technical change and its role in economic growth has been a central issue among economists since Schumpeter first published his key writing on invention and innovation (Schumpeter 1934, Scherer 1982, Ruttan 2001). However, even though more than half century has passed, several controversial issues remain.

The first and most controversial issue is the role of demand in inducing technological innovation. Since Grilliches (1957) and Schmookler (1962, 1966) demonstrated the importance of the role of demand in stimulating inventive activity, arguments about the relative priority of demand- and supply-side in inducing technological innovation have intensified. After much research (Lucas 1967, Ben-Zion and Ruttan 1978, Ruttan 1997, 2001), economists have mostly settled on the view that both demand and supply factors play an important role in innovation and the life cycles of technology (Mowery and Rosenberg 1979, Walsh 1984, Scherer 1982). However, there has been no attempt to empirically implement an integrated factor and demand induced innovation model (Ruttan 2001). Therefore, important questions remain unanswered. If both sources play an important role in inducing technological innovation, how different is their role? Does their relative importance change over the life cycle of technology? Does it differ depending on the technology under consideration?

The second unsettled argument is about the role of innovation sources in the late stage of technology life. Economists generally accept that, even when the initial path (technological "lock-in") of technological development is generated by technology-push in the early stage of technology life where increasing returns to scale are important, factor market forces often act to modify the path of technical change (Arthur et al. 1987, Ruttan 2001). However, there has been little discussion of how firms or industries escape from lock-in and how the innovation sources change as technical progress slows down or scale economies erode. What happens when the scale economies resulting from an earlier change in technology have been exhausted and the industry enters a constant or decreasing returns stage?

The third remaining question concerns the lack of empirical analysis of technological innovation and its sources from the perspective of evolutionary economics (Arrow 1995). Although there is ongoing debate about the Schumpeter

Mark I and II discussions, both induced innovation and evolutionary theory suggest that, as scale economies are exhausted, the pressure of growth in demand will force research efforts to be directed to removing the technological constraints on growth or inelastic factor supplies.[1] However, economists have made only limited efforts to test the evolutionary theory against historical experience (Ruttan 2001). Does the actual development of industries verify evolutionary economists' point of view on technological innovation?

In response to these questions, this paper recommends an integrated factor and demand induced innovation model which analyzes the dynamic balancing act between the innovation sources, technology-push and demand-pull, over the technology life cycle and empirically supports one of the evolutionary theories of technological innovation by applying it to the global DRAM (Dynamic Random Access Memory) market in the semiconductor industry.

The paper proceeds as follows. In Section II, we introduce a simple model of competition among differentiated oligopolists based on Anderson, de Palma, and Thisse (1992) to model technological innovation. A key assumption of our model is that a product's quality improves over time (Adner and Zemsky 2003). The supply-side quality improvement can be generally thought of in terms of the increasing memory density of DRAM, the increasing size of flat panel displays or the increasing speed of broadband network connections. On the demand-side, we focus on the dynamics of consumers' willingness-to-pay for the quality of products, which decreases with the improvement of products' quality over the technology life cycle. By considering these dynamic changes of the demand environment, we suggest a new perspective on the interaction between technological innovation and demand. In Section III, we describe the DRAM market. In Section IV, we empirically apply the model to the global DRAM market and suggest policy implications. Section V concludes.

## II. The model

We employ two important elements from the traditional models of product differentiation (Anderson et al. 1992). The first element is the notion of heterogeneity of consumers and of technological innovation of products. The extent of technological

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[1] Schumpeter Mark I suggests that innovations are carried out by individual entrepreneurs who create new firms by means of borrowed money. In contrast, the Mark II discussion suggests that innovations are permanently performed by many large corporations in their monopolistic competition.

innovation differs across products, and consumers differ in their willingness to pay for the products. Secondly, we consider a discrete choice situation where a consumer buys a unit of a technologically innovative durable product.

**A. Demand-side**

The quality perception of a consumer ($q_i$) can be described as $q_i = x_i^{\eta}$, $x_i$ is the performance level of the product's main attribute representing the level of technological innovation of the firm producing the product, and $\eta$ (with $0 < \eta \leq 1$) is the degree of *decreasing marginal utility* from technology innovation (i.e., the extent of technology saturation in the market where saturation is represented by smaller values of $\eta$).[2] If $x_i > 1$, $q_i$ is marginally decreasing with $x_i$ describing the situation where the additive technological innovation of product is not valued as much as it would have been in earlier periods. In order to simplify matters, the analysis is restricted to $x_i > 1$ as in Adner and Zemsky (2002). The maximum willingness-to-pay of consumers for product $i$ can be expressed as $w_i = \alpha \cdot q_i = \alpha \cdot x_i^{\eta}$ where $\alpha$ is the marginal willingness-to-pay for the unit improvement of a product's quality.

Each individual is supposed to have a deterministic utility function $U_i$ defined on $C_n$, where $C_n$ is a finite choice set of differentiated products. $U_i$ is modeled by the random variable

$$\tilde{U}_i = V_i + \varepsilon_i . \tag{1}$$

Here, $V_i$ is a consumer's conditional indirect utility from purchasing product $i$, while $\varepsilon_i$ takes into account idiosyncratic taste differences. Products $i = 1,\ldots,n$ are the variations of a differentiated product sold at prices $p_1,\ldots,p_n$. We assume that a consumer's conditional indirect utility is given by the following additive form:

$$V_i = w_i - \beta \cdot p_i = \alpha \cdot x_i^{\eta} - \beta \cdot p_i , \qquad i = 1,\ldots,n. \tag{2}$$

Then, a multinomial logit demand function represents the probabilistic demand for the product $i$ with $\underline{q} = (q_1 \cdots q_n)$, a vector of qualities, and $\underline{p} = (p_1 \cdots p_n)$, a vector of prices. The demand for product $i$, $D_i$, is as follows:

[2] *Technology saturation* means that further technological improvement of a product could not give as much utility increase as the previous innovation did, ceteris paribus. In other words, consumers become indifferent to innovation, since they feel that their technological needs have been already satisfied. See Kim, Lee and Kim (2005) for a more detailed explanation.

$$D_i(\underline{p};\underline{q}) = M \cdot s_i(\underline{p};\underline{q}) = M \frac{\exp(\alpha \cdot q_i - \beta \cdot p_i)}{\sum_i^n \exp(\alpha \cdot q_i - \beta \cdot p_i)}, \qquad i = 1,\dots,n, \tag{3}$$

where $M$ denotes total demand and the rest of the variables is as before.

## B. Supply-side

Let us assume that each firm produces only one product and that it is the sole producer of that product, so the index $i = 1$ through $n$ denotes a specific firm producing a specific product. Firm $i$'s production costs comprise sunk costs $K$ that are constant and equal for all firms, and the technology-dependent marginal cost $c(q_i)$. The $n$ firms are players of a non-cooperative game (when the model involves the outside alternative $n + 1$, there is no player associated with it). Suppose also that firms set prices and set the levels of performance of those product attributes, which represent the firm's technological innovation. The firms supply consumers with the quantities demanded at the prices set. In other words, firm $i$'s strategy is setting prices and choosing the level of its products' attributes. Firm $i$'s (expected) profit can then be defined as follows:

$$\pi_i(\underline{p};\underline{q}) = \left[p_i - c(q_i)\right] \cdot D_i(\underline{p};\underline{q}) - K \tag{4}$$

where $D_i$ is the demand for product $i$ in equation (3).

Now suppose that the marginal cost is constant with respect to quantity but is increasing and strictly convex representing the technological innovation of a firm, so that we can define the marginal cost of technological innovation as $c(q_i) \equiv c(x_i) = x_i^{\delta}$, where $\delta > 1$, which results in $c'(x_i) = \delta \cdot x_i^{\delta - 1} > 0$.[3] We also define a firm's *innovation capability*, $\lambda = 1/\delta$, , where the capability of a firm's innovation, specifically the process innovation, increases with the increase of $\lambda$ resulting in a lower cost to produce a product with the same level of performance.[4]

We now turn to a subgame perfect Nash equilibrium, following Anderson et al. (1992). Here, firms first choose the level of quality attributes –which is the performance

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[3] We assume that $\alpha < \lim_{x \to \infty} c'(x_i)$, which explains that the consumer valuation of quality is smaller than the marginal cost of the highest possible quality.

[4] We follow Utterback and Abernathy (1975) and Porter (1983) here in defining *process innovation* as an innovation that reduces production costs, resulting in the decrease of a product's price. By contrast, *product innovation* means an innovation that improves product performance.

level of the product's main attribute– and then choose prices. Given qualities $\underline{q}$ selected in the first stage, the corresponding price subgame is solved by $p_1^*(\underline{q})\cdots p_n^*(\underline{q})$, such that

$$\pi_i(p_i^*, \underline{p}_{-i}^*; \underline{q}) \geq \pi_i(p_i, \underline{p}_{-i}^*; \underline{q}) \quad \text{for all } q_i \text{ and } i = 1,\ldots,n. \tag{5}$$

Denote the profit functions evaluated at the second-stage equilibrium $p^*(\underline{q})$ as $\tilde{\pi}_i(\underline{q}) \equiv \pi_i(\underline{p}^*(\underline{q}); \underline{q})$. The equilibrium of the quality game is then given by $q_1^* \cdots q_n^*$ satisfying

$$\tilde{\pi}_i(q_i^*, \underline{q}_{-i}^*) \geq \tilde{\pi}_i(q_i, \underline{q}_{-i}^*) \quad \text{for all } q_i \text{ and } i = 1,\ldots,n. \tag{6}$$

A subgame perfect Nash equilibrium is defined by $\underline{q}^*$ and by $\underline{p}^*(\underline{q})$ for all quality configurations $\underline{q}$. The corresponding equilibrium path is $\underline{q}^*$ and $\underline{p}^*(\underline{q})$. In what follows we restrict the analysis to the case of a symmetric equilibrium in which all firms choose the same quality.

**C. The Nash equilibrium of technological innovation (NETI)**

If we consider the second stage of the game where firm $i$ has chosen quality $q_i$ while all other firms have selected $q$, then there is a unique price equilibrium for the game that gives us the following relationship:[5]

$$\beta \cdot (p^* - p_i^*) = \beta \cdot (c(q) - c(q_i)) + \frac{1}{n - 2 + \Phi} - \frac{\Phi}{n - 1}, \tag{7}$$

where $\Phi \equiv \exp\left\{\alpha \cdot (q_i - q) - \beta \cdot (p_i^* - p^*)\right\}$,

$$p_i^* = c(q_i) + \frac{1}{\beta \cdot \left[1 - \left\{\exp(\alpha \cdot q_i - \beta \cdot p_i^*)\right\} / \Delta\right]},$$

$$p_j^* = c(q) + \frac{1}{\beta \cdot \left[1 - \left\{\exp(\alpha \cdot q - \beta \cdot p_i^*)\right\} / \Delta\right]}, j = 1,\ldots,n \text{ and } j \neq i,$$

[5] See chapter 6 of Anderson et al. (1992) for the proof of the existence and uniqueness of the price equilibrium.

$$\Delta \equiv \exp(\alpha \cdot q_i - \beta \cdot p_i^*) + \sum_{\substack{j=1 \\ j \neq i}}^{n} \exp(\alpha \cdot q - \beta \cdot p_j^*) = \exp(\alpha \cdot q_i - \beta \cdot p_i^*)$$
$$+(n-1) \cdot \exp(\alpha \cdot q - \beta \cdot p^*).$$

Therefore, the payoff function for the first-stage game from the evaluation of firm $i$'s profit at the equilibrium can be derived by inserting equations (3) and (7) into equation (4) as follows:

$$\tilde{\pi}_i = \frac{M}{\beta \cdot (n-1)} \Phi - K. \tag{8}$$

The first-order condition with respect to $x_i$ is

$$\frac{\partial \tilde{\pi}_i}{\partial x_i} = \frac{M}{\beta \cdot (n-1)} \left( \frac{\partial \Phi}{\partial x_i} \right) = \frac{M \cdot \Phi}{\beta \cdot (n-1)} \left[ \alpha \cdot \eta \cdot x_i^{\eta-1} + \beta \cdot \frac{\partial}{\partial x_i} (p_i^* - p^*) \right] = 0, \tag{9}$$

since $q_i = x_i^{\eta}$, $0 < \eta \leq 1$ and $\dfrac{\partial q_i}{\partial x_i} = \eta \cdot x_i^{\eta-1}$.

Based on equation (7), the second term in equation (9) becomes

$$\beta \cdot \frac{\partial}{\partial x_i} (p^* - p_i^*) = -\beta \cdot c'(q_i) - \frac{1}{\beta} \left\{ \frac{1}{(n-2+\Phi)^2} + \frac{1}{n-1} \right\} \frac{\partial \Phi}{\partial x_i} = -\beta \cdot c'(q_i), \tag{10}$$

where $\dfrac{\partial \Phi}{\partial x_i} = 0$ for any solution of the first-order condition based on equation (9).

Thus, equation (9) becomes

$$\frac{\partial \tilde{\pi}_i}{\partial x_i} = \frac{M \cdot \Phi}{\beta \cdot (n-1)} \left[ \alpha \cdot \eta \cdot x_i^{\eta-1} - \beta \cdot c'(q_i) \right] = 0. \tag{11}$$

Equation (11) has a unique solution $x_i^*$ since $c'$ is increasing, such that

$$x_i^* = \left\{ \frac{\beta \cdot c'(q_i)}{\alpha \cdot \eta} \right\}^{\frac{1}{\eta-1}}. \tag{12}$$

Then, as we assumed $c(x_i) = x_i^{\delta}$, where $\delta > 1$ and $\lambda = 1/\delta$, equation (12) becomes:

$$x_i^* = \left\{ \frac{\beta}{\alpha \cdot \lambda \cdot \eta} \right\}^{\frac{\lambda}{\lambda \cdot \eta - 1}}. \tag{13}$$

### D. The role of technology-push and demand-pull in technological innovation

To derive the role of technology-push in technological innovation, we simplify the model with the assumption of a duopolistic market structure. Two firms produce two types of products, each with different levels of the main quality attribute. Therefore, the marginal costs of the two firms differ depending on the quality level of each product's main attribute. We have the same marginal prices for both products (i.e. $\beta = \beta_1 = \beta_2$) under the assumption that product features are standardized across brands and vertically differentiated as in the case of the DRAM market. In addition, the decreasing marginal utility is the same for both products (i.e.,$\eta = \eta_1 = \eta_2$) under the assumption of homogeneous consumers in a specific period of time. By definition, the entrant's (firm 2) product is superior to the incumbent's (firm 1) with respect to the performance level of its main attribute, $x_2^* > x_1^*$. Then, we can define the payoff function of the entrant for the first-stage game as

$$\tilde{\pi}_2 = \frac{M}{\beta}\Phi - K, \tag{14}$$

where $\Phi = \exp\left\{\alpha \cdot (x_2^\eta - x_1^\eta) - \beta \cdot (p_2^* - p_1^*)\right\}$. The entrant has incentives to innovate if $\tilde{\pi}_2 \geq 0$, which gives

$$TP \equiv x_2^\eta - x_1^\eta \geq \tau + \varpi, \tag{15}$$

where $\tau = \dfrac{\beta}{\alpha} \cdot (p_2^* - p_1^*)$ and $\varpi = \dfrac{1}{\alpha} \ln\left\{\dfrac{\beta \cdot K}{M}\right\}$. We define the incentive to innovate, the entrant's incentive to introduce the product with better quality ($x_2^\eta - x_1^\eta \geq 0$) into the market, as *technology-push* (*TP*). In addition, we define $\tau$ as the *minimum difference in process innovation for technology-push* (*MI*), which represents the critical point up to which consumers prefer the existing product. We also define $\varpi$ as the *critical level of demand for technological innovation* (*CD*), which represents the minimum level of demand needed for the entrant's technological innovation to enter the market.

In order to derive demand-pull, we define consumer's marginal benefit from firm's perspective as[6]

[6] This is the marginal benefit of demand-side from the perspective of a firm, which is different from consumer surplus (or utility). Under this definition, we do not consider the price coefficient $\beta$ which

$$dp_i = \alpha \cdot x_i^{*\eta} - p_i^* . \tag{16}$$

When the entrant expects this marginal benefit of an entrant's product (product 2) to be greater than that of incumbent's (product 1), i.e. $dp_2 > dp_1$, the entrant expects higher sales of its product (product 2) than the incumbent's (product 1) and has incentives to innovate and introduce product 2. Therefore, we define *demand-pull* (*DP*) as follows:

$$DP = \frac{DP'}{\alpha} = x_2^{\eta} - x_1^{\eta} - \xi > 0, \tag{17}$$

where $DP' \equiv dp_2 - dp_1 = \alpha(x_2^{\eta} - x_1^{\eta}) - (p_2^* - p_1^*)$, $\alpha > 0$, and $\xi = \frac{1}{\alpha} \cdot (p_2^* - p_1^*) > 0$. Here $\xi$ is the *minimum difference in equilibrium prices for demand pull* (*MP*), which represents the critical difference in price up to which consumers prefer the existing product when the technological innovation of products is given.

The relationship between the *MI* ($\tau$) of technology-push and *MP* ($\xi$) of demand-pull is easily derived as follows:

$$\tau = \beta \cdot \xi \tag{18}$$

This enables us to derive the following propositions about the relationship between technology-push and demand-pull.

**Proposition 1.** *Technology-push is always greater than demand-pull when consumers are relatively indifferent to the price change of the product, that is, when $\beta < 1$, under the assumption that the incumbent has a positive price advantage. However, when consumers are relatively sensitive to the price change of the product, $\beta > 1$, the main derivative of the technological innovation is determined in a more complex manner* (refer to Appendix for the proof).

**Proposition 2.** *Demand-pull is always greater than technology-push when consumers are relatively sensitive to the price change of the product, $\beta > 1$, under the assumption that there is no critical level of demand for technological innovation (CD), $\varpi = 0$. Otherwise technology-push is always greater than demand-pull* (refer to Appendix for the proof).

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comes from the consumer utility's perspective. Here we assume that entrant's product has not been introduced into the market and the entrant firm considers the absolute price it will charge in its estimation of product's benefit of demand-side before it introduce its product.

Propositions 1 and 2 show that consumer price sensitivity is an important factor for the determination of the derivative of technological innovation. This result not only gives us a new perspective on the development of technological innovation, it also suggests the answer to the long dispute over the sources of technological innovation. That is, it describes how the two different sources of technology innovation, technology-push and demand-pull, are interrelated and develop through the market signal of price sensitivity.

Based on the above propositions, we further assume decreasing marginal utility in a market over the technology life cycle. Then, Proposition 3 allows us to identify the dynamic change of the relative role between technology-push and demand-pull.

**Proposition 3.** *The role of technology-push in technological innovation is greater than that of demand-pull in the early-stage of the technology life cycle, if we assume that the marginal price* ($\beta$) *of technological innovation increases with the evolution of technology life cycle. However, in the later-stage of technology life cycle, the role of technology-push rapidly decreases and the role of demand-pull becomes greater than that of technology-push* (refer to Appendix for the proof).

Based on equation (18), proposition 2, and 3, we can have the following *L-type curve*, shown in Figure 1. Figure 1 describes the dynamic relationships between *TP* and *DP*, when we define the difference between *TP* and *DP* as $\Gamma$, so

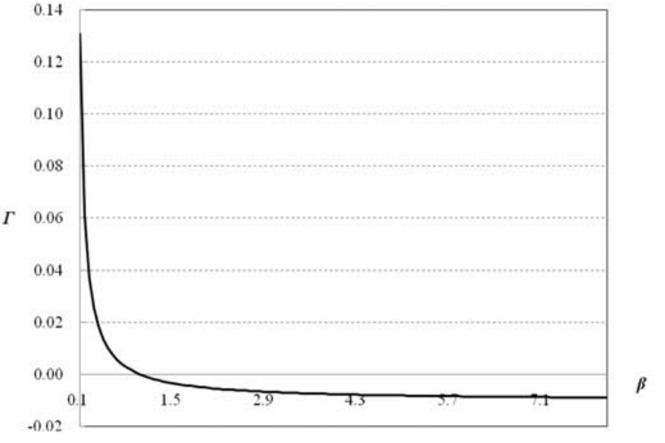
$$\tilde{A} = TP - DP = (x_2^{\eta} - x_1^{\eta} - \tau) - (x_2^{\eta} - x_1^{\eta} - \xi) = \tau \cdot (\frac{1-\beta}{\beta}), \tag{19}$$

where $\beta > 0$ and $\tau > 0$.[7]

Figure 1 describes the dynamic change of the relative importance of the two sources of technological innovation, technology-push and demand-pull, depending on changes in marginal price. Here the increase of $\beta$ corresponds to the time elapsed over the technology life cycle under the assumption of the Nash equilibrium of technological innovation (NETI). At the same time consumers' price sensitivity increases also. In Figure 1, when the marginal price is low ($\beta < 1$), the relative role of technology-push is far greater than that of demand-pull. However, it exponentially decreases with the increase of marginal price. In other words, the incentive to *push* the innovation from the supply side dramatically decreases as consumers become more sensitive to the price of products. Therefore, the consumer's price sensitivity serves as an important signal for firms when they map out their product innovation strategy.

[7] When $\beta > 0$, we have $\tau > 0$ based on equations (17) and (18).

Figure 1. The $\Gamma$ curve, representing the dynamic changes in the relative importance of technology-push and demand-pull over the technological life cycle (L-type)




On the other hand, when the marginal price is greater than 1 ($\beta > 1$), the role of demand-pull is greater than that of technology-push in the development of technological innovation. This makes sense when consumers are more concerned about the price rather than the quality of products. In these situations, there are few incentives for the firm to innovate. This leads firms to focus on a strategy of cutting prices. However, the incentive to innovate derived from demand-pull in this stage is smaller than the amount of technology-push when the marginal price is high or when it is almost constant.

From the perspective of economic history, Schumpeter's (1934) view that technology-push plays a major role in technological innovation has long been dominant. The early stage of the technology life cycle with $\beta$ less than 1 (in Figure 1) clearly supports this view of the role of technology-push. On the other hand, the increasing role of demand-pull in the later stage of the technology life cycle with $\beta$ greater than 1 (in Figure 1) supports the view of Schmookler (1966) and Scherer (1967), and Barzel (1968). They challenged Schumpeter's view on technological innovation, insisting that the greater the demand for a set of products, the more profitable innovations to these products were likely to be. They also argued that we should expect more innovations aimed at satisfying consumers' demands for those products. Therefore, the increasing role of demand-pull in the later stage of the technology life cycle in Figure 1 clearly supports their arguments on the other side. Therefore, Proposition 3 and Figure 1 help to disentangle the long dispute over the role and process of innovation in economics by illustrating the two sides of innovations and describe how those two major derivatives of technological innovation develop over the technology life cycle interactively.

Consequently, these results give us new strategic and public policy perspectives. From a firms' managerial point of view, dynamic innovation strategies should depend on a products' technology life cycle. A firm can allocate their resources on R&D for new product introduction and for product innovation in the early stages of the technology life cycle. On the other hand, in the later stages, they can focus on process innovation in order to reduce the production cost of their product and hence its price. The result of propositions based on the Nash equilibrium of technological innovation (NETI) suggests that firms will have optimal profit levels if they use their resources following the dynamic change of the derivatives of technological innovation.

From the perspective of public policy, the government can modulate industry regulations and supports, depending on an industry's stage in its technology life cycle. For example, in the case of the biotechnology industry that is currently in the early stages of technology development, government can use regulations and subsidizations to encourage firms to emphasize R&D, new technology development, and subsequently commercialization. This will lead to greater returns from the dynamic perspective of technology development. Therefore, the results encourage us to have a dynamic perspective regarding public policy for technology innovation in public sectors as well. The results also strongly support direct investment in R&D, reduction or exemption of taxes related to R&D activities in the early state of the technology life cycle. In addition, promotion of the interaction between product development and markets, such as the institutional support of market formation for specific products, will enable public policy to be more effective when we consider the role of demand in the later stage of technology life cycle.

## III. The DRAM market

Memory chips are the largest single segment in the semiconductor market and DRAMs are the highest volume commodity semiconductors with more than 11% of the total semiconductor market.[8] Dynamic random access memory (DRAM) is the most common kind of random access memory (RAM) for personal computers and workstations. *Random access* indicates that the PC processor can access any

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[8] *Status Report on Semiconductor Industry*, Integrated Circuit Engineering Corporation (2000).

part of the memory directly in any order. DRAM is *dynamic* in that it needs to have its storage cells refreshed or given a new electronic charge every few milliseconds.

DRAM has shown clear discrete innovations in its product characteristics, especially in memory density, making it a typical multi-generation product. The standardized features of DRAM, which allows for almost perfect substitution among successive generations and brands, enhance competition and cause product innovation to occur in discrete steps, while maximizing the number of generations in order to skim the high margins associated with early introduction. Since the introduction of integrated circuits (IC) in 1959, more than 10 generations have been brought onto the market, each having four times higher memory density compared to the previous generation up until the recent 256M generation.

The source of the recent rapid innovation in DRAM products can be found in the demand, supply and technological sides of the market. On the demand side, DRAM has mainly been used in PCs, workstations, mainframes and other computer related equipment, such as hard disk drives, printers and scanners. However, DRAM has been expanding its scope of applications to include the mobile handsets and other telecommunication equipment, such as notebooks, PDA's (Personal Digital Assistants), GPS (Global Positioning Systems) as well as digital consumer applications, such as digital video recorders and gaming consoles. Therefore, we understand that the increasing total demand and the increasing number of DRAM varieties accelerate the innovation of DRAM, as the general communication technology accelerates its transformation from analog to digital and from wired to wireless.

On the supply side, the intense competition among the DRAM manufacturers spurred the rapid introduction of new DRAM generations resulting in substantial restructuring of the industry, which caused the market to evolve from a state of almost perfect competition to an oligopolistic one. The market leaders have made a desperate attempt to survive the severe competition by introducing successive generations earlier than the other competitors and have enjoyed a significant cost advantage over the smaller companies by reaching the economies of scale earlier than others.

On the technological side, since DRAM supports the storage of information of the CPU (Central Processing Unit), a complementary technological innovation in both CPU and DRAM has come about with developments in one triggering complementary developments in the other. As the system software becomes more complex to meet the demand of consumers for ever more advanced programs, the CPU has grown faster and more powerful. Recently, to match the advancement of

CPU, DRAM has been developed also into three different types of SDRAM (Synchronous), DDR (Double Data Rate) SDRAM, and RDRAM (Rambus DRAM). With these fast and dynamic developments of demand, supply, and technology, the DRAM market seems to be one of the most motivating and appropriate markets to examine the relationship between technology push and demand pull.

## IV. The empirical analysis for the global DRAM market

In this section, we verify the dynamics of technology-push and demand-pull by applying the suggested model to the global DRAM market. In order to verify the dynamics, we estimate equation (19), the interrelationship between technology-push and demand-pull. Therefore, we first estimate $\tau$ of equation (15). However, since $\tau$ is a function of $\alpha$ and $\beta$, we first estimate the demand function of equation (3). In order to estimate equation (3), we assume the multinomial logit demand model and follow the estimation approach suggested by Kim et al. (2005).

### A. Data set

The dataset we use is provided by Victor and Ausubel (2002) and consists of 25 yearly observations of worldwide DRAM shipments and their price per megabit, for 7 successive generations from 1974 to 1998: 4K ($t_1$=1974), 16K ($t_2$=1976), 64K ($t_3$=1978), 256K ($t_4$=1982), 1M ($t_5$=1985), 4M ($t_6$=1987), 16M ($t_7$=1991). Table 1 shows the summary statistics for DRAM generations. The means of global DRAM shipment constantly increase from 26.37 to 707.01 million units as DRAM generations evolve from 4K to 16M.[9] In the case of price, the annual prices per bit drastically decrease from 1228.41 to 3.01 dollar per megabit (Mbit) as DRAM generations evolve, which reflects technological innovation, learning-by-doing, and increasing competitiveness of DRAM market.

Figure 2 below represents the cumulative unit shipment of DRAM generations. Each generation clearly shows an S-type diffusion curve of its technology life cycle. As we can expect from the summary statistics, the market saturation points for each generation has drastically increased as generations evolved over time. In other words, demand for DRAM has radically increased with the evolution of DRAM

[9] For 64M DRAM, the mean of shipment, 160.67 millions units, is smaller than 16M DRAM, because 64M DRAM were introduced in 1994 with only 5 years of product life in the market compared to 8 years of 16M DRAM. Average product life of DRAMs is 12.3 years for 4K to 1M DRAMs.

Table 1. Summary statistics for DRAM generations (1974-1998)

| DRAM generation (bit) | Global DRAM shipment by IC density (million units) | | | Annual DRAM price-per-bit ($ per Mbit) | | |
|---|---|---|---|---|---|---|
| | Mean | Max | Min | Mean | Max | Min |
| 4K | 26.37 | 73.30 | 0.45 | 1228.41 | 6101.33 | 389.38 |
| 16K | 127.56 | 266.41 | 0.68 | 646.66 | 3357.38 | 68.66 |
| 64K | 178.97 | 854.61 | 0.39 | 412.98 | 2771.25 | 15.88 |
| 256K | 415.88 | 955.37 | 0.18 | 75.09 | 656.20 | 5.92 |
| 1M | 359.09 | 827.00 | 1.16 | 16.69 | 119.84 | 1.30 |
| 4M | 660.12 | 1649 | 0.68 | 17.42 | 117.81 | 0.35 |
| 16M | 707.01 | 2115.00 | 0.10 | 4.71 | 17.38 | 0.95 |
| 64M | 160.67 | 706.00 | 0.11 | 3.01 | 6.86 | 0.14 |

Note: K stands for kilobite, M for megabite.

generations. This notable expansion of demand for DRAM can be attributed to the "IT revolution" in the late 80's and 90's. During this period, the demand for computers and peripheral equipments, mobile handsets, telecommunication related equipments, and digital consumer applications notably expanded. Corresponding to this epochal expansion of IT products, demand for DRAM had the highest rate of increase over the past decades, because DRAM is one of the key components for most of those IT products.

Figure 2. Cumulative DRAM unit shipments by DRAM generations (1974-1998)

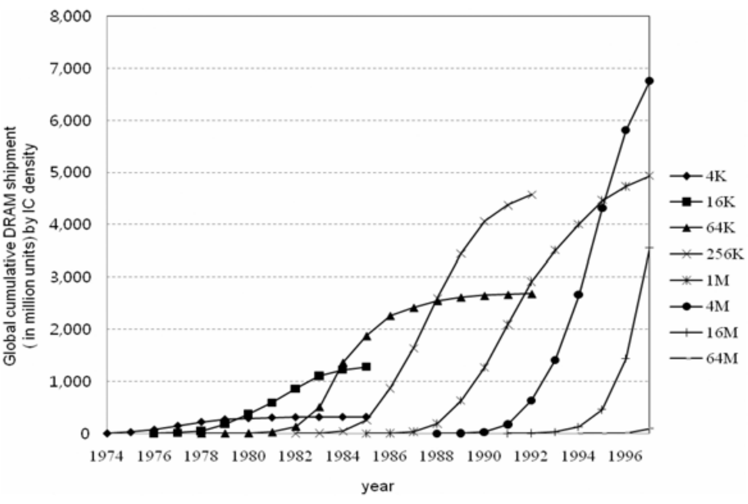
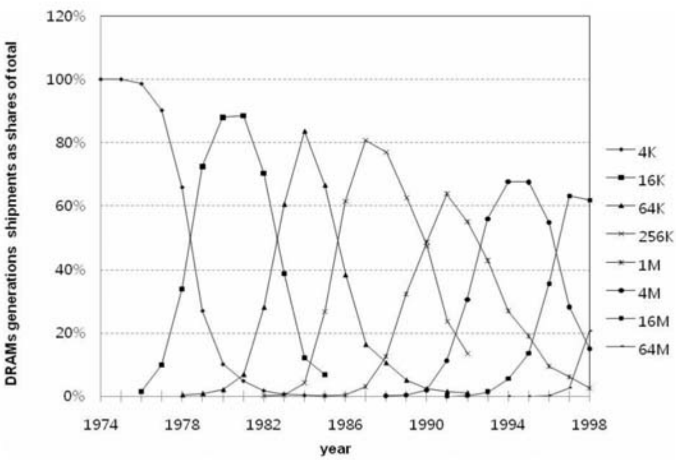


Figure 3 shows the cumulative market share of each DRAM generation. As generations evolve, the maximum market share of each generation decreased significantly, 8 % on average.[10] The decrease of maximum market share results from the increased product life and significant price reduction of later generations stemming from accelerated technological innovation. The DRAMs are products with a high rate of innovation in their technological attributes, especially in their memory densities (Mbit). Therefore, the development of their technological innovation can be clearly classified by the "generations" defined by their memory densities. Of course, the DRAMS have other technological attributes, such as frequency (MHz). However, the development of frequency (MHz) with each generation of DRAMS shows a similar trajectory to that of the memory density.

Figure 3. DRAM market share by generations (1974-1998)




## B. Estimation

A "choice situation" is defined as the one in which a consumer is faced with a choice among a set of alternatives which is finite, mutually exclusive and includes all possible alternatives (Train 2002). A consumer chooses one alternative, which

[10] The case of 4M DRAM has been excluded in the calculation, since the DRAM market between 1990 and 1993 experienced an overall depression when 1M DRAM was the major memory chip. The maximum market share of 4M DRAM increased 4% compared to 1M DRAM after the DRAM market recovered from the depression.

maximizes his/her utility under a limited budget. In the case of multi-generational products, consumers should decide which generation to purchase in each period.

We denote a choice set for all DRAM generations at time $t$ with $J$ alternatives as $C_t = \{1,2,\cdots,J_t\}$, a *memory density* vector of a DRAM generation as $MD(t)_{ij}$ observed by consumer $i$, the *price* as $p(t)_{ij}$, and the time variable represented by the age of the product as $a_{jt} = t - t_j + 1$, where $t$ is the time index and $t_j$ is the introduction time of the $j^{\text{th}}$ generation. Then, the utility of consumer $i$ when he/she chooses generation $j$ from the set $C_t$ can be defined as follows,

$$u(t)_{ij} = U_i(MD(t)_{ij}, p(t)_{ij}, a_{jt}) = V_i(MD_{jt}, p_{jt}, a_{jt}) + \varepsilon_{ijt}. \tag{20}$$

Here, the utility function $u(t)_{ij}$ can be partitioned into two parts. The first, $V_i(MD_{jt}, p_{jt}, a_{jt})$, depends on the memory density, prices, and generation, which can be captured by the data. The second part is the random error term which represents all the other factors of utility that cannot be captured as data represented by $\varepsilon_{ijt}$. Acting on the assumption of additive separability in the utility function, we can specify $V_i$ of product $j$ at time $t$,

$$V_i(\mathrm{MD}_{jt}, p_{jt}, a_{jt}) = \alpha_j MD_{jt} + \beta_j p_{jt} + \gamma_j a_{jt}. \tag{21}$$

Consequently, the market share of generation $j$ at time $t$ can be represented directly by the average probability of a consumer choosing this particular generation based on the product characteristics.[11] Under the assumption that the random variable $\mathring{a}_{ijt}$ is independently, identically distributed with extreme value distribution,[12] we can have market share function as follows,

$$S_j(t) = \bar{P}_j(t) = \sum_i \frac{\exp(V_i(MD_{jt}, p_{jt}, a_{jt}))}{\sum_{k \in J_t} \exp(V_i(MD_{kt}, p_{kt}, a_{kt}))}, \quad \text{for all } k \text{ in } C_t, \tag{22}$$

[11] In estimating discrete choice models of consumer demand on market-level data, aggregate estimates can be obtained from the above choice probability situation by sample enumeration. Here, the choice probabilities of each consumer in a sample are summed, or averaged, over a set of consumers. See Kim et al. (2005) for a more detailed explanation.

[12] We approach the demand analysis with a simple logit model as a primitive case. However, applying various discrete choice models, such as probit and nested logit, results in a more realistic estimation of demand.

by employing the inversion routine suggested by Berry (1994)[13], equation (22) becomes[14]

$$\ln(f_j(t)) - \ln(f_0(t)) = \alpha_j MD_{jt} + \beta_j p_{jt} + \gamma_j a_{jt}, \tag{23}$$

where $f_j(t)$ is the market share of product $j$ at time $t$ in equation (22) and $f_0(t)$ is the market share of *outside goods*.[15]

Following Kim et al. (2003), we use OLS to estimate equation (23) for each generation independently within the framework of a time-series data analysis. This not only has the advantages of Seemingly Unrelated Regressions (SUR), but also avoids the problem of price endogeneity, since the product characteristics of one generation generally do not change over time until that particular generation disappears from the market. Table 2 reports the estimation results for seven generations using OLS. We performed an F-test for our panel data in order to test whether our model allows the coefficients to vary across generations with the null hypothesis of $H_0$: $\alpha_1 = \cdots = \alpha_7$, $\beta_1 = \cdots = \beta_7$ and $\gamma_1 = \cdots = \gamma_7$. We reject the hypothesis of parameter homogeneity over generations, since the F-statistic is 51.95 (for 1% level of significance, the critical value is about 2.10). Therefore, our model can have different coefficients across generations, allowing separate estimations of equation (23) for each generation.

All the coefficients of prices ($\beta_j$) turn out to be statistically significant with 1% significance except 16M (5% significance) and have negative values as we would reasonably expect: unit sales decrease with the increase of price. In the case of age ($\gamma_j$) coefficients, we also have negative values with 1% significance for 4K, 16K, and 64K describing the situation where the unit sales decrease as the generation become older corresponding to the introduction of new generations. Regarding the coefficients of Memory Density ($\alpha_j$), only 4K has a significant and positive coefficient.

Based on these estimation results, we analyze the development of the demand environment with respect to technological innovation. Figure 4 summarizes the dynamic changes of demand corresponding to the evolution of DRAM generations.

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[13] Berry (1994) suggested the method of inverting market share function to overcome the nonlinear instrumental variables (IV) problem in estimating discrete choice models with unobserved product characteristics, allowing for traditional (linear) IV methods.

[14] See Kim et al. (2005) for more details.

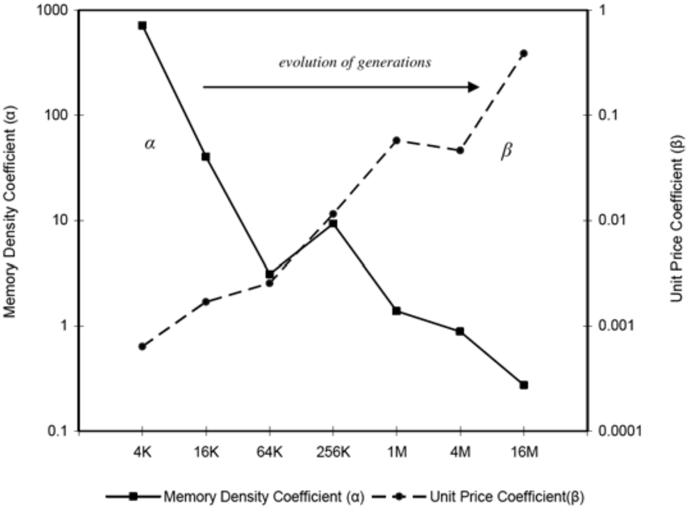
[15] We assume the existence of an outside good, $j = 0$, as suggested by Berry (1994). The *outside good* is a good which the consumer can purchase instead of one of the $J$ inside goods in his choice set, but whose price is not set in response to the prices of the inside goods. See Berry (1994) for more details.

**Table 2. Estimates for seven generations of DRAM by multinomial logit function**

| Generations | Estimates | | | $Adj\_R^2$ |
|---|---|---|---|---|
| | Memory density $MD_{jt}$ | Unit price $p_{jt}$ | Age $a_{jt}$ | |
| | $(\alpha_j)$ | $(\beta_j)$ | $(\gamma_j)$ | |
| 4K | 718.313 | -0.001 | -0.822 | 0.96 |
| | (103.892)*** | (0.000)*** | (0.047)*** | |
| 16K | 40.243 | -0.002 | -0.358 | 0.68 |
| | -58.494 | (0.000)*** | (0.129)*** | |
| 64K | -3.115 | -0.003 | -0.289 | 0.69 |
| | -12.977 | (0.000)*** | (0.082)*** | |
| 256K | -9.299 | -0.012 | 0.079 | 0.83 |
| | -4.307 | (0.002)*** | -0.145 | |
| 1M | -1.390 | -0.057 | -0.124 | 0.53 |
| | -1.109 | (0.015)*** | -0.115 | |
| 4M | -0.886 | -0.046 | 0.179 | 0.74 |
| | (0.291)*** | (0.014)*** | -0.154 | |
| 16M | -0.274 | -0.389 | 0.407 | 0.98 |
| | (0.059)*** | (0.062)** | (0.145)*** | |

Notes: K stands for kilobite, M for megabite. Standard errors are in parentheses. *** denotes 1% significance, ** 5% significance, and * 10% significance.

**Figure 4. Saturation of technology in the global DRAM market**



As the generations evolve from 4K to 16M, the coefficient of memory density ($\alpha_j$) decreases in contrast to the increase of the absolute values of the unit price coefficient ($\beta_j$), although not all of $\alpha_j$ are significant. Therefore, the effects of technological factors on consumers' choices become smaller, whereas price sensitivity increases with each successive generation.

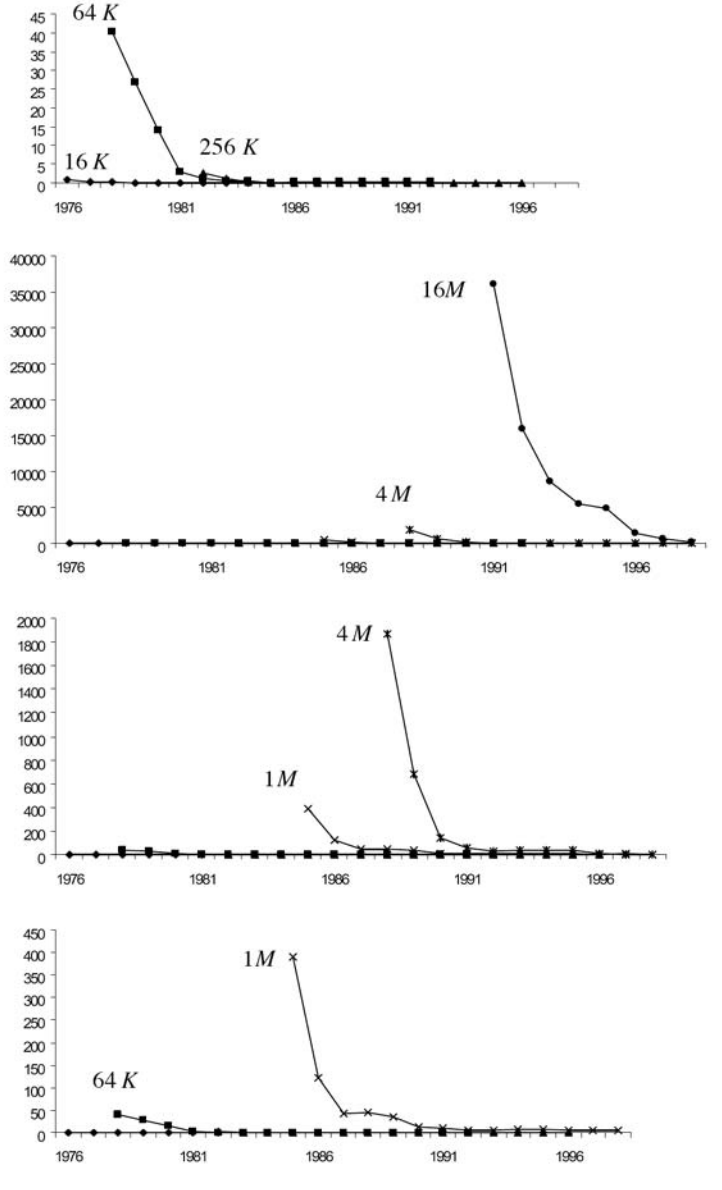
In other words, Figure 4 shows that consumer markets become saturated by technological innovation over the technology life cycle. Consumers become indifferent to the additive increase of memory density in choosing DRAM, since they feel that their technological needs for memory density have already been satisfied. Thus, consumers choose whatever generation has the lowest price per bit for the required DRAM configuration, while whatever generation provides the highest margin for the DRAM manufacturer is produced in the extreme case (Kim et al. 2005). Therefore, we find that the evolution of a market into a condition of technology saturation which supports the important role of the demand-side in the development of technological innovation.

From the estimated results of the demand function in equation (23), we also derive the relationship between *technology-push* and *demand-pull* suggested by equation (19) in Proposition 3.[16] Figure 5 shows the derived results for the DRAM generations (16K, 64K, 256K, 1M, 4M, and 16M). The y-axis is the difference between *TP* and *DP*, i.e. $\Gamma$. Surprisingly, all the patterns of $\Gamma$ clearly exhibit the *L*-type curve, as in Figure 1, suggested by Proposition 3. The curves in Figure 5 show the distinctive feature of the DRAM market in which technology-push is the major derivative of technological innovation in their early periods of their technology life as we would expect. As for the 256K DRAM, the role of technology-push does not look distinctive its early periods. This could be explained by the rapid growth of demand for 256K DRAMs in the period of 1982 to 1985 compared to other periods. This results in an unexpectedly large role of demand-pull in the technological innovation of DRAM.

In Figure 5, the absolute scale of the $\Gamma$ curves in the early periods of the technology life increases with each DRAM generation, which explains the increasing role of technology-push in the technological innovation of the DRAM market. One reason for this phenomenon could be the increasing competition in the DRAM market over time. This intense competition led to substantial restructuring of the industry until recently from a state of almost perfect competition to an oligopolistic one. Until

[16] In deriving this relationship, we assume a duopolistic market structure in which only two successive generations compete with each other in the market.

Figure 5. The $\Gamma$ curve in the global DRAM market




1997, there were more than 10 suppliers, each with less than 20% of the market share. However, after the enormous consolidations that started in 1998, the top four companies, Micron, Samsung, Hynix and Infineon, increased their overall market share to 71.6% by 2000[17]. The market leaders have made a desperate attempt to survive the severe competition by expanding their market share in order to exploit the cost advantage from economies of scale. Since, for these companies, the expansion of market share comes mainly from introducing new product generations before their competitors, technological innovation which originated from the internal derivatives, technology-pull, has been accelerated.

Consequently, we find that the role of technology-push and demand-pull change dynamically with the evolution of time, and also with DRAM generations. The role of technology-push in technological innovation is greater in the early periods of the technology life than the role of demand-pull in their later periods. Demand-pull's relatively low degree of importance in the later periods provides an opportunity for distinctive innovation driven by technology-push from the supply side. This results in the introduction of successive generations of the DRAM market.

The *L*-type curve representing the sources of technological innovation gives some important strategic insight for semiconductor manufacturing firms. When their products are in the later periods in an *L*-type curve, the innovation of products, especially *process innovation* which consequently decreases the price of the products, needs to be responsive to market demand. This can be captured through market signals, such as marginal price and marginal return of technological innovation, because the major derivative of their innovation comes from demand-pull in this stage. By contrast, when their products are in the early periods of their technology life cycle, the innovation strategy should focus on *product innovation* which enables firms to introduce new features of products or new products, since the source of innovation is technology-push.

## V. Conclusions

In this paper, technology-push and demand-pull, the two principal driving forces of technological innovation, are modeled. The equilibrium is determined by the interaction between technological innovation and the dynamic evolution of the demand environment. The model shows that the two driving forces of technological innovation are highly interrelated. Each one is a necessary condition for the innovation process as a whole.

By adopting the multinomial logit (MNL) within the framework of oligopolistic competition in describing demand for differentiated products, the unique subgame

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[17] Source: Cahners In-Stat Group, "DRAM Market Forecast Detailed Update", 2000.

perfect Nash equilibrium of technological innovation (NETI) is derived under demand- and supply-side constraints considering the prices and the product attributes which represent firms' technological innovations. Our key insight is that the marginal prices of products are the major factor in determining the principal forces of technological innovation between technology-push and demand-pull.

The empirical results from the global DRAM market show the L-shaped curves describing technology-push is greater than demand-pull in the early periods of a technology's life and decreases with the evolution of the life cycle. All the DRAM generations in our empirical analysis shows that technology-push is greater than demand-pull in the early stage and decreases over the course of time. In addition, the intensity of technology-push in the early stage becomes magnified with the introduction of new generations and the increase of competition.

These findings are important in several aspects. First, the results give possible answers for the long dispute over the source of technical changes and its role in economic growth. Economists have long argued about the role of demand and supply in inducing technological innovation. Our findings suggest that the role of supply and demand is different in inducing technological change and their relative importance changes over technological life cycle with an L-shape curve.

Secondly, we provide, to our knowledge, the first integrated model regarding the role of supply and demand in inducing technological innovation. There have been many attempts to examine the role of supply and demand in inducing technological innovation since Schumpeter first published his central writing on invention and innovation. However, those attempts have been limited to the one-sided role of supply or demand, without any integrated model and corresponding empirical examination. In this paper, we also empirically verify the interactive relationship between the two roles of innovation sources.

Thirdly, these findings give us important policy implications regarding R&D investment. R&D investment in basic technology is distinguished by high risk so that governments have been major sources of supply-push investment. However, governments need to pay attention to demand-pull policies. These policies can include support for the commercialization of specific technologies and the related product markets, as well as investment in the early stages of technology development.

In the case of public goods markets, such as energy technology, environmental technology, and telecommunication networks markets, firms generally face difficulties in successful commercialization of technology resulting in market failure. Therefore, governments need to intervene in these markets for social welfare reasons. However, demand-pull policy has been a minor issue in government policy making because its role and impact on technology innovation has not been fully understood. Our findings illuminate the important role of demand pull, so governments need to have dynamic policies for industries and firms depending on the stage of the technology life cycle.

On the other hand, there are limitations in our model. Our model is developed under the assumption of oligopolistic competition in which Schumpeter's Mark II is dominant. Therefore, the model has some limitations in the case of Mark I conditions where small firms prevail. In future research, the assumptions of our model will be relaxed encompassing various market conditions. For example, we can extend our model to monopolistic and competitive markets. We can also explore a model in which marginal cost depends on innovation, or fixed costs depend on R&D.

We also need to apply the model to other durable goods markets, such as computer and related equipments, telecommunication applications, and automobiles in which consumers are more direct decision makers in purchasing behavior. In these markets, demand pull seems to play a more important role than in the DRAM market. We expect that we will find market dependent development patterns of the relative importance between supply and demand in inducing technological innovation from these applications.

## Appendix

### A. Proof of Proposition 1

Let $A$ be defined as $\mathrm{A} \equiv x_2^{\eta} - x_1^{\eta}$. Then, from the equation (15) and (17), and using the equation (18), $TP \equiv \mathrm{A} - \tau + \varpi$ and $DP \equiv \mathrm{A} - \frac{\tau}{\beta}$.

The following relationship between TP and DP holds:

$$TP = DP + \frac{\tau}{\beta} - \tau + \varpi = DP + \tau \cdot (\frac{1-\beta}{\beta}) + \varpi.$$

Therefore, $TP - DP = \tau \cdot (\frac{1-\beta}{\beta}) + \varpi$, where $\beta > 0$ and $\varpi > 0$. When $\beta < 1$, equation (19) is always positive, since $\tau = \frac{\beta}{\alpha} \cdot (p_2^* - p_1^*) > 0$, where $p_2^* - p_1^* > 0$.

However, when $\beta > 1$, the main derivative of technological innovation is determined as follows;

(a) *DP* becomes the major derivative of technological innovation, when

$$\left|\tau \cdot (\frac{1-\beta}{\beta})\right| > \varpi. \quad \text{(A1)}$$

(b) Otherwise, *TP* becomes the major derivative of technological innovation.

**B. Proof of Proposition 2**

Let *A* be defined as $\mathrm{A} \equiv x_2^{\eta} - x_1^{\eta}$. Then, *under the assumption that there is no critical level of demand for technological innovation* (*CD*), $\varpi = 0$, equation (15) and (17) become as follows: $TP \equiv \mathrm{A} - \tau$ and $DP \equiv \mathrm{A} - \xi = A - \frac{\tau}{\beta}$ where $\tau = \beta \cdot \xi$. (equation 18)

The following relationship between *TP* and *DP* holds:

$$TP = DP + \frac{\tau}{\beta} - \tau = DP + \tau \cdot (\frac{1-\beta}{\beta}).$$

Therefore, $TP - DP = \tau \cdot (\frac{1-\beta}{\beta})$, where $\beta > 0$. Therefore, if $\beta > 1$, then *DP* is always greater than *TP*. Otherwise, the situation is reversed.

**C. Proof of Proposition 3**

If we define the difference between technology-push and demand-pull as

$$\Gamma \equiv TP - DP = \tau \cdot (\frac{1-\beta}{\beta}),$$

where $\beta > 0$, we have an inverse relationship between $\Gamma$ and $\beta$. The first-order condition confirms the negative relationship, $\frac{\partial \Gamma}{\partial \beta} = -\tau \cdot \frac{1}{\beta^2}$, where $\beta > 0$ and $\tau > 0$.

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