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Dynamics of Market Power over the Product Life Cycle: The Case of the DRAM Industry

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Abstracts

We estimate an oligopoly model for the 1M DRAM market and measure variations in market power over the various stages of the product life cycle. In the model, we consider the impacts of economies of scale, learning-by-doing, and spillover as characteristics of firms' marginal costs, and we take into account their varying effects over the product life cycle. We verify that market power varies over the product life cycle such that it is higher at the beginning, eventually weakens in the middle, and strengthens slightly at the end. The empirical results confirm that learning-by-doing and spillover effects are prevalent, and their effects are stronger at the beginning and weaker at the end of the product life cycle.

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Ⅰ. Introduction

The product life cycle traces the development of a product from the initial stages of innovation and introduction to product death. Two of the most important issues in the literature on the product

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life cycle involve analyzing 1) entry and exit patterns of firms over the cycle and 2) the evolution of market structure. Gort and Klepper (1982) developed a theory of market evolution based on five different stages. Greenstein and Wade (1998), who analyzed the product life cycle in the commercial mainframe computer market from 1968 to 1982, found that product introduction and exit were predicted by the characteristics of market structure. Klepper (2002) analyzed firm survival patterns and common underlying forces governing their distinctive evolution for such diverse products as automobiles, tires, televisions, and penicillin. These markets exhibited similar characteristics: an initial increase in the number of producers, followed by a sharp drop or "shakeout" in the markets, and finally evolution into an oligopolistic structure. Gruber (1995), who investigated the link between learning and the dynamics of production innovation in the semiconductor industry, as well as the impact of these variables on market structure, found that profit margins in the semiconductor industry fluctuated considerably over the life cycle of a generation. Margins, which were large at the beginning and end of the product life cycle, shrunk in the middle stages because of firm entry and strong competition. However, no study has yet estimated empirically the varying market power over the product life cycle. Therefore, this paper represents a first attempt to fill this gap in the literature.

The paper analyzes the link between degree of market competition and product life cycle and measures how firm conduct varies as the product life cycle passes from one stage to another. We divide the product life cycle of the Dynamic Random Access Memory (DRAM) market into three periods, following Gort and Klepper (1982) we also measure variations in the conduct parameter (see, e.g., Bresnahan 1982, 1989; Genesove & Mullin, 1998), which may rise and fall in accordance with product life cycle stages. The DRAM market was chosen to measure variations in the conduct parameter because the market exhibits a relatively brief product life cycle.[1] In the model, we include the effects of economies of scale, learning-by-doing, and spillover as characteristics of a firm's marginal costs, and wetake into account their varying effects over the product life cycle (see, e.g., Siebert, 2003). We employ the 1M generation of DRAM as the main focus of the study primarily because 1M is the most recent generation to complete the entire product life cycle.

The empirical results support our hypothesis that the conduct parameter varies across the stages of the product life cycle. The estimated conduct parameter is greater than it would be under Cournot competition and less than it would be under full collusion at the beginning of the product life cycle. Market power eventually attenuates, and the conduct parameter decreases to a level that is less than that of perfect competition through the middle stage of the product life cycle. At the end of the product life cycle, the conduct parameter increases slightly. The empirical results also verify that learning-by-doing and spillover effects are prevalent in the market and that they, too, begin higher and fall to lower levels by the end of the product life cycle.

The paper is organized as follows. Section II provides background on the DRAM market. In section III, we present our estimation model. Section IV reports and analyzes the empirical results. We summarize and conclude in section V.

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1) Previous studies of the DRAM industry have focused mainly on the effects of learning-by-doing and spillovers in relation to policy debates over such issues as price dumping and protection of domestic industries. Dick (1991) analyzed price dumping in the early product life cycle under the presence of learning-by-doing. Gruber (1992) estimated learning-by-doing with economies of scale and generation age for DRAM, EPROM, and SRAM. Irwin & Klenow (1994) provided evidence that learning rates were, on average, 20% with three times as many spillovers, using firm-level quarterly data on seven generations of DRAMs from 1974 to 1992.

Ⅱ. The DRAM Industry

The semiconductor is essential to an information-oriented society, and its development is largely responsible for continued progress in the development of products such as computers, consumer electronics, wired communications, cell phones, and automobiles. Indeed, it is no exaggeration to say that semiconductors have changed the world. More than six decades have elapsed since the first transistor was invented at Bell Laboratories in New Jersey in 1947. Since then, worldwide sales of semiconductors have continued to increase, totaling $291.6 billion as of 2012. The largest markets for semiconductors in 2012 were the Asia/Pacific region (accounting for 57% of the global market) followed by Japan (20% of the global market), the United States (13% of the global market), and Europe (11% of the global market) (Semiconductor Industry Association－SIA－2012).

Semiconductor devices are produced as single discrete devices and as integrated circuits (ICs). ICs contain quantities of transistors that range from a only a few to millions on a single chip. ICs are classified into three major types: memory chips, microprocessors, and application-specific integrated circuits. Memory chips are ICs that store data in binary form and consist of dynamic random-access memory (DRAM), static random-access memory (SRAM), mask read-only memory (Mask ROM), erasable programmable read-only memory (EPROM), electrically erasable programmable read-only memory (EEPROM), and flash memory. DRAM is the leading product line among memory chips. The primary markets for DRAM sales were electronic calculators, videotape recorders, and color televisions in the 1980s recently, computers have emerged as the largest market. DRAM for computers was standardized in terms of data transfer capacity and is therefore called general-purpose DRAM or commodity DRAM (Tanimitsu, 2002). DRAM is classified as volatile memory because its memory information is lost when the power supply is removed. Information stored on the memory can be written and read at any moment, but information eventually fades unless it is periodically refreshed.

The DRAM market exhibits oligopolistic characteristics due to substantial fixed (sunk) costs, such as R&D and investment in plants and equipment. DRAM manufacturing is an example of the mass production of standardized products. DRAM circuitry itself is simple; however, the most up-to-date equipment and clean rooms are needed to produce the latest-generation DRAM chips. Moreover, in order to make a substantial profit early in the product cycle as first movers, firms must invest heavily in R&D. The DRAM industry spends almost 20% of its sales revenue on capital investment and 15% of its sales revenue on R&D (SIA). Firms currently spend more than $2 billion to construct a single fabrication plant.

Toshiba, a major Japanese electrical appliance manufacturer, initially developed 1M DRAM at its Dallas plant and began sending sample shipments in 1985 (*The Japan Economic Journal*, 1985). AT&T, Hitachi, Fujitsu, and TI followed and began their own sample shipments. The success of Japanese firms in the development of 1M DRAMs was supported by government projects, such as the VLSI development project, backed by Nippon Telegraph and Telephone (NTT), and the VLSI technology and research association, backed by the Ministry of International Trade and Industry (MITI). The development of new-generation DRAMs was worthwhile in the early stages because the price was relatively high in this period and firms could lower their costs by implementing learning-by-doing earlier than rival firms. Toshiba made a substantial profit during this period (Tanimitsu, 2002). Enz (2003) showed empirical evidence of a first-mover advantage both at the firm level and in the overall market for five generations of DRAM chips. The evidence demonstrated high profitability at early stages in the product life cycle.

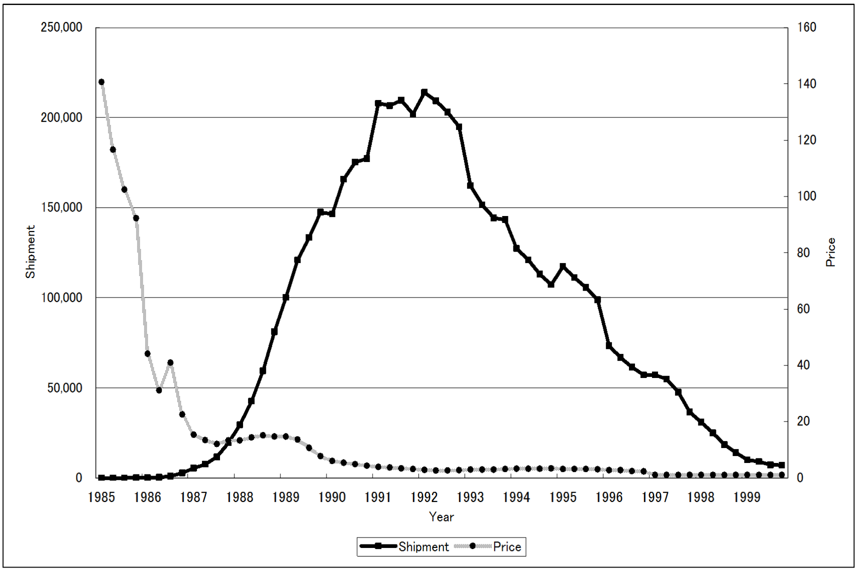
In March 1986, the United States Department of Commerce concluded that Japanese manufacturers were guilty of "price dumping" by exporting various types of semiconductors at extremely low prices (*The Wall Street Journal*, 1986). In the aftermath of trade friction, the U.S. and Japanese governments concluded the U.S.-Japan Semiconductor Trade Agreement in September 1986. Under the agreement, the price of Japanese semiconductors was regulated so that firms could not set prices under the fair market value (FMV). Korean firms, including Samsung, Hyundai, and LG, which were not restricted by FMV, established their competitive positions at that time. Samsung held a 16% share of the 1M DRAM market in 1990.

Figure 1 shows price and shipment trends for 1M DRAMs over the product life cycle. The price dropped approximately 84% in the first two years before firms started mass production. After that, price movements became relatively stable. The price decreased as product shipments and the number of firms increased. Product shipments peaked in 1991 and then decreased starting in 1993, after mass production of the next generation of DRAM chips commenced.

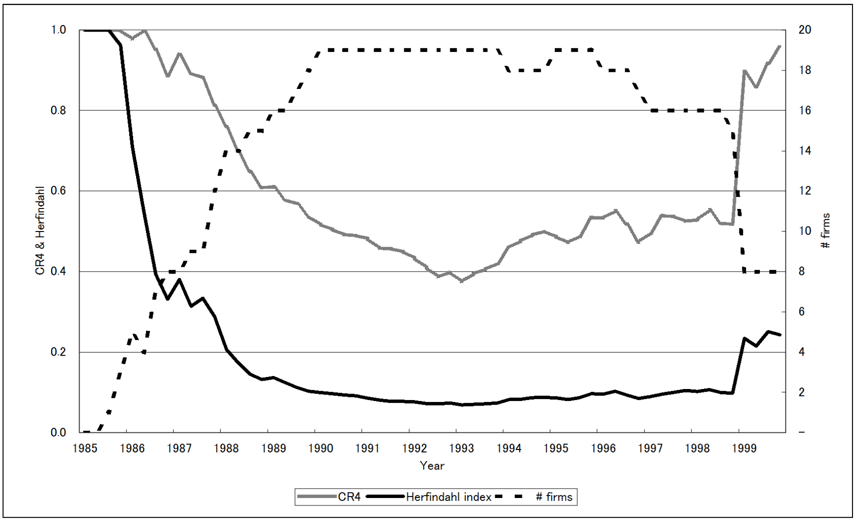
Figure 2 illustrates the four-firm concentration ratio, CR4, Hirschman-Herfindahl Index, and the total number of firms. The price and concentration ratio displayed similar movements. The Hirschman-Herfindahl Index fell below 0.2 in the second quarter of 1988 and below 0.1 in the second quarter of 1990. Thus, the change in market structure might have affected firms' market power or price-cost margin over the product life cycle. Gruber (1996) argued that price-cost margins were high at the beginning and end of the product life cycle but depressed in the middle of the life cycle due to the entry of new firms and intense competition in the DRAM market. However, the argument has never been tested empirically in the literature.

To investigate the dynamics of market power over the product life cycle, the life cycle of DRAM is divided into three periods: Period 1 (from 1985 Q3 to 1990 Q1), period 2 (from 1990 Q2 to 1994 Q4), and period 3 (from 1995 Q1 to 1999 Q4). Period 1 is characterized as the introduction and growth stage. Nineteen firms progressively entered the market and the price level reached its lower bound by the end of period 1. Period 2 is the intensive competition stage. The number of firms stabilized at 19. The Hirschman-Herfindahl Index posted its lowest levels, from 0.07 to 0.1, during this stage. Period 3 is the stage of decline. Eleven firms exited from the 1M DRAM market during this stage, and product shipments dropped sharply. Each period is distinguished by different characteristics in terms of price, product shipments, the number of firms, and concentration ratio therefore, the degree of competition may vary with the period or product life cycle.

【Figure 1】Price and Shipment Trends for 1M DRAM, 1985-1999 (Source: Dataquest)



【Figure 2】 Concentration Ratio and Number of Firms, 1985-1999 (Source: Dataquest)



Ⅲ. Empirical Specifications

A general New Empirical Industrial Organization (NEIO) model of quantity competition with a homogeneous good can be derived from a firm's profit maximization problem.[2] Firm i's profit maximization problem is given as:

$$Max: \ \pi_i(q_i) = P(Q)q_i - c_i(q_i) \qquad (1)$$
$$s.t. \ \ Q = q_i + \Sigma_{i \neq j}\, q_j$$

where P is price, Q is total quantity, $P(Q)$ is the inverse demand function, q_i is firm i's quantity, $c_i(q_i)$ is firm i's total cost function, and $\Sigma_{i \neq j}\, q_j$ is $Q - q_i$. The first-order condition for profit

2) For other types of model specification for the DRAM industry, see Siebert (2003) and Zulehner (2003). Siebert considers a multi-product specification, and Zulehner (2003) develops a dynamic oligopoly model utilizing closed-loop no-memory strategies.

maximization is:

$$\frac{\partial \pi_i}{\partial q_i} = P + q_i \frac{\partial P}{\partial Q} \bullet \frac{\partial Q}{\partial q_i} - \frac{\partial c_i(q_i)}{\partial q_i} = 0, \tag{2}$$

where $\frac{\partial c_i(q_i)}{\partial q_i}$ is firm i's marginal cost function, and $\frac{\partial Q}{\partial q_i} = 1 + \frac{\partial \sum_{i \neq j} q_j}{\partial q_i} = \theta$ is the conduct parameter that represents firm i's expectation of firm j's behavior or its conjecture about the extent to which firm j would change the output in response to firm i's output change. Rewriting (2) using θ, we get firm i's supply relation:

$$P = mc_i - \theta \frac{\partial P}{\partial Q} q_i \tag{3}$$

When $\theta = 0$ or $P = MC$, the market is perfectly competitive. If $\theta = 1$, the market is in a state of Cournot-Nash equilibrium because firm i then expects that firm j's output does not change in response to firm i's behavior. When $\theta = N$, θ reflects a monopoly or full collusion.[3)]

To estimate variations in the conduct parameter, our empirical model consists of the inverse demand equation and the supply relation. We first estimate an inverse demand equation to obtain the slope of a demand equation, and then we use it to estimate a supply relation. The inverse demand equation is linear, given as:

$$P_t(Q_t) = \gamma_0 + \gamma_1 Q_t + \gamma_2 Q_t^p + \gamma_3 Q_t^f + \gamma_4 Q_t^* dGDP_t + \gamma_5 t + \varepsilon_t \tag{4}$$

3) Refer to Corts (1999) for the definition and limitations of the conduct parameter.

where $\gamma_i{}'s$ are the parameters to be estimated, P_t is the average market price at time t, Q_t is the industry output at time t, Q_t^p and Q_t^f are the industry output of preceding generation DRAMs and succeeding generation DRAMs, respectively, $dGDP_t$ is the first difference of GDP in G7 countries as a proxy of the world GDP, t is a time trend, and ε_t is the error term.[4] $\gamma_4 Q_t^* dGDP_t$ is the interaction term that is included to identify market power (Bresnahan, 1982; Lau, 1982). The term $\gamma_1 + \gamma_4 dGDP_t$ indicates the own-price effect, and its sign (coefficient) is expected to be negative. The parameters, γ_2 and γ_3, refer to the cross-price effect, and the signs are expected to be positive (negative) if DRAM generations are substitutes (complements).

Learning-by-doing and spillover effects play crucial roles in the DRAM models. These effects are included in the marginal cost function to allow us to consider the dynamic character of firms' cost structures. The marginal cost function is assumed to be in semi-log-linear form (e.g., Siebert, 2003). Assuming that firms choose quantities of homogeneous outputs to maximize their profits given learning-by-doing and spillover effects, the supply relation for firm i is given as:

$$P_t = mc_{i,t} - \theta q_{i,t}^* + \nu_{i,t} \tag{5}$$

$$\begin{aligned} mc_{i,t} = {} & \varphi_{0,i} + \varphi_1 \ln q_{i,t} + \varphi_2 (\ln q_{i,t})^2 + \varphi_3 \ln LBD_{i,t} \\ & + \varphi_4 (\ln LBD_{i,t})^2 + \varphi_5 \ln Spill_{i,t} + \varphi_6 (\ln Spill_{i,t})^2 \\ & + \varphi_7 \ln SIL_t + \varphi_8 \ln L_{i,t} + \varphi_9 \ln K_{i,t} + \varphi_{10} \ln OFC_{i,t} + \delta_{i,t} \end{aligned} \tag{6}$$

4) To identify oligopolistic market power, demand shifters should be introduced in the demand curve to shift or to rotate the demand curve. The industry outputs of preceding and succeeding generations were intended to shift the demand curve and the first difference of GDP was introduced to capture the effects of the rotation of demand curve corresponding to the change in the overall demand shock.

where φ_i $i=0,\cdots,10$ and θ are parameters to be estimated, SIL_t is the market price of silicon at time t, $L_{i,t}$ is the labor cost for firm i at time t, $K_{i,t}$ is firm i's capital cost in terms of the prime interest rate, and $OFC_{i,t}$ is the other unknown factor cost for firm i. The signs for parameters of factor costs are expected to be positive because an increase in factor costs leads to an increase in firms' marginal costs. Firm-specific heterogeneity is captured by the term $\varphi_{0,i}$.

The term $q_{i,t}$ is the output of firm i at time t, and it measures the economies of scale. The expected sign for φ_1 is negative if economies of scale exists. The parameter, φ_2, picks up varying effects of economies of scale over the product life cycle.

$LBD_{i,t}$ is firm i's cumulative past output, i.e., $LBD_{i,t} = \sum_{s=1}^{t-1} q_{i,s}$, and it measures the learning-by-doing effect. $Spill_{i,t}$ is the industry's cumulative past output except for firm i, i.e., $Spill_{i,t} = \sum_{j \neq i} \sum_{s=1}^{t-1} q_{j,s}$, which measures the spillover effect. The squared terms, $(\ln LBD_{i,t})^2$ and $(\ln Spill_{i,t})^2$, capture the varying learning-by-doing and spillover effects over the product life cycle. The learning elasticity, $\lambda^{LBD} = (\varphi_3 + 2\varphi_4 \overline{\ln LBD}) / \overline{\frac{\partial C}{\partial q}}$, is expected to be negative if a learning-by-doing effect is prevalent. In the elasticity, the upper bar represents the average of the corresponding variable over time. In addition, the spillover elasticity evaluated at the sample means, $\lambda^{Spill} = (\varphi_5 + 2\varphi_6 \overline{\ln Spill}) / \overline{\frac{\partial C}{\partial q}}$, is expected to be negative if the spillover effect is working. The learning rate and spillover rate are calculated by $1 - 2\lambda^{LBD}$ and $1 - 2\lambda^{Spill}$, respectively (see, for example, Siebert, 2003).

The conduct parameter, $\theta = \frac{\partial Q}{\partial q_i}$, captures the degree of competition, and q_i^* is equal to the $\partial P_t / \partial Q_t$ from the demand equation times the current output of firm i, $q_i^* = (\gamma_1 + \gamma_4 dGDP_t)q_i$. To capture variations in the conduct parameter over the product life cycle, we introduce dummy variables for period 2 and period 3. Then our conduct parameter is:

$$\theta = \theta_1 + \psi_2 D_2 + \psi_3 D3 \tag{7}$$

where $D2$ and $D3$ are dummy variables for period 2 and period 3, respectively. Thus, the conduct parameter for period 1 is θ_1. The conduct parameter for period 2 is given as $\theta_2 = \theta_1 + \psi_2$ the conduct parameter for period 3 is specified as $\theta_3 = \theta_1 + \psi_3$. By plugging (6) and (7) into (5), the supply relation is changed to:

$$\begin{aligned} P = {} & \varphi_{0,i} + \varphi_1 \ln q_{i,t} + \varphi_2 (\ln q_{i,t})^2 + \varphi_3 \ln LBD_{i,t} \\ & + \varphi_4 (\ln LBD_{i,t})^2 + \varphi_5 \ln Spill_{i,t} + \varphi_6 (\ln Spill_{i,t})^2 \\ & + \varphi_7 \ln SIL_t + \varphi_8 \ln L_{i,t} + \varphi_9 \ln K_{i,t} + \varphi_{10} \ln OFC_{i,t} \\ & - (\theta_1 + \psi_2 D2 + \psi_3 D3) q^*_{i,t} + \eta_{i,t} \end{aligned} \tag{8}$$

For empirical purposes, both the inverse demand equation (4) and the supply relation (8) are estimated. We utilize 1M DRAM as the focus of this study because 1M is the latest generation of DRAM that completed the product life cycle. In addition, we analyze semiconductor firms from three countries—the U.S., Japan, and South Korea. These firms account for more than 90% of total output over the product life cycle. For empirical analyses, we use firm-level data on the DRAM industry.[5] Our data include quarterly average sale prices and firm-level shipments by each producer. The data sample period spans 26 years from 1974:Q1 to 1999:Q4 this represents a total of 104 data points. DRAM prices are deflated by

5) The data used in this paper were collected by Dataquest Inc.

【Table 1】 Summary Descriptive Statistics

Variables	Description	Obs	Mean	Std. Dev.	Min	Max
(the industry level)						
P_t	Average selling of one chip ($)	60	14.27	28.45	1.03	140.67
Q_t	Total output of 1M chips (in thousands)	60	8.59E+04	7.22E+04	0	2.14E+05
Q_t^p	Total output of 256K chips (in thousands)	60	7.79E+04	8.41E+04	0	2.37E+05
Q_t^f	Total output of 4M chips (in thousands)	60	1.22E+05	1.35E+05	0	4.19E+05
$dGDP_t$	First difference of GDP for G7 countries ($)	60	1.17E+05	5.41E+04	-1.16E+04	2.80E+05
(the firm level)						
$q_{i,t}$	Firm i's output (in thousands)	770	6.17E+03	6.43E+03	4	3.15E+04
$LBD_{i,t}$	Firm i's cumulative past output (in thousands)	770	1.56E+05	1.62E+05	1	7.64E+05
$Spill_{i,t}$	Industry's cumulative past output except firm i (in thousands)	770	2.66E+06	1.74E+06	3	5.07E+06
SIL_t	Price of Silicon ($)	770	1.54E+03	1.75E+02	1.25E+03	1.95E+03
$L_{i,t}$	Firm i's labor costs ($)	770	41.30	14.31	9.67	59.91
$OFC_{i,t}$	Firm i's other factor costs ($)	770	121.55	33.70	41.89	201.63
$K_{i,t}$	Firm i's capital costs in terms of prime interest rate (%)	770	5.61	2.57	0.32	16.62

using the quarterly PPI from the U.S. Bureau of Labor Statistics.[6] We regard shipments as output, assuming inventory level is low due to constantly falling prices. We use four main input prices in real terms as cost shifters: material costs, capital costs, labor costs, and other unknown factor costs. The market price of silicon is used as material costs and is obtained from the yearly *Handbook of Metal Bulletin* (1974 to 1999). Prime interest rates are used as capital costs and are taken from the IMF International Financial Statistics (IFS)database. Labor costs by country are calculated using industry

6) The Dickey-Fuller test of unit root for the DRAM prices reject the null hypothesis of unit root at the 1% significance level. The test static was -8.22 and the 1% critical value was -3.6. Therefore, the possibility of spurious regression may not be a concern in this paper.

wages per worker for ISIC 30 of the third revision, and they are obtained from the OECD STAN database. Other unknown factor costs are constructed by multiplying the real exchange rate from the IFS and PPI as provided by the U.S. Bureau of Labor Statistics (see Park, 2002).

We use three variables as demand shifters: global GDP, the quantity of preceding DRAM generations, and the quantity of succeeding DRAM generations. The real GDP in G7 countries, a proxy for global GDP, is taken from the OECD STAN database.

Ⅳ. Results

To estimate the inverse demand equation (4), we employ the generalized method of moments (GMM), which is robust to heteroskedasticity and serial correlation. The estimation result is reported in Table 2. We use several variables from the supply side, such as the number of firms, silicon price, labor costs, capital costs, and other unknown factor costs, as well as exogenous demand sifters as instrumental variables to control for endogeneity.

We find that all coefficients are statistically significant at the 10% level. The coefficient on the output of the current DRAM generation is statistically significant at the 1% level, and the own-price effect, $\widehat{\gamma_1}+\widehat{\gamma_4}dGDP_t$, shows the expected negative sign, suggesting that higher price leads to lower demand. The own-price elasticity calculated at the mean in price and output, $\varepsilon_{Q,P}=-\frac{\partial Q}{\partial P}\frac{\overline{P}}{\overline{Q}}$, is 1.324, which is consistent with the results of previous studies (e.g. Flamm, 1993; Zulehner, 2003). The coefficients for the preceding DRAM generation and succeeding generations are statistically significant at the 1% level and indicate a negative sign, as both generations are substitutes to the current DRAM generation. The estimate for the time trend is negative and significant at the 1% level, reflecting the declining trend of DRAM price.

【Table 2】 Demand Equation Results

Variables	Parameter	Robust Standard error	z-statistics
$Constant$	200.64 *	16.62	12.07
Q	-1.85E-04 *	2.33E-05	-7.95
Q^p	-3.23E-04 *	3.75E-05	-8.63
Q^s	-5.52E-05 *	1.11E-05	-4.98
$Q \cdot dGDP$	5.14E-10 ***	2.65E-10	1.94
t	-1.904 *	0.16	-11.99
First-stage R^2	0.96		
Obs.	60		
Over-identification $\chi^2(4)=3.752$			

Note: *significant at 1%, **significant at 5%, ***significant at 10%.

The supply relation (8) is estimated by a two-stage least-squares random-effects estimator, G2SLS, to control for unobserved firm heterogeneity and serial correlation. The estimated parameters from the inverse demand equation, $(\widehat{\gamma}_1+\widehat{\gamma}_4 dGDP_t)q_{i,t}$, are plugged into the supply relation to identify the conduct parameter.7) The estimation result for equation (8) is reported in Table 5. Several variables from the demand side, such as $dGDP_t$, $Q_t^* dGDP_t$, output of neighboring generation DRAMs, and the time trend, as well as exogenous supply shifters, are used as instrumental variables to control for simultaneity. In order to decide whether to use a random- or fixed-effects model, we conducted the Hausman test. The Hausman test could not reject the null hypothesis that the difference in the coefficients of the two models is not systematic, with a p-value of

7) We estimated the demand and the supply relation separately due to the tractability of the estimation even though the joint estimation may improve the efficiency of the parameter estimation.

.611. We therefore use the random-effects estimator, which is efficient under the null hypothesis.

All estimates except those of the coefficients for current output and other unknown factor costs are significantly different from zero. The parameters for factor costs, such as the price of silicon, labor costs, capital costs, and other unknown factor costs, show the expected positive sign. The parameters suggest that a 100% increase in the price of silicon, labor costs, capital costs, and other unknown factor costs leads to an increase in the DRAM price by \$2.51, \$0.58, \$0.84, and \$0.77, respectively.

【Table 2】 Supply Relation Results

Variables	Parameter	Standard error	z-statistics
Constant	36.884 *	10.378	3.55
$\ln q$	1.945	3.173	0.61
$(\ln q)^2$	-0.090	0.220	-0.41
$\ln LBD$	-3.098 *	0.995	-3.11
$(\ln LBD)^2$	0.113 **	0.052	2.18
$\ln Spill$	-6.267 *	0.493	-12.71
$(\ln Spill)^2$	0.202 *	0.025	8.24
$\ln SIL$	2.509 ***	1.289	1.95
$\ln L$	0.579 **	0.261	2.21
$\ln K$	0.844 *	0.252	3.35
$\ln OFC$	0.772	0.573	1.35
θ_1	5.447 *	1.006	5.41
ψ_2	-5.766 *	0.570	-10.12
ψ_3	-5.542 *	0.931	-5.95
Conduct parameters			
θ_2	-0.319		
θ_3	-0.095		
First-Stage R^2	0.85		
Obs.	770		
Number of firms	19		
Over-identification $\chi^2(4) = 19.20$			

Note: *significant at 1%, **significant at 5%, ***significant at 10%.

Concerning the effect of economies of scale, the parameter estimates for $\ln q_{i,t}$ and $(\ln q_{i,t})^2$ show unexpected signs, but they are not statistically different from zero. Therefore, we cannot confirm evidence of economies-of-scale effects. Regarding the learning-by-doing effect, the parameter estimates for $\ln LBD_{i,t}$ and $(\ln LBD_{i,t})^2$ are statistically different from zero at both the 1% level and the 5% level, and they show the expected negative sign and positive sign, respectively. The overall effect of LBD on firm i's marginal cost, $\partial mc_i/\partial LBD_i$, is negative, suggesting that firm i's marginal cost declines as the firm increases its own production. The positive coefficient of $(\ln LBD_{i,t})^2$ indicates that the learning-by-doing effect is stronger at the beginning and weaker at the end of the product life cycle. Table 4 describes the learning elasticity and the learning rate evaluated at the sample means. The calculated learning elasticity and the learning rate are -0.12 and 0.08, respectively. The learning rate of 8.0% indicates that firm i's marginal cost decreases by 8.0% if its cumulative output doubles. The calculated learning rate is somewhat low relative to those calculated in previous studies, such as Irvin and Klenow (1994) and Zulehner (2003). Their reported values are approximately 20% and 13%, respectively.

【Table 4】 The Size of Learning and Spillover Effects

	Elasticity	Rate
$Learning\ Effect$	-0.120	0.080
$Spillover\ Effect$	-0.089	0.060

With regard to spillover effects, the parameter estimates for $\ln Spill_{i,t}$ and $(\ln Spill_{i,t})^2$ are statistically significant at the 1% level, and they have the expected negative sign and positive sign, respectively. Similar to the learning-by-doing effect, the overall effect of spillover on firm i's marginal cost, $\partial mc_i / \partial Spill_i$, is negative therefore, firm i's marginal cost decreases as other firms accumulate experience. The positive coefficient of $(\ln Spill_{i,t})^2$ suggests that the spillover effect is stronger at the beginning and weaker at the end of the product life cycle. The estimated spillover elasticity is -0.089, which is equivalent to a spillover rate of 0.06. This implies that firm i's marginal cost goes down by 6.0% if the cumulative output of other firms doubles. The size of the spillover rate is similar to those reported in previous studies (see, for example, Irvin and Klenow, 1994; Zulehner, 2003).

The estimates related to the conduct parameters, $\widehat{\theta_1}$, $\widehat{\psi_2}$, and $\widehat{\psi_3}$, are statistically significant at the 1% level. Thus, the result supports our hypothesis that the conduct parameter or the degree of competition changes over the product life cycle. The conduct parameters for period 2 and period 3, $\widehat{\theta_2} = \widehat{\theta_1} + \widehat{\psi_2}$ and $\widehat{\theta_3} = \widehat{\theta_1} + \widehat{\psi_3}$, are reported in Table 3. The size of the conduct parameters for period 1, period 2, and period 3 are 5.4, -0.32, and -0.095, respectively. The Wald tests are employed to test the market structure of the DRAM industry. The hypotheses for each period are as follows: i) the market structure is perfectly competitive, i.e., $\theta_i = 0$; ii) the market structure is in Cournot competition, i.e., $\theta_i = 1$; and iii) the market structure is perfectly collusive, i.e., $\theta_i = N$. Table 5 shows the results of the Wald tests.

For period 1, the coefficient of the conduct parameter is 5.4. We reject the null hypotheses of perfect competition, Cournot competition, and perfect collusion at the 1% level of statistical significance. The test statistic, $\chi^2(1)$, for each hypothesis is 29.32, 19.54, and 31.03, respectively. We therefore conclude that the conduct parameter for period 1 is more collusive than it would be under Cournot competition and less collusive than it would be under perfect collusion. In addition, we calculate the price-cost margin or the Lerner index for period 1. The Lerner index is given as:

$$L = \frac{P - mc_i}{P} = \frac{-\theta_i \cdot q_i^*}{P}. \tag{9}$$

Table 6 describes the estimated Lerner indices. The Lerner index using the estimated marginal cost is 0.19, while it is 0.21 when using the conduct parameter. Thus, the estimated price-cost margin for period 1 is about 20%.

【Table 5】 Wald Test for Conduct Parameter

Period	Hypotheses	Test statistic, $\chi^2(1)$	P-value
1	$\theta_1 = 0$	29.32 *	0.00
	$\theta_1 = 1$	19.54 *	0.00
	$\theta_1 = N$	31.03 *	0.00
2	$\theta_2 = 0$	0.28	0.60
	$\theta_2 = 1$	4.76 **	0.03
	$\theta_2 = N$	1000.03 *	0.00
3	$\theta_3 = 0$	0.02	0.90
	$\theta_3 = 1$	2.13	0.14
	$\theta_3 = N$	421.57 *	0.00

Note: *significant at 1%, **significant at 5%, ***significant at 10%.
N is the average number of firms for each period.

【Table 6】 Estimated Price Cost Margin for Period 1

	using the estimated marginal cost	using the conduct parameter
Lerner index	0.192	0.212

For period 2, the estimated conduct parameter is -0.32. We fail to reject the null hypothesis of perfect competition at the 10%

statistical significance level. On the other hand, the tests for Cournot competition and perfect collusion are rejected at the 10% and 1% statistical levels, respectively. The test statistic, $\chi^2(1)$, for each hypothesis is 0.28, 4.76, and 1000.03, respectively. Accordingly, we conclude that the market was in perfect competition during period 2. For period 3, the estimated conduct parameter is -0.095. We cannot reject the null hypotheses of perfect competition or Cournot competition at the 10% level of significance, but we can reject that of perfect collusion. The test statistic, $\chi^2(1)$, for each hypothesis is 0.02, 2.13, and 421.57, respectively. Thus, the result for period 3 is inconclusive. Consequently, we confirm evidence that market power varies over the product life cycle such that it is higher at the beginning of the life cycle, eventually fades out in the middle, and then increases slightly at the end. The result is consistent with the argument suggested by Gruber (1996).

This is a reasonable result. After the first mover developed technology to produce 1M DRAM, firms in the market posted positive profit margins at the beginning of the product life cycle. This level of profitability induced other firms to enter under free-entry conditions. As mentioned above, 19 firms entered the 1M DRAM market during period 1. Market power gradually disappeared with the market entries, and the market became perfectly competitive in the middle of the product life cycle. During period 2, some firms earned negative profits and exited the market. As firms exited, market power rose toward the end of the product life cycle. Market power for period 1 might have been reinforced by limited output capacity. The total capacity of the market might have been constrained due to a low yield rate at the beginning of the product life cycle. However, once firms established sufficient capacity, it was difficult to maintain market power under a relatively brief product life cycle.

Ⅴ. Conclusion

In this paper, we model the effect of the product life cycle in an oligopoly model and measure variations in the conduct parameter or market power over the various stages of the product life cycle. In particular, we take into account the varying effects of economies of scale, learning-by-doing, and spillover over the course of the product life cycle.

The empirical results support our hypothesis that firm conduct varies over the different stages of the product life cycle. The estimated conduct parameter is greater than it would be under Cournot competition and less than it would be under perfect collusion at the beginning of the product life cycle. Market power eventually weakens in the middle of the product life cycle. At the end of the product life cycle, the conduct parameter rises slightly, even though we can reject neither perfect competition nor Cournot competition. In addition, we provide evidence of the presence of learning-by-doing and spillover effects with magnitudes similar to those found in previous studies. The estimated learning and spillover rates are 8.1% and 5.6%, respectively. We also confirm the varying effects of learning-by-doing and spillover effects. Our model suggests that learning and spillover effects are stronger at the beginning and weaker at the end of the product life cycle.

In the paper, we link market power to the product life cycle under learning-by-doing and technological spillover. Similar research can be conducted focusing on other markets with relatively brief product life cycles. Another possible avenue of research is to analyze the links between the degree of competition and firm-leveldecisions, pertaining explicitly to market entry and exit. Our model alsocould be extended to a dynamic oligopoly model that incorporates firms' inter-temporal strategic behavior.

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제품생명주기에 따른 시장지배력의 동태적 변화과정에 대한 연구: DRAM 산업을 중심으로

김 동 훈* · Osamu Yoshioka**

논문초록

논문은 제품생명 주기에 따른 시장지배력의 변화과정을 고찰하기 위하여 동태적 과점모형을 설정하고 1메가 DRAM을 중심으로 실증분석 하였다. 한계비용 설정에 있어서 규모의 경제, 경험에 의한 학습 (learning-by-doing), 기술확산(spillover)효과를 고려하였으며 이들이 제품 생명주기에 따라 어떻게 변화하는지 분석하였다. 1메가 DRAM산업의 경우 시장지배력은 제품생명주기를 따라 변화하는 것이 증명이 되었으며 생명주기 초반에 높고 중간에 사라졌다가 생명주기 후반에 소폭으로 증가하는 것으로 나타나고 있다. 경험에 의한 학습효과나 기술확산 효과는 제품생명주기 전반에 강하게 나타나고 있으며 후반에는 약해지는 것으로 추정이 되었다.

주제분류 : B030904
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