Multiproduct Firms, Learning by Doing and Price-Cost Margins over the Product Life Cycle: Evidence from the DRAM Industry

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Abstract

In this paper we specify and estimate a structural model of multiproduct firms for the semiconductor industry. In addition, we explicitly consider dynamics over the product life cycle. We find that these two aspects have important implications and provide evidence that (*i*) Learning by Doing, Economies of Scale, and price-cost margins are higher for multiproduct firms than for single product firms. Furthermore, we find that, once multiproduct firms are introduced, firms behave like Cournot players in the product market, whereas a single product specification leads to firms behaving as if in perfect competition. We also find that (*ii*) Learning by Doing, Economies of Scale, and Spillover effects vary over the product cycle. Learning by Doing and Economies of Scale effects are higher at the end of the life cycle. We specify a dynamic theoretical model and estimate a structural model by using quarterly firm-level output and cost data as well as industry prices for the Dynamic Random Access Memory (DRAM) industry from 1974 to 1996

JEL: C1, L1, L6, O3
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1 Introduction

In the 1980s an extensive policy debate in the United States focused on the semiconductor industry. The discussions centered on the increased competition brought on by the larger number of foreign competitors in the United States market, targeting in particular the below-cost sales of Japanese firms. The US-firms asserted that foreign competitors were charging dumping prices that could erect a barrier and thereby prevent US-firms from entering the semiconductor market even after the period of predatory low prices was over.

Late in 1985, the US government began investigating allegations of dumping against Japanese producers of 64K and 256K DRAM chips and EPROM chips. The Commerce Department and the International Trade Commission, in carrying out the investigations into dumping, required each Japanese producer to file a quarterly estimate of the full cost of production for its chips. The two investigating bodies isolated the total cost data for specific periods, when all of the different kinds of chips were being produced simultaneously, and investigated the dumping margins. One problem with this procedure was that each chip was investigated at different stages of its product cycle. For instance, the 64K DRAM chip was much further along in its product cycle, whereas the 256K DRAM chip was still in the early stages of its product cycle. Sales of chips are very much characterized by the product life cycle, and firms' chosen mark-ups are different over this life cycle.

In March 1986, the United States Department of Commerce and the International Trade Commission concluded that Japanese firms set dumping prices for the 64K DRAM chips[1] and that they sold varieties of their semiconductors in the United States at prices below their current fair market value or cost of production. The dumping case against the 256K, however, was suspended through the Semiconductor Agreement between the United States and Japan.[2]

A considerable number of economic research and policy suggestions have been made with regard to this investigation, requiring a sufficient understanding of both how firms behave in the industry and which factors determine their behavior. Recent analyses found, once Learning by Doing effects were taken into consideration, only little evidence that Japanese semiconductor firms engaged in dumping.

When firms engage in Learning by Doing their unit costs decline over time, for

[1]The United States antidumping laws are included in the United States Trade Agreements Act of 1979, 19 U.S.C. §1673.

[2]The agreement required that Japanese producers not sell at a price below their cost of production (see American Society of International Law, Japan-United States: Agreement on Semiconductor Trade, 25 Int. Legal Matters 1409-27 (1986)).

production experience is accumulated through past output. Learning by Doing brings an intertemporal dimension to a firm's output strategy, because its optimal strategy is to overproduce in order to invest in future cost reductions. This strategy induces firms to make their optimal output decisions based not on current period costs but, rather, on their shadow costs of production.[3]

There is a relatively large body of theoretical work but little empirical work in this area. Numerous authors have shown that learning has an enormous impact on costs, strategic decisions, and market power; see, for example, Wright (1936), Boston Consulting Group (1972), Spence (1981), Fudenberg and Tirole (1983), Lieberman (1982 and 1984), Dick (1991), Gruber (1996), and Nye (1996). However, none of these studies endogenize firms' pricing behavior. They do not take the intertemporal feature into account: namely, that dynamic marginal costs lie below static marginal costs. Rather, the authors of these studies assume constant price-cost margins, which they often justify through the assumption of complete and symmetric spillovers, an assumption that is incongruous with the semiconductor industry. On the contrary, it is evident that price-cost margins change over time. As a consequence, using price as a proxy for unit costs is not easily justified. On the assumption of firms behaving like Cournot players, with both constant Economies of Scale (ECS) and Learning by Doing (LBD) effects being constant over time, Irwin and Klenow (1994) endogenized firms' pricing behaviors and implemented dynamic marginal costs.

Brist and Wilson (1997) took into account the intertemporal output decisions as well and estimate a structural model similar to that of Jarmin's (1994). They estimated four different models of the DRAM industry by imposing different assumptions about the ECS and the firms' pricing behavior. They found that increasing returns to scale are prevalent in the industry, which lowers the LBD effects in comparison with when ECS are assumed to be constant, suggesting that an *omitted variable bias* occurs if the interrelation between LBD and ECS effects are not taken into consideration.

All these studies find evidence of LBD effects in the DRAM industry, which confirms that firms follow an intertemporal strategy and optimize their strategies over the entire product life cycle. It is often claimed that mark-ups and LBD effects vary over the product cycle. However, in previous empirical specifications these effects are estimated as constants and, thus, are not allowed to vary over the product life cycle. It is always asserted that LBD is higher at the beginning of the cycle, yet, evidence to support this claim has never been given.

Furthermore, all these models assume single product firms. A detailed industry description in Section 3 illustrates that multiproduct firms are a more appropriate assumption for the industry. We show that multiproduct firms in-

[3]Another aspect of 'Learning by Doing' is the 'Organizational Forgetting' hypothesis. With regard to the airline industry, Benkard (1998) found evidence to show that a firm's production experience depreciates over time.

ternalize externalities, which has important implications for the firms' output decisions and for the LBD, ECS and/or Spillover effects. Focusing on multiproduct firms (and assuming for the moment that the behavior of multiproduct firms is identical to that of single product firms), we find that output decisions may have two opposing effects. On the one hand, firms have an incentive to increase their current output decisions in order to yield cost reductions through ECS and LBD effects. On the other hand, a higher current output reduces the revenues of the neighboring generations, which then induces firms to lower their output. In single product models a lower current output decision is attributed to the incentive to yield cost reductions. But because econometricians only know about observed quantities, but not about the unobserved and neglected quantity reductions that result from internalized effects, we expect that LBD, ECS and/or Spillover effects as well as price-cost margins will be higher in multiproduct competition than in a single product market.

The literature on multiproduct competition is closely related to multimarket contact. Bulow, Geanakoplos, and Klemperer (1985) investigate the effects of cost- and demand-based linkages across markets. Bernheim and Whinston (1990) concentrate on linkages in strategic interaction across markets. They argue that multimarket contact may affect firms' abilities to sustain collusive outcomes through repeated interactions. Parker and Röller (1997) estimate a structural model for the U.S. cellular telephone industry. They show that regulation may lead to higher prices where cross-ownership and multimarket contact are important factors in explaining noncompetitive prices.

This study concentrates on two aspects: multiproduct firms and dynamics over the product life cycle. We begin by specifying a theoretical model of multiproduct firms and show how firms' objective functions are different from those of single product firms. We show the implications of various effects and derive two hypotheses, which are then tested empirically:

(*i*) LBD, ECS, and/or Spillover effects are greater for multiproduct firms than for single product firms if neighboring products are substitutes and multiproduct firms do not behave too 'toughly' in the product market. As a consequence, firms' price–cost margins are larger.

(*ii*) LBD, ECS, and/or Spillover effects vary over the product life cycle.

We estimate a structural dynamic model of demand and pricing relations using quarterly firm-level output and cost data as well as industry prices for the DRAM industry from 1974 to1996.

This analysis also investigates whether the enormous price decrease over time is induced by LBD or ECS effects or by a change in firms' market shares over the product life cycle. We show that firms follow an intertemporal output strategy and provide evidence that LBD, and ECS effects are underestimated when assuming single product firms. As a consequence, firms' price-cost margins are larger for multiproduct firms. Finally, we provide evidence that firms behave like Cournot players in a multiproduct model. We show that LBD, ECS, and Spillover effects are significant and vary over the product life cycle. LBD and ECS effects are shown to be greater at the end of a cycle when new production technologies are developed, which creates better opportunities for yielding further cost reductions.

The next Section provides some background for dynamic marginal costs and Learning by Doing. Section 3 describes the industry. Section 4 presents the theoretical model whereas Section 5 presents the empirical model that tests the two hypotheses. We then turn to a description of the data in Section 6 and present the results in Section 7. We summarize and conclude this chapter in Section 8.

2 Dynamic Marginal Costs

In this section we show how dynamic marginal costs are determined through LBD and ECS effects. The learning curve may be affected by many different aspects, depending on the particular nature of production. *LBD* occurs mainly in labor-intensive industries, such as the aircraft, ship-building, and semiconductor industries, in which workers and managers learn from their experiences and become more efficient by improving operations in order to reduce time, labor costs, or material waste. In addition, production processes are improved through gaining experience as technical improvements and newer technologies are applied. Small changes are made to the process, with the result that productivity gradually improves.[4] Fudenberg and Tirole (1983) described the LBD process as follows: 'Practice makes perfect, that is, through repetition of an activity one gains proficiency'. In reviewing the engineering literature, Wright (1936) found wide acceptance of the premise that labor, material, and overhead requirements decline by 20% when production doubles.

LBD has an impact on firms' static or contemporaneous marginal costs as well as on dynamic or shadow marginal costs. LBD affects the static marginal cost function because firms' unit costs decline as production experience increases through accumulated past output. LBD also creates an intertemporal dynamic effect which indicates that the current output yields cost savings in the future. Considering both aspects yields the shadow marginal costs which lie below the static marginal costs. Firms follow a dynamic production strategy by means of which they earn positive profits over the entire product cycle. They optimize their

[4] The literature has occasionally differentiated learning effects from experience curve effects: the former was confined to the increased effectiveness of workers, whereas the latter incorporated the complete effects of experience from workers' training, better management, and technical improvements.

production by setting marginal revenues equal to marginal shadow costs (MC^D) and incur marginal losses in each period in order to benefit in the future. In many studies it is asserted that firms receive highest LBD effects at the beginning of the product life cycle. Figure 1 shows the enormous decline in the current (static) marginal cost curve (MC^s), depending on the increase in accumulated output, in particular during the early stages of the life cycle.

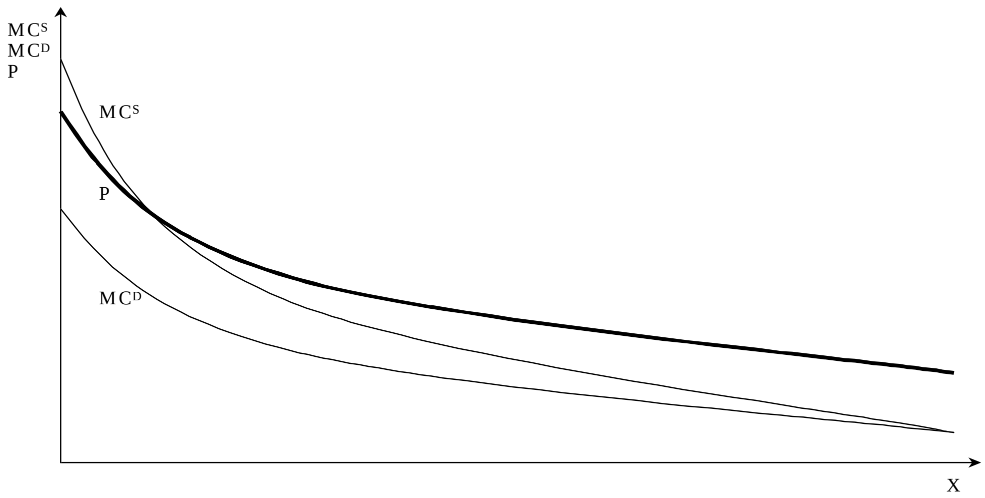

Figure 1: Price setting with respect to shadow marginal costs

According to previous studies, firms increase output most during the early stage of the product life cycle and may even obtain negative mark-ups by pricing according to their dynamic (shadow) marginal costs (see also Figure 1). The gap between dynamic (shadow) marginal costs and static marginal costs narrows as the LBD effects become smaller at the end of the product life cycle. The enormous decrease in industry prices is often explained as the outcome of firms' pricing strategy in accordance with their shadow marginal costs.

Another aspect of cost reduction is the existence of *ECS,* which result in a contemporaneous unit cost decline by increasing output. ECS arise from large fixed-capital expenditures, physical-technical relationships, laws of nature (known as the 'two-thirds' rule), and optimized production plans, especially those at the beginning of a product cycle. If ECS are prevalent, it may be rational to reduce prices in order to achieve higher output levels at lower unit costs. Ignorance of ECS coincides with an inappropriate omission of the current output variable. The cost reduction effect is exclusively attributed to the learning curve, though part of it is in fact due to the presence of ECS: an *omitted variable bias* will occur.

For instance, if ECS are assumed to be constant in the model but in reality are increasing the estimation will yield an overestimated learning curve elasticity (see Berndt [1991] and Brist and Wilson [1997]). Moreover, LBD and ECS are interrelated. A higher current output lowers current unit costs and also leads to further cost reductions in the future. In turn, a lower cost structure in the future enables further increases in output levels. Therefore, considering both LBD and ECS effects together is necessary, for both influence each other; otherwise, the analysis may lead to either overestimated or underestimated effects.

The major problem with estimating LBD effects is that cost data are often not available. Previous studies used prices as a proxy for unit costs, which entails the assumption that price-cost margins are constant. The Boston Consulting Group (1972) argued that prices decline in most industries as learning proceeds and that profit margins remain constant over time. Lieberman (1982) justified constant price-cost margins by arguing that experience, or the learning process, is often a public good and imposes symmetric and complete spillovers. Lieberman (1984) noted that, when price-cost margins are constant over time or substitute directly with other variables, prices are justified as a proxy for costs. He investigated 37 chemical products in order to test for LBD effects with respect to alternative learning indexes. In his study learning is found to be a function of cumulated industry output rather than that of calendar time. Though significant, the ECS effect appears to be small in magnitude in comparison with the LBD effect. He also found that R&D expenditure reinforce the steepness of the learning curve, which indicates that past output also influences process innovation and reduces costs. Gruber (1996) also used average selling price as a proxy for unit costs. He found that ECS have a higher cost-reducing impact than LBD. Nye (1996) used average unit costs for every generation and estimated LBD and ECS effects by applying a reduced-form estimation. He found evidence that firm-specific learning is rather important. For this reason, the assumptions of either complete and symmetric spillovers or constant price-cost margins are not appropriate for the semiconductor industry. It is well known that price-cost margins fluctuate considerably over the life cycle (Gruber [1994]). Gruber argued that the margins are large at the beginning and the end of the product life cycle, but smaller during the intervening period. Spence (1981) argued that firms lower prices slower than costs, and this causes price-cost margins to widen over time when the number of firms is constant and learning occurs. However, because price-cost margins change over time, using prices as a proxy for costs is not justified.

In some theoretical models certain functional forms have been implemented, which causes price-cost margins to change over time. Dick (1991) concluded that Japanese firms set prices corresponding to their shadow marginal costs in order to achieve higher future cost reductions. He rejected the dumping hypothesis for the industry on the basis that firms may have incentives to sell products even below their static marginal costs during the early periods of the product cycle. However, this theoretical explanation of price-setting behavior has never been empirically supported. Thus far, no evidence has been given of whether LBD effects are greater at the beginning or at the end of the product cycle . A counterintuitive example of greater LBD effects at the beginning might be the conclusion drawn by the United States Department of Commerce that Japanese firms were dumping the 64K DRAM chip. Taking into consideration that the data date back to 1986, when the chip was already in the final stage of the product cycle, we would expect, in accordance with the theoretical findings, that firms charge positive mark-ups.

3 The Industry

In this section we briefly describe the DRAM industry by focusing on its most important characteristics. We later use these characteristics in order to formulate a theoretical model and derive hypotheses, which are then empirically tested.

The DRAM chip is one among many in the semiconductor industry. The largest market for semiconductors is the United States, followed by Japan and Europe, with a 32%, 31%, and 19% share of the global market, respectively (Gruber [1996]). In 1995, companies from the United States, Japan, Europe, and other countries in the Asian-Pacific region were selling semiconductors worldwide, accounting for market shares of 39.6%, 40.1%, 8.5%, and 11.8%, respectively (Dataquest [1995]). Sales of semiconductors vary over geographic region as well as over industries (Gruber [1996]). Semiconductors are mainly used as inputs for the computer industry (45% of its sales), consumer electronics (23%), and communications equipment (13%). The semiconductor market consists of memory chips, micro components, and Logic devices. Memory chips (designed for the storage of information in binary form) represent the highest market share (30%). Memory chips consist of DRAM, SRAM, ROM, EPROM, EEPROM, and flash memory. DRAM and SRAM are volatile memory chips, for they lose memory once the power is switched off. They account for about 90% of the memory chip market. All of the others are non-volatile chips, which do not lose memory (Gruber [1996]).

The DRAM market is characterized with worldwide selling companies from the United States, Japan, Europe, and other countries in the Asian-Pacific region, with a 20.3%, 44.5%, 3.1%, and 32.0% market share, respectively (Dataquest [1995]). Because of the rapidly decreasing prices over the life cycles, the DRAM industry is one of the industries most subject to LBD. As shown in Figure 2, the price is very high in the beginning and quickly falls to a competitive level. After two to three years, prices reach a lower bound and do not fall much thereafter.

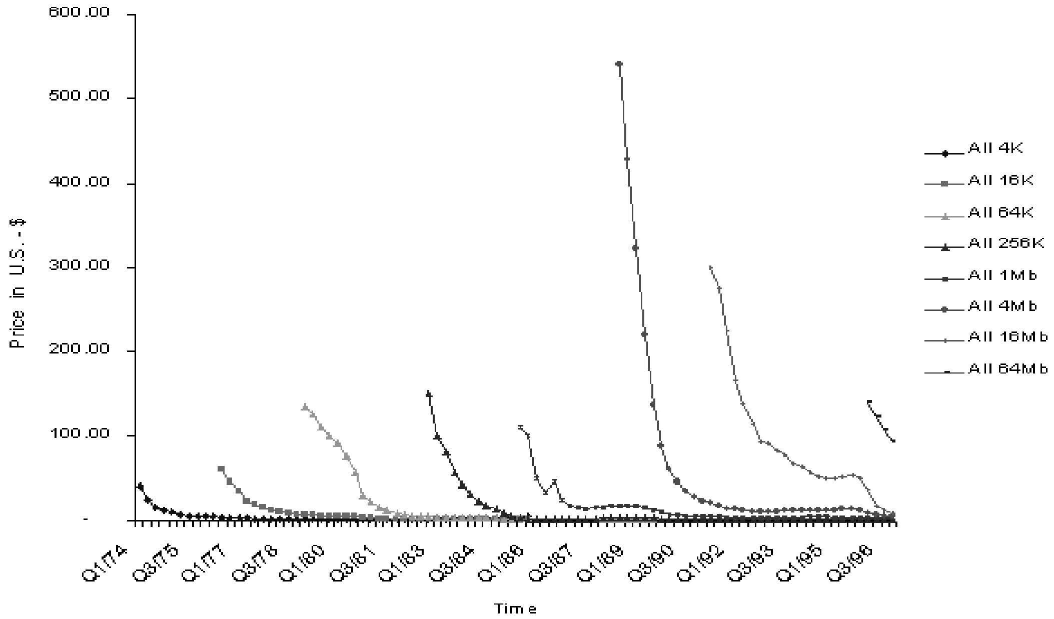

Figure 2: Price decline per generation over time

DRAMs are classified into generations according to their storage capacity, which increases by a factor of four. Every generation is a homogeneous good in itself, but different generations represent differentiated goods. The DRAM market consists of many different generations, the life-cycles of which survive for about five years and look very similar to each other. Once a generation is born, shipments increase enormously and begin to fall when a new generation is established. The generations overlap one another, see Figure 3.

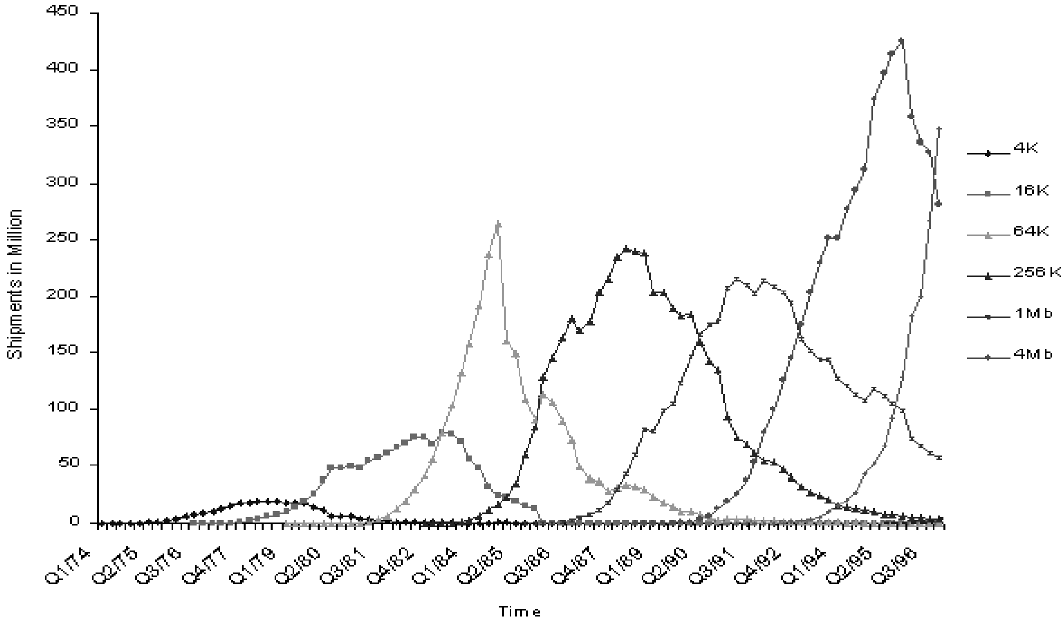

Figure 3: Units of shipments per generation over time (quarterly)

Table 1 gives the firms per generation and provides evidence for an oligopolistic industry structure.[5] The industry is characterized with multiproduct firms that offer subsequent generations from the time they enter the industry to the point at which they exit the industry. For instance, the 64K and the 256K chip (both chips have been under investigation in the United States) are sold by firms that offer at least one further, neighboring chip. Of the 256K chip producers 70% produce both neighboring generations.

[5]See also Albach, Troege, and Jin (1999) for a study on market evolution with respect to Learning by Doing.

Firms	Gener.	4K	16K	64K	256K	1Mb	4Mb	16Mb	64Mb
Adv. Micro Dev.	3	x	x	x	.	.	.	.	.
Alliance	1	.	.	.	.	.	x	.	.
Am. Microsyst.	1	x	.	.	.	.	.	.	.
AT&T	2	.	.	.	x	x	.	.	.
Eurotechnique	1	.	x	.	.	.	.	.	.
Fairchild	3	x	x	x	.	.	.	.	.
Fujitsu	8	x	x	x	x	x	x	x	x
G-Link	2	.	.	.	.	x	x	.	.
Hitachi	8	x	x	x	x	x	x	x	x
Hyundai	6	.	.	x	x	x	x	x	x
IBM	4	.	.	.	.	x	x	x	x
Inmos	2	.	.	x	x	.	.	.	.
Intel	5	x	x	x	x	x	.	.	.
Intersil	2	x	x	.	.	.	.	.	.
LG Semicon	5	.	.	.	x	x	x	x	x
Matsushita	6	.	x	x	x	x	x	x	.
Micron	5	.	.	x	x	x	x	x	.
Mitsubishi	7	.	x	x	x	x	x	x	x
Mosel Vitelic	5	.	.	x	x	x	x	x	.
Mostek	4	x	x	x	x	.	.	.	.
Motorola	8	x	x	x	x	x	x	x	x
Nan Ya Techn.	1	.	.	.	.	.	.	x	.
Ntl. Semic.	4	x	x	x	x	.	.	.	.
NEC	8	x	x	x	x	x	x	x	x
Nippon Steel	4	.	.	.	x	x	x	x	.
OKI	5	.	.	x	x	x	x	x	.
Ramtron Int.	1	.	.	.	.	.	x	.	.
Samsung	6	.	.	x	x	x	x	x	x
Sanyo	3	.	.	.	x	x	x	.	.
SGS-Ates	2	x	x	.	.	.	.	.	.
Sharp	4	.	.	x	x	x	x	.	.
Siemens	7	.	x	x	x	x	x	x	x
Signetics	2	x	x	.	.	.	.	.	.
STC-ITT	3	x	x	x	.	.	.	.	.
Texas Instr.	8	x	x	x	x	x	x	x	x
Toshiba	7	.	x	x	x	x	x	x	x
Vanguard	2	.	.	.	.	.	x	x	.
Zilog	1	.	x	.	.	.	.	.	.

Table 1: Multiproduct firms in the DRAM industry

Computer memory chips are produced by etching circuitry design onto wafers of silicon. The manufacturing process is carried out very precisely in terms of temperature, dust, vibration levels, and other determinants. Learning takes place in many different ways over the entire product life cycle. First, firms decrease costs for a given technology by increasing the yield rate and reducing the required amount of silicon material. The yield rate is measured by the ratio of usable chips to the total number of chips on the wafer. During the life cycle, workers improve their skills. Once no further efficiency can be gained, a new technology is adopted with a smaller design rule. This process is similar from one generation to the next and is part of the learning process (see Dick [1991] and Gruber [1996]).

It is often claimed that the learning rate is about 28%, which means that each doubling in cumulative output reduces average costs by 28%. Irwin and Klenow (1994) identified a learning rate of about 20%. As mentioned above, it is often asserted that firms learn most at the beginning of the life cycle. A common claim is that DRAMs are 'technology drivers', indicating that intergenerational learning exists and that it lowers costs in subsequent generations. A report from the Federal Interagency Staff Working Group (1987, p. 57) stated that the transfer of learning from one chip to another can result in better and faster starting yields. Irwin and Klenow (1994) found significant intergenerational spillovers from 4K to 16K and from 256K to 1MB chips.

4 The Model

The above description of the DRAM industry is useful for understanding our theoretical model. The industry has an oligopolistic multiproduct market structure in which chips within a generation represent a homogeneous good but are differentiated between generations. The behavior of the firms and the fact that LBD is present indicate that the producers compete in terms of quantities rather than in terms of prices. The existence of multiproduct firms leads to output decisions being made through the internalization of the externalities on neighboring generations. Moreover, intertemporal effects caused by LBD and the presence of a product life cycle are important features that have to be taken into account. The following structural model derives pricing relations from a dynamic oligopoly model with multiproduct firms. By using this model, we obtain precise estimates for LBD, ECS, and Spillover effects throughout the product cycle. Furthermore, we estimate firms' conduct and derive the firm-level price-cost margins.

We shall consider a game similar to that introduced by Jarmin (1994). Because LBD has an impact on firms' profits in an intertemporal way, we model a dynamic game with n firms, indexed by $i = 1...n$. The fact that the DRAM industry is characterized by multiproduct firms requires that firms offer subsequent generations ($k = 1...K$). Firms choose quantities in order to maximize their profit over the entire product life cycle, characterized by T discrete time periods, and take into account the effects on the profits of their neighboring generations. Firm i's objective function is

$$\Pi_i = \sum_{k=1}^{K} \sum_{t=1}^{T} \delta^{t-1} \left\{ P_{k,t} \left(Q_{k-1,t}, Q_{k,t}, Q_{k+1,t} \right) q_{i,k,t} - C_{i,k,t} \left(q_{i,k,t}, w_{i,k,t}, x_{i,k,t}, X_{i,k,t} \right) \right\}$$

subject to

$$\begin{aligned} X_{i,k,t} &= X_{i,k,t-1} + Q_{-i,k,t-1} \\ X_{k,0} &= 0. \end{aligned}$$

for $i = 1...n$ and $t = 1...T$, where δ is the discount rate and $P_{k,t}$ is the market price. Thus, $P_{k,t}\left(Q_{k-1,t}, Q_{k,t}, Q_{k+1,t}\right)$ represents the inverse demand function for a given generation (k) in period (t). As can be seen, the multiproduct effect enters at the demand side, because the market price $P_{k,t}$ not only depends on the total industry quantity $Q_{k,t} = \sum_{i=1}^{n} q_{i,k,t}$ of generation k, but also on the total quantities $Q_{k-1,t} = \sum_{i=1}^{n} q_{i,k-1,t}$, and $Q_{k+1,t} = \sum_{i=1}^{n} q_{i,k+1,t}$ of the neighboring generations. Firm i's costs for generation k in period t, given by $C_{i,k,t}\left(q_{i,k,t}, w_{i,k,t}, x_{i,k,t}, X_{i,k,t}\right)$, depends on the contemporaneous firm-level output $q_{i,k,t}$, the firm-level factor prices $w_{i,k,t}$, the cumulative own past output $x_{i,k,t} = \sum_{v=1}^{t-1} q_{i,k,v}$, and the past output of all other firms $X_{i,k,t} = \sum_{j \neq i}^{n} x_{j,k,t}$ until period $t-1$. LBD enters firm i's cost function through its own experience in production indicated by the cumulative past output $x_{i,k,t}$. But firms are not only supposed to learn from their own experience but are also supposed to benefit from spillovers and thus learn from others' experience, given by $X_{i,k,t}$. It is assumed that total costs increase in current output $(\frac{\partial C_{i,k,t}}{\partial q_{i,k,t}} > 0)$ and factor prices $(\frac{\partial C_{i,k,t}}{\partial w_{i,k,t}} > 0)$ and decrease in cumulative past output $(\frac{\partial C_{i,k,t}}{\partial x_{i,k,t}} < 0$, and $\frac{\partial C_{i,k,t}}{\partial X_{i,k,t}} < 0)$.

Because the production of a certain generation is plant-specific, firms are required to construct new plants with a specific capacity for producing new generations. Firms often publicly announce these investments as well as their production plan for the future. Hence, they precommit to a path of history, which allows us to focus on open-loop strategies.[6]

The necessary condition with respect to the quantity of generation k is

$$\frac{\partial \Pi_i}{\partial q_{i,k,t}} = P_{k,t} + \frac{\partial Q_{k,t}}{\partial q_{i,k,t}} \left[\frac{\partial P_{k-1,t}}{\partial Q_{k,t}} q_{i,k-1,t} + \frac{\partial P_{k,t}}{\partial Q_{k,t}} q_{i,k,t} + \frac{\partial P_{k+1,t}}{\partial Q_{k,t}} q_{i,k+1,t} \right]$$

$$- \frac{\partial C_{i,k,t}}{\partial q_{i,k,t}} - \sum_{s=t+1}^{T} \delta^{s-t} \left[\frac{\partial C_{i,k,s}}{\partial x_{i,k,s}} \frac{\partial x_{i,k,s}}{\partial q_{i,k,t}} + \frac{\partial C_{i,k,s}}{\partial X_{i,k,s}} \frac{\partial X_{i,k,s}}{\partial q_{i,k,t}} \right] = 0.$$

Rearranging yields

[6] Open- and closed-loop strategies refer to two different information structures for dynamic games. In open-loop strategies, firms commit to an output path in the future. In closed-loop strategies, it is assumed that firms decide on their future strategies at any point in time conditioning on their past. Hence, firms are able to react to the deviations of their rivals from the equilibrium path. But the concept of closed loop strategies assumes that firms are able to observe the play of opponents and are able to easily adjust their production plan, which is difficult to realize in the DRAM industry.

However, a closed loop model has been tested and rejected.

$$P_{k,t}+\frac{\partial Q_{k,t}}{\partial q_{i,k,t}}\left[\frac{\partial P_{k-1,t}}{\partial Q_{k,t}}q_{i,k-1,t}+\frac{\partial P_{k,t}}{\partial Q_{k,t}}q_{i,k,t}+\frac{\partial P_{k+1,t}}{\partial Q_{k,t}}q_{i,k+1,t}\right]=$$
$$\frac{\partial C_{i,k,t}}{\partial q_{i,k,t}}+\sum_{s=t+1}^{T}\delta^{s-t}\left[\frac{\partial C_{i,k,s}}{\partial x_{i,k,s}}\frac{\partial x_{i,k,s}}{\partial q_{i,k,t}}+\frac{\partial C_{i,k,s}}{\partial X_{i,k,s}}\frac{\partial X_{i,k,s}}{\partial q_{i,k,t}}\right]. \quad (1)$$

The first line in the first order condition, equation (1), shows the marginal revenue term. The term $\frac{\partial Q_{k,t}}{\partial q_{i,k,t}}$ indicates the conduct parameter introduced by Bresnahan (1989). If firms behave like Cournot players, $\frac{\partial Q_{k,t}}{\partial q_{i,k,t}}$ is equal to one, whereas it is supposed to be zero when firms behave as if in perfect competition. In comparing to the standard marginal revenue term for the single product market, we observe not only the own-price effect $\frac{\partial P_{k,t}}{\partial Q_{k,t}}$ in equation (1) but also the cross-generational price effects given by $\frac{\partial P_{k-1,t}}{\partial Q_{k,t}}$ and $\frac{\partial P_{k+1,t}}{\partial Q_{k,t}}$. When the neighboring products are substitutes (complements), the cross-price effects are supposed to be negative (positive). The second line shows firms' dynamic marginal costs and illustrates how LBD affects them. The first term $\frac{\partial C_{i,k,t}}{\partial q_{i,k,t}}$ represents the common contemporaneous or static marginal costs and indicates how current output affects current costs through ECS. The second expression $\sum_{s=t+1}^{T}\delta^{s-t}\frac{\partial C_{i,k,s}}{\partial x_{i,k,s}}\frac{\partial x_{i,k,s}}{\partial q_{i,k,t}}$ refers to the intertemporal LBD effect, indicating that the own current output yields cost savings in the future. If LBD effects are present, the term is expected to be negative. Finally, the term $\sum_{s=t+1}^{T}\delta^{s-t}\frac{\partial C_{i,k,s}}{\partial X_{i,k,s}}\frac{\partial X_{i,k,s}}{\partial q_{i,k,t}}$ represents the intertemporal LBD effect caused by Spillovers, which is supposed to yield future cost savings as well. All of these terms taken together represent the dynamic marginal shadow costs.

In a multiproduct specification, firms' marginal revenues are determined by a further component, the cross-generational price effects. These effects have implications for firms' output decisions because they cause negative (positive) external effects on the neighboring generations when products are substitutes (complements). Firms take into account that a higher output of generation k lowers (increases) the prices of the neighboring generations, which impacts revenues. Ceteris paribus, the internalization of these externalities induces firms to reduce (increase) their quantities in order to prevent losses on neighboring generations. In the presence of LBD and ECS, the output decisions of multiproduct firms are determined by two effects that depend on the nature of the products. When neighboring generations are substitutes, firms' output decisions are characterized by a trade-off between increasing the output in order to achieve higher cost reductions through LBD and ECS and decreasing the output because revenues of the neighboring products are negatively affected. When neighboring generations are complements, the two effects go in the same direction: achieving cost reductions through LBD and ECS as well as internalizing the externalities lead to an increase in output. Multiproduct firms have a higher (lower) incentive to increase quantity than do single product firms that depend on the nature of the products. However, from an empirical perspective through which output and prices are observed (let us also assume for the moment that elasticities are exogenous), the single product firm specification ignores the externalities. Firms' incentive to reduce (increase) output is omitted. Finally, this ignorance leads, in the case of the single product firm specification, to price-cost margins being smaller, dynamic marginal costs being higher, and LBD, ECS and/or Spillover effects being smaller. In single product models a lower (higher) output incentive is attributed to the incentive to yield cost reductions, which understates (overstates) LBD, ECS, and/or Spillover effects. Because these effects are underestimated (overestimated), firms' dynamic marginal costs are overestimated (underestimated) which consequently understates (overstates) the margin between price and dynamic marginal costs.[7]

However, the difference between price and marginal cost is not only determined by the nature of the products (whether products are substitutes or complements) but also by firms' conduct parameter. The conduct parameter describes other firms' reactions to a firm's output increase. In general, a lower conduct parameter indicates 'tougher' behavior by firms in the market, whereas a higher parameter signifies a 'softer' behavior by firms. For example, a conduct parameter equal to zero refers to 'perfect competition', where firms behave 'toughly' in the market, whereas a parameter equal to one indicates that firms behave like Cournot players, which coincides with 'softer' behavior. When comparing single and multiproduct firms, we must take into account that their behavior might be different in the market. Multiproduct firms take account of their neighboring products and may behave 'softer', identically, or 'tougher' in the market. Let us first consider the case of multiproduct firms behaving more 'softly' or identically. It follows from observed output and given price effects from the demand equation that the price-cost margin is larger (smaller) for multiproduct firms when neighboring products are substitutes (complements). Dynamic marginal costs are lower (higher) when products are substitutes (complements). When dynamic marginal costs are supposed to be lower (higher), LBD, ECS, and/or Spillover effects must be higher (lower) when multiproduct firms are investigated and neighboring products are substitutes (complements). When firms behave 'tougher' in the product market, the implications of the effects under investigation are ambiguous and depend on the amount of decrease in the conduct parameter. When the conduct parameter decreases only slightly, the resulting decline in the price-cost margin will still be overcompensated for by the externality effects. The net effect on the price-cost margin is still greater in the multiproduct specification and has the same impact on the effects as above. However, when the conduct

[7] In order to simplify the argument, we will denote the difference between price and dynamic marginal costs as the price-cost margin.

parameter declines more drastically, such that firms behave much more 'tough' in the market, then the externality effect will be overcompensated for, and the price-cost margin will become smaller in a multiproduct specification. In this case, LBD, ECS, and/or Spillover effects are lower for multiproduct firms than for single product firms, irrespective of the nature of the neighboring products.

We can therefore conclude that analyzing multiproduct firms has enormous implications for LBD, ECS, and/or Spillover effects and, thus, for price-cost margins that depend on the nature of the products and changes in firms' conduct. We specify the following hypothesis:

(*i*) LBD, ECS, and/or Spillover effects are greater for multiproduct firms than for single product firms if neighboring products are substitutes and multiproduct firms do not behave too 'toughly' in the product market. As a consequence, firms' price–cost margins are larger.

As is often claimed in the literature, LBD effects are greater at the beginning of the product life cycle. It is intuitive that higher LBD effects coincide with more rapidly declining static marginal costs. As a consequence, firms continue to increase output in order to take advantage of the learning effects. In order to correctly estimate the varying LBD effects over the life cycle, we also must control for varying ECS and Spillover effects, for they are also dependent on firm-level output. If we neglect to do so, LBD effects may be overestimated (underestimated) at some stages of the life cycle, when ECS effects are specified as being constant over the life cycle but are indeed increasing (decreasing) at some stages (see Section 2). The same argument applies when specifying Spillover effects, because they reduce marginal costs as well. We conclude with the following hypothesis:

(*ii*) LBD, ECS, and/or Spillover effects vary over the product life cycle.

In the next section we present an empirical model that tests the two hypotheses. We estimate a structural model by using the first order condition from the theoretical model, shown in equation (1).

5 The Empirical Model

In this section we empirically investigate how the specification of multiproduct firms has an impact on LBD, ECS, and Spillover effects as well as on firms' conduct. We also calculate the difference between price and dynamic marginal costs. In addition, we investigate how LBD, ECS, and Spillover effects and the dynamic marginal costs evolve over the product cycle. In the following we briefly summarize the main facts in order to introduce the two hypotheses.

Analyzing multiproduct firms has important implications for firms' objective functions, for firms internalize the externalities on neighboring generations. Given that products are substitutes, the internalization of externalities in a multiproduct environment leads to underestimated LBD, ECS, and/or Spillover effects when firms' behavior in the market is not too 'tough'. Because LBD, ECS, and/or Spillover effects are expected to be greater for multiproduct firms in the case of substitutable neighboring products, we expect dynamic marginal costs to be lower, which increases the margin between price and dynamic costs, see hypothesis (i).

As is often claimed in the literature, LBD effects are greater at the beginning of the product life cycle. In order to investigate varying LBD effects, it is necessary to account for varying ECS and Spillover effects as well. We estimate and analyze the dynamics of these effects over the product life cycle, see hypothesis (ii).

In order to test the hypotheses (i) and (ii), the following empirical model is estimated, having been derived from the theoretical model. The empirical model consists of three inverse demand functions and one pricing relation, which are explained in the following.

5.1 The Inverse Demand Functions

The inverse demand functions are linear specifications given by[8]

$$\begin{aligned} P_{k-1,t} &= a_0 + a_1 * Q_{k-2,t} + a_2 * Q_{k-1,t} + a_3 * Q_{k,t} \\ &\quad + a_4 * GDPEL_t + a_5 * t_{k-1} + \varepsilon_{k-1,t} \end{aligned} \tag{2}$$

$$\begin{aligned} P_{k,t} &= b_0 + b_1 * Q_{k-1,t} + b_2 * Q_{k,t} + b_3 * Q_{k+1,t} \\ &\quad + b_4 * GDPEL_t + b_5 * t_k + \mu_{k,t} \end{aligned} \tag{3}$$

$$\begin{aligned} P_{k+1,t} &= c_0 + c_1 * Q_{k,t} + c_2 * Q_{k+1,t} + c_3 * Q_{k+2,t} \\ &\quad + c_4 * GDPEL_t + c_5 * t_{k+1} + \omega_{k+1,t} \end{aligned} \tag{4}$$

For the sake of convenience, let us consider the inverse demand equation (3) only; the same procedure applies to equations (2) and (4). As can be seen in equation (3), the price $P_{k,t}$ depends on the quantities sold of the generation under consideration ($Q_{k,t}$) and also takes into account the output of the neighboring

[8]The pricing relations are estimated for the 256K DRAM generation. Therefore, we must estimate the demand equations for the 256K DRAM generation (k) as well as for the neighboring generations ($k-1$) and ($k+1$), which are the 64K and the 1MB DRAM generation, respectively.

generations $Q_{k-1,t}$ and $Q_{k+1,t}$. The parameter b_2 indicates the own-price effect. The sign is expected to be negative, for a higher output results in lower prices. The parameters b_1 and b_3 refer to the cross-price effects and are supposed to be negative (positive) when the neighboring products are substitutes (complements). The sign of the estimated cross-price effects has important implications for firms' price-cost margins, as shown in the theoretical model. The variable $GDPEL_t$ refers to the worldwide GDP in electronics and electronic products and is measured through the production output of the five leading countries selling electronic products, such as the USA, Japan, Germany, France, and the UK. These five countries account for more than 90% of the worldwide GDP among the OECD countries. The variable t_k represents a time trend indicating the length of time a particular generation has been in the market.

The inverse market demand functions, equations (2), (3), and (4) are estimated by using the GMM estimator corrected for serial correlation, see also Andrews (1991 and 1992). Because the industry outputs for the current and the neighboring generations are endogenously chosen by the firms, we are using instruments. The instruments are several market characteristics, such as the average market shares $AMS_{k,t}$ and the number of firms $NOF_{k,t}$ for every generation and every time period. We also use the worldwide Purchase Power Parity (PPP), constructed by taking an average of the PPPs of Japan, Germany, France, Italy, and Korea. Furthermore, we use the marketsize given by $GDPEL_t$ and the time trend t_k.[9] We estimate the demand equations (2), (3), and (4) in order to obtain the corresponding cross-price effects, given by the estimated parameters $\widehat{a_3}$, $\widehat{b_2}$ and $\widehat{c_1}$, which are plugged into the pricing relation in a second step.

5.2 The Pricing Relation

The pricing relation is given in the first-order condition from the theoretical model, see equation (1). We begin by describing firms' dynamic marginal costs, which are part of the pricing relation. As described above, the dynamic marginal costs consist of the static marginal costs and the intertemporal cost reduction. We begin with firms' static marginal costs, which are determined by their own LBD effects through their own past production as well as by the Spillover effects through their rivals' past production. Furthermore, ECS enter the static marginal cost function through current own production as well as factor prices. The static marginal cost function is specified in the following semilog linear form

$$\frac{\partial C_{i,k,t}}{\partial q_{i,k,t}} = \gamma_i + \gamma_1 \ln LBD_{i,k,t} + \gamma_2 \ln LBD^2_{i,k,t} + \gamma_3 \ln ECS_{i,k,t} + \gamma_4 \ln ECS^2_{i,k,t}$$
$$+\gamma_5 \ln Spill_{i,k,t} + \gamma_6 \ln Spill^2_{i,k,t} + \gamma_7 \ln MAT_t + \gamma_8 \ln UCC_{i,t}$$

[9]The selection of these instruments yields robust results. Different specifications do not change the results very much.

$$+\gamma_9 \ln LAB_{i,k,t} + \gamma_{10} \ln E_{i,k,t} + \gamma_{11} \ln FP_{i,k,t} + \eta_{i,k,t}$$

where γ_i is positive and represents firm-specific effects that are supposed to capture unobserved heterogeneities. The variables LBD and LBD^2 indicate firms' own LBD effects. LBD measures firm i's experience in production and is constructed by taking the logarithm of the accumulated past production of firm i for generation k until period $t-1$, indicated by x, in the theoretical model. LBD^2 is the squared expression of LBD. By including the squared expression in the equation, we are able to test whether the learning curve has a different slope over the product cycle. The learning effect is given by $\left(\gamma_1 + \gamma_2 \overline{\ln LBD_k}\right) \big/ \overline{\frac{\partial C_{ik}}{\partial q_{ik}}}$ (a bulk indicates the average of the corresponding variable over time), which is expected to have a negative sign since a higher degree of experience is supposed to reduce marginal costs. The sign of the parameter γ_2 indicates whether the learning curve is concave or convex and tells us whether the learning effects are greater at the beginning or the end of the life cycle. The parameter is positive (negative) when the learning effects are higher (lower) at the beginning of the life cycle.

ECS effects are measured by the variables ECS and ECS^2, which are constructed by using firms' current output in generation k in period t. The ECS effect is given by the expression $\left(\gamma_3 + \gamma_4 \overline{\ln ECS_k}\right) \big/ \overline{\frac{\partial C_k}{\partial q_k}}$. The sign is expected to be negative, zero, or positive when increasing, constant, or decreasing returns are present. The squared expression ECS^2 captures varying ECS effects over the product life cycle.

The variables $Spill$ and $Spill^2$ measure the LBD effect that firms gain from the rivals' experience through spillovers. The variable $Spill$ represents the logarithm of the accumulated past production of all other firms for generation k until period $t-1$, indicated by X, in the theoretical model. $Spill^2$ gives information if the learning curve, influenced by spillovers, has a different slope over the product cycle. The spillover effect given by $\left(\gamma_5 + \gamma_6 \overline{\ln Spill_k}\right) \big/ \overline{\frac{\partial C_k}{\partial q_k}}$ is expected to have a negative sign, because a higher past production by other firms is supposed to reduce firm i's marginal costs. The sign of the parameter γ_6 is positive if firm i is able to benefit more from others' experience at the beginning of the life cycle.

Furthermore, we use four different input prices. The variable MAT measures the price of material during a certain period and is taken from the 'Metal Bulletin'. The other three input prices are calculated on a firm-level basis. The variable UCC is the firm-specific user cost of capital, which is calculated on the basis of the business reports. For the remaining two factor prices LAB and E (labor and energy costs), we take into account the international generation-specific production locations for each firm and correct for different factor prices in different countries (production locations). We use the number of different production plants for each firm, each generation, and each period, in every country. In addition, we use country-specific wages and energy prices. The country-specific input prices are then weighted with the proportion of plants that each firm operates for each generation, in every country. The labor costs for firm i, offering generation k in period t, are indicated by $LAB_{i,k,t}$ and are collected for the Semiconductor Industry (SIC 3674) and taken from the Annual Survey of Manufacturers. The energy prices for firm i, offering generation k in period t, are indicated by $E_{i,k,t}$ and are taken from the International Energy Agency, OECD. The parameter estimates of the input prices are expected to have a positive sign since higher input prices increase marginal costs.

The variable FP captures all other factor prices. Because the firms produce in different countries and the other factor prices vary considerably from country to country, we construct the variable by multiplicatively combining the Producer Price Index with the Purchase Power Parity of each of the countries where production takes place, such as the USA, Japan, Germany, the UK, Korea, and Taiwan. These indexes are then weighted with the proportion of plants that each firm operates in each country.

Because LBD not only has an impact on firms' static marginal costs but also induces an intertemporal aspect, we must account for the fact that firms price below their static marginal costs. In order to enable the estimation procedure, we capture the dynamic effects in firm-specific constants as set out in Roberts and Samuelson (1988) and Jarmin (1994), given by

$$\lambda_i = \sum_{s=t+1}^{T} \delta^{s-t} \left[\frac{\partial C_{i,k,s}}{\partial x_{i,k,s}} \frac{\partial x_{i,k,s}}{\partial q_{i,k,t}} + \frac{\partial C_{i,k,s}}{\partial X_{i,k,s}} \frac{\partial X_{i,k,s}}{\partial q_{i,k,t}} \right].$$

The term is expected to be negative because contemporaneous output decisions yield future cost savings.

Inserting the static marginal cost function and the dynamic effects into the first order condition (equation (1)) of the theoretical model and solving for the price P gives the pricing relation. The pricing relation depends on the dynamic marginal costs, on quantities, and on the price effects of the corresponding and the neighboring generations.

Multiproduct Firm Specification

The pricing relation for the multiproduct firm specification is given in the following form[10]

$$\begin{aligned} P^*_{k,t} \quad = \quad & \beta_{0,i} + \beta_1 \ln LBD^*_{i,k,t} + \beta_2 \ln LBD^{2*}_{i,k,t} + \beta_3 \ln ECS^*_{i,k,t} + \beta_4 \ln ECS^{2*}_{i,k,t} \\ & + \beta_5 \ln Spill^*_{i,k,t} + \beta_6 \ln Spill^{2*}_{i,k,t} + \beta_7 \ln MAT^*_t + \beta_8 \ln UCC^*_{i,t} \\ & + \beta_9 \ln LAB^*_{i,k,t} + \beta_{10} \ln E^*_{i,k,t} - \beta_{11} COND^{M*}_{i,k,t} + \epsilon_{i,k,t}. \qquad (5) \end{aligned}$$

[10]In order to guarantee that the cost function is well-behaved, it is necessary to impose a linear homogeneity of degree 1 in input prices. The restriction is taken care of by correcting the variables with $\ln FP$. All corrected variables are indexed by *.

The parameter $\beta_{0,i}$ is a composite of several firm-specific constants given by $\beta_{0,i} = \gamma_i + \lambda_i$, whereby the sign of the composite can be positive or negative depending on whether the amount of γ_i is larger or smaller than λ_i. The parameter β_{11} represents the (multiproduct) conduct parameter given by $\frac{\partial Q_{k,t}}{\partial q_{i,k,t}}$ in the first order condition, equation (1), where $COND^{M*}_{i,k,t}$ represents the expression $\left[\frac{\partial P_{k-1,t}}{\partial Q_{k,t}} q^*_{i,k-1,t} + \frac{\partial P_{k,t}}{\partial Q_{k,t}} q^*_{i,k,t} + \frac{\partial P_{k+1,t}}{\partial Q_{k,t}} q^*_{i,k+1,t}\right]$ from the first order condition, equation (1). We use the estimated parameters $\widehat{a_3}$, $\widehat{b_2}$ and $\widehat{c_1}$ from the demand equation for the price effects $\frac{\partial P_{k-1,t}}{\partial Q_{k,t}}$, $\frac{\partial P_{k,t}}{\partial Q_{k,t}}$, and $\frac{\partial P_{k+1,t}}{\partial Q_{k,t}}$ respectively, and multiply each with the corresponding firm-level output.[11]

Single Product Firm Specification

We also estimate the pricing relation for the single product firm specification in order to compare the different effects. The specification is the same as for multiproduct firms, and given by

$$\begin{aligned} P^*_{k,t} \;=\; & \delta_{0,i} + \delta_1 \ln LBD^*_{i,k,t} + \delta_2 \ln LBD^{2*}_{i,k,t} + \delta_3 \ln ECS^*_{i,k,t} + \delta_4 \ln ECS^{2*}_{i,k,t} \\ & + \delta_5 \ln Spill^*_{i,k,t} + \delta_6 \ln Spill^{2*}_{i,k,t} + \delta_7 \ln MAT^*_t + \delta_8 \ln UCC^*_{i,t} \\ & + \delta_9 \ln LAB^*_{i,k,t} + \delta_{10} \ln E^*_{i,k,t} - \delta_{11} COND^{S*}_{i,k,t} + \psi_{i,k,t}. \end{aligned} \tag{6}$$

The parameter δ_{11} represents the term $\left[\frac{\partial P_{k,t}}{\partial Q_{k,t}} q^*_{i,k,t}\right]$ from the first order equation (1) for single product firms and indicates the conduct parameter $COND^{S*}_{i,k,t}$for the single product firm specification. Because the difference between the single product and multiproduct specification is given in that cross-price effects do not enter the pricing relation in a single product specification, we only have to substitute the own-price effect $\frac{\partial P_{k,t}}{\partial Q_{k,t}}$ with the estimated parameter $\widehat{b_2}$ from the demand equation.

The pricing relation for the multiproduct and the single product specification is estimated by using 2-stage least squares. For the multiproduct estimation, equation (5), we use the number of firms and the average market shares of the current and the neighboring generations, the variable $GDPEL_t$, and all other exogenous variables (except the LBD, ECS, and $COND$ variables) as instruments. We use the same instruments (except the number of firms and the average market shares of the neighboring generations) for the single product estimation, equation (6).

[11] Note that the firm-level output is corrected by the variable $\ln FP$, as well.

6 Data

The analysis requires data from a variety of different sources. The database, provided by Dataquest, consists of two different parts. The first part consists of quarterly firm-level shipments and average industry prices for ten different generations beginning in 1974 for the 4K generation and ending in 1996 for the 64MB generation. The second part consists of factor prices. Summary statistics and definitions of the variables used in the estimation are given in Table 2.

Variables	Description	N	Median	Min.	Max.
$P_{k,t}$	Average selling price of one chip of generation k in period t.	57	2.39	1.52	150.00
$Q_{k-1,t}$	Total number of chips of the k-1'th generation being sold in period t.	57	10E+6	0	26.4E+7
$Q_{k,t}$	Total number of chips of the k'th generation being sold in period t.	57	46E+6	10E3	24.2E+7
$Q_{k+1,t}$	Total number of chips of the k+1'st generation being sold in period t.	57	80E+6	0	21.5E+7
$GDPEL_t$	GDP in electronics in period t.	57	5.28E+13	4.18E+12	2.72E+16
t_k	Time trend for generation k	57	16.00	9.00	23.00
$P_{k,t}$	Average selling price of k in period t.	761	2.36	1.52	150.00
$\ln LBD_{i,k,t}$	LBD measure for firm i offering generation k in period t.	761	15.63	0	20.63
$\ln LBD^2_{i,k,t}$	LBD measure (squared) for firm i ,generation k, period t.	761	244.36	0	425.74
$\ln ECS_{i,k,t}$	Measure of ECS for firm i offering generation k in period t.	761	12.74	2.94	17.86
$\ln ECS^2_{i,k,t}$	ECS measure (squared) for firm i offering generation k in period t.	761	162.25	8.62	319.00
$\ln Spill_{i,k,t}$	'Spillover' measure for firm i offering generation k in period t.	761	17.20	-4.65	25.01
$\ln Spill^2_{i,k,t}$	'Spillover' measure (squared) for firm i offering generation k in period t.	761	295.99	7.43	625.46
$\ln MAT_t$	Logarithm of material cost in period t.	761	8.41	-0.14	14.08
$\ln UCC_{i,t}$	Logarithm of firm i's User Cost of Capital in period t.	761	-3.71	-10.28	-0.86
$\ln LAB_{i,k,t}$	Logarithm of firm i's Labor Cost for generation k in period t.	761	14.76	0.76	20.34
$\ln E_{i,k,t}$	Logarithm of firm i's Energy Cost for generation k in period t.	761	2.25	-9.03	8.46

(Table continues)

Variables	Description	N	Median	Min.	Max.
$q_{i,k-1,t}$	Firm i's number of chips from the k-1'st generation being sold in period t.	761	0	0	31.5E06
$q_{i,k,t}$	Firm i's number of chips of the k'th generation being sold in period t.	761	22.0E05	3000	39E06
$q_{i,k+1,t}$	Firm i's number of chips of the k+1'st generation being sold in period t.	761	26E05	0	31.5E06
$NOF_{k,t}$	Number of firms competing in the market of generation k at period t.	761	13	1	20
$AMS_{k,t}$	Average market share of firms in generation k at period t.	761	0.04	5E-05	1

Table 2: Variable definitions and summary statistics

7 Results

The estimation results of the inverse demand equations (2), (3), and (4) are presented in Table 3. For the estimation procedure of the three demand equations for generations $k-1$, k, and $k+1$, 68, 57, and 48 observations could be used, respectively. All three estimations have a remarkably good fit. The adjusted R-squares are 0.70 and higher. Nearly all estimates are significant at the 1% level. The own-price effects carry the expected negative sign, indicating that a higher industry output decreases prices. The negative cross-price effects show that neighboring generations represent substitutable products and indicate that a negative externality enters firms' pricing relations. The estimates of the previous generation have a more inelastic impact on the generation under consideration than the estimates of the subsequent generation. This fact indicates that an increase in output of the previous generation reduces the price of the current generation to a higher extent than an increase in output of the subsequent generation. The GDP in electronics has a negative impact on price but is not significant in either of the demand equations. The time trend is negative, which is a plausible outcome, for consumers substitute away from the generation as time passes.

GMM Estimates for						
	64K Generation		256K Generation		1Mb Generation	
Variables	Estimates	Std. Err.	Estimates	Std. Err.	Estimates	Std. Err.
$Constant$	176.86**	11.54	222.45**	21.24	144.66**	31.36
Q_{k-2}	-1.15E-6**	1.33E-7	-	-	-	-
Q_{k-1}	-2.45E-7**	4.93E-8	-5.83E-7**	1.04E-7	-	-
Q_k	-2.60E-7**	3.11E-8	-2.68E-7**	3.01E-8	-2.17E-7**	8.44E-8
Q_{k+1}	-	-	-1.26E-7**	3.93E-8	-1.33E-7**	3.43E-8
Q_{k+1}	-	-	-	-	-4.13E-8	4.02E-8
$GDPEL$	-2.00E-16	1.93E-16	-7.93E-17	1.44E-16	-2.78E-16	3.62E-16
t	-8.27**	0.56	-9.59**	0.89	-5.20**	1.42
	Obs.=68, adj. R^2=0.77		Obs.=57, adj. R^2=0.70		Obs.=46, adj. R^2=0.74	

**significant at the 1% level.

Table 3: Demand equations

With regard to the estimation of the pricing relation for the multiproduct and the single product specification, a Durbin-Watson statistic by Bhargava, Franzini, and Narendranathan (1982) indicated a positive correlation, which we corrected for by applying a first order moving average process.[12] The estimates are given in Table 4. In both regressions, 761 observations could be used. Both estimations have a very good fit. The adjusted R-square for the multiproduct and the single product specification is 0.76 and 0.75, respectively. The autocorrelation tests of 1.72 and 1.76 show that no further serial correlation exists. Almost every parameter estimate is significant at the 1% level. From the estimates of the pricing relations, we were able to test the two hypotheses.

[12] Note that, because of the panel data structure the first observation for every firm must be dropped for the correction procedure of autocorrelation.

Variables	Multiproduct Comp. Estimates	Std. Err.	Single-Product Comp. Estimates	Std. Err.
$\ln LBD^{*}$	5.28**	0.48	5.49**	0.49
$\ln LBD^{2*}$	-0.19**	0.01	-0.19**	0.01
$\ln Spill^{*}$	-5.81**	0.31	-5.81**	0.32
$\ln Spill^{2*}$	0.13**	0.01	0.12**	0.01
$\ln ECS^{*}$	1.08*	0.60	-1.23*	0.65
$\ln ECS^{2*}$	-0.11**	0.02	0.004	0.03
$\ln MAT^{*}$	0.68**	0.15	0.82**	0.15
$\ln UCC^{*}$	2.81**	0.23	2.99**	0.23
$\ln LAB^{*}$	0.007	0.11	-0.06	0.11
$\ln E^{*}$	-0.006	0.06	-0.02	0.07
$COND^{M,S*}$	0.87**	0.12	-0.001	0.16
$\beta_{0,1}$	44.95**	4.74	53.37**	4.94
$\beta_{0,2}$	43.82**	4.83	57.22**	4.90
$\beta_{0,3}$	43.80**	4.66	55.84**	4.77
$\beta_{0,4}$	39.46**	4.89	52.14**	5.03
$\beta_{0,5}$	35.36**	5.06	46.41**	5.22
$\beta_{0,6}$	35.96**	4.68	47.24**	4.85
$\beta_{0,7}$	42.54**	5.08	55.35**	5.21
$\beta_{0,8}$	40.27**	4.79	51.81**	4.92
$\beta_{0,9}$	41.94**	4.67	53.52**	4.77
$\beta_{0,10}$	41.62**	4.83	55.22**	4.89
$\beta_{0,11}$	36.61**	4.58	47.67**	4.75
$\beta_{0,12}$	37.79**	4.97	48.43**	5.22
$\beta_{0,13}$	36.04**	4.55	46.84**	4.70
$\beta_{0,14}$	33.67**	6.13	45.08**	6.37
$\beta_{0,15}$	46.15**	4.95	59.53**	5.05
$\beta_{0,16}$	40.44**	6.07	50.21**	6.28

(Table continues)

Variables	Multiproduct Comp. Estimates	Multiproduct Comp. Std. Err.	Single-Product Comp. Estimates	Single-Product Comp. Std. Err.
$\beta_{0,17}$	42.65**	4.75	54.57**	4.85
$\beta_{0,18}$	39.19**	4.84	51.52**	4.98
$\beta_{0,19}$	41.39**	4.98	54.01**	5.09
$\beta_{0,20}$	41.04**	4.80	52.73**	4.97
$\beta_{0,21}$	41.26**	4.50	52.57**	4.60
$\beta_{0,22}$	40.47**	4.80	53.99**	4.90
$\beta_{0,23}$	38.01**	4.57	49.39**	4.69
$MA(1)$	-0.39**	0.03	-0.36**	0.03
	Obs.=761, adj. R^2=0.76, DW=1.72		Obs.761, adj. R^2=0.75, DW=1.76	

**significant at the 1% level, *significant at the 10% level.

Table 4: Pricing relation

The parameter estimates of the LBD variables LBD and LBD^2 are highly significant and have a positive and negative sign (respectively) for the multiproduct and the single product specification. Table 5 provides the calculated learning elasticity and learning rates.[13] The learning elasticity of -0.16 (-0.1) for the multiproduct (single product) model corresponds to a 10.5% (6.7%) learning rate. Thus, in the multiproduct model, doubling a firm's output (at the sample mean) reduces the marginal costs by 10.5%. In general, we find evidence that a higher degree of past experience reduces marginal costs. The learning rates for the single product model are similar to those of previous findings, indicating that the model specifications support reliable results. Comparing the learning rates for both models, we find strong support for the contention that the LBD effects are greater for multiproduct firms than for single product firms, and we find evidence that the omitted quantity reduction results in underestimated LBD effects in a single product specification, see hypothesis (i). The parameter estimates for ECS and ECS^2, measuring the ECS, are shown to be significantly negative in the multiproduct model, indicating that returns to scale are evident. The elasticity is -0.45, indicating that a 1% increase in output decreases marginal costs by 0.45%. For the single product model we see that decreasing returns to scale are prevalent. The elasticity of 0.06 shows that the ECS are smaller in the single product specification, which supports hypothesis (i). In general, we see that the ECS rate is higher than the LBD rate, indicating that ECS effects seem to be more important. Furthermore we see that ECS have an enormous cost-reducing impact, which is, on average, four times higher than the LBD effect. Turning to the parameter estimates of the spillover effects $Spill$ and $Spill^2$, we find that they are significant in both models. Table 5 shows that the learning elasticity is

[13]The learning rate is calculated by $1 - 2^{\beta}$, where β represents the learning elasticity.

-0.03 (-0.04) for the multiproduct (single product) specification corresponding to a learning rate of 2.1% (3%). In both models the own-cost reduction obtained through rivals' past experience is a significant factor, which gives evidence for the existence of spillovers in the market.

	Multiproduct Comp.		Single-Product Comp.	
Variables	Elast.	Rate	Elast.	Rate
LBD	-0.16	10.5%	-0.1	6.7%
ECS	-0.45	45%	0.06	-6%
$Spill$	-0.03	2.1%	-0.04	3%

Table 5: LBD, ECS, and Spillover effects

In Table 4 we also see that the estimate for the conduct parameter $COND^M$ for the multiproduct specification is close to one, indicating that firms behave like Cournot players.[14] This result is very important for our model specification and supports the claim that the multiproduct firm model describes firms' behavior very well. The parameter estimate for the single product model indicates that firms behave as if in perfect competition, which is not convincing for this industry, as it is characterized by significant LBD effects. We therefore gain support for hypothesis (i) that multiproduct firms behave more 'softly' than do single product firms. In a next step, we calculated the fitted average firm-specific price-cost margins for the multiproduct and the single product specification. Table 6 shows that firms' price-cost margins are indeed higher for multiproduct firms than for single product firms. This result supports hypothesis (i).

Turning to our hypothesis (ii), we see that the parameter estimate for LBD^2 is negative in both models, indicating that LBD effects are different over the product life cycle, which confirms our hypothesis. Learning effects are smaller at the beginning of the life cycle, an outcome that runs contrary to previous assumptions. The parameter estimate of ECS^2 indicates that ECS are constant throughout the product life cycle in the single product model, but that they increase over time in a multiproduct model. Furthermore, the parameter estimates of $Spill^2$ show that the Spillover effect varies over the product life cycle in both models. Thus, in the multiproduct and the single product model the LBD effects through Spillovers become smaller throughout the product life cycle.

The estimated firm-specific effects are significant, indicating that unobserved heterogeneities among firms and shadow marginal cost pricing are important features. Firm-specific effects are shown to be significantly different from each other. The parameter estimates for user material prices and user cost of capital are positive and significant, giving support to the argument that an increase in

[14] We tested and found evidence that the parameter is not significantly different from 1.

prices for material and capital increases marginal costs. The estimates for energy and labor costs are insignificant.

Country	Firms	Price-Cost Margin in Multiproduct Comp.	Price-Cost Margin in Single Product Comp.
USA	AT&T	0.38	0.37
	Inmos	-0.23	0.18
	Intel	0.40	0.14
	Micron	1.70	0.77
	Mosel Vitelic	0.34	0.20
	Mostek	0.01	0.004
	Motorola	1.51	0.34
	Ntl. Semiconductor	-0.06	0.002
	Texas Instruments	2.86	1.57
	Mean	**0.77**	**0.40**
JAP	Fujitsu	1.73	1.18
	Hitachi	1.28	1.29
	Matsushita	0.51	0.29
	Mitsubishi	1.28	1.13
	NEC	2.65	2.05
	Nippon	1.16	0.53
	OKI	1.23	0.70
	Sanyo	0.27	0.04
	Sharp	0.45	0.36
	Toshiba	3.23	0.77
	Mean	**1.38**	**0.83**
KOR	Hyundai	1.71	0.38
	LG Semicon	1.29	0.18
	Samsung	2.99	1.01
	Mean	**2.00**	**0.52**
GER	Siemens	1.43	0.26
	Mean	**1.43**	**0.26**

Table 6: Firm- and country-specific price-cost margins

8 Conclusion

In this chapter, we theoretically derive a dynamic oligopoly model and compare a multiproduct with a single product firm specification. We empirically estimate and compare the impact of the different specifications on LBD, ECS, and Spillover effects as well as on firms' behavior. Furthermore, we allow the effects to vary over the product life cycle. We find that two aspects, multiproduct firms and allowing for dynamics over the product life cycle, have important implications and yield results that differ from previous findings or expectations. In the theoretical model we show that external effects on neighboring generations enter firms' objective functions once multiproduct firms are specified. We derive two hypotheses from the theoretical model and test them by estimating a structural dynamic model of demand and pricing relations under the assumption of multiproduct as well as single product firms. Using quarterly firm-level output and cost data as well as industry prices from 1974 to 1996, we obtain precise estimates for LBD, ECS, and Spillover effects throughout the product life cycle. Furthermore, we estimate firms' conduct parameter and compare the firm specific price-cost margins for multiproduct and single product firms.

Estimating the inverse demand functions yields negative cross-price effects, which indicates that neighboring generations are substitutable goods, confirming the notion that negative externalities enter firms' pricing relations under multiproduct specification. Focusing on multiproduct firms reveals that firms take into account losses for their neighboring generations in their output decisions, for a higher output reduces neighboring revenues. Because, in the assumption of single product firms, externalities previously have not been taken into account, a lower output incentive has been attributed to firms, yielding underestimated LBD, ECS, and/or Spillover effects as well as smaller price–cost margins. We obtained evidence that LBD and ECS effects are greater, whereas Spillover effects are smaller, for multiproduct firms. The significant LBD effects and the heterogeneous firm-level fixed effects show that firms invest in future cost reductions by increasing output and that they set prices that are consistent with their marginal shadow costs. The analysis shows that the enormous price decrease over time is induced by LBD, ECS, and Spillover effects with ECS having a higher cost-reducing impact on average than LBD effects. Moreover, we were able to show that ECS effects are around four times higher than LBD effects. In addition, we obtained evidence to show that multiproduct firms behave like Cournot players, whereas single product firms behave as if in perfect competition. Thus, multiproduct firms behave more 'softly' in the product market than do single product firms. We can therefore conclude that a multiproduct specification better suits this industry, for perfect competition is not very convincing for an industry that is characterized by LBD effects. As a consequence, price-cost margins are larger for multiproduct firms than for single product firms.

Furthermore, we have provided evidence that LBD, ECS, and Spillover effects vary throughout the product life cycle in a multiproduct environment, see hypothesis (*ii*). In a multiproduct environment, LBD and ECS effects are higher at the end of the life cycle, whereas Spillover effects are smaller. One reason LBD and ECS effects are higher at the end of the life cycle might be that new processes and technologies are developed over time, which induces higher cost savings and influences firms' marginal costs such that they become more intensive as new technologies are developed. Thus, new processes and technologies, which are often developed over time, bring about higher LBD and ECS effects. Firms achieve high LBD effects by producing new technologies at the end of the generation, which also reduces the adoption costs for the next generation. This fact explains why firms continue to stay in the market at the end of the life cycle, despite their small chosen price-cost mark-ups. It is often argued in the literature that process innovations can be carried over to the next generation, which is characterized by intergenerational spillovers. Irwin and Klenow (1994), for example, found significant spillovers from the 256K to the 1MB chip. The fact that LBD effects are relatively low at the beginning and greater at the end of the life cycle explains the drastic price decline more accurately (see Figure 4) than does the former explanation, in which below-cost pricing should have been practiced at the beginning (see Figure 1).

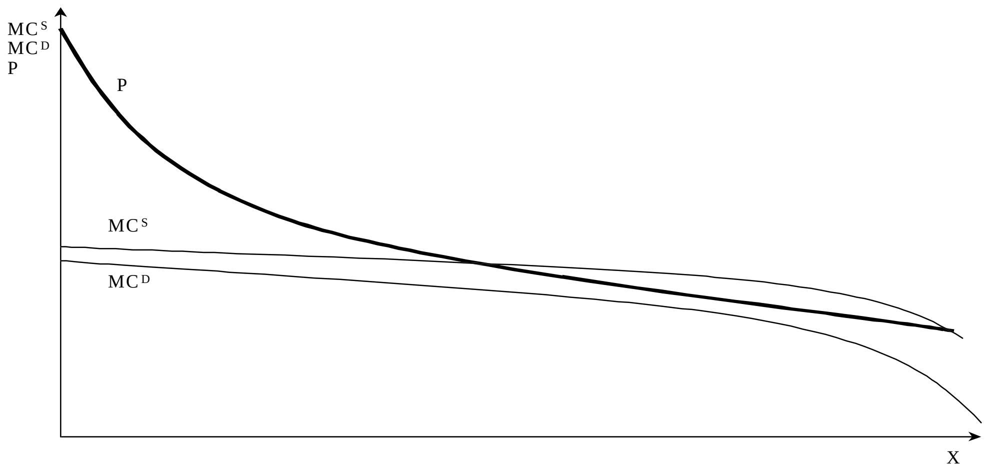

Figure 4: Price setting with respect to shadow marginal costs

Evidence from the data is provided in Figure 5 which shows quarterly prices versus firms' average marginal shadow costs over time.

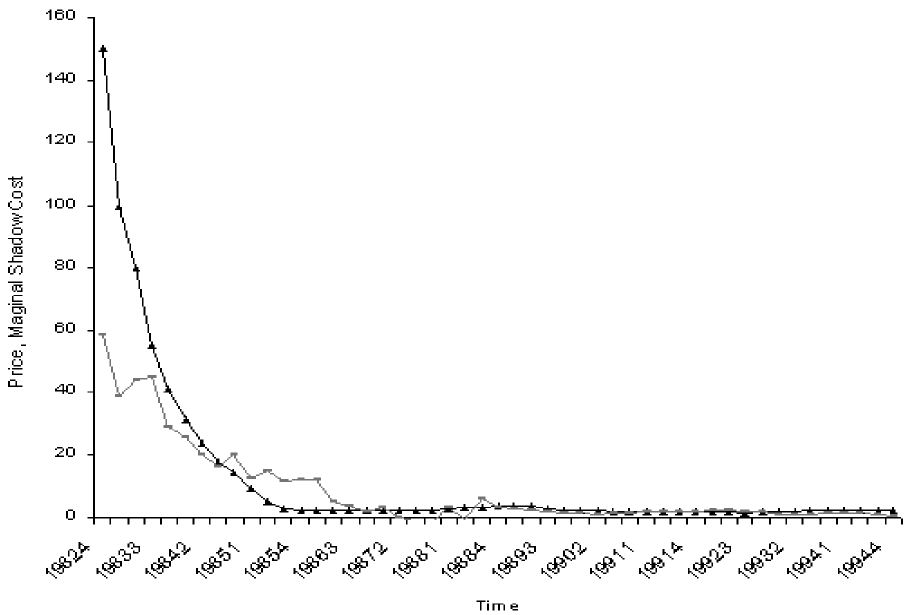

Figure 5: Quarterly prices versus marginal shadow costs over time

This study provides evidence that Japanese firms did not engage in dumping with regard to the 256K DRAM generation. The reason dumping margins have been found for the 64K DRAM chip is that the product life cycle was already far advanced when the investigation took place. According to the previous theory, the fact that LBD effects are greater at the beginning of the life cycle should lead to firms' price-cost margins being rather small (if not negative) at the beginning but large at the end of the life cycle. However, finding smaller or even negative mark-ups at the end of the life cycle does not seem to be consistent with the former explanation of price-setting behavior in the presence of LBD.

Moreover, the results of this study support the notion that LBD effects are greater at the end of the life cycle, which induces firms to charge larger mark-ups at the beginning and smaller mark-ups at the end of the cycle. The calculated dumping margins of 20% at the end of the 64K life cycle (see Dick [1991]) would be equivalent to the common learning rate of 20% in the semiconductor industry (see Irwin and Klenow [1994]) and illustrates quite clearly the finding of marginal shadow cost pricing at the end of the life cycle, which is again consistent with the findings of this study.

The results of this study suggest that one should take into account the form of competition and the dynamics over the life cycle when evaluating an industry. We can conclude that both the existence of multiproduct firms and dynamics over the product life cycle have important implications for cost reductions because of LBD, ECS, and Spillover effects. Depending on how far product cycles have advanced firms' price-cost margins can be very different. This study demonstrates the importance of adjusting for multiproduct firms and the dynamics over the product life cycle in future investigations of the semiconductor industry.

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