Multiproduct Firms, Market Conduct, and Dynamic Marginal Costs over the Product Life Cycle: Evidence from the DRAM Industry

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Abstract

In this study 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*) Spillover and Economies of Scale effects are lower for multiproduct firms than for single product firms, whereas Learning by Doing effects are slightly higher. We also find that firms follow an intertemporal output strategy. Furthermore, we provide evidence that, once multiproduct firms are introduced, firms behave as if in perfect competition. A single product specification leads to firms behaving even 'softer' than Cournot players in the product market. We show that (*ii*) Learning by Doing, Economies of Scale, and Spillover effects vary over the product cycle. We specify a dynamic theoretical model and estimate a dynamic 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-costs 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 costs of production for its chips. The two investigating bodies isolated the total costs 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 costs of production. The dumping case against the 256K chip, 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 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 costs reductions. This strategy induces firms to make their optimal output decisions based not on current period

[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)).

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-costs margins, an assumption that is incongruous with the semiconductor industry. On the contrary, it is evident that price-costs margins change over time. As a consequence, using price as a proxy for unit costs is not easily justified. Irwin and Klenow (1994) allowed price-costs margins to change over time. 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, they endogenized firms' pricing behavior 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). Four different models of the DRAM industry are estimated 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 output strategy and optimize their production plan over the entire product life cycle.

However, 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 internalize the externalities on their neighboring products.[4] Focusing on multiproduct firms, 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 costs reductions through

[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.

[4]The literature on multiproduct competition or firms 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.

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. Because econometricians only know about observed quantities, but not about the unobserved and neglected quantity reductions that result from internalized effects in a multiproduct specification, (ceteris paribus) a lower current output decision is attributed to the incentive to yield costs reductions in single product models. Moreover, we expect that the internalization of externalities leads multiproduct firms to behave differently in the product market than single product firms do, which may have a further impact on the measurement of LBD, ECS and/or Spillover effects.

Furthermore, it is often claimed that LBD effects vary over the product cycle, such that LBD effects are higher at the beginning of the cycle, yet, evidence to support this claim has never been given. Previous empirical specifications estimated the LBD effect as constant and, thus, is not allowed to vary over the product life cycle.

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:

(*i*) When multiproduct firms behave more 'aggressively' in the product market than single product firms, or when Spillover effects are relatively smaller than LBD effects in a multiproduct specification, then LBD, ECS, and/or Spillover effects are smaller for multiproduct firms.

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

The hypotheses are then tested empirically by estimating a structural dynamic model of demand and pricing relations using quarterly firm-level output and costs data as well as industry prices for the DRAM industry from 1974 to 1996.

The remainder of this study is organized as follows. We begin with a description of the underlying effects influencing the measurement of Learning by Doing in Section 2. Section 3 presents some structural and behavioral characteristics of the semiconductor industry and, in particular, of the DRAM industry. In Section 4 we develop and analyze a theoretical model of Learning by Doing with asymmetric multiproduct firms, and two hypotheses are derived. In Section 5 we present an 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 study 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.[5] 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' marginal costs because firms' unit costs decline as production experience increases through accumulated past output. LBD also creates an intertemporal effect which indicates that the current output yields costs 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 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 marginal costs (MC^s), depending on the increase in accumulated output, in particular during the early stages of the life cycle.

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.

[5]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.

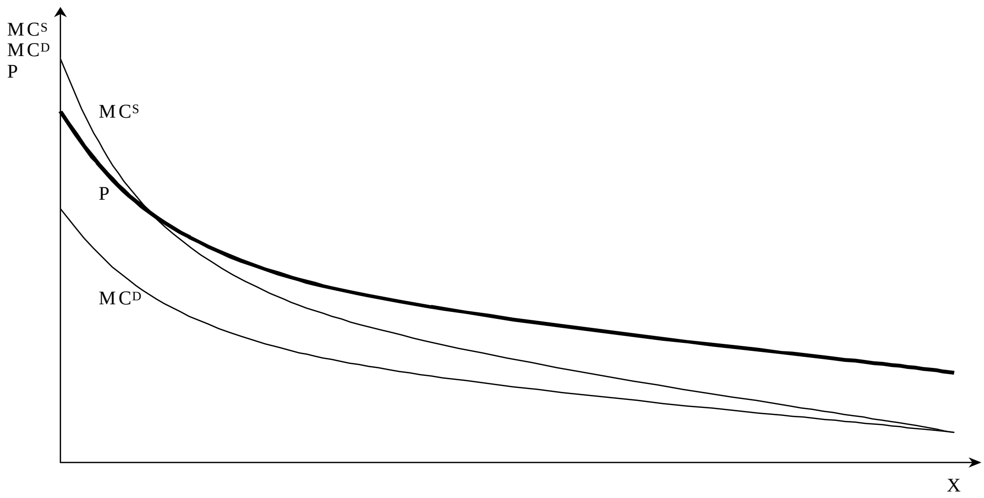

Figure 1: Price setting with respect to shadow marginal costs

Another aspect of cost reduction is the existence of ECS, which result in a contemporaneous unit costs 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 which impacts the learning effects. 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 costs 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-costs 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 costs 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]).

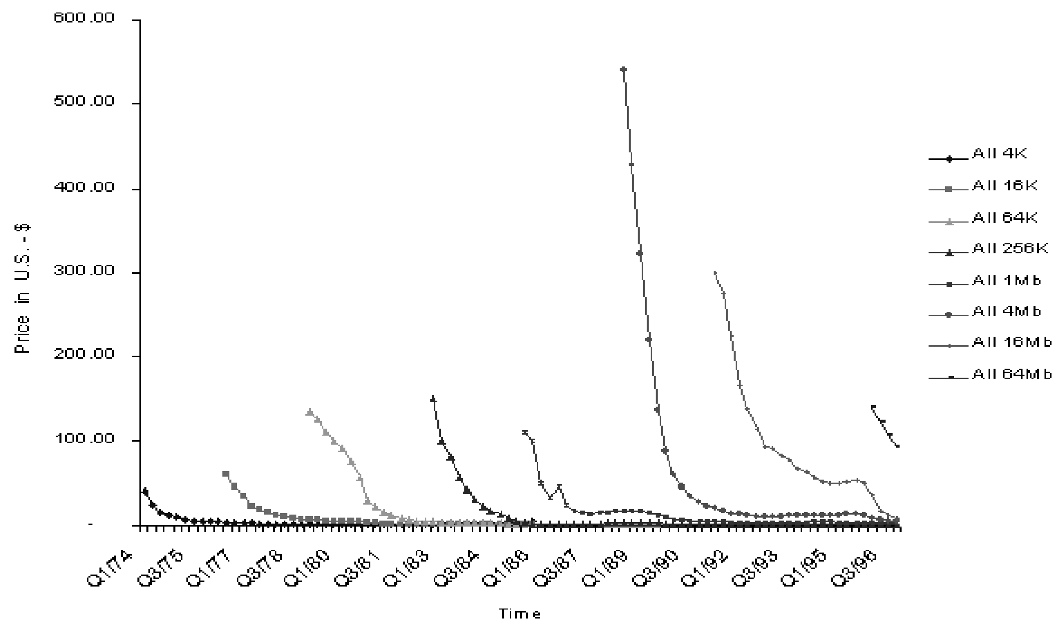

Figure 2: Price decline per generation over time

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 at 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.

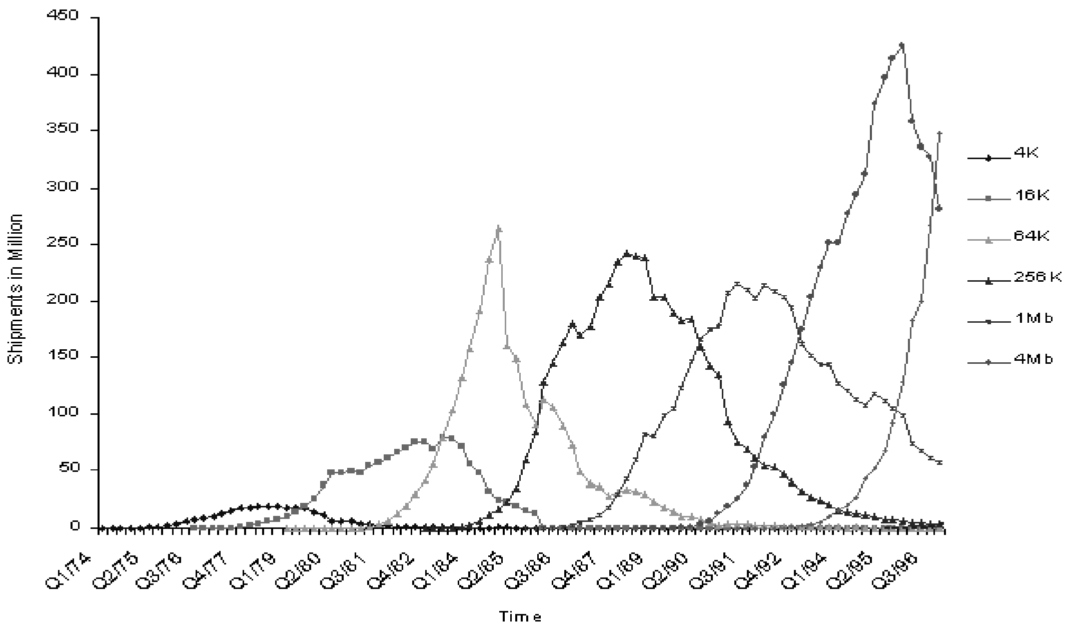

Figure 3: Units of shipments per generation over time (quarterly)

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.

Table 1 gives the firms per generation and provides evidence for an oligopolistic industry structure.[6] 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. Focusing on the 64K chip producers, 15 out of 22 produce the 16K DRAM chip, whereas 19 firms produce the 256K DRAM chip and

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

12 firms produce both neighboring generations.[7]

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

[7]The firm-level shipments of each generation, as well as evidence that multiproduct firms simultaneously produce distinct generations, are provided in the Semiconductor Database Description in Siebert (2000) in Section 8.2.

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%, whereas Flamm (1996) found a learning rate of 38% for the 1Mb chip. 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 in five of seven generations.

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 in the product market.

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 maximize their profit over the entire product life cycle, characterized by T discrete time periods, and take into account the effects on neighboring generations. Moreover, firms consider their current output as investment in the future, because a higher contemporaneous output will lower the unit costs in the future. 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

$$\begin{aligned} X_{i,k,t} &= X_{i,k,t-1} + \sum_{j \neq i} q_{j,k,t-1} \\ X_{k,0} &= 0. \end{aligned}$$

for $i = 1...n$ and $t = 1...T$, where δ is the discount rate and $P_{k,t}$ is the market price for a given generation (k) in period (t). Thus, $P_{k,t} \left(Q_{k-1,t}, Q_{k,t}, Q_{k+1,t} \right)$ represents the inverse demand function. 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 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 costs 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 $\frac{\partial C_{i,k,t}}{\partial X_{i,k,t}} < 0$).

We focus on closed-loop strategies which allow firms to 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.[8]

Firms choose quantities in order to maximize their profit over the entire product life cycle and take into account the intertemporal effects on their unit costs as well as the effects on profits of their neighboring generations. The necessary condition with respect to the quantity of generation k is

[8] Closed-loop equilibrium strategies are subgame perfect. The opponent to a closed-loop strategy is called open-loop strategy. In general, open-loop 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.

$$
\begin{aligned}
\frac{\partial \Pi_i}{\partial q_{i,k,t}} &= P_{k,t} + \frac{\partial Q_{k,t}}{\partial q_{i,k,t}} \left[\frac{\partial P_{k-1,t}}{\partial Q_{k,t}} q_{i,k-1,t} + \frac{\partial P_{k,t}}{\partial Q_{k,t}} q_{i,k,t} + \frac{\partial P_{k+1,t}}{\partial Q_{k,t}} q_{i,k+1,t} \right] - \frac{\partial C_{i,k,t}}{\partial q_{i,k,t}} \\
&\quad + \sum_{s=t+1}^{T} \delta^{s-t} \left\{ \frac{\partial Q_{k,s}}{\partial x_{i,k,s}} \frac{\partial x_{i,k,s}}{\partial q_{i,k,t}} \left(\frac{\partial P_{k-1,s}}{\partial Q_{k,s}} q_{i,k-1,s} + \frac{\partial P_{k,s}}{\partial Q_{k,s}} q_{i,k,s} + \frac{\partial P_{k+1,s}}{\partial Q_{k,s}} q_{i,k+1,s} \right) \right. \\
&\quad - \left(\frac{\partial C_{i,k,s}}{\partial x_{i,k,s}} \frac{\partial x_{i,k,s}}{\partial q_{i,k,t}} + \sum_{j \neq i} \frac{\partial C_{i,k,s}}{\partial X_{i,k,s}} \frac{\partial X_{i,k,s}}{\partial q_{j,k,t}} \frac{\partial q_{j,k,t}}{\partial q_{i,k,t}} + \frac{\partial C_{i,k,s}}{\partial q_{i,k,s}} \frac{\partial q_{i,k,s}}{\partial x_{i,k,s}} \frac{\partial x_{i,k,s}}{\partial q_{i,k,t}} \right) \\
&\quad \left. - \delta \left(\frac{\partial C_{i,k,s+1}}{\partial x_{i,k,s+1}} \frac{\partial x_{i,k,s+1}}{\partial q_{i,k,s}} \frac{\partial q_{i,k,s}}{\partial x_{i,k,s}} \frac{\partial x_{i,k,s}}{\partial q_{i,k,t}} + \sum_{j \neq i} \frac{\partial C_{i,k,s+1}}{\partial X_{i,k,s+1}} \frac{\partial X_{i,k,s+1}}{\partial q_{j,k,s}} \frac{\partial q_{j,k,s}}{\partial x_{i,k,s}} \frac{\partial x_{i,k,s}}{\partial q_{i,k,t}} \right) \right\} \\
&= 0, \qquad (1)
\end{aligned}
$$

for $t < s$. The first line in the first order condition, equation (1), shows firm i's marginal profits in a static environment without LBD. It gives the direct effect of firm i's output choice on its profits. The first terms (except the last term) represents firm i's marginal revenues. The term $\frac{\partial Q_{k,t}}{\partial q_{i,k,t}}$ indicates the conduct parameter introduced by Bresnahan (1989). If firms behave as if in perfect competition $\frac{\partial Q_{k,t}}{\partial q_{i,k,t}}$ is equal to zero, whereas it is supposed to be one when firms behave like Cournot players. A higher conduct parameter indicates a higher chosen price mark-up. In comparing to the standard marginal revenues 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 last term in the first line $\frac{\partial C_{i,k,t}}{\partial q_{i,k,t}}$ represents the common contemporaneous or static marginal costs and indicates how current output affects current costs through ECS.

The following lines show the dynamic link between the firms' current output decisions and the firms' environment they find themselves in the future. This dynamic strategic effect results from learning. The second line shows the interaction between firm i's current output decision and its future revenues, through LBD. The term $\sum_{s=t+1}^{T} \delta^{s-t} \frac{\partial Q_{k,s}}{\partial x_{i,k,s}} \frac{\partial x_{i,k,s}}{\partial q_{i,k,t}}$ indicates an *intertemporal* conduct parameter and shows that firm i's output decision in period t will have an effect on its experience in the next period s, which affects firms' output decisions in period s. The intertemporal reaction impacts firms' revenues in the future and is taken into account in their objective function. The sign of the *intertemporal* conduct parameter is ambiguous and depends on the relative magnitude of the LBD and Spillover effects, see Jarmin (1994). When LBD effects are relatively high compared to Spillover effects, an increase in firm i's output today reduces its marginal costs in the future, which

enlarges the asymmetry between firms' marginal costs in the market and induces the rival firms to reduce output in the future. The current output of firm i ($q_{i,k,t}$) and the rivals' output in the future ($Q_{k,s}$) are strategic substitutes and the *intertemporal* conduct parameter will be negative. When Spillover effects increase $q_{i,k,t}$ may be seen as a strategic complement for the rival's output in the future and the *intertemporal* conduct parameter will be positive. When LBD and Spillover effects are balancing each other or no firm benefits from firm i's experience or when firm i behaves as if it did not the term should be zero.

The last two lines show firms' dynamic marginal costs and illustrate how LBD affects them. The first term $\sum\limits_{s=t+1}^{T} \delta^{s-t}\frac{\partial C_{i,k,s}}{\partial q_{i,k,t}}$ refers to the *current* LBD effect, indicating that the own current output increases own experience in the future and yields further costs savings. If LBD effects are present, the term is expected to be negative. The term $\sum\limits_{s=t+1}^{T}\sum\limits_{j\neq i} \delta^{s-t}\frac{\partial C_{i,k,s}}{\partial X_{i,k,s}}\frac{\partial X_{i,k,s}}{\partial q_{j,k,t}}\frac{\partial q_{j,k,t}}{\partial q_{i,k,t}}$ represents the *current* Spillover effect. Firm i's current output decision will affect the other firms' current output decision which impacts their experience in the future and finally has an effect on firm i's costs in the future, through Spillovers. Because Spillovers yield future cost savings the effect is supposed to have a negative sign.

The expression $\sum\limits_{s=t+1}^{T} \delta^{s-t}\frac{\partial C_{i,k,s}}{\partial q_{i,k,s}}\frac{\partial q_{i,k,s}}{\partial x_{i,k,s}}\frac{\partial x_{i,k,s}}{\partial q_{i,k,t}}$ indicates a cost reduction through *intertemporal* ECS. This effect is a combination of the *current* LBD effect and the *current* ECS effect. A higher current output increases experience which reduces unit costs in the future. As a result, firm i increases its output in the future which reduces current costs in the future.

The last line shows the *intertemporal* learning effects. The first term shows the *intertemporal* LBD effect. Firm i's current output impacts its experience and influences firm i's output decision in the future which affects experience and costs, thereafter. Finally, the last term represents the *intertemporal* Spillover effect, saying that firm i's current output impacts its rivals' future output decisions through Spillovers which has an effect on their experience in the next period, and impacts firm i's costs through Spillovers.
Rearranging equation (1) and setting $\frac{\partial x_{i,k,s}}{\partial q_{i,k,t}} = \frac{\partial x_{i,k,s+1}}{\partial q_{i,k,s}} = \sum\limits_{j\neq i}\frac{\partial X_{i,k,s}}{\partial q_{j,k,t}} = \sum\limits_{j\neq i}\frac{\partial X_{i,k,s+1}}{\partial q_{j,k,s}} = 1$, yields

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

$$+ \sum_{s=t+1}^{T}\delta^{s-t}\left\{\frac{\partial Q_{k,s}}{\partial q_{i,k,t}}\left(\frac{\partial P_{k-1,s}}{\partial Q_{k,s}}q_{i,k-1,s} + \frac{\partial P_{k,s}}{\partial Q_{k,s}}q_{i,k,s} + \frac{\partial P_{k+1,s}}{\partial Q_{k,s}}q_{i,k+1,s}\right)\right\}$$

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

$$\left. + \delta \left(\frac{\partial C_{i,k,s+1}}{\partial x_{i,k,s+1}} \frac{\partial q_{i,k,s}}{\partial q_{i,k,t}} + \sum_{j \neq i} \frac{\partial C_{i,k,s+1}}{\partial X_{i,k,s+1}} \frac{\partial q_{j,k,s}}{\partial q_{i,k,t}} \right) \right\}. \tag{2}$$

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). In order to simplify the following argument and to focus on the main issue, let us assume that neighboring products are substitutes.[9] Firms take into account that a higher output of generation k lowers the prices of the neighboring generations, which impacts revenues. Ceteris paribus, the internalization of these externalities induces firms to reduce their quantities in order to prevent losses on neighboring generations. In the presence of LBD and ECS, the output decisions of multiproduct firms are characterized by a trade-off between increasing the output in order to achieve higher costs reductions through LBD and ECS and decreasing the output because revenues of the neighboring products are negatively affected.[10] However, from an empirical perspective through which output and prices are observed, firms' incentive to reduce output is omitted since the single product firm specification ignores the externalities. Finally, this ignorance leads, in single product models to a lower output incentive which is attributed to the incentive to yield cost reductions, which understates LBD, ECS, and/or Spillover effects. Because these effects are underestimated, firms' dynamic marginal costs are overestimated which consequently understates the margin between prices and dynamic marginal costs.

However, the difference between prices and dynamic marginal costs is not only determined by the nature of the products (whether products are substitutes or complements) but also by firms' conduct in the market. The conduct parameter (shown by $\frac{\partial Q_{k,t}}{\partial q_{i,k,t}}$ in equation (1)) describes firms' contemporaneous output reactions to firm i's output increase. In general, a lower conduct parameter indicates a more 'aggressive' 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 'aggressively' 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.

[9] Note, when the neighboring products are complements the effects will go in the opposite direction.

[10] 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 take account of their neighboring products and may behave more 'softly', 'identically', or more 'aggressively' in the market.

Let us first consider the case of multiproduct firms behaving more 'softly' or 'identically'. It follows from observed output and prices as well as given price effects from the demand equation that the margin between prices and shadow costs is larger for multiproduct firms when neighboring products are substitutes. Marginal shadow costs are lower and LBD, ECS, and/or Spillover effects are higher when multiproduct firms are under investigation.

When firms behave more 'aggressively' in the product market, the implications of the effects under investigation are ambiguous and depend on the relative decrease in the conduct parameter. When firms behave only slightly more 'aggressive' (the conduct parameter decreases only a little), the resulting decline in the price-shadow cost margin will still be overcompensated for by the externality effects. The net effect on the price-shadow cost margin as well as the impact on the LBD, ECS, and Spillover effects are similar to the latter case for multiproduct firms.

However, when the conduct parameter declines more drastically, such that firms behave very 'aggressively' in the market, the externality effect will be overcompensated for by the decline in the conduct parameter. As a result, the price-shadow cost margin becomes smaller and the LBD, ECS, and/or Spillover effects are lower for multiproduct firms than for single product firms.

Furthermore, from the second line in equation (2) we see that the margin between price and shadow costs is also determined by the *intertemporal* marginal revenues consisting of the *intertemporal* conduct parameter and the price effects. The *intertemporal* conduct parameter refers to the firms' output reaction in the future when firm i increases its current output. As mentioned above, the sign depends on the relative magnitude of the LBD and Spillover effects.

When in a multiproduct specification the Spillover effects are relatively smaller than the LBD effect the *intertemporal* conduct parameter will be smaller (more negative) for multiproduct firms. Taking into account that negative price effects enter the intertemporal marginal revenue term in a multiproduct specification, it turns out that the combined effect reduces the price-shadow cost margin for multiproduct firms. As a result, the dynamic marginal costs are supposed to be higher, such that LBD, ECS, and/or Spillover effects are smaller for multiproduct firms.

We can therefore conclude that analyzing multiproduct firms has enormous implications for LBD, ECS, and/or Spillover effects that depend on the nature of the products and changes in firms' conduct, as well as the relative magnitude of the Spillover and LBD effects. We specify the following hypothesis:

(i) When multiproduct firms behave more 'aggressively' in the product market than single product firms, or when Spillover effects are relatively smaller than LBD effects in a multiproduct specification, then LBD, ECS, and/or Spillover effects are smaller for multiproduct firms.

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 marginal costs over time. 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 higher (lower) 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 (2).

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 in the product market. In addition, we investigate how LBD, ECS, and Spillover effects 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. When the behavior of multiproduct firms is more 'aggressive' or when Spillover effects for multiproduct firms are relatively smaller than LBD effects, the internalization of externalities in a multiproduct environment leads to smaller LBD, ECS, and/or Spillover effects, see hypothesis (i). Because LBD, ECS, and/or Spillover effects are expected to be smaller for multiproduct firms, we expect dynamic marginal costs to be higher, which decreases the price-shadow cost margin.

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[11]

$$\begin{aligned} P_{k-1,t} &= a_0 + a_1 * Q_{k-2,t} + a_2 * Q_{k-1,t} + a_3 * Q_{k,t} \\ &\quad + a_4 * t + \varepsilon_{k-1,t} \end{aligned} \tag{3}$$

$$\begin{aligned} P_{k,t} &= b_0 + b_1 * Q_{k-1,t} + b_2 * Q_{k,t} + b_3 * Q_{k+1,t} \\ &\quad + b_4 * t + \mu_{k,t} \end{aligned} \tag{4}$$

$$\begin{aligned} P_{k+1,t} &= c_0 + c_1 * Q_{k,t} + c_2 * Q_{k+1,t} + c_3 * Q_{k+2,t} \\ &\quad + c_4 * t + \omega_{k+1,t}. \end{aligned} \tag{5}$$

[11]The pricing relations are estimated for the 64K DRAM generation (k). Therefore, we must estimate the demand equations for the 64K DRAM generation (k) as well as for the neighboring generations ($k-1$) and ($k+1$), which are the 16K and the 256K DRAM generation, respectively.

For the sake of convenience, let us consider the inverse demand equation (4) only; the same procedure applies to equations (3) and (5). As can be seen in equation (4), the price $P_{k,t}$ depends on the total quantities sold of the generation under consideration ($Q_{k,t}$) and also takes into account the total output of the neighboring 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 negat

$$\frac{\partial C_{i,k,t}}{\partial q_{i,k,t}} = \gamma_{0,i}+\gamma_1 \ln LBD_{i,k,t}+\gamma_2 \left(\ln LBD_{i,k,t}\right)^2+\gamma_3 \ln ILBD_{i,k,t}+\gamma_4 \left(\ln ILBD_{i,k,t}\right)^2$$
$$+\gamma_5 \ln Spill_{i,k,t} + \gamma_6 \left(\ln Spill_{i,k,t}\right)^2 + \gamma_7 \ln ISpill_{i,k,t} + \gamma_8 \left(\ln ISpill_{i,k,t}\right)^2$$
$$+\gamma_9 \ln ECS_{i,k,t} + \gamma_{10} \left(\ln ECS_{i,k,t}\right)^2 + \gamma_{11} \ln IECS_{i,k,t} + \gamma_{12} \left(\ln IECS_{i,k,t}\right)^2$$
$$+\gamma_{13} \ln MAT_t + \gamma_{14} \ln UCC_{i,t} + \gamma_{15} \ln LAB_{i,k,t} + \gamma_{16} \ln E_{i,k,t} + \gamma_{17} \ln FP_{i,k,t}$$
$$+\eta_{i,k,t}$$

where $\gamma_{0,i}$ is positive and represents firm-specific effects that are supposed to capture unobserved heterogeneities.

For the empirical specification of firms' marginal costs we take into account that dynamic effects reduced static marginal costs, through *current* as well as *intertemporal* effects from former periods.

The variables LBD and LBD^2 indicate firms' *current* LBD effects which determine static marginal costs through the firms' own past production; $\ln LBD_{i,k,t}$ 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 $t-1$. LBD^2 tests whether the learning curve has a different slope over the product cycle.

The variables $ILBD$ and $ILBD^2$ indicate firms' *intertemporal* LBD effects which occur through intertemporal output reactions in the past. *Intertemporal* LBD effects result from the *current* LBD effects the firms achieved in the former period $t-1$ which impact firms' output decisions in period $t-1$ and finally determine the accumulated past production in period t; $\ln ILBD_{i,k,t}$ measures each 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 $t-2$. $ILBD^2$ is the squared expression of $ILBD$ and captures the variation over the product cycle.

The overall LBD elasticity is the combined effect of the *current* and the *intertemporal* LBD elasticities, given by $\left(\gamma_1 + \gamma_2 \overline{\ln LBD_k} + \gamma_3 + \gamma_4 \overline{\ln ILBD_k}\right) / \overline{\frac{\partial C_k}{\partial q_k}}$ (a bar indicates the average of the corresponding variable over time). The overall elasticity is expected to have a negative sign since a higher degree of experience is supposed to reduce marginal costs. The sign of the parameters $\gamma_2 + \gamma_4$ indicates whether the LBD curve is concave or convex and tells us whether the LBD effects are greater at the beginning or the end of the life cycle. A positive (negative) sign shows that the learning effects are higher (lower) at the beginning of the life cycle.

The variables $Spill$ and $Spill^2$ measure the *current* LBD effect that firms gain from the rivals' experience through Spillovers; $\ln ISpill_{i,k,t}$ represents the logarithm of the accumulated past production of all other firms for generation k until period $t-1$. $Spill^2$ tests if the learning curve, influenced by Spillovers, has a different slope over the product cycle.

The variables $ISpill$ and $ISpill^2$ measure the *intertemporal* LBD effect that firm i gains from the rivals' experience through Spillovers and initiated by its own output

decision in period $t-2$. The variable $ISpill$ represents the logarithm of its production in period $t-2$. $ISpill^2$ gives information if Spillovers affect firms' learning curve differently over the product cycle.

The overall Spillover effect is given by $\left(\gamma_5 + \gamma_6 \overline{\ln Spill_k} + \gamma_7 + \gamma_8 \overline{\ln ISpill_k}\right) \diagup \overline{\frac{\partial C_k}{\partial q_k}}$. The sign of $\gamma_6 + \gamma_8$ is positive (negative) if firm i is able to benefit more from others' experience at the beginning (end) of the life cycle.

The *current* ECS effects are measured by the variables ECS and ECS^2, which are constructed by using the logarithm of firms' current output of generation k in period t.

The variables $IECS$ and $IECS^2$ indicate firms' *intertemporal* ECS effects. They are constructed by using firms' output in generation k in period $t-1$.

The overall ECS effect is given by the expression $\left(\gamma_9 + \gamma_{10} \overline{\ln ECS_k} + \gamma_{11} + \gamma_{12} \overline{\ln IECS_k}\right) \diagup \overline{\frac{\partial C_k}{\partial q_k}}$. The sign is expected to be negative, zero, or positive when increasing, constant, or decreasing returns are prevalent. The squared expressions ECS^2 and $IECS^2$ capture varying ECS effects over the product life cycle.

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 costs 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.

As mentioned above dynamic marginal costs also induces a dynamic aspect which yield future costs reduction. For that reason we must account for the fact that firms price below their static marginal costs in order to achieve future costs reductions.

In order to enable the estimation procedure, we capture the future effects in firm-specific constants as set out in Roberts and Samuelson (1988) and Jarmin (1994).[13]

$$\begin{aligned}\lambda_{0,i} &= \sum_{u=t+2}^{T} \delta^{s-u} \left\{ \frac{\partial Q_{k,u}}{\partial q_{i,k,t}} \left(\frac{\partial P_{k-1,u}}{\partial Q_{k,u}} q_{i,k-1,u} + \frac{\partial P_{k,u}}{\partial Q_{k,u}} q_{i,k,u} + \frac{\partial P_{k+1,u}}{\partial Q_{k,u}} q_{i,k+1,u} \right) \right. \\ &\quad - \sum_{s=t+1}^{T} \delta^{s-t} \left[\frac{\partial C_{i,k,s}}{\partial q_{i,k,t}} + \sum_{j\neq i} \frac{\partial C_{i,k,s}}{\partial X_{i,k,s}} \frac{\partial q_{j,k,t}}{\partial q_{i,k,t}} + \frac{\partial C_{i,k,s}}{\partial q_{i,k,s}} \frac{\partial q_{i,k,s}}{\partial q_{i,k,t}} \right. \\ &\quad \left. \left. + \delta \frac{\partial C_{i,k,s+1}}{\partial x_{i,k,s+1}} \frac{\partial q_{i,k,s}}{\partial q_{i,k,t}} + \delta \sum_{j\neq i} \frac{\partial C_{i,k,s+1}}{\partial X_{i,k,s+1}} \frac{\partial q_{j,k,s}}{\partial q_{i,k,t}} \right] \right\}.\end{aligned}$$

The sign of λ is ambiguous. Current output decisions yield future costs savings which requires a negative sign. However, intertemporal output reactions like $\frac{\partial Q_{k,u}}{\partial q_{i,k,t}}$ may have a positive or negative sign, depending on the strategic nature of the products and the relative magnitude of the Spillover and LBD effects, as mentioned in the theoretical part.

Inserting the static marginal costs function and the dynamic effects into the first order condition (equation (2)) of the theoretical model and solving for the price P gives the pricing relation.

Multiproduct Firm Specification

The pricing relation for the multiproduct firm specification is given in the following form[14]

$$\begin{aligned}P_{k,t} = {} & \beta_{0,i} + \beta_1 \ln LBD_{i,k,t} + \beta_2 (\ln LBD_{i,k,t})^2 + \beta_3 \ln ILBD_{i,k,t} + \beta_4 (\ln ILBD_{i,k,t})^2 \\ & + \beta_5 \ln Spill_{i,k,t} + \beta_6 (\ln Spill_{i,k,t})^2 + \beta_7 \ln ISpill_{i,k,t} + \beta_8 (\ln ISpill_{i,k,t})^2 \\ & + \beta_9 \ln ECS_{i,k,t} + \beta_{10} (\ln ECS_{i,k,t})^2 + \beta_{11} \ln IECS_{i,k,t} + \beta_{12} (\ln IECS_{i,k,t})^2 \\ & + \beta_{13} \ln MAT_t + \beta_{14} \ln UCC_{i,t} + \beta_{15} \ln LAB_{i,k,t} + \beta_{16} \ln E_{i,k,t} + \beta_{17} \ln FP_{i,k,t} \\ & - \beta_{18} COND^M_{i,k,t} - \beta_{19} ICOND^M_{i,k,t} + \omega_{i,k,t}. \qquad (6)\end{aligned}$$

The parameter $\beta_{0,i}$ is a composite of several firm-specific constants given by $\beta_{0,i} = \gamma_{0,i} + \lambda_{0,i}$, whereby the sign of the composite can be positive or negative. The

[13] Note that the marginal revenues for period $t+1$ enter the pricing relation directly in order to get an estimate for the *intertemporal* conduct parameter $\frac{\partial Q_{k,t+1}}{\partial q_{i,k,t}}$.

[14] 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 setting the parameter for the remaining factor prices $ß_{17} = 1 - \sum_{\beta_0}^{\beta_{16}}$.

parameter β_{18} represents the conduct parameter for the multiproduct specification, given by $\frac{\partial Q_{k,t}}{\partial q_{i,k,t}}$ in the first order condition, equation (2) where $COND^M_{i,k,t}$ represents the expression $\left[\frac{\partial P_{k-1,t}}{\partial Q_{k,t}} q_{i,k-1,t} + \frac{\partial P_{k,t}}{\partial Q_{k,t}} q_{i,k,t} + \frac{\partial P_{k+1,t}}{\partial Q_{k,t}} q_{i,k+1,t}\right]$. The parameter β_{19} represents the *intertemporal* conduct parameter given by $\frac{\partial Q_{k,s}}{\partial q_{i,k,t}}$ in the first order condition, equation (2). The variable $ICOND^M_{i,k,t}$ represents the expression, $\delta\left[\frac{\partial P_{k-1,t+1}}{\partial Q_{k,+1}} q_{i,k-1,t+1} + \frac{\partial P_{k,t+1}}{\partial Q_{k,t+1}} q_{i,k,t+1} + \frac{\partial P_{k+1,t+1}}{\partial Q_{k,t+1}} q_{i,k+1,t+1}\right]$, where the discount factor δ is set equal to 0.9. We use the estimated parameters $\widehat{a_3}$, $\widehat{b_2}$ and $\widehat{c_1}$ from the demand equation for the price effects $\frac{\partial P_{k-1,v}}{\partial Q_{k,v}}$, $\frac{\partial P_{k,v}}{\partial Q_{k,v}}$, and $\frac{\partial P_{k+1,v}}{\partial Q_{k,v}}$ for $v = t, t+1$. Because firms' output is endogenously chosen we use instruments for the LBD, $ILBD$, ECS, $IECS$, $COND$ and $ICOND$ variables. As instruments we use the number of firms, NOF, the average market shares, AMS, of the current (k) and the neighboring generations ($k-1$, and $k+1$), the GDP in electronics $GDPEL$, and all other exogenous variables from the equation. We assume additive econometric disturbance terms, which are identically distributed with mean zero and variance Φ. The pricing relation is estimated by using 2-stage least squares.

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[15]

$$\begin{aligned}
P_{k,t} = {} & \delta_{0,i} + \delta_1 \ln LBD_{i,k,t} + \delta_2 \left(\ln LBD_{i,k,t}\right)^2 + \delta_3 \ln ILBD_{i,k,t} + \delta_4 \left(\ln ILBD_{i,k,t}\right)^2 \\
& + \delta_5 \ln Spill_{i,k,t} + \delta_6 \left(\ln Spill_{i,k,t}\right)^2 + \delta_7 \ln ISpill_{i,k,t} + \delta_8 \left(\ln ISpill_{i,k,t}\right)^2 \\
& + \delta_9 \ln ECS_{i,k,t} + \delta_{10} \left(\ln ECS_{i,k,t}\right)^2 + \delta_{11} \ln IECS_{i,k,t} + \delta_{12} \left(\ln IECS_{i,k,t}\right)^2 \\
& + \delta_{13} \ln MAT_t + \delta_{14} \ln UCC_{i,t} + \delta_{15} \ln LAB_{i,k,t} + \delta_{16} \ln E_{i,k,t} + \delta_{17} \ln FP_{i,k,t} \\
& - \delta_{18} COND^S_{i,k,t} - \delta_{19} ICOND^S_{i,k,t} + \psi_{i,k,t}. \qquad (7)
\end{aligned}$$

The parameter δ_{18} represents the conduct parameter given by $\frac{\partial Q_{k,t}}{\partial q_{i,k,t}}$ for the single product firm specification where the variable $COND^S_{i,k,t}$ represents the expression $\left[\frac{\partial P_{k,t}}{\partial Q_{k,t}} q_{i,k,t}\right]$ from equation (2). The parameter δ_{19} represents the *intertemporal* conduct parameter. The variable $ICOND^S_{i,k,t}$ represents the expression $\delta\left[\frac{\partial P_{k,t+1}}{\partial Q_{k,t+1}} q_{i,k,t+1}\right]$, with $\delta = 0.9$. Because the difference between the single product and multiproduct specification is given in that cross-price effects do not enter the pricing relation in

[15]Note that we impose the same restriction as for the multiproduct specification on the cost parameters, which is given by $\delta_{17} = 1 - \sum_{\delta_0}^{\delta_{16}}$.

a single product specification, we only have to substitute the own-price effect $\frac{\partial P_{k,v}}{\partial Q_{k,v}}$ for $v = t, t+1$ with the estimated parameter $\widehat{b_2}$ from the demand equation. The estimation procedure as well as the instruments are the same as for the multiproduct firm specification.

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 shown in Table 2.

Variables	Description	N	Median	Min.	Max.
$P_{k,t}$	Average selling price of one chip of generation k in period t.	68	1.49	0.75	135.00
$Q_{k-1,t}$	Total number of chips of the k-1'th generation being sold in period t.	68	0.00	0.00	78.54E+06
$Q_{k,t}$	Total number of chips of the k'th generation being sold in period t.	68	70.86E+05	3000	26.44E+07
$Q_{k+1,t}$	Total number of chips of the k+1'st generation being sold in period t.	68	23.52E+06	0	24.24E+07
t	Time trend.	68	13.63	5.25	22.00
$P_{k,t}$	Average selling price of k in period t.	546	1.47	0.75	100.00
$\ln LBD_{i,k,t}$	LBD for firm i offering generation k in period t.	546	18.01	8.70	19.62
$\ln ILBD_{i,k,t}$	Intertemporal LBD for firm i offering generation k in period t.	546	14.22	6.91	17.27
$\ln Spill_{i,k,t}$	Spillover measure for firm i offering generation k in period t.	546	21.36	9.55	21.66
$\ln ISpill_{i,k,t}$	Intertemp. Spillover measure for firm i offering generation k in period t.	546	21.30	8.70	21.66
$\ln ECS_{i,k,t}$	Measure of ECS for firm i offering generation k in period t.	546	14.22	8.52	17.27
$\ln IECS_{i,k,t}$	Measure of intertemp. ECS for firm i offering generation k in period t.	546	14.22	6.91	17.27
$\ln MAT_t$	Logarithm of material costs in period t.	546	8.49	2.27	16.74

(Table continues)

Variables	Description	N	Median	Min.	Max.
$\ln UCC_{i,t}$	Logarithm of firm i's User Cost of Capital in period t.	546	-2.38	-4.61	-0.69
$\ln LAB_{i,k,t}$	Logarithm of firm i's Labor Cost for generation k in period t.	546	14.56	1.39	24.69
$\ln E_{i,k,t}$	Logarithm of firm i's Energy Cost for generation k in period t.	546	2.20	-5.71	15.84
$q_{i,k-1,t}$	Firm i's number of chips from the k-1'st generation being sold in period t.	546	0	0	123E+05
$q_{i,k,t}$	Firm i's number of chips of the k'th generation being sold in period t.	546	15E+05	5000	315E+05
$q_{i,k+1,t}$	Firm i's number of chips of the k+1'st generation being sold in period t.	546	15E+05	0	39E+06
$GDPEL_t$	GDP in electronics in period t.	546	1.24E+13	1.68E+12	2.63E+16
$NOF_{k,t}$	Number of firms competing in the market of generation k at period t.	546	9.5	0	20
$AMS_{k,t}$	Average market share of firms in generation k at period t.	546	0.05	6E-05	1

Table 2: Variable definitions and summary statistics

7 Results

The estimation results of the inverse demand equations (3), (4), and (5) are presented in Table 3. For the estimation procedure of the three demand equations for generations $k-1$, k, and $k+1$, 38, 68, and 57 observations could be used, respectively. All three estimations have a remarkably good fit. The adjusted R-squares are 0.64 and higher. All estimates but one 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 time trend is negative, which is a plausible outcome, for consumers substitute away from the generation as time passes.

GMM Estimates for						
	16K Generation		64K Generation		256K Generation	
Variables	Estimates	Std. Err.	Estimates	Std. Err.	Estimates	Std. Err.
Constant	92.68**	10.98	142.01**	21.23	222.08**	25.02
Q_{k-2}	-3.06E-6**	5.72E-7	-		-	-
Q_{k-1}	-3.94E-7**	9.67E-8	-7.19E-7**	2.16E-7	-	-
Q_k	-7.89E-8	7.65E-8	-2.91E-7**	4.14E-8	-5.90E-7**	1.17E-7
Q_{k+1}	-	-	-1.78E-7**	4.07E-8	-2.81E-7**	3.15E-8
Q_{k+1}	-	-	-	-	-1.32E-7**	5.73E-8
t	-6.07**	1.45	-6.73**	0.99	-9.49**	0.94
	Obs.=38, adj. R^2=0.64		Obs.=68, adj. R^2=0.73		Obs.=57, adj. R^2=0.70	

**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 that the residuals are positively correlated, which we corrected for by applying a first order moving average process.[16] The estimates are given in Table 4. In both regressions, 526 observations could be used. Both estimations have a very good fit. The adjusted R-squares for the multiproduct and the single product specification are 0.75 and 0.77. The autocorrelation tests of 1.89 and 1.91 show that no further serial correlation exists. Most of the parameter estimates are significant at the 1% level. From the estimates of the pricing relations, we were able to test the two hypotheses.

[16] Because of the panel data structure the first observation for every firm must be dropped for the correction procedure.

	Multiproduct Comp.		Single-Product Comp.	
Variables	Estimates	Std. Err.	Estimates	Std. Err.
LBD	66.06**	8.38	47.01**	8.67
LBD^2	-2.65**	0.31	-1.96**	0.32
$ILBD$	-46.61**	7.23	-34.39**	7.21
$ILBD^2$	1.99**	0.28	1.51**	0.28
$Spill$	11.37**	2.19	-15.18**	6.29
$Spill^2$	-0.25**	0.06	0.37**	0.15
$ISpill$	-2.08	2.20	-0.91	2.11
$ISpill^2$	0.08	0.09	0.05	0.08
ECS	7.69**	2.16	13.79**	2.32
ECS^2	-0.33**	0.08	-0.60**	0.09
$IECS$	-9.14**	2.95	-4.52*	2.97
$IECS^2$	0.37**	0.11	0.21*	0.11
MAT	0.03	0.09	0.003	0.08
UCC	0.20	0.28	0.21	0.26
LAB	0.10	0.07	0.07	0.07
E	-0.02	0.05	-0.004	0.05
$COND^{M,S}$	0.15	0.10	1.81**	0.35
$ICOND^{M,S}$	0.01	0.11	0.05	0.28
$\beta_{0,1}$	-3.51*	1.81	-3.11*	1.73
$\beta_{0,2}$	-6.63*	3.35	-6.31*	3.21
$\beta_{0,3}$	-3.43**	1.07	-1.99*	1.05
$\beta_{0,4}$	-5.88**	1.79	-5.04**	1.70
$\beta_{0,5}$	-2.65*	1.66	-1.66	1.59
$\beta_{0,6}$	-6.73**	1.82	-6.20**	1.74
$\beta_{0,7}$	5.79**	1.73	7.18**	1.75
$\beta_{0,8}$	2.29	1.53	3.68*	1.54
$\beta_{0,9}$	1.39	1.72	3.23*	1.70
$\beta_{0,10}$	-2.35**	1.33	-0.59	1.29
$\beta_{0,11}$	-2.56*	1.17	-1.56	1.11
$\beta_{0,12}$	1.06	1.05	2.38*	1.06
$\beta_{0,13}$	1.40	1.47	2.80*	1.50
$\beta_{0,14}$	-5.08	3.89	-7.16*	3.77
$\beta_{0,15}$	2.61	2.53	6.43*	2.33
$\beta_{0,16}$	0.73	1.21	2.05*	1.21

(Table continues)

Variables	Multiproduct Comp. Estimates	Std. Err.	Single-Product Comp. Estimates	Std. Err.
$\beta_{0,17}$	-1.61	4.05	-2.54	3.95
$\beta_{0,18}$	-0.91	0.94	0.17	0.87
$\beta_{0,19}$	0.50	1.29	2.01	1.30
$\beta_{0,20}$	-0.23	1.15	1.58	1.16
$MA(1)$	-0.56**	0.04	-0.56**	0.04
	Obs.=526, adj. R^2=0.75, DW=1.89		Obs.526, adj. R^2=0.77, DW=1.91	

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

Table 4: Pricing relation

The parameter estimates of the *current* LBD variables LBD and LBD^2 as well as the *intertemporal* LBD variables $ILBD$ and $ILBD^2$ are highly significant for the multiproduct and the single product specification. In general, we find evidence that a higher degree of past experience reduces marginal costs in both specifications. Table 5 shows the calculated learning elasticities and learning rates for both model specifications.[17] The learning elasticity for the multiproduct (single product) specification is -1.28 (-1.15) which corresponds to a 58% (55%) learning rate. As can be seen, the LBD effects for multiproduct firms are slightly higher than those for single product firms. A doubling in firm's accumulated output (at the sample mean) reduces the marginal costs by more than 50%. We find that the learning effects are about double as high as in the previous literature. At first glance, the learning effects seem to be incredible high. However, keeping in mind that the learning effect refers to a firm's accumulated past output which is on average 43 times higher than its current output, a doubling of its current output reduces marginal costs by around 1.3% through learning, which is a very reasonable number.

Turning to the parameter estimates of the *current* and *intertemporal* Spillover effects measured by the variables $Spill$, $Spill^2$, $ISpill$,and $ISpill^2$, we find that *current* Spillover effects are highly significant in both models, whereas *intertemporal* Spillover effects are not. However, Table 5 shows that the learning elasticity is positive for the multiproduct specification corresponding to non-existing Spillover effects. For the single product model the learning rate through Spillovers is 6.7%. However, because the accumulated past output of the total number of firms is referred to the Spillover effect (see $\sum\limits_{j\neq i} \frac{\partial C_{i,k,s}}{\partial X_{i,k,s}} \frac{\partial q_{j,k,t}}{\partial q_{i,k,t}}$ in equation (2)) we have to divide the Learning Rate of 6.7% by the average number of firms in the market, which is 7.9. A doubling in output decreases marginal costs by 0.85% through Spillovers. Comparing the Spillover with the LBD effects for single product firms, we see that own experience reduces costs to a higher extent (1.28%) than rivals' experience through Spillovers (0.85%).

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

The results show that the costs reduction obtained through Spillovers is a significant factor in a single product specification, but has no cost-reducing effect for multiproduct firms. Single product firms achieve higher Spillover effects than multiproduct firms, which supports hypothesis (i).

The parameter estimates for the *current* ECS measured by ECS and ECS^2, as well as the estimates for *intertemporal* ECS effects, given by $IECS$ and $IECS^2$, are shown to be significant in both models. Table 5 shows that the overall ECS elasticity is negative in both specifications indicating that increasing returns to scale are evident. Moreover, we see that the elasticity for the multiproduct firm specification is -0.11, indicating that a doubling in output decreases marginal costs by 11%. The elasticity of -0.55 for the single product model shows that the ECS are higher compared to the multiproduct specification, which supports hypothesis (i). Furthermore, we see that *current* and *intertemporal* ECS have a much higher costs-reducing impact than LBD or Spillover effects. Note, also that the *intertemporal* ECS effect is a combination of *current* ECS and LBD effects, which has a highly costs-reducing impact.

Comparing the LBD, Spillover and ECS effects under both specifications we find strong support for the contention that ECS and Spillover effects are different for single and multiproduct firms. Whereas ECS and Spillover effects are smaller for multiproduct firms than for single product firms, LBD effects are slightly higher. We provide evidence that the omitted quantity reduction results in overestimated Spillover and ECS effects in a single product specification, see hypothesis (i). The LBD effects are rather similar under both specifications. In general, the learning and ECS rates indicate that the model specifications support reliable results.

	Multiproduct Comp.		Single-Product Comp.	
Effects	Elast.	Rate	Elast.	Rate
LBD	-1.28	58% (1.35%)	-1.15	55% (1.28%)
$Spill$	1.56	/	-0.1	6.7% or 0.85%
ECS	-0.11	11%	-0.55	55%

Table 5: LBD, Spillover and ECS effects

Table 4 also shows the estimates for the *current* conduct parameters $COND^{M,S}$ for the multiproduct and single product specification. As we see in Table 4 the conduct parameter for the multiproduct model is close to zero, indicating that multiproduct firms charge prices close to static marginal costs and behave as if in perfect competition. The parameter estimate for the single product model indicates that firms charge higher price mark-ups than Cournot players. This result is consistent with the previous literature indicating that the model specification gives reliable results. Moreover, the comparison of the conduct parameters is very important for

our model specification and supports the claim that a different model specification describes firms' behavior in the market differently. We therefore gain support for hypothesis (i) that multiproduct firms behave more 'aggressively' than do single product firms.

Furthermore, we see in Table 4 that the *intertemporal* conduct parameter $ICOND^{M,S}$ is not significantly different from zero under both model specifications. Since we know that the *intertemporal* LBD and ECS effects are significant we can exclude the argument that the *intertemporal* conduct parameter may not be important because firm i's output decision in period t may have no effect on other firms' output decisions in period s. As mentioned above, when Spillover and LBD effects are balancing each other the *intertemporal* conduct parameter is zero.

In a next step, we calculated the fitted average firm-specific price-marginal shadow costs margins for the multiproduct and the single product specification.

Country	Firms	Price-Cost* Margin in Multiproduct Comp.	Price-Cost* Margin in Single Product Comp.
USA	Adv. Micro Dev.	0.10	0.65
	Fairchild	0.43	0.40
	Inmos	0.19	0.99
	Intel	0.22	0.65
	Micron	0.75	1.69
	Mosel Vitelic	0.40	0.42
	Ntl. Semiconductor	0.10	0.73
	STC	0.04	0.21
	Texas Instruments	1.02	2.92
	Mean	**0.36**	**0.96**
JAP	Fujitsu	0.84	3.23
	Hitachi	1.55	4.93
	Matsushita	0.36	1.10
	Mitsubishi	1.40	4.41
	NEC	3.20	2.31
	OKI	0.74	1.63
	Sharp	0.15	0.27
	Toshiba	0.02	0.85
	Mean	**1.03**	**2.34**
KOR	Hyundai	0.39	0.02
	Samsung	1.06	2.17
	Mean	**0.73**	**1.10**
GER	Siemens	0.31	1.40
	Mean	**0.31**	**1.40**

* the costs refer to the marginal shadow costs.

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

Table 6 shows that firms' price-costs margins are indeed lower for multiproduct firms than for single product firms. Because prices are observed in the market, marginal shadow costs are higher for multiproduct than for single product firms. This result supports the finding that multiproduct firms behave more 'aggressively' in the market and achieve lower learning effects. Keep in mind, that the *intertemporal* ECS effect, which is a combination of the LBD effect and the *current* ECS effect, is much smaller for multiproduct firms.

Turning to our hypothesis (*ii*), we see that the parameter estimates for LBD^2 and $ILBD^2$ are significantly different from zero in both models, indicating that LBD effects are different over the product life cycle, which confirms our hypothesis. The negative signs show that LBD effects are smaller at the beginning of the life cycle, an outcome that runs contrary to previous assumptions.

The parameter estimates of ECS^2 and $lECS^2$ indicate that the increasing ECS effects diminish throughout the product life cycle in the multiproduct model, but increase over time in a single product model. Finally, the parameter estimate of $Spill^2$ shows that *current* Spillover effects vary over the product life cycle in both models. The Spillover effects are larger at the beginning of the life cycle for single product firms.

We find evidence for our hypothesis (*ii*) that LBD, Spillover, and ECS effects vary throughout the product life cycle. In the multiproduct model the LBD and Spillover effects become larger whereas the ECS effects become smaller throughout the product life cycle.

Most of the estimated firm-specific effects are negatively significant, indicating that unobserved heterogeneities among firms and shadow marginal cost pricing are important aspects. Firm-specific effects are shown to be significantly different from each other. The parameter estimates for material prices, user costs of capital, and labor are positive but not highly significant. The estimates for energy is negative but not significant. We find support to the argument that marginal costs are significantly determined by LBD, Spillover, and ECS effects but not as much by factor prices.

8 Conclusion

In this study, we derive a dynamic oligopoly model and compare a multiproduct with a single product firm specification. In the theoretical model we show that cross-price 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 empirically estimate and compare the impact of the different specifications on *current* and *intertemporal* LBD, ECS, and Spillover effects, as well as on firms' behavior in the product market. We then compare the firm specific price-cost margins for multiproduct and single product firms. Furthermore, we allow the effects to vary over the product life cycle. We find that these 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.

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, LBD, ECS, and Spillover effects as well as firms' behavior in the product market and their price–cost margins yield different results. We provide evidence for our hypothesis (i) that ECS and Spillover effects are overestimated when assuming single product firms. LBD effects are slightlyects multdregycycouyyznderryonymmtSymeyyssyameyz,ysmFinyzthayzcty

the end of the life cycle. One reason might be that new processes and technologies are developed over time, which induces more intensive costs savings at the end of the generation. It is often argued in the literature that process innovations can be carried over to the next generation, which is characterized by intergenerational Spillovers, see Irwin and Klenow (1994). This fact explains why firms produce new technologies mainly at the end of the life cycle and keep staying in the market, despite their small chosen price-cost mark-ups.

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).

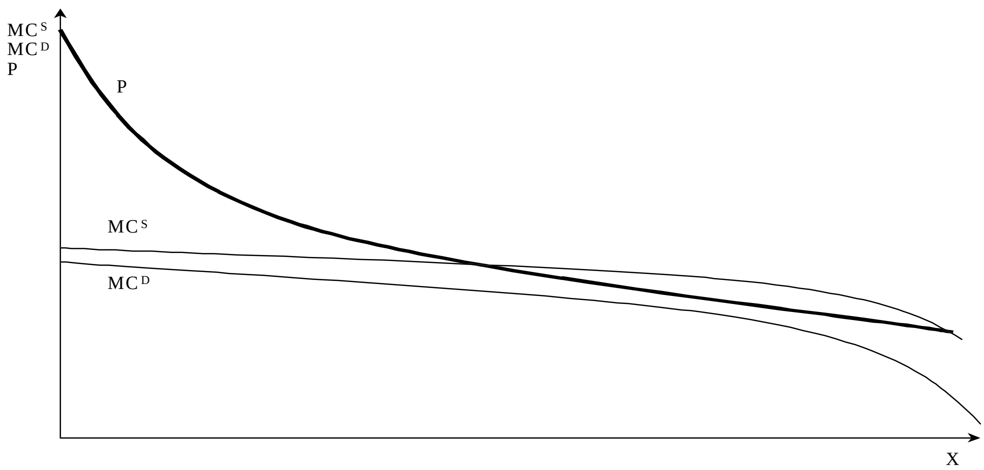

Figure 4: Price setting with respect to shadow marginal costs

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

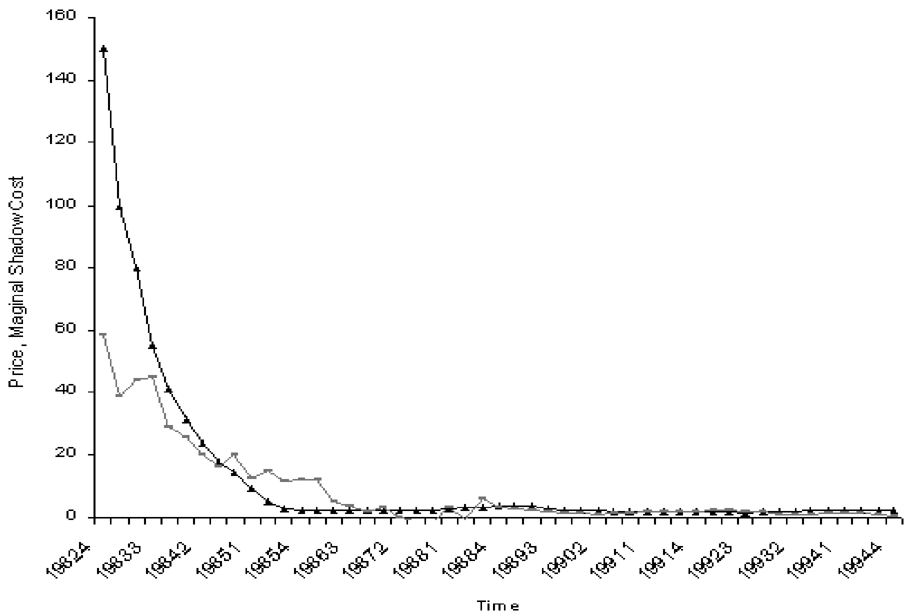

Figure 5: Quarterly prices versus marginal shadow costs over time

This study suggests that Japanese firms did not engage in dumping with regard to the 64K 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-costs 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 (when the investigation took place) 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 (or even negative) 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]) illustrates quite clearly the finding of marginal shadow cost pricing, which is again consistent with the findings of this study.

We can conclude that both the existence of multiproduct firms and the dynamics over the product life cycle have important implications for LBD, ECS, and Spillover effects, as well as firms' behavior in the market. 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 firms' behavior in the product market. This study demonstrates the importance of adjusting for these two aspects in future antitrust investigations.

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