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ABSTRACT

Testing Dynamic Oligopolistic Interaction: Evidence from the Semiconductor Industry

by Christine Zulehner*

This paper analyzes the impact of a dynamic specification on the estimation of the conduct parameter in an oligopolistic market. Various empirical studies have shown that in the semiconductor industry, in particular in the Dynamic Random Access Memory (DRAM) market, one has to account for dynamic elements as learning-by-doing within firms and learning spillovers among them. Therefore this market seems to be appropriate to investigate whether firms behave strategically in a dynamic sense and how open-loop or closed-loop as equilibrium concepts alter the size of the estimated parameters. I apply a structural oligopolistic model of dynamic nonprice competition that incorporates learning-by-doing and spillovers. Theory shows that learning-by-doing and learning spillovers have important consequences for firm behavior. Whether firms in the DRAM industry take the strategic effects of learning-by-doing and learning spillovers actually into account when choosing their output strategies, is answered with empirical evidence. Using quarterly data from 1974-1996 at the firm level, I estimate demand and pricing relations for three different generations of DRAM chips. The empirical results show that the game theoretic specification has an important impact and that firms behave strategically. The assumption of an open-loop specification would underestimate the conduct parameter on average about 50%.

Keywords: Oligopoly, dynamic games, semiconductor industry
JEL Classifications: L13, L63, C73

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ZUSAMMENFASSUNG

Testen dynamischer oligopolistischer Interaktion: Empirische Evidenz aus der Halbleiterindustrie

In diesem Arbeitspapier wird der Einfluß einer dynamischen Spezifikation auf die Schätzung des Verhaltensparameters in einem oligopolistischen Marktes untersucht. Verschiedene empirische Studien haben gezeigt, daß die Halbleiterindustrie, im speziellen der Dynamic Random Access Memory (DRAM) Markt, von dynamischen Elementen wie Learning-by-doing in Unternehmen und Learning spillovers zwischen Unternehmen geprägt ist. Das wirft die Frage auf, ob sich Unternehmen in einem dynamischen Sinne strategisch verhalten und wie open-loop beziehungsweise closed-loop als Gleichgewichtskonzepte die Größe der geschätzten Parameter verändern. In diesem Papier wird ein strukturelles oligopolistisches Modell in einem dynamischen Kontext betrachtet, indem Unternehmen Mengen setzten und Learning-by-doing und Learning spillovers relevant sind. Die Theorie zeigt, daß Learning-by-doing und Learning spillovers wichtige Konsequenzen für das Verhalten von Unternehmen haben. Ob die Unternehmen in der DRAM Industrie tatsächlich die strategischen Effekte aus Learning-by-doing und Learning spillovers in Betracht ziehen, wird auf empirische Weise versucht zu beantworten. Unter der Verwendung vierteljährlicher firmenspezifischer Daten der Jahre 1974-1996 werden die Nachfrage- und die Angebotsgleichung für drei Generationen von DRAMs geschätzt. Die Schätzergebnisse zeigen, daß die spieltheoretische Spezifikation einen wichtigen Einfluß hat und daß sich Unternehmen strategisch in einem dynamischen Sinne verhalten. So unterschätzt die Annahme einer open-loop Gleichgewichtslösung den Verhaltensparameter im Durchschnitt um 50% unterschätzen.

1 Introduction

In studying repeated games strategies are considered in which past play influences current and future strategies. Usually economists focus their attention on equilibria in a smaller class of Markov or state-space strategies. In this case the past influences the current play only through its effect on a state variable that summerizes the direct effect of the past on the current enviroment. There are two strategy concepts. Firms either use open-loop or closed-loop strategies. The terms open-loop and closed-loop are used to distinguish between two different information structures in multi-stage games. Open-loop strategies are functions of calendar time only. In an open-loop equilibrium players simultaneously commit themselves to entire paths of history. In a closed-loop information structure players can condition their play on the history of the game. The term closed-loop equilibrium usually means subgame-perfect equilibrium of the game, where players can observe and respond to their opponents' actions at the end of each period. Closed-loop strategies consider the state-space variable(s) as a strategic variable(s).

The objective of this paper is first to empirically investigate whether firms act strategically, in the sense of using closed-loop strategies, when they formulate their output strategies. And if they do, what is the sign of this strategic effect. Do firms consider future output of other firms as strategic substitutes or as strategic complements. The second issue of this paper is to analyze how the different equilibrium concepts in state-space games influence the estimated parameters in a structural model of dynamic quantity competition. The industry, I concentrate on, is the semiconductor industry, in particular the Dynamic Random Access Memory (DRAM) market. DRAMs are memory components (chips) and are classified into generation. Various empirical papers have shown, that in this industry one has to account for dynamic elements like learning-by-doing within firms and learning spillovers among firms (see e.g. Irwin and Klenow [13], Gruber [10], Briest and Wilson [4] and Siebert [19]). Therefore this market seems to be appropriate to investigate whether firms behave strategically in a dynamic sense and how open-loop or closed-loop as equilibrium concepts alter the size of the estimated parameters, where the main point of interest lies on cost-price margins. Another reason why I direct my attention to that particular industry is, that semiconductors are an important input to several high-technology industries. And DRAMs are usually thought of as technology drivers.

In learning-by-doing models firms learn either from their own experience, from the experience of other firms, or both. Learning-by-doing introduces an intertemporal component to firms decisions. Under the assumption that an appropriate measure of experience is past cumulative output, current production adds to the firm's stock of experience. Increases in the firm's stock of experience reduce firm's unit costs in future periods. Theoretical research demonstrate that learning can have sizable impact on cost and strategic decisions and market performance (e.g. Spence [20], Fudenberg and Tirole [7]). If the firm's experience is completely proprietary, its optimal strategy is to overproduce in early periods in order to invest in future cost reduction. Incumbent firms can exploit the learning curve and will have an absolute cost advantage over potential entrants. Thus entry barriers can be erected. However, if there are spillovers among firms the incentives for overproducing diminish.

A lot of empirical studies have been made for the DRAM market. Most of the papers investigate, whether learning-by-doing and spillovers are prevalent in that industry and when yes, how large are these effects. The different setups vary to certain degree. Baldwin and Krugman [1] did a simulation study for the 16K generation and this was the pioneering attempt to incorporate learning economies into a stylized empirical model of the semiconductor industry. Flamm [6] also completed a simulation study, but on the 1MB generation. Further he used another theoretical model allowing for closed-loop strategies in capacity and open-loop strategies in output. However, his simulations were extremely sensitive to the specification of some parameters. These two papers deal with calibrating theoretical models. Another part of the semiconductor literature considers econometric models. Gruber [9], [10] estimated reduced form relation assuming constant cost-price margins and he found economies of scale rather than learning-by-doing effects for various generations of DRAMs. Irwin and Klenow [13] implemented a recursive dynamic specification. They assumed constant returns to scale, Cournot behavior and used fixed elasticities of demand. Their results are learning-by-doing within and learning spillovers among firms, but no spillovers among generations. Briest and Wilson [4] estimated both a demand and a pricing relation of a dynamic game with open-loop strategies. Neglecting learning spillovers among firms they showed learning-by-doing to be smaller in the presence of economies of scale and estimated markups. Siebert [19] used a dynamic model with closed-loop strategies and allowed for multiproduct firms and firms' dynamics over the product cycle. He found that learning spillovers and economies of scale effects and that multiproduct firms behave as if in perfect competition. Learning by doing, learning spillovers and economies of scale vary over the product cycle.

Given the reviewed literature the contribution of this paper is to test a dynamic closed-loop specification, to compare the estimated parameters with those of the open-loop specification and investigate the influence of the equilibrium concept on learning-by-doing, learning spillovers, economies of scale and the conduct parameter.

The implication of learning by doing in production technology for market conduct and performance can be modeled within a dynamic oligopoly game. Thus the consequences of firms' using experience as a strategic variable can be considered. I apply the model to the DRAM market. Departing from a dynamic oligopoly game the first order conditions for the open-loop and the closed-loop equilibrium are derived in order to implement an econometric model. The closed-loop specification then enables me to evaluate the effect of firm's strategy on the objective function of other firms in future periods. I assume a single product market. A structural econometric approach is used for evaluating market power, learning-by-doing, learning spillovers, economies of scale and strategic behavior. The methodology involves a specification of demand and marginal cost functions and hypotheses about the strategic interactions of the participants. Different behavioral assumption about firms in the DRAM market are tested and the parameters for the demand and the cost functions, including the parameters for market power, learning-by-doing effects, learning spillovers, economies of scales and strategic behavior are estimated.

Section 2 contains a description of the DRAM market. In Section 3 I set up the theoretical model allowing firms to have open-loop and closed-loop strategies. The implemented econometric model is given in Section 4. The data and the estimation procedure are discussed in Section 5. Estimation results for three different DRAM generations are also provided in this section. Conclusions are given in Section 6.

2 The DRAM Market

In this section I give a short description of the DRAM industry. More detailed descriptions of that industry can be found in e.g. Gruber [12], [11], Irwin and Klenow [13] and Flamm [6]. DRAM stands short for Dynamic Random Access Memory devices. These are memory components (chips) designed for storage and retrieval of information in binary form. One characteristic of DRAMs is that they loose memory once they are switched off. They are classified into 'generations' according to their storage capacity in terms of binary information units (BITS). DRAMs are a relatively homogeneous standardized products. There are hardly any differences among quality. However, different generations of DRAMs represent differentiated products. DRAMs are part of the semiconductor industry, in particular of memory chips. Semiconductors are a key input for electronic goods. The main segments are computers, consumer electronics, communications equipment, industrial applications and cars (Gruber [11]). DRAMs are used when memory storage need not to be permanent.

Memory chips like DRAMs are produced in batches on silicon wafers. The production of semiconductors requires a complex sequence of photolithographic transfer of circuit patterns from photo masks onto the wafer and of etching processes. The manufacturing process has to be very precise in terms of temperature, dust, vibration levels and other determinants. It is of fundamental importance that this process occurs in clean rooms, as even tiny dust particles on the wafer surface interrupt the connecting pattern and thus the chip useless. The raw silicon wafer itself has to be free from any imperfections. The wafer, once processed, is cut and the single chips are then assembled. The wafer processing stage is the most critical and also the most costly. The main cost determinant of a chip is the silicon material. Learning-by-doing takes place over the entire product cycle. In the beginning of the chip production a large proportion of the output is usually defective and has to be discarded. The yield rate, which is measured by the ratio of usable chips to the total number of chips on the wafer, is very low then. Later on the yield rate increases as firms learn. Thus the necessary amount of silicon and firms' cost decrease at the same time. Therefore the use of the traditional measure of learning, namely cumulative output, fits this pattern very well. Part of the semiconductor production knowledge can be viewed as plant specific, because of the difficulty of production knowledge transfer even within one firm. However, there are several research and production joint ventures among firms. Thus learning spillovers seem to be of some importance in that industry. Further as capital expenditures for a state of the art production facility are very high, a firm's primary concern is ensuring the ability to expand output as a means of spreading the fixed costs over a larger base to take advantage of the benefits of economies of scale.

Table 1 shows in which year which generation of DRAMs were in the market. The very first generation of DRAMs, namely the 4K generation, emerged in 1974 and stayed in the market until 1985. Two years after the start off of the 4K generation the 16K generation was on the market. On average two to three years after one generation has emerged the following generations goes on market. The last generation - 64MB - went on the market in 1995 and is still at the beginning of its product cycle. Two exceptions are the 2MB and the 8MB generations. These are byproducts and do not follow the general pattern.

One of the most interesting features of the DRAM market is the price decline at the beginning of a new generation (see Figure 1). This price decline is very extreme. Within the first year the price for e.g. the 256K (1MB) generation fell about 60% (70%). Life cycles of different semiconductor industries and generations are surprisingly comparable and short-lived, very much fitting standard product cycles. After introducing a new generation into the market, sales begin to take off slowly but at an increasing rate. Later on the growth rate falls but sales continue to grow until the peak of the life cycle is reached (see Figure 2). The time between introduction of a new chip and the peak in sales is relatively short compared to other products. Different generations overlap form one generation to the other. Entry into one generation occurs in the growth phase but not in the decline phase (see Figures 3 to 5). Out of the description of the DRAM market one can conclude that learning-by-doing, learning spillovers and economies of scale are evident. Thus a theoretical model should take care of these features.

3 The theoretical model

In this section I present two models and implications of the theoretical models for the estimations. In these two models firms are assumed to maximize their profits over the product cycle. The first model considers the case of learning-by-doing within each firm. The law of motion for the state variable (i.e. cumulative output) describes how cumulative output evolves over time within each firm. The second model allows firms not only to learn from their own experience, but also from learning spillovers from other firms. Therefore the law of motion for the state variable describes the industry experience vector (i.e. cumulative output vector). Both models I solve for equilibria in open-loop and closed-loop strategies, respectively. I divide into a model with learning-by-doing and a model with learning-by-doing and learning spillovers, because it is then easier to explain all the different effects that occur in that model. In fact, the model with learning-by-doing is included in the other model.

In studying repeated games strategies are considered in which past play influences current and future strategies. Usually economists focus their attention on equilibria in a smaller class of Markov or state-space strategies. In this case the past influences the current play only through its effect on a state variable that summarizes the direct effect of the past on the current environment. I will use two strategy concepts. Firms can either use open-loop or closed-loop strategies. The terms open-loop and closed-loop are used to distinguish between two different information structures in multi-stage games. Open-loop strategies are functions of calendar time only. In an open-loop equilibrium players simultaneously commit themselves to entire paths of history. Thus the open-loop equilibria are really static, in that there is only one decision point for each player. The open-loop equilibria are just like Cournot-Nash equilibria, but with a larger strategy space (Fudenberg and Tirole [8]). In a closed-loop information structure players can condition their play at time t on the history of the game until that date. The term closed-loop equilibrium usually means subgame-perfect equilibrium of the game, where players can observe and respond to their opponents' actions at the end of each period. Open-loop strategies are not perfect, as they ignore deviations by subsets of positive measure (Fudenberg and Tirole [7]). An other information structure would be feedback strategies. These strategies are like closed-loop strategies, but do not depend on the initial value of the state-space variable as closed-loop strategies do (see e.g. Feichtinger and Hartl [5]).

3.1 Model with learning-by-doing

Competition in an industry characterized by learning-by-doing can be modeled as a dynamic game, as learning-by-doing introduces an intertemporal component to firm's decisions. In the theoretical model firms are modeled to maximize their profit over the product cycle. Assume there are $i = 1, \ldots, n$ firms and $t = 1, \ldots, T$ discrete time periods[1]. At the beginning of each period, firms choose quantities of a homogeneous output, q_{it}. Firm i's cost in period t, $C_{it} := C(q_{it}, x_{it}, \mathbf{W}_{it})$, is a function of current output, firm i's experience and input prices. Experience is assumed to be measured by past cumulative output. Thus, firm i's stock of experience is $x_{it} := \sum_{s=1}^{t-1} q_{is}$. Output choices play an additional role as investment into experience. The more output is produced today, the lower unit costs will be tomorrow. Each firm i chooses q_{it} in order to maximize intertemporal profits defined

[1]Appendix C gives an overview of the used notation.

as

$$
\begin{aligned}
Max_{q_{it}}\Pi_i &= \sum_{t=1}^{T}\delta^{t-1}\left\{P_t\cdot q_{it} - C(q_{it},x_{it},\mathbf{W}_{it})\right\} \\
&\qquad\quad \text{s.t.}\;\; x_{it} = x_{it-1} + q_{it+1} \\
&\qquad\qquad\quad x_{i0} = 0
\end{aligned} \tag{1}
$$

where δ is the discount rate, $q_t := \sum_{i=1}^{n} q_{it}$ is industry output and $P_t := P(q_t)$ is the inverse market demand function for a given generation. Firms are assumed to move simultaneously like in a Cournot game.

The necessary conditions for an open-loop Nash equilibrium of (1) are

$$
P_t + \frac{\partial P_t}{\partial q_t}\cdot\frac{\partial q_t}{\partial q_{it}}\cdot q_{it} = \frac{\partial C_{it}}{\partial q_{it}} + \sum_{s=t+1}^{T}\delta^{s-t}\cdot\frac{\partial C_{is}}{\partial x_{is}}\cdot\frac{\partial x_{is}}{\partial q_{it}} \tag{2}
$$

for all $i = 1,\ldots,n$ and $t = 1,\ldots,T$. The left-hand side term of equation (2) is the standard Cournot marginal revenue. The first term of the right-hand side is the contemporaneous effect of output on marginal cost, the standard marginal cost without learning-by-doing. The second term is the discounted future cost saving of learning-by-doing gained through the contemporaneous output decision. In case of learning-by-doing effects, this term should be negative [2]. Both terms together denote dynamic marginal cost. Firms set marginal revenue equal to dynamic marginal costs, which lie below static marginal cost and increase output in order to benefit from learning-by-doing and reduce future costs.

The necessary conditions for a closed-loop Nash equilibrium of (1) are

$$
\begin{aligned}
P_t + \frac{\partial P_t}{\partial q_t}\cdot\frac{\partial q_t}{\partial q_{it}}\cdot q_{it} = \frac{\partial C_{it}}{\partial q_{it}} &+ \sum_{s=t+1}^{T}\delta^{s-t}\cdot\frac{\partial C_{is}}{\partial x_{is}}\cdot\frac{\partial x_{is}}{\partial q_{it}} \\
&- \sum_{s=t+1}^{T}\delta^{s-t}\cdot\frac{\partial P_s}{\partial q_s}\cdot q_{is}\cdot\frac{\partial q_s}{\partial q_{is}}\cdot\frac{\partial q_{is}}{\partial x_{is}}\cdot\frac{\partial x_{is}}{\partial q_{it}}
\end{aligned} \tag{3}
$$

for all $i = 1,\ldots,n$ and $t = 1,\ldots,T$. The first terms of equation (3) are again the standard first order condition from the static Cournot problem without learning-by-doing.

[2] A positive term would mean 'forgetting'.

With closed-loop strategies learning-by-doing creates an explicit intertemporal link between strategies firms employ today and the competitive environment in which firms find themselves tomorrow. Firms anticipate correctly that profits from the next period forward will be simultaneously determined by the output decisions of all firms in the current period and by a similar set of decisions in all subsequent periods. The last term in the first line of Equation (3) is the discounted future cost saving of learning-by-doing gained through firm's contemporaneous output decision. This effect is the direct effect of firm's output choices on its payoffs. In case of learning-by-doing effects, this term should be negative. Both terms together denote dynamic marginal cost. The terms in the second line show the strategic effect. These effects arise from the intertemporal nature of strategies due to learning-by-doing. Changes in firm i's strategy at time t affect firm i's objective function in period $s = t+1, \dots, T$ through x_{is}. This is true for all firms i. When learning-by-doing reduces future costs, q_{it} and q_{is} will be strategic substitutes and firms may, by overinvesting in experience, erect entry barriers (see e.g. Spence [20], Fudenberg and Tirole [7]). Firms set marginal revenue equal to dynamic marginal costs, and they consider also the strategic effect. In case of strategic substitutes this effect has the same sign of the direct effect, i.e. future cost savings can be strengthened by the strategic effect. If there is no learning-by-doing and therefore no strategic effect, open-loop and closed-loop equilibrium result in the same first-order conditions.

3.2 Model with learning-by-doing and learning spillovers

This model now incorporates not only propriety learning but also learning spillovers among firms. It is a similar model Jarmin [14] applied to the early rayon industry. Firms' maximization problem is the same as before, only the cost function will additionally depend on the experience of all other firms. Thus firm i's cost in period t, $C_{it} := C(q_{it}, \mathbf{X}_t, \mathbf{W}_{it})$, are now a function of current output, input prices, firm i's experience and experience of all firms other than i. $\mathbf{X}_t$ is the vector of cumulative output of each firm i, representing the experience gain due to the learning-by-doing within the own firm and among other firms in the industry. Experience is assumed to be measured by past cumulative output. Each firm i choose q_{it} in order to maximize intertemporal profits defined as

$$\begin{aligned} Max_{q_{it}} \Pi_i &= \sum_{t=1}^{T} \delta^{t-1} \left\{ P_t \cdot q_{it} - C(q_{it}, \mathbf{X}_t, \mathbf{W}_{it}) \right\} \\ &\qquad \text{s.t.} \;\; \mathbf{X}_t = \mathbf{X}_{t-1} + \mathbf{Q}_{t-1} \\ &\qquad\qquad \mathbf{X}_0 = \mathbf{0} \end{aligned} \tag{4}$$

where δ is the discount rate, $q_t := \sum_{i=1}^{n} q_{it}$ is industry output and $P_t := P(q_t)$ is the inverse market demand function for a given generation.

The necessary conditions for a open-loop Nash equilibrium of (4) are

$$P_t + \frac{\partial P_t}{\partial q_t} \cdot \frac{\partial q_t}{\partial q_{it}} \cdot q_{it} = \frac{\partial C_{it}}{\partial q_{it}} + \sum_{s=t+1}^{T} \delta^{s-t} \cdot \sum_{j=1}^{n} \frac{\partial C_{is}}{\partial x_{js}} \cdot \frac{\partial x_{js}}{\partial q_{it}} \tag{5}$$

for all $i = 1, \ldots, n$ and $t = 1, \ldots, T$. The difference of equation (5) to the first-order condition of the model with learning-by-doing lies in the second term on the righthand side. Discounted future cost savings through the contemporaneous output decision are not only due to own experience but also to learning spillovers from other firms. The righthand side again denotes dynamic marginal cost. Firms set marginal revenue equal to dynamic marginal cost, which lie below static marginal cost and increase output in order to benefit from learning-by-doing and spillovers and reduce future cost.

The necessary conditions for a closed-loop Nash equilibrium of (4) are

$$\begin{aligned} P_t + \frac{\partial P_t}{\partial q_t} \cdot \frac{\partial q_t}{\partial q_{it}} \cdot q_{it} = \frac{\partial C_{it}}{\partial q_{it}} &+ \sum_{s=t+1}^{T} \delta^{s-t} \cdot \sum_{j=1}^{n} \frac{\partial C_{is}}{\partial x_{js}} \cdot \frac{\partial x_{js}}{\partial q_{it}} \\ &- \sum_{s=t+1}^{T} \delta^{s-t} \cdot \frac{\partial P_s}{\partial q_s} \cdot q_{is} \cdot \sum_{j=1}^{n} \frac{\partial q_s}{\partial q_{js}} \cdot \frac{\partial q_{js}}{\partial x_{is}} \cdot \frac{\partial x_{is}}{\partial q_{it}} \end{aligned} \tag{6}$$

for all $i = 1, \ldots, n$ and $t = 1, \ldots, T$.

The first terms of equation (6) are again the standard first order condition from the static Cournot problem without learning-by-doing and without spillovers. With closed-loop strategies learning-by-doing and spillovers create an explicit intertemporal link between strategies firms employ today and the competitive environment in which firms find themselves tomorrow. Firms anticipate correctly that profits from the next period forward will be simultaneously determined by the output decisions of all firms in the current period and by a similar set of decisions in all subsequent periods. The last term in the first line of Equation (6) is the discounted future cost saving of learning-by-doing and spillovers gained through firm's contemporaneous output decision. This effect is the direct effect of firm's output choices on its payoffs. In case of learning-by-doing and spillovers, this term should be negative. Both terms together denote dynamic marginal cost. The terms in the second line show the strategic effect. These effects arise from the intertemporal nature of strategies due to learning-by-doing and spillovers. Changes in firm i's strategy at time t affect firm $j \neq i$'s objective function in period $s = t+1, \ldots, T$ through x_{is}. When learning is proprietary, q_{it} and q_{js} will be strategic substitutes and incumbent firms may, by overinvesting in experience, erect entry barriers (Spence [20], Fudenberg and Tirole [7]). Spillovers reduce the ability of incumbents to deter entry by accumulating experience. Firms set marginal revenue equal to dynamic marginal costs, and they consider also the strategic effect.

3.3 Some implications for estimation

The term $\theta_{1it} := \frac{\partial q_t}{\partial q_{it}}$ defines the conduct parameter and measures the market power of firm i in an industry (see e.g. Bresnahan [3]). The price-cost markup can be defined as $\frac{P - MC_i}{P} := -\frac{\theta_i}{\beta_1} \cdot s_{it}$, with $\frac{1}{\beta_1} = \frac{\partial P_t}{\partial q_t} \cdot \frac{q_t}{P_t}$ and $s_{it} = \frac{q_{it}}{q_t}$ representing the elasticity of demand and market shares, respectively. In a competitive market a change in firm i's output would not have any consequences on prices. Firms price according to their marginal costs. Thus the conduct parameter and the price-cost markup would be both equal to zero. In a Cournot game a change in firm i's output has impact on prices. Firms price higher than their marginal costs and the conduct parameter would be one, the price-cost markup equal to $\frac{1}{\beta_1}$. If firms maximize joint profits, the conduct parameter would be equal to the number of firms in the industry and the price-cost markup also that times higher. In empirical studies the conduct parameter is often estimated. Parameter values other than above described then indicate for example, whether market behavior is more competitive than Cournot in case of a value lower than one, or more collusive than Cournot in case of a value greater than one. The conduct parameter is important for determining firms' behavior in an industry.[3]

In the model with learning-by-doing and spillovers I define the term $\theta_{2it} := \frac{\partial q_{js}}{\partial x_{is}} \cdot \frac{\partial x_{is}}{\partial q_{it}}$ as the strategic parameter.[4] It varies over firms and measures how a change in firm i's output at time t changes firm j's output at time $s, s > t$. If firm i's experience is proprietary and it behaves rationally, the expected sign of the strategic parameter is negative. q_{it} and q_{js} are then strategic substitutes. If firm i's experience benefits no one, the estimate of this parameter should be zero. The expected sign of the strategic parameter when i rival benefit from its experience is ambiguous. If learning spillovers are strong enough, the strategic parameter could be positive. And if this strategic parameter is positive, then q_{it} and q_{js} are strategic complements.

The term $DMC = SMC + CMC$ denotes dynamic marginal cost with statically marginal cost $SMC = \frac{\partial C_{it}}{\partial q_{it}}$ and cumulative marginal cost $CMC_{it} = \sum_{s=t+1}^{T} \delta^{s-t} \cdot \sum_{j=1}^{n} \frac{\partial C_{is}}{\partial x_{js}} \cdot \frac{\partial x_{js}}{\partial q_{it}}$. The first term indicates the contemporaneous marginal cost, whereas the second expression refers to the intertemporal effect of learning-by-doing and spillovers. If learning-by-doing and/or spillovers are present, then the intertemporal effect will be negative. The derivative of DMC with respect to q_{it} is equal to $\partial DMC = \partial SMC + \partial CMC$. With economies of scale the first term is negative and consistent learning curves and spillovers imply the second term to be negative as well (see also Berndt [2] and Jarmin[14]). This results in a negative derivative of dynamic marginal cost.

Comparing the outputs of the open-loop and closed-loop equilibria in the model with learning-by-doing and learning spillovers, leads us to following corollary.

[3]For a thorough discussion on conjectural variation see for e.g. Martin [15].

[4]See also Jarmin [14] for a discussion on that parameter.

Corollary 1. *Assuming a linear demand function the output in a closed-loop equilibrium is greater (smaller) than in an open-loop equilibrium for all firms and for points in time, iff q_{it} and q_{js} are strategic substitutes (complements) for all and across all firms in the industry and for all $s = t+1, \ldots, T$.*

Proof. The proof is shown when q_{it} and q_{js} are strategic substitutes, i.e. the strategic parameter $\frac{\partial q_{is}}{\partial x_{js}} \cdot \frac{\partial x_{js}}{\partial q_{it}} < 0$ for $\forall i, j$ and $\forall s = t+1, \ldots, T$. For the case of strategic complements the proof is analogous.

At equilibrium the first-order conditions (5) and (6) in open-loop and closed-loop strategies, respectively, are equal to zero with identity; i.e. $FOC^O(q_{it}^O) \equiv 0$ and $FOC^C(q_{it}^C \equiv 0$.

Evaluating the first-order conditions in closed-loop strategies at q_{it}^O gives:

$$FOC^C(q_{it}^O) = FOC^O(q_{it}^O) - \sum_{s=t+1}^{T} \delta^{s-t} \cdot \frac{\partial P_s}{\partial q_s}(q_{it}^O) \cdot q_{is}^O \cdot \sum_{j=1}^{n} \frac{\partial q_s}{\partial q_{js}} \cdot \frac{\partial q_{js}}{\partial x_{is}} \cdot \frac{\partial x_{is}}{\partial q_{it}}(q_{it}^O) \tag{7}$$

Iff $\dfrac{\partial q_{is}}{\partial x_{js}} \cdot \dfrac{\partial x_{js}}{\partial q_{it}} < 0$,

$$\text{then} \sum_{s=t+1}^{T} \delta^{s-t} \cdot \frac{\partial P_s}{\partial q_s}(q_{it}^O) \cdot q_{is}^O \cdot \sum_{j=1}^{n} \frac{\partial q_s}{\partial q_{js}} \cdot \frac{\partial q_{js}}{\partial x_{is}} \cdot \frac{\partial x_{is}}{\partial q_{it}}(q_{it}^O) > 0, \tag{8}$$

$$\text{as} \quad \delta > 0, \frac{\partial P_s}{\partial q_s}(q_{it}^O) < 0, q_{is}^O > 0 \ \text{ and } \ \frac{\partial q_s}{\partial q_{js}} > 0.$$

From equation (7) and inequality (8) it follows then that

$$FOC^C(q_{it}^O) > 0 \ \ \forall i, t \tag{9}$$

and this is equivalent with $q_{it}^C > q_{it}^O, \forall i, t$. □

This corollary states the equivalence of strategic substitutability (complementarity) and that then the output path in closed-loop strategies is greater than the output path in open-loop strategies. Fudenberg and Tirole [7] have already shown for a two period game, that the output in closed-loop equilibrium is always higher than that in the open-loop equilibrium. Given this corollary and the first order conditions the consequences for the estimations can be written down.

In fact, the first order conditions give following advice for empirical testing. The difference between open-loop and closed-loop first order conditions can be pinned down by the strategic parameter θ_{2it}. If this term is not equal zero, we can conclude that firms use closed-loop strategies. On other hand if this term equals zero, nothing can be said. The situations where firms either use open-loop strategies or closed-loop strategies without a strategic impact cannot be distinguished. If there is strategic interaction, two possibilities emerge: i) $\theta_{2it} < 0$, i.e. q_{it} and q_{js} are then strategic substitutes. There is either only learning-by-doing or learning-by-doing and not large enough learning spillovers. That means the learning-by-doing effect still exceeds the learning spillovers. ii) $\theta_{2it} > 0$, i.e. q_{it} and q_{js} are then strategic complements. Here we have learning-by-doing and large enough learning spillovers. The learning spillovers are larger than learning-by-doing effects. The sign and the significance of θ_{2it} can be tested.

From the corollary (1) the implications on the estimates of various parameters can be explored, when the true strategies are closed-loop but one estimates the open-loop specification. How does the estimate of the conduct parameter change? An other question I want to address is, how do dynamic marginal cost change in a closed-loop equilibrium compared to an open-loop. Further the implications for the estimation of economies of scale, learning-by-doing and learning spillovers are asked and stated in the following corollary.

Corollary 2. *If q_{it} and q_{is} are strategic substitutes (complements) for all and across all firms in the industry and the closed-loop specification is true, then in an open-loop specification*

i) the estimated conduct parameter $\theta_{1it}; i = 1, \ldots, n$ would be underestimated (overestimated); or

ii) dynamic marginal cost DMC_{it} would be underestimated (overestimated); or

iii) economies of scale, learning-by-doing and learning spillovers would be overestimated (underestimated).

Proof. The proof is shown for the case of strategic substitutes, i.e. the strategic parameter $\frac{\partial q_{js}}{\partial x_{is}} \cdot \frac{\partial x_{is}}{\partial q_{it}} < (>)\ 0$ for $\forall i, j$ and $\forall s = t+1, \ldots, T$. The arguments for the other case are analogous.

i) I denote now the conduct parameter in the open-loop setting with θ_{1it}^{O} and that in the closed-loop setting with θ_{1it}^{C}. Setting $q_{it}^{O} = q_{it}^{C}$ and subtracting then equation (6) from equation (5) and transforming gives

$$\frac{\partial q_t}{\partial q_{it}}^{O} = \frac{\partial q_t}{\partial q_{it}}^{C} + \left\{ \sum_{s=t+1}^{T} \delta^{s-t} \cdot \frac{\partial P_s}{\partial q_s} \cdot q_{is} \cdot \sum_{j=1}^{n} \frac{\partial q_s}{\partial q_{is}} \cdot \frac{\partial q_{is}}{\partial x_{is}} \cdot \frac{\partial x_{is}}{\partial q_{it}} \right\} / \left\{ \frac{\partial P_t}{\partial q_t} \cdot q_{it} \right\} \tag{10}$$

If q_{it} and q_{is} are strategic substitutes the inequality (8) is true and the second term of the righthand side of equation (10) is negative and gives an underestimated conduct parameter in the open-loop specification.

ii) Now I denote dynamic marginal cost with respect to their equilibrium, DMC^C and DMC^O. Arguing like in i) gives

$$DMC^{O}(q_{it}) = DMC^{C}(q_{it}) - \delta^{s-t} \cdot \frac{\partial P_s}{\partial q_s} \cdot q_{is} \cdot \sum_{j=1}^{n} \frac{\partial q_s}{\partial q_{js}} \cdot \frac{\partial q_{js}}{\partial x_{is}} \cdot \frac{\partial x_{is}}{\partial q_{it}} \tag{11}$$

The second term on the righthand side of equality (11) is positive and therefore dynamical marginal cost are underestimated in the open-loop specification.

iii) follows from ii). □

Corollary (2) describes empirically testable hypotheses, which are derived from a theoretical model. Thus if e.g. strategic substitutability is prevalent in an industry an open-loop setup would underestimate the conduct parameter, dynamic marginal cost and would overestimate economies of scale, learning-by-doing and learning spillovers.

4 Econometric Implementation

For the empirical implementation I now consider the model with learning-by-doing and with learning spillovers. The empirical model of the DRAM industry consists of a demand equation and of two pricing relations for each firm based on equations (5) and (6). This gives two systems of equations, one for the model open-loop strategies and one in closed-loop strategies. For estimation structure has to be placed on the demand and on the cost function, as demand and cost parameters enter the pricing relations. Also econometric error terms have to be introduced in order to estimate the model.

4.1 Inverse demand equation

The elasticity of demand play an important role in the pricing relations. The inverse demand function is specified as

$$ln(P_t) = \beta_0 + \beta_1 \cdot ln(q_t) + \beta_2 \cdot ln(q_t^{S_1}) + \beta_3 \cdot ln(q_t^{S_2}) + \beta_4 \cdot ln(Y_t) + \beta_5 \cdot t + \mu_t, \quad (12)$$

where $\beta_i, i = 1, \ldots, 5$ are the parameters to be estimated. P_t is the average selling price of a chip at time t , q_t is the output of the chip at time t, $q_t^{S_1}$ and $q_t^{S_1}$ are respective quantities of substitute semiconductors, Y_t is a vector of other nonprice demand shifters and t is a time trend. The parameters to be estimated reflect the own elasticity of demand, cross elasticities of demand, the effect of demand shifters on a DRAM generation, and a trend that captures the effect of time a particular generation has been on the market. As substitute semiconductors I take the proceeding and the following generation of DRAMs.

4.2 Pricing relations

The empirical model of pricing is a generalized first order condition which allows market structure to be estimated rather than imposed. The econometric implementation of the open-loop equilibrium goes in one line with Brist and Wilson [4]. However, they do not consider learning spillovers and neither input prices. Additionally, I set up the first-order conditions in closed-loop strategies in an analogous way. Then I compare the two estimated parameter sets.

4.2.1 Specification of the marginal cost function

The empirical pricing relations require expressions for marginal cost. These expressions include parameters that measure learning-by-doing and learning spillovers. The marginal cost function I approximate with a Cobb-Douglas type function. Marginal cost look like

$$MC_{it} = \gamma_{1i} + \gamma_{2i} \cdot ln(q_{it}) + \gamma_{3i} \cdot ln(x_{it}) + \gamma_{4i} \cdot ln(\sum_{l \neq i} \sum_{j=0}^{t-1} q_{lj}) + \sum_{h} \gamma_{hi} \cdot ln(P^I_{hit}) \quad (13)$$

for $i, j = 1, \ldots, n$ and $t = 1, \ldots, T$. Like Brist and Wilson [4] I allow for nonconstant returns to scale in the empirical marginal cost function, too. Learning-by-doing is measured by cumulative output x_{it}. Learning spillovers are assumed to be symmetric and are defined by past cumulative output of other firms ($\sum_{l \neq i} \sum_{j=0}^{t-1} q_{lj}$). $P^I_{h_1 it}$ denote various input prices, i.e. price for silicon, for energy, for wages and for capital.

4.2.2 Equilibrium relation

Structure has to be placed also on the contemporaneous and on the dynamic effects contained in the first order conditions. I then test the effect of a firm's strategy on the objective functions of other firms in future periods by comparing the open-loop specification with the closed-loop specification. However, the model would be overparameterized if all terms that measure future effects were to be estimated. Following Roberts and Samuelson [18] and Jarmin [14], I capture all dynamic effects that occur two or more periods into the future via a firm specific constant. For the open-loop equilibrium relation the firm-specific constants are defined as follows

$$\alpha_{1ij} = \sum_{s=t+1}^{T} \delta^{s-t} \cdot \frac{\partial C_{is}}{\partial x_{js}} \cdot \frac{\partial x_{js}}{\partial q_{it}}$$

$$\alpha_{1i} = \sum_{j=1}^{n} \alpha_{1ij}.$$

In the closed-loop equilibrium relation they are defined as

$$\begin{aligned}
\alpha_{2ij} &= \sum_{s=t+2}^{T} \delta^{s-t} \cdot \frac{\partial P_s}{\partial q_s} \cdot q_{is} \cdot \sum_{j=1}^{n} \frac{\partial q_s}{\partial q_{js}} \cdot \frac{\partial q_{js}}{\partial x_{is}} \cdot \frac{\partial x_{is}}{\partial q_{it}} - \sum_{s=t+1}^{T} \sum_{j=1}^{n} \frac{\partial C_{is}}{\partial x_{js}} \cdot \frac{\partial x_{js}}{\partial q_{it}} - \frac{\partial C_{is}}{\partial q_{it}} \\
\alpha_{2i} &= \sum_{j=1}^{n} \alpha_{2ij}.
\end{aligned}$$

Firm specific fixed effects capture different 'things' in these two settings, respectively.

I then specify the following strategic parameters

$$\begin{aligned}
\theta_{1i} &= \frac{\partial q_t}{\partial q_{it}} \\
\theta_{2ij} &= \frac{\partial q_{jt+1}}{\partial x_{it+1}} \cdot \frac{\partial x_{it+1}}{\partial q_{it}} \\
\theta_{2i} &= \sum_{j=1}^{n} \theta_{2ij}
\end{aligned}$$

where θ_{1i} reflects the conduct parameter. If, for example, it is zero, then competitive prices result, is the conduct parameter equal to one, Cournot prices result. θ_2 captures the effect of firms' strategy on the objective function of other firms in the next period and it appears in the closed-loop specification only. If firm i's experience is proprietary and it behaves rationally, the expected sign for θ_{2i} is negative. q_{it} and q_{jt+1} are then strategic substitutes. The econometric model of the pricing relations is then for the open-loop equilibrium

$$\begin{aligned}
P_t = \gamma_{1i} + \gamma_{2i} \cdot ln(q_{it}) + \gamma_{3i} \cdot ln(x_{it}) + \gamma_{4i} \cdot ln(\sum_{l \neq i} \sum_{j=0}^{t-1} q_{lj}) + \sum_{h} \gamma_{hi} \cdot ln(P^I_{hit}) \\
+ \alpha_{1i} - \beta_1 \cdot \theta_{1i} \cdot P_t \cdot s_{it} + \mu_{it} \qquad (14)
\end{aligned}$$

and for the closed-loop equilibrium

$$\begin{aligned}
P_t = \gamma_{1i} + \gamma_{2i} \cdot ln(q_{it}) + \gamma_{3i} \cdot ln(x_{it}) + \gamma_{4i} \cdot ln(\sum_{l \neq i} \sum_{j=0}^{t-1} q_{lj}) + \sum_{h} \gamma_{hi} \cdot ln(P^I_{hit}) \\
+ \alpha_{2i} - \beta_1 \cdot \theta_{1i} \cdot P_t \cdot s_{it} - \beta_1 \cdot \theta_{1i} \cdot \theta_2 \cdot P_{t+1} \cdot s_{it+1} + \mu_{it} \qquad (15)
\end{aligned}$$

for $i, j = 1, \ldots, n$ and $t = 1, \ldots, T$ and where $s_{it} = \frac{q_{it}}{q_t}$.

5 Estimation results

Two systems of equations are estimated, namely equations (12) and (14) for the open-loop equilibrium and equations (12) and (15) for the closed-loop equilibrium. I run the estimations for three different generations of DRAMs, namely the 64K, the 256K, and the 1MB generation.[5] This selection relies primarily on the fact that not all generations of DRAMS were in the market for a long period of time (see Table 1). Thus I do not consider generations, which give too less data points. Especially, the generations 64K and 256K are of further interest as these were under dumping investigations by the US Commerce Department and the International Trade Commission (see e.g. Flamm [6]).

In Table 2 all firms which produce the 64k, 256K or 1MB generation of DRAMs are listed with their respective market shares. The Herfindahl Indices for each year are given for these generations in Table 4.

For estimating the demand and price relations for three different generations I use single equation techniques, in particular 2SLS for the estimations. The instruments in the inverse demand equation consist of the exogenous variables in the demand equation and summary measures from the supply side, like average market share, number of firms in the industry, and cumulative world output. I also include lagged prices as instruments. For the pricing relation I use exogenous variables in the specification, the age of the generation, the nonprice demand shifters, and lagged (input) prices as instruments.

The estimates of the demand equation with their respective standard errors in parenthesis are reported in Table (5) for three different generations of DRAMs. This table further gives the results of a General Method of Moments estimation, which has been conducted because of poor Durbin-Watson statistics in the 2SLS estimations. However, the estimated parameters do not differ substantially. Each generation's own demand elasticity is negative and significant. The estimates across generations with respect to their own demand elasticity range from -0.3370 to -0.7607 and -0.6192 for 64K, 256K and 1MB,

[5] In Section D a detailed description of the used data is given.

respectively. The results for the elasticities of one's generation own demand are in one line with previous literature (see e.g. Flamm [6] or Brist and Wilson [4]). The elasticities of a previous generation are positive and significant, those of the following generations are negative and are significant for the 64K and the 256K generation. The nonprice demand shifters have the right sign and are significant for the 64K and the 256K generation. The remaining demand determinant, the time trend, should be negative, suggesting that buyers substitute away from the generation as time elapses. The estimations results show that for the 64K and the 256K generation.

For the pricing relation I estimate the two specifications: The first one assumes non-constant returns to scale, learning by doing, learning spillovers and a estimated conduct parameter, corresponding the open-loop equilibrium. The other specification has an additional strategic interaction parameter and reflects the closed-loop equilibrium relation. Table 6 contains parameter estimates for the open-loop and the closed-loop pricing relations for all estimated generations. Economies of scale are measured by the logarithm of current output (LQI). The coefficient of this variable is significantly negative for both specifications and for all generations estimated. It is smaller in the open-loop setting than in the closed-loop setting. Contemporaneous output has a significant effect on marginal cost in the 64K, 256K and 1MB generation. However, in an open-loop setting one would slightly underestimate this effect.

Now consider the parameter that measures learning-by-doing. The parameter is negative and significant for 254K and 1MB. The learning-by-doing parameter in the open-loop setting is smaller in absolute values than in the closed-loop specification. This is true for all generations. Learning spillovers are significant in the 64K and 256K generation. The estimated conduct parameter θ_1 of the 64K generation equals 4.169 in the open-loop and 9.513 in the closed-loop specification. In case of the 256K (1MB) generation this parameter has a value of 1.412 (1.748) in the open-loop specification and 2.687 (2.903) in the closed-loop specification. These results indicate on the one hand above Cournot pricing and on the other hand an underestimation of this parameter in the open-loop setting. The coefficients are all significant at the 5% level. The coefficient of the second strategic parameter θ_2 is significantly negative for all estimated generations suggesting that firms react strategically on the objective function of other firms in the next period. The negative sign of these parameters suggests q_{it} and q_{js} to be strategic substitutes.

6 Conclusions

In this article, I develop and estimate an empirical model that incorporates the strategic implications of learning by doing and learning spillovers. I derive a structural model from a dynamic oligopoly game. I then estimate the model with firm-level data from the DRAM semiconductor industry. The estimation results support economies of scale, learning by doing and learning spillovers. Further they suggest that firms consider the reactions of their rivals when formulating their output strategies.

References

[1] Richard E. Baldwin and Paul R. Krugman. Market access and international competition: A simulation study of 16k random access memories. pages 171–97, 1988. in Robert C. Feenstra, ed.: Empirical methods for international trade, Cambridge: MIT Press.

[2] Ernst R. Berndt. *The Practice of Econometrics.* Addison Wesley, Reading Massachusetts, 1991.

[3] Timothy F. Bresnahan. Empirical studies of industries with market power. pages 1011–1057, 1989. in R. Schmalensee and R. D. Willig, eds.: Handbook of industrial economics, Volume II, North-Holland, Amsterdam.

[4] Lonnie E. Brist and Wesley W. Wilson. Economies of scale, markups and learning by doing in dram markets. mimeo, 1997.

[5] Gustav Feichtinger and Richard F. Hartl. *Optimal Kontrolle ökonomischer Prozesse.* de Gruyter, Berlin, 1986.

[6] Kenneth Flamm. Semiconductor dependency and strategic trade policy. *Brooking Papers: Microeconomics 1993*, ??:249–333, 1993.

[7] Drew Fudenberg and Jean Tirole. Learning-by-doing and market performance. *The BELL Journal of Economics*, 14:522–530, 1983.

[8] Drew Fudenberg and Jean Tirole. *Dynamic Models of Oligopoly.* Harwood, London, 1986.

[9] Harald Gruber. The learning curve in the production of semiconductor memory chips. *Applied economics*, 24:885–894, 1992.

[10] Harald Gruber. Learning by doing and spillovers: further evidence for the semiconductor industry. mimeo, 1996.

[11] Harald Gruber. *The semiconductor industry: review of the sector and financing opportunities.* European Investmentbank, Luxembourg, 1996.

[12] Harald Gruber. Trade policy and learning-by-doing: The case of semiconductor. *Research policy*, 25:723–739, 1996.

[13] Douglas A. Irwin and Peter J. Klenow. Learning-by-doing in the semiconductor industry. *Journal of Political Economy*, 102(6):1200–1227, 1994.

[14] Ronald S. Jarmin. Learning by doing and competition in the early rayon industry. *The RAND Journal of Economics*, 25(3):441–454, 1994.

[15] Stephen Martin. *Advanced industrial economics.* Basil Blackwell, Oxford, 1993.

[16] OECD. *STAN database.* OECD, Paris, 1998.

[17] OECD/IEA. *Energy prices and taxes: First quarter to fourth quarter, 1984-1998.* OECD, Paris, 1998.

[18] Mark J. Roberts and Larry Samuelson. An empirical analysis of dynamic, nonprice competition in an oligopolistic industry. *The RAND Journal of Economics*, 19(2):201–220, 1988.

[19] Ralph Siebert. Multiproduct competition and learning-by-doing over the product life cycle: Evidence from the dram industry. *WZB Discussion Paper Series*, FS IV 99-21, 1999.

[20] A. M. Spence. The learning curve and competition. *The BELL Journal of Economics*, 12:49–70, 1983.

A Appendix: Tables

Table 1: Generations of DRAM in the market over time

Year	**4K**	**16K**	**64K**	**256K**	**1MB**	**2MB**	**4MB**	**8MB**	**16MB**	**64MB**
1974	x	-	-	-	-	-	-	-	-	-
1975	x	-	-	-	-	-	-	-	-	-
1976	x	x	-	-	-	-	-	-	-	-
1977	x	x	-	-	-	-	-	-	-	-
1978	x	x	-	-	-	-	-	-	-	-
1979	x	x	x	-	-	-	-	-	-	-
1980	x	x	x	-	-	-	-	-	-	-
1981	x	x	x	-	-	-	-	-	-	-
1982	x	x	x	x	-	-	-	-	-	-
1983	x	x	x	x	-	-	-	-	-	-
1984	x	x	x	x	-	-	-	-	-	-
1985	x	x	x	x	-	-	-	-	-	-
1986	-	-	x	x	x	-	-	-	-	-
1987	-	-	x	x	x	-	-	-	-	-
1988	-	-	x	x	x	-	x	-	-	-
1989	-	-	x	x	x	-	x	-	-	-
1990	-	-	x	x	x	-	x	-	-	-
1991	-	-	x	x	x	-	x	-	x	-
1992	-	-	x	x	x	x	x	-	x	-
1993	-	-	x	x	x	x	x	-	x	-
1994	-	-	x	x	x	x	x	-	x	-
1995	-	-	x	x	x	x	x	-	x	x
1996	-	-	-	x	x	x	x	x	x	x

Table 2: Market shares for the 64K, 256K and 1MB generation in % averaged over the product cycle

Firm	**64K**	**256K**	**1MB**
Advanced Micro Devices	0.13	-	-
AT&T Microelectronics	-	1.21	0.68
Fairchild	0.00	-	-
Fujitsu	11.53	7.85	4.39
G-Link	-	-	0.06
Hitachi	7.50	15.90	3.76
Hyundai	0.13	2.15	2.29
IBM Microelectronics	-	-	0.29
Inmos	0.55	0.07	-
Intel	0.92	0.42	0.28
LG Semicon	-	0.76	1.54
Matsusihu	14.18	2.45	1.32
Micron	4.03	2.33	2.09
Mitsubishi	5.36	5.15	6.11
Mosel Vitalic	0.01	1.12	1.19
Mostek	2.01	0.04	-
Motorola	6.66	0.53	1.94
National Semiconductor	0.14	0.01	-
NEC	6.07	16.08	4.33
Nippon Steel	-	1.23	1.53
OKI	8.90	6.28	3.18
Samsung	17.86	6.15	5.27
Sanyo	-	1.74	1.88
Sharp	0.61	1.25	0.63
Siemens	0.73	0.68	2.60
STC-ITT	0.10	-	-
Texas Instruments	11.31	6.58	3.55
Toshiba	1.28	3.81	18.71

Table 3: Summary statistics for the 64k, 256K, and 1MB generation

Variable	**Statistic**	**64K**	**256K**	**1MB**
Industry price	Mean	13.0212	11.8362	14.5490
	Std. dev.	30.7383	27.2328	22.0765
	Min.	0.750	1.624	3.132
	Max.	135.000	150.000	110.000
	Nobs	68	57	46
Industry output	Mean	38717563	88039188	103296567
	Std. dev.	60386120	83457093	6357646
	Min.	3000	10000	11000
	Max.	264395000	242412000	215632700
	Nobs	68	57	46
Firm output	Mean	3799125	5734476	6692453
	Std. dev.	5855855	7726461	6357646
	Min.	1000	3000	1000
	Max.	31525000	39000000	31500000
	Nobs	693	817	710

Table 4: Herfindahl indices for the 64K, 256K and 1MB generation over the product cycle

Year	**64K**	**256K**	**1MB**
1979	0.525	-	-
1980	0.264	-	-
1981	0.177	-	-
1982	0.128	1.000	-
1983	0.108	0.265	-
1984	0.092	0.213	-
1985	0.091	0.164	0.964
1986	0.099	0.135	0.369
1987	0.106	0.102	0.337
1988	0.170	0.091	0.151
1989	0.261	0.078	0.104
1990	0.309	0.085	0.094
1991	0.218	0.092	0.080
1992	0.296	0.110	0.073
1993	0.319	0.118	0.070
1994	0.370	0.131	0.084
1995	0.344	0.133	0.087
1996	-	0.290	0.093
Average	0.228	0.201	0.209

Table 5: Parameter estimates for the inverse demand equation
Two-stage least square estimation

Variable	**64K**	**256K**	**1MB**
Constant	-60.2666**	-193.1450**	-88.9195
	(22.44)	(19.83)	(74.04)
LQ	-0.3370**	-0.7607**	-0.6192**
	(0.02)	(0.06)	(0.21)
LQ^{S_1}	0.0295**	0.7953*	0.7904**
	(0.01)	(0.14)	(0.46)
LQ^{S_2}	-0.0243*	-0.0244**	-0.0017
	(0.01)	(0.01)	(0.01)
GNP	2.7940**	7.6425**	3.2758
	(0.91)	(0.75)	(2.90)
TIME	-0.3640**	-0.1767**	0.1512
	(0.06)	(0.06)	(0.25)
R-squared	0.964	0.979	0.908
Durbin-Watson	0.571	0.905	1.138
Number of observations	68	53	46

General method of moments estimation

Variable	**64K**	**256K**	**1MB**
Constant	-55.8031**	-178.3104**	-76.2658*
	(11.32)	(15.32)	(41.85)
LQ	-0.3447**	-0.6941**	-0.6160**
	(0.02)	(0.06)	(0.12)
LQ^{S_1}	0.0295**	0.6384**	0.7785**
	(0.01)	(0.14)	(0.29)
LQ^{S_2}	-0.0192*	-0.0308**	-0.0001
	(0.01)	(0.01)	(0.00)
GNP	2.6198**	7.1540**	2.7884*
	(0.46)	(0.56)	(1.69)
TIME	-0.3585**	-0.2224**	0.1609
	(0.03)	(0.05)	(0.16)
R-squared	0.984	0.950	0.907
Number of observations	68	53	46

*Significant at the 10%level
**Significant at the 5% level
Standard Errors in parenthesis.

Table 6: Pricing relation results: Parameter estimates for the open-loop and for the closed-loop model

Variable	**64K** open-loop	**64K** closed-loop	**256K** open-loop	**256K** closed-loop	**1MB** open-loop	**1MB** closed-loop
Constant	131.600**	206.018**	4.375	5.785	244.233**	257.527**
	(27.73)	(35.60)	(28.90)	(30.41)	(23.17)	(23.55)
LQI	-2.054**	-2.209**	-0.816**	-0.874**	-1.657**	-1.713**
	(0.25)	(0.26)	(0.25)	(0.25)	(0.22)	(0.22)
Learning	-0.153	-0.422	-0.096	-0.341**	-0.510**	-0.680**
	(0.31)	(0.40)	(0.21)	(0.24)	(0.23)	(0.24)
Spillovers	-0.812	-0.922**	-0.722*	-0.447*	0.187	0.294
	(0.35)	(0.41)	(0.22)	(0.25)	(0.26)	(0.26)
$\theta_1 \cdot \beta_1$	1.437**	3.279**	0.980**	1.865**	1.077**	1.788**
	(0.07)	(0.88)	(0.03)	(0.21)	(0.06)	(0.14)
θ_1	4.169**	9.513**	1.412**	2.687**	1.748**	2.903**
	(0.20)	(2.55)	(0.04)	(0.30)	(0.10)	(0.23)
$\theta_2 \cdot \theta_1 \cdot \beta_1$	-	-2.986**	-	-1.538**	-	-1.332**
	-	(1.14)	-	(0.33)	-	(0.19)
θ_2	-	-0.911**	-	-0.825**	-	-0.745**
	-	(0.34)	-	(0.17)	-	(0.11)
Material	-4.336*	-6.713**	-2.940**	-3.224**	1.068	1.014
	(2.28)	(2.37)	(1.07)	(1.12)	(0.93)	(0.94)
Energy	5.750**	11.883**	1.675	1.529	10.805	11.391**
	(0.74)	(2.60)	(1.47)	(1.53)	(1.21)	(1.23)
Labor	-2.748**	-3.660**	4.363*	4.499*	-15.150**	-15.860**
	(0.88)	(0.99)	(2.49)	(2.63)	(1.21)	(1.63)
Capital	-4.966**	-14.214**	3.678**	3.944**	-1.108	-1.960
	(0.95)	(2.70)	(1.01)	(1.60)	(0.78)	(0.80)
Other inputs	7.299**	13.705**	-5.775**	-5.748**	5.340**	6.415**
	(3.27)	(3.43)	(2.91)	(3.05)	(1.03)	(1.15)
F-Test	90.667**	81.792**	118.407**	105.303**	77.928**	81.321**
adj. R-squared	0.775	0.765	0.808	0.791	0.762	0.755
DW	0.772	0.809	0.710	0.725	0.920	1.041
Nobs	693	693	817	817	710	710

*Significant at the 10%level
**Significant at the 5% level
Standard Errors in parenthesis.

B Appendix: Figures

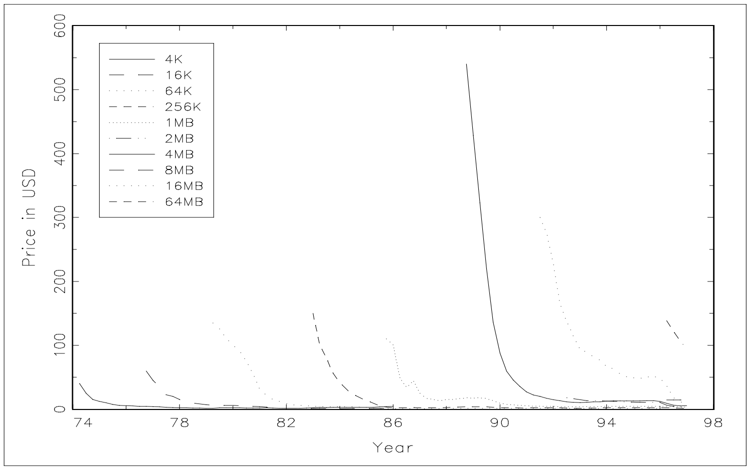

Figure 1: Average selling prices in USD for different generations of DRAMs, 1974-1996

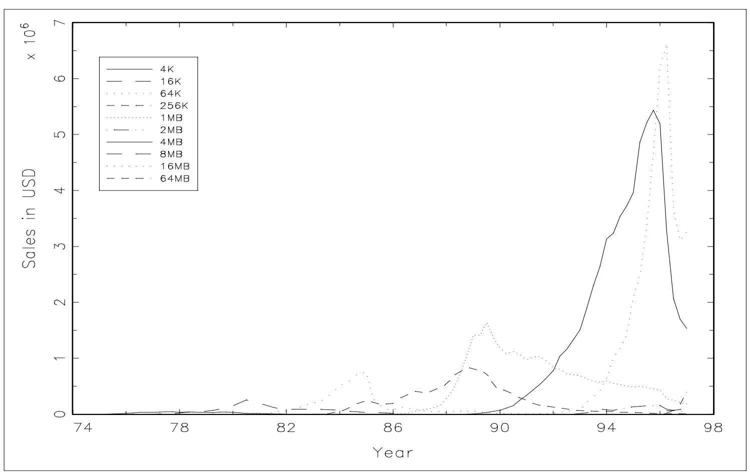

Figure 2: Industry units shipped for different generations of DRAMs, 1974-1996

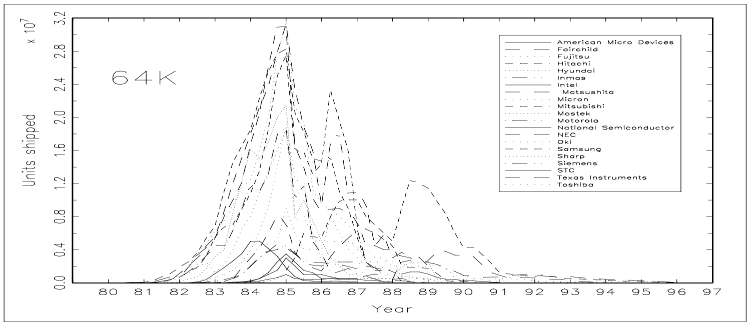

Figure 3: Firm specific output for the 64K generation, 1974-1996

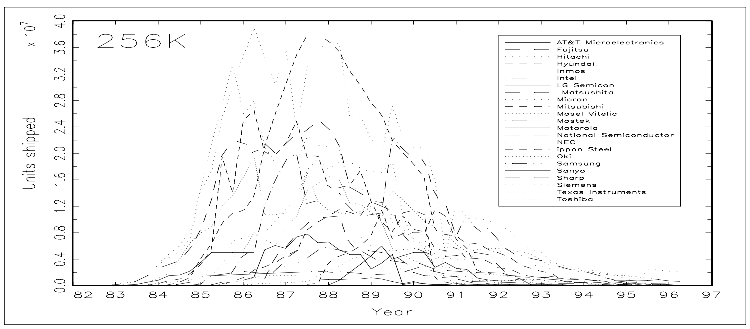

Figure 4: Firm specific output for the 256K generation, 1974-1996

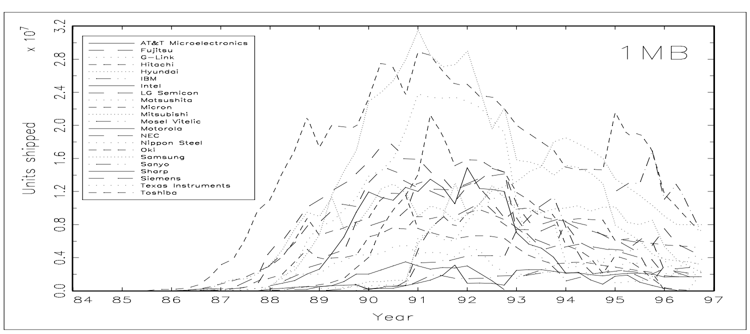

Figure 5: Firm specific output for the 1MB generation, 1974-1996

C Appendix: Notation

q_{it}	...	output of firm i at time t, $i = 1, \ldots, n; t = 1, \ldots, T$
$q_t := \sum_{i=1}^{n} q_{it}$	...	industry output at time t
$x_{it} := \sum_{s=1}^{t-1} q_{is}$	...	cumulative output of firm i at time t
$x_t := \sum_{i=1}^{n} x_{it}$	...	cumulative industry output at time t
$x_{-it} := (x_{1,t}, \ldots, x_{i-1,t}, x_{i+1,t}, \ldots, x_{n,t})$	...	vector of cumulative output of each firm except of firm i at time t
$\mathbf{X}_t = (x_{it})_{i=1}^{n}$	...	industry experience vector at time t
$\mathbf{W}_{it}$	...	vector of input prices at time t
$C_{it} := C(q_{it}, x_{it})$	...	cost function of firm i at time t
$P_t := P(q_t)$	...	inverse demand function at time t
$s_{it} := P_t \cdot \frac{q_{it}}{q_t}$	...	price times shares of firm i at time t

D Appendix: Data description

The data used for estimating represent firms producing DRAMs and are compiled by Dataquest Inc. The data covers firms' units shipped from the 4K generation to the 64MB generation and the average selling price. These generations span a time period from January 1974 to December 1996. The data are available at a quarterly basis. Table 1 shows in which year which generation of DRAMs were in the market. The very first generation of DRAMs, namely the 4K generation, emerged in 1974 and stayed in the market until 1985. Two years after the start off of the 4K generation the 16K generation was on the market. On average two to three years after one generation has emerged the following generations goes on market. The last generation - 64MB - went on the market in 1995 and is still at the beginning of its product cycle. Two exceptions are the 2MB and the 8MB generations. These are byproducts and do not follow the general pattern. From the firm-level output data I construct three variables. Namely, current output, own past cumulative output and other firms' past cumulative output. Current output serves as measure for economies of scale. The own cumulative output variable represents learning-by-doing. The cumulative past output of all other firms proxies learning spillovers. Further I use price data for four important inputs - price of silicon, energy cost, wages for production and user cost of capital. For the material cost I use the world market price of silicon compiled by Metal Bulletin. Energy costs and wages of production are compiled in the following way: according to each firms production location the energy prices and the industry wages (ISIC 3825) of the concerned location (country) is used. The source for energy prices is OECD/IEA [17], that for industry wages OECD [16]. User cost of capital is constructed for each firm and year by exploiting firms annual reports. As a nonprice demand shifter I use a proportion of GNP directly attributed to electronic and electrical equipment from the OECD [16]. A time variable also enters the demand equation as a proxy for the incremental changes in a generation over the life cycle. As substitutes for one generation I assume its proceeding and following generation. Table 3 gives some summary statistics.

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1999, Deutscher Universitäts-Verlag/Gabler Verlag

Christian Wey
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Monitoring European Deregulation 1
1998, Centre for Economic Policy Research

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The Contribution of JETRO to Japanese Competitiveness
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1995, The MIT Press.

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1995, Avebury

Horst Albach
The Transformation of Firms and Markets: A Network Approach to Economic Transformation Processes in East Germany
Acta Universitatis Upsaliensis, Studia Oeconomiae Negotiorum, Vol. 34
1994, Almqvist & Wiksell International (Stockholm).

Horst Albach
"Culture and Technical Innovation: A Cross-Cultural Analysis and Policy Recommendations"
Akademie der Wissenschaften zu Berlin (Hg.)
Forschungsbericht 9, S. 1-597
1994, Walter de Gruyter.

Horst Albach
Zerissene Netze. Eine Netzwerkanalyse des ostdeutschen Transformationsprozesses
1993, edition sigma.

Zoltan J. Acs/David B. Audretsch (eds)
Small Firms and Entrepreneurship: An East-West Perspective
1993, Cambridge University Press.

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