Testing dynamic oligopolistic interaction: Evidence from the semiconductor industry

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Abstract

The objective of this paper is to test whether firms in the Dynamic Random Access Memory (DRAM) industry take the intertemporal strategic effect of their contemporaneous output decision on their rivals' future output decision into account or whether they precommit themselves to a production plan. Learning-by-doing and spillovers are present in this industry and introduce an intertemporal component to firms' strategies. A simplified version of Jarmin (1994)'s dynamic oligopolistic model is applied to firm-level data. Demand and pricing relations for five DRAM generations are estimated. The empirical results show that firms behave strategically and price-cost margins are likely overestimated in a precommitment specification.

Keywords: Oligopoly; Dynamic games; Semiconductor industry

JEL Classifications: L13, L63, C73

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1 Introduction

Learning-by-doing and spillovers are prevalent in the semiconductor industry and in particular in the Dynamic Random Access Memory (DRAM) market.[1] Firms in this market deal with a production process that yields cost reductions the more output has been fabricated in the past. This adds an intertemporal component to firms' output decisions. However, do firms take their rivals' future reactions into account when they choose their output strategies today? Jarmin (1994) asked this question for the early rayon industry and found empirical evidence of dynamic strategic behavior.

The objective of this paper is to empirically test whether firms in a dynamic oligopolistic industry like the DRAM industry consider the strategic effect of learning-by-doing and spillovers on their rivals' future output decision or whether they pre-commit themselves to a production plan. And if they act strategically, what is the sign of this strategic effect? Do firms consider the future output of other firms as strategic substitutes or as strategic complements? The second objective of the paper is to analyze how the estimated parameters in a structural model of quantity competition change when the dynamic strategic effect is not accounted for. The point of interest lies on the estimates of learning-by-doing, spillovers and price-cost margins. How do they change depending on the intertemporal strategic effect and what are the consequences for market power and competition policy?

In learning-by-doing models with spillovers, firms learn from their own experience and from the experience of other firms. Under the assumption that past cumulative output is an appropriate measure of experience, current production adds to a firm's stock of experience. Theoretical research (Spence (1981), Fudenberg and Tirole

[1]See, for example, Gruber (2000), Siebert (1999), Brist and Wilson (1997) and Irwin and Klenow (1994). Another industry, which is also prominent for learning effects, is the aircraft production industry. See, for example, Benkard (2000) and there cited literature.

(1983)) demonstrates that such learning can have a sizable impact on cost, strategic decisions, and market performance: If learning is completely proprietary, firms overproduce in early periods as an investment in experience and, hence, future cost reduction. Incumbent firms can gain an absolute cost advantage over potential entrants. However, if there are spillovers among firms, the incentives for overproducing and erecting entry barriers diminish.

There are many studies of the DRAM market. Most investigate whether learning-by-doing and spillovers are present in the industry and if so, how large these effects are. The different setups vary. Baldwin and Krugman (1988) did a simulation study for the 16K generation. This was the pioneering work to incorporate learning economies into a stylized empirical model of the semiconductor industry. Flamm (1993) also completed a simulation study, but on the 1MB generation. The simulations of his theoretical model, where firms first compete in capacity and then in output, showed the importance of learning.

Another part of the semiconductor literature considers econometric models. Gruber ((2000), (1994), (1992)) estimated reduced form relationships assuming constant price-cost margins and found economies of scale rather than learning-by-doing effects for various generations of DRAM chips. Irwin and Klenow (1994) implemented a recursive dynamic specification. They assumed constant returns to scale, Cournot behavior and fixed elasticities of demand. Their results imply learning-by-doing within and spillovers across firms, but no spillovers across generations. Brist and Wilson (1997) estimated both a demand and a pricing relation for a dynamic game with precommitment strategies. Neglecting spillovers among firms and intertemporal strategic behavior, they found learning-by-doing to be smaller in the presence of economies of scale and estimated markups. Siebert (1999) used a dynamic model and investigated the influence of a multi-product specification on the estimated parameters. He found that multiproduct firms behave as if in perfect competition.

Most of the literature about the semiconductor industry has considered learning-by-doing extensively, but has not considered its dynamic strategic implications. However, Jarmin (1994) investigated these dynamic effects for the early rayon industry. His results show that firms take their rivals' reactions into account when choosing their output strategies. Karp and Perloff (1989) estimated a dynamic oligopoly model and the degree of competition for the rice export market. Their model nests various market structures with firms that either precommit themselves to a production plan or that consider the strategic effect of their own output on their rivals' future output decision. The results show that the estimated feedback model implies a less competitive market-structure than the estimated precommitment model. However, in this market learning-by-doing or spillovers do not matter. Slade (1995) estimated a dynamic model for a market in which firms compete in prices and advertising intensity. Within this model she then can qualify and quantify firms' strategic behavior with respect to pricing and advertising. In contrast to these papers Steen and Salvanes (1999) proposed a dynamic oligopoly model in an error correcting framework. Using data from the French market for fresh salmon they separated the long-run effects from the short-run effects.

In this paper I apply a simplified version of Jarmin (1994)'s dynamic oligopoly model, a T-period extension of the two period game by Fudenberg and Tirole (1983), to the DRAM industry. The empirical framework for examining the dynamic effects of learning-by-doing and spillovers is an intraindustry study of the kind described in Bresnahan (1989). The contribution of this paper is to investigate whether firms in the DRAM industry take the intertemporal strategic effect of learning-by-doing and spillovers on their rivals' future output decision into account, and thus to test, formally, a closed-loop no memory specification for the DRAM industry. Further, I test whether and how the intertemporal strategic effect chances over time. Then I compare the estimated parameters with those of the precommitment specification and investigate the influence on learning-by-doing, spillovers, economies of scale and price-cost margins. In a conceptually analogous way Röller and Sickles (2000) showed that for the airline industry market conduct in a two-stage set-up of a game in capacity and prices is significantly less collusive than in a one-stage set-up.

The implications of learning-by-doing and spillovers in production technology for market power and performance can be modelled within a dynamic oligopoly game. Thus the consequences of firms using experience as a strategic variable can be considered. The first order conditions for the closed-loop no memory and the precommitment equilibrium are derived to implement a structural econometric model. The methodology involves the specification of a demand and a marginal cost function and hypotheses of the strategic interactions among the participants. The closed-loop no memory specification then enables me to evaluate the effect of a firm's strategy on the objective function of other firms in future periods and to compare its parameter estimates with that of the precommitment specification. Anticipating, the empirical results show that firms behave strategically and price-cost margins are likely overestimated in a precommitment specification.

Section 2 contains a description of the DRAM market. In Section 3 I set up the model. A description of the theoretical model, allowing firms in an dynamic oligopolistic industry either to consider the effect of learning-by-doing and spillovers on their rivals' output decisions tomorrow or to precommit themselves to a production plan, is given in Section 3.1. The econometric model is implemented in Section 3.2. In Section 4 I discuss the data and the estimation procedure. I also provide estimation results for five different DRAM generations in this section. Conclusions are given in Section 5.

2 The DRAM industry

A short description of the DRAM industry is given here.[2] DRAM devices are memory components (chips) designed for storage and retrieval of information in a binary form. One characteristic of DRAM chips is that they lose memory once they are switched off and they are therefore used when memory storage need not be permanent. They are classified into 'generations' according to their storage capacity in terms of binary information units. DRAM chips are part of semiconductors, which are a key input for electronic goods like computers, consumer electronics, communications equipment, industrial applications and cars (Gruber (1996)). Semiconductors are an important input to several high-technology industries and DRAM components are usually thought of as technology drivers (Irwin and Klenow (1994), p. 1206).

Memory chips, like DRAM chips, are produced in batches on silicon wafers. The production of semiconductors is a complex photolithographic and manufacturing process, which has to be very precise in terms of many physical determinants (for example, temperature, dust, vibration levels). After processing, the wafer is cut and the single chips are then assembled. The wafer processing stage is the most critical and also the most costly with the silicon material as the main cost determinant of a chip (Gruber (1996)). 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 initial yield rate, which is measured by the ratio of usable chips to the total number of chips on the wafer, is very low. Later, the yield rate increases as firms learn. The necessary amount of silicon and firms' costs decrease simultaneously. Therefore the use of the traditional measure of

[2] More detailed descriptions can be found in Gruber (1996), (1994), Irwin and Klenow (1994) and Flamm (1993).

learning, past cumulative output, fits this pattern very well (see, for example, Irwin and Klenow (1994)). For illustration I calculate learning rates of different DRAM generations at the industry level by using this measure. In Table 1 the estimated learning coefficients of five generations are shown.[3] From these, learning rates[4] can be derived. We find, for example, a learning rate of 26% for the 16K generation. Or equivalently, if past cumulative production doubles cost (price) declines to 74% of its previous level. The learning rates of the other generations are of similar size (64K: 25%, 256K: 21%, 1MB: 18% and 4MB: 18%).

Table 1 about here

At the industry level it is not possible to distinguish between proprietary learning and spillovers. However, learning spillovers are important in this industry. There are several research and development, and production, joint ventures among firms (see, for example, Martin (1996)). Further, production experience is also said to be transferable across firms due to mobility among engineers and other skilled personnel (Irwin and Klenow (1994)). Furthermore, as capital expenditures for a state-of-the-art production facility are very high, a firm's concern is to take advantage of the benefits of economies of scale (Brist and Wilson (1997)).

Life cycles of different semiconductor industries and generations are comparable and short-lived. The time between the introduction of a new chip and the peak in output is relatively short compared to other products. Figure 1 shows industry outputs of the 4K to the 4MB DRAM generation. Different generations overlap. A new generation is on average introduced two and a half years after the emergence of

[3]These results are derived by estimating an industry learning curve for each of the five depicted DRAM generations. The average industry price serves as dependent variable and a constant and past cumulative industry output as independent variables.

[4]Learning rates are calculated by $1-2^{Learning}$. For a detailed discussion of learning curves and a derivation of learning rates see, for example, Berndt (1991, pp. 66)). See also Section 3.2.2.

the generation before. After the first firm has started to sell a new DRAM generation the other firms follow rather rapidly. Also in the end of the product cycle firms' exits take place nearly simultaneously. In spite of the overlapping intergenerational spillovers are not significant (Irwin and Klenow (1994)).

Figure 1 about here

At the beginning of a new generation we can observe very extreme price declines (see Figure 2). Within the first year the average industry price, for example, of the 256K (1MB) generation fell about 60% (70%).

Figure 2 about here

In the 1980s there was an extensive policy debate in the US about the pricing behavior of Japanese semiconductor firms. The general allegation was price dumping. Late in 1985, the US government started investigations. Japanese producers of 64K and 256K DRAM chips were asked to file a quarterly estimate of their full cost data. Japanese 64K DRAM producers were found guilty of charging prices below their current fair market value or cost of production. The dumping case against Japanese 256K DRAM producers was suspended (see, for example, Nye (1996)). If learning-by-doing is present in an industry as in the DRAM industry, firms may have an incentive to sell products below their static marginal costs during the early periods of the product cycle.[5] Dick (1991) rejected the dumping hypothesis for the DRAM industry on the basis of this incentive.

However, do firms take this incentive into account? This paper tries to answer this question and further, to empirically investigate price-cost margins in the presence of learning-by-doing and spillovers. The above mentioned incentive is given

[5]To be more precise, a firm could set itself to an output path that makes its static marginal revenue less than its static marginal cost early in the product cycle and greater than its static marginal cost later in the life cycle.

whether firms play strategically or precommit themselves to a production plan. Firms can use their current output to build up experience and thereby affect the cost structure of their rivals in the future. In contrast, if firms precommit themselves to an output path, they believe that the future cost structure of the industry will not influence its rival's future production (Fudenberg and Tirole (1983)). However, the consequences on price-cost margins should be different. We wish to quantify the magnitude of this incentive on the price-cost margins. The consequences for market power and competition policy should also be considered.

3 The model

In this section I present the model, the implications of the theoretical model for estimation, and the econometric implementation. In the theoretical model firms are assumed to choose quantities and to maximize their profits over the product cycle. The model allows firms not only to learn from their own experiences, but also from spillovers from other firms. The law of motion for the state variable describes how each firm's experience evolves over time. The model is then solved for equilibria in closed-loop no memory[6] and open-loop[7] strategies, respectively. It is a T-period

[6]In a closed-loop information structure players can condition their play at time t on the history of the game until that date (see, for example, Basar and Olsder (1991)). With Markov state-space or feedback strategies 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 (Fudenberg and Tirole (1983)). In a memoryless perfect state information structure the past influences the current play only through its effect on a state variable like in the feedback information pattern and additionally on the initial value of the state, which is known a priori.

[7]If firms precommit themselves to production plans, firms use open-loop strategies. Open-loop strategies are functions of calendar time only. In an open-loop equilibrium players simultaneously commit to entire time paths of production. 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 (1986)). These equilibria are

extension of Fudenberg and Tirole (1983)'s two-period game and a simplified version of the model Jarmin (1994) applied to the early rayon industry. Fudenberg and Tirole showed, that when firms consider the effect of their learning-by-doing on the actions of their rivals, these strategic incentives can induce firms to choose decreasing output paths. Further, small spillovers across firms increase output if firms use open-loop strategies, but decrease output if firms play strategically. Fudenberg and Tirole derived analytical output paths under the assumption of a linear demand in closed-loop and open-loop strategies. Like Jarmin (1994), I do not derive analytical output paths but rather first order conditions, which are empirically implemented later on.

A particular drawback of the use of quantity competition[8] to study learning-by-doing arises, according to Fudenberg and Tirole (1986), because it neglects another strategic aspect. Firms not only can influence the industry's future cost structure by their current output decision, but also can increase their opponents' future cost by reducing their current market share and preventing them from learning today (Fudenberg and Tirole (1986), pp. 21). Price competition reflects this strategic element, whereas with quantity competition the opponents' current output is taken to be fixed and therefore the strategic link in closed-loop strategies cannot be used in such a way.

3.1 A model with learning-by-doing and spillovers

Learning-by-doing and spillovers give a firm's output decision the additional role as investment into experience. The more output a firm produces today, the faster it will learn and the lower unit cost will be tomorrow. To model competition in an

imperfect Nash equilibria and rely on threats which firms would not want to carry out.

[8]To test whether firms might set quantities rather than prices is beyond the scope of the paper. How to test for either price or quantity competition is probably best shown in Feenstra and Levinsohn (1995).

industry characterized by learning-by-doing and spillovers a dynamic game can be set up.

Assume there are $i = 1, \dots, n$ firms and $t = 1, \dots, T$ discrete time periods. At the beginning of each period, firms choose quantities of a homogeneous good, q_{it}. The output of all other firms in the market is denoted by $q_{-it} = \sum_{j \neq i} q_{jt}$. Firm i's costs in period t, $C_{it} = C(q_{it}, ex_{it}, W_{it})$, are a function of current output q_{it}, of firm i's experience ex_{it} and of input prices W_{it}. Firm i's experience ex_{it} is the sum of past cumulative output $x_{it} = \sum_{s=1}^{t-1} q_{is}$ and a fraction $\alpha \in [0, 1]$ of the past cumulative output $x_{-it} = \sum_{j \neq i} \sum_{s=1}^{t-1} q_{js}$ of all firms other than i. The first term represents then learning-by-doing, the second spillovers from the industry. Each firm i chooses q_{it} in order to maximize its present discounted value over the product cycle,

$$Max_{q_{it}} \Pi_i = \sum_{t=1}^{T} \delta^{t-1} \left\{ P_t q_{it} - C(q_{it}, ex_{it}, W_{it}) \right\} \tag{1}$$

$$\text{s.t.} \;\; ex_{it+1} = q_{it} + \alpha q_{-it} + ex_{it} \tag{2}$$

$$\text{and} \;\; ex_{i0} = 0 \tag{3}$$

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 state equation (2) describes how firm i's experience ex_{it} evolves from t to $t+1$. Firm i's experience is an additive function of its own production, a fraction of its rivals' production gained through spillovers and of its experience one period before. Equation (3) states the initial conditions. At the beginning of the product cycle there is no experience.

The necessary conditions for a no memory closed-loop Nash equilibrium[9] of (1)

[9] The existence of a Nash equilibrium in an infinite game with a no memory closed-loop information structure is guaranteed, when the objective function is continuously differentiable and the state equation is convex and continuously differentiable. For further details see Basar and Olsder (1991).

are

$$P_t + \frac{\partial P_t}{\partial q_t}\, q_{it} = \frac{\partial C_{it}}{\partial q_{it}} \; + \sum_{s=t+1}^{T} \delta^{s-t} \left\{ \frac{\partial C_{is}}{\partial ex_{is}} \frac{\partial ex_{is}}{\partial q_{it}} - \frac{\partial P_s}{\partial q_s}\, q_{is} \sum_{j \neq i} \frac{\partial q_{js}}{\partial ex_{js}} \frac{\partial ex_{js}}{\partial q_{it}} \right\} \tag{4}$$

for all $i, j = 1, \ldots, n$ and $t = 1, \ldots, T$. The first terms of (4) are the standard first order conditions from the static Cournot problem. The first term in brackets are discounted future cost savings due to learning-by-doing and spillovers gained through firm's contemporaneous output decision. It is the direct future cost savings effect. The second term in brackets shows the intertemporal strategic effect due to learning-by-doing and spillovers. If firms play strategically they consider the future cost structure $(C_{is>t})_{i=1}^{n}$ of their rivals as a function of their own output today. Thus, future industry output $q_s = q_s((C_{is>t})_{i=1}^{n})$ is a function of current output q_{it} through spillovers αx_{-is}. A change in firm i's strategy at time t affects firm $j \neq i$'s objective function in period s through the state variable ex_{is}. In the case of learning-by-doing and no or small spillovers q_{it} and q_{js} will be strategic substitutes. If spillovers are large enough q_{it} and q_{js} will be strategic complements (Jarmin (1994)).

The necessary conditions[10,11] for an open-loop Nash equilibrium of (1) are included in the first order conditions (4) but lack the intertemporal strategic terms. Firms set themselves to an output path that makes their marginal revenue equal to dynamic marginal costs, the sum of marginal costs and future marginal costs.

[10] The existence of a Nash equilibrium in an infinite game with an open-loop information structure is guaranteed, when the objective function is continuously differentiable and the state equation is convex and continuously differentiable. For further details see Basar and Olsder (1991).

[11] There are two cases when the closed-loop no memory and the open-loop equilibria coincide (Cellini and Lambertini (2001)): i) the state variable of any firm does not depend on other firms' control and state variables and ii) for any firm the first-order conditions taken with respect to the control variables are independent of other firms' state variables.

3.2 The econometric implementation

The empirical model of the DRAM industry consists of a demand equation and two pricing relations based on the first-order conditions (4) and their open-loop counterpart. This gives two systems of equations, one for closed-loop no memory strategies and one for open-loop strategies. For estimation, structure has to be placed on the demand and on the cost functions, as demand and cost parameters enter the pricing relations.

3.2.1 Inverse demand equation

To be able to identify the pricing relation an estimate for the elasticity of demand is necessary. The inverse demand function is specified log-linearly as

$$ln(P_t) = \beta_0 + \beta_1 \; ln(q_t) + \beta_2 \; ln(q_t^{S_1}) + \beta_3 \; ln(q_t^{S_2}) + \beta_4 \; ln(Y_t) + \beta_5 \; time + \mu_t \tag{5}$$

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 $q_t^{S_2}$ are the respective quantities of substitute semiconductors, Y_t is a vector of other nonprice demand shifters and *time* is a time trend. As substitute semiconductors I take the proceeding and the following DRAM generation.

The parameters to be estimated reflect the own inverse elasticity of demand, the cross elasticities of demand, the effect of a general demand shifter, and a time trend. We predict a negative sign for the own (inverse) elasticity of demand β_1. The parameters β_2 and β_4 refer to the cross-price elasticities and are supposed to be negative (positive) if the respective generations are substitutes (complements) to the generation under investigation. Further, we await a positive sign for the demand shifter β_4. The expected sign of the time trend coefficient β_5 is negative. It captures the effect of the time length that a particular generation has been in the market.

3.2.2 Pricing relations

The empirical pricing equations are derived from the first order conditions (4) and their counterpart in open-loop strategies. The price is a function of marginal cost, future cost savings and in the case of the closed-loop no memory setting also of the intertemporal strategic effects. Thus the closed-loop pricing relations nest the open-loop pricing relations. I set up the two specifications, test for the superior model and can then compare the two estimated parameter sets.

In the dynamic model (1) and its first-order conditions (4) firms are represented to be able to act in a very flexible way. In particular, firm i reacts at time t on the objective function of firms $j, j \neq i$ at time $s > t$ and the (re)actions can be different at every point in time s. For example, firm 1 reacts at time t to the objective function of other firms at time $t + 3$ and this reaction does not need to be the same at the beginning and in the end of the product cycle. When it comes to the implementation of the model for estimation one has to impose restrictions. Otherwise the econometric model would not be identified. The strategy I will follow is to concentrate on firm i's reaction at time t to firms' $j, j \neq i$ objective function at time $t + 1$ and model the effects that lie further in the future via firm specific constants. However, the strategic effect from t to $t + 1$ I will allow to change monotonically over time. The strategy I adopt for future cost effects is simpler. They are modelled within the dynamic marginal cost function also via firm specific constants.

Intertemporal strategic parameter As there is no intertemporal strategic interaction in the open-loop model this parameter has to be defined only for the closed-loop model. As already mentioned, the model is not identified, if all terms that measure dynamic strategic effects were estimated separately. Thus I follow

Jarmin (1994) and assume

$$\theta_{it} := \sum_{j \neq i} \frac{\partial q_{jt+1}}{\partial ex_{jt+1}} \frac{\partial ex_{jt+1}}{\partial q_{it}} \tag{6}$$

as the intertemporal strategic parameter. The theoretical model allows different reactions of firm i at time t to firms $j \neq i$ at time $t+1$. These reactions are described by $\frac{\partial q_{jt+1}}{\partial ex_{jt+1}} \frac{\partial ex_{jt+1}}{\partial q_{it}}$ for all $i, j = 1, \ldots, n$ and $j \neq i$. However, econometrically only the sum of these reactions is identified by the output q_{it+1} of firm i at time $t+1$ (see first-order conditions (4)). The intertemporal strategic parameter θ_{it} then measures how a change in firm i's output at time t changes the output of all other firms at time $t+1$. It further varies over time. In particular, when the end of the product cycle is approaching it should be decreasing (in absolute terms). However, θ_{it} cannot be identified for all i and t. If we assume a kind of linear separability between firms and time, θ_{it} in equation (6) can be expressed as follows

$$\theta_{it} = \theta_0 + \theta_1 \; time_i. \tag{7}$$

The intertemporal strategic parameter is the sum of a firm-invariant constant and a firm-specific linear time trend, which exposes variation over firms due to their different entry and exit dates. With this definition it is assumed that θ_{it} varies over firms and time, although in a restricted way. By evaluating $time_i$ at their sample means (or medians) we get firm specific intertemporal parameters. This definition is in contrast to Jarmin's (1994) set-up, in which the intertemporal strategic parameter is not allowed to vary over time.

The first-order conditions give the following indications for empirical testing. The difference between closed-loop no memory and open-loop first order conditions can be pinned down by the intertemporal strategic parameter θ_{it}. If this term is not zero, we can conclude that firms use closed-loop no memory strategies. On other hand if this term equals zero, nothing can be said. The situations where firms use either closed-loop no memory strategies with a strategic impact that is equal to zero or open-loop strategies cannot be distinguished. If there is strategic interaction, q_{it} and q_{jt+1} are either strategic substitutes or complements. In the first case the expected sign of θ_{it} is negative. This situation goes along with learning-by-doing and no or small spillovers. The cost reduction gains through proprietary learning exceeds the effect of spillovers. In the second case we await a positive sign for θ_{it} that is in line with learning-by-doing and large spillovers. Firms' cost reductions due to spillovers are that large to view their rivals' output tomorrow as a strategic complement.[12] The sign and the significance of θ_{it} can be tested.

Specification of (future) marginal cost The pricing relations further require expressions for marginal costs and for future cost savings. These expressions include parameters that measure contemporaneous output, learning-by-doing, spillovers and input prices. The marginal cost function I approximate with a linear function assuming that the cost function $C_{it} = f(q_{it}, ex_{it}, W_{it})$ itself has a quadratic form. Marginal costs $MC_{it} = \frac{\partial C_{it}}{\partial q_{it}}$ and future cost savings $FMC_{it} = \sum_{s=t+1}^{T} \delta^{s-t} \frac{\partial C_{is}}{\partial ex_{is}} \frac{\partial ex_{is}}{\partial q_{it}}$ add up to dynamic marginal cost DMC_{it} as follows

$$\begin{aligned} DMC_{it} = {} & \gamma_0 + \gamma_1\ firm_i + \gamma_2\ q_{it} + \gamma_3\ x_{it} + \gamma_4\ x_{-it} + \gamma_5\ MAT_{it} + \gamma_6\ ENE_{it} \\ & + \gamma_7\ LAB_{it} + \gamma_8\ CAP_{it} \end{aligned} \tag{8}$$

for $i = 1, \ldots, n$ and $t = 1, \ldots, T$.[13] Dynamic marginal costs vary across firms through a firm-specific intercept $\gamma_1\ firm_i$. Like Brist and Wilson (1997) I allow for

[12] For a more detailed discussion on θ_{it} see Jarmin (1994).

[13] Given the literature about learning curves one would expect a log-linear marginal cost function. I also explored this specification, but it did not perform well. Only, when I do not separate learning-by-doing and spillovers into two variables but use the log of the sum of the both, the results are plausible. However, the separation of these two effects is important given the theoretical model and the respective first-order conditions.

economies of scale. Firm i's experience ex_{it} is measured by the sum of learning-by-doing and spillovers from the industry. Learning-by-doing is measured by cumulative past output $x_{it} := \sum_{s=1}^{t-1} q_{is}$. The predicted sign for this variable is negative. The more output has been produced in the past the lower dynamic marginal costs. By using the parameter estimate γ_3 it is also possible to calculate the learning rate for a given DRAM generation at the firm-level. Learning curves are usually in log-linear form. Thus, in a linear case like here one has to calculate first the learning elasticity $\gamma_3^{'} = \gamma_3 \frac{\overline{x_{it}}}{\overline{P_t}}$ evaluated at the respective sample means $\overline{x_{it}}$ and $\overline{P_t}$. The learning rate then can be measured by $1-2^{\gamma_3^{'}}$.[14] Spillovers are assumed to be symmetric and are a fraction of the sum of all past cumulative output of other firms $x_{-it} := \sum_{j \neq i} \sum_{s=0}^{t-1} q_{js}$. Irwin and Klenow (1994) distinguish between countrywide and worldwide spillovers. Their estimation results, however, do not show significant differences between these two kinds of spillovers. Again, we expect a negative sign for γ_4. Higher spillovers yield lower dynamic marginal costs. If we assume that there is only one single learning curve for proprietary learning and for learning from spillovers, the fraction α that spills over from other firms can be derived from the ratio of the two estimates γ_3 and γ_4. The last four variables are input prices: MAT denotes the price of silicon, ENE the price of energy, LAB the price of wages and CAP the price of capital. Generally one would anticipate a positive influence of factor prices on marginal cost. Negative signs can reflect some degree of factor substitution (see, for example, Neven and Röller (1999)).

Further dynamic effects Like Jarmin (1994) and Roberts and Samuelson (1988), I capture all intertemporal strategic effects that occur in two or more future periods $FDE_{it} = \sum_{s=t+2}^{T} \delta^{s-t} \frac{\partial P_s}{\partial q_s} q_{is} \sum_{j \neq i} \frac{\partial q_{js}}{\partial q_{it}}$ via a firm specific constant and define them in

[14]For a thorough discussion of learning curves and a derivation of learning rates the interested reader should go, for example, to Berndt (1991, pp. 66)).

the following way

$$FDE_{it} = \gamma_9 \; firm_i \tag{9}$$

for $i = 1, \ldots, n$ and $t = 1, \ldots, T$.[15] However, the firm-specific dummy variables do not only measure future dynamic effects, but firm-specific effects in the dynamic marginal cost function and any remaining firm-specific heterogeneity. The future dynamic effects FDE_{it} are relevant only for the closed-loop specification.

Equilibrium relation Incorporating all definitions made before leads to the following econometric models of the pricing relations. Using (7), (8) and (9) we arrive at the following for the closed-loop no memory equilibrium

$$\begin{aligned} P_t = {} & \gamma_0 + (\gamma_1 + \gamma_9) \; firm_i + \gamma_2 \; q_{it} + \gamma_3 \; x_{it} + \gamma_4 \; x_{-it} + \gamma_5 \; MAT_{it} + \gamma_6 \; ENE_{it} \\ & + \gamma_7 \; LAB_{it} + \gamma_8 \; CAP_{it} - \beta_1' \; q_{it} - \beta_1' \; (\theta_0 + \theta_1 \; time_i) \; q_{it+1} + \mu_{it} \end{aligned} \tag{10}$$

for $i = 1, \ldots, n$ and $t = 1, \ldots, T$. The term $\beta_1' = \frac{\partial P_t}{\partial q_t}$ represents the inverse demand effect and will be derived from the estimated inverse demand elasticity β_1 in the inverse demand equation (5). The price for a particular DRAM generation is a function of dynamic marginal costs, the inverse demand effect and of the intertemporal strategic behavior measured by the parameters θ_0 and θ_1. The econometric pricing relation for open-loop strategies is nested in (10) lacking the intertemporal strategic terms. I can now test the effect of a firm's strategy on the objective functions of other firms in future periods by testing the joint significance of θ_0 and θ_1 and calculating θ_{it} for each firm i. The implications for various parameters can be explored by identifying the superior model and comparing the estimated values of dynamic marginal cost.

[15]Future dynamic effects are kept to be constant over time. This is rather restrictive. I tested firm-specific linear time trends. However, this specification then suffers from the multicollinearity of the firm-specific linear time trends with linear time trend of the intertemporal strategic effect.

3.2.3 Average price-cost margins

The instantaneous degree of market power of firms in an oligopoly market is measured by the extent to which firms can hold price above marginal cost. Dynamic price-cost margins can be derived by transforming the first-order conditions (4) analogously to the static price-cost margins and expressed as follows:

$$\frac{P_t - DMC_{it}^c}{P_t} = -\beta_1 s_{it} - \beta_1 \left(\theta_0 + \theta_1 \; time_i\right) \; s_{it+1} \frac{P_{t+1}}{P_t} - \frac{FDE_{it}}{P_t} \; , \tag{11}$$

where the superscript c marks the estimated parameters from the closed-loop specification. The price-cost margins are calculated with respect to dynamic marginal cost DMC_{it}. The righthand side of (11) is the sum of the static index of market power and the intertemporal effects. In the open-loop setting the later effects are equal to zero. Thus in this case the price-cost margins are equal to the static ones:[16]

$$\frac{P_t - DMC_{it}^o}{P_t} = -\beta_1 \; s_{it} \; , \tag{12}$$

where the superscript o marks the estimated parameters in the open-loop setting. If the strategic parameter θ_{it} is, for example, negative and q_{it} and q_{jt+1} are strategic substitutes, then the average price-cost margins in the strategic dynamic setting, calculated from (11), are lower than the average price-cost margins in the precommitment setting, derived from (12), as $-\beta_1 \; s_{it}$ is equal in both settings. Or equivalently, price-cost margins would be overestimated in the later setting. This statement is independent of a possible change in the parameter estimates of dynamic marginal costs due to an omitted variable bias with respect to θ_{it}.

[16] The right hand side of (12) is often multiplied by a conduct parameter. This parameter indexes the competitiveness of oligopoly conduct (Bresnahan (1989)). Like in Cournot games, the conduct parameter for closed-loop no memory and open-loop specifications is equal to one. If firms collude or they are price takers, then the closed-loop no memory and the precommitment model are the same (see, for example, Karp and Perloff (1989)).

To state above claim, one has to be more precise about the intertemporal strategic behavior for the periods $t+2$ onward: It is not only necessary that θ_{it} is negative, but it is also necessary that FDE_{it} corresponds to strategic substitutability or, if it corresponds to strategic complementary, that its magnitude is not larger than that of θ_{it}. Otherwise, the price-cost margins in the closed-loop setting can be larger than those in the open-loop setting. As the firm-specific constants in the estimated pricing relations (10) measure both firm-specific dynamic marginal cost and intertemporal strategic effects occurring $t+2$ periods onward, empirically no exact answer can be given. However, to assume that either θ_{it} and FDE_{it} reflect the same intertemporal strategic behavior or that, if this behavior changes over time, the effect between t and $t+1$ is the largest in absolute terms and outweighs all other future effects, that correspond to strategic complementarity, is not implausible. Otherwise, effects occurring later in the future would have more weight than those in the more immediate future.

4 Data and estimation results

The data consist of firms producing DRAM chips and are compiled by Dataquest Inc. The data cover 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 on a quarterly basis. From the firm-level output data, I construct three variables: current output, own past cumulative output and other firms' past cumulative output. Current output is used to test for economies of scale. Own cumulative output is used to test for learning-by-doing. The cumulative past output of all other firms is used to test for spillovers. I further 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 firm's production location, the energy prices and the industry wages (ISIC 3825) of the respective location (country) are used.[17] User cost of capital is constructed for each firm and year by exploiting the annual reports of each firm. As a nonprice demand shifter I use a proportion of GNP directly attributed to electronic and electrical equipment from the OECD (1998). Table 2 gives some summary statistics.

Table 2 about here

In the empirical analysis of the DRAM industry I analyze whether firms take the intertemporal strategic effect of learning-by-doing and spillovers into account, i.e. I test whether the estimates of θ_0 and θ_1 in the pricing equation (10) are significantly different from zero. And if firms do consider the effect of their own output decision in t on their rivals output decision in $t+1$, what is the sign of the intertemporal effect? The second part of the analysis takes a closer look at the consequences of a possible misspecification by ignoring significant intertemporal strategic effects. First, I concentrate on the estimated values of economies of scale, learning-by-doing and spillovers and investigate the differences between the estimates of the closed-loop and the open-loop specification. Second, I compare the price-cost margins of the two settings and calculate the differences for each DRAM generation.

For this purpose two systems of equations are estimated: equations (5) and (10) for the closed-loop no memory equilibrium. For the open-loop specification I also use these equations with θ_0 and θ_1 simultaneously restricted to zero. I run the estimations for five different generations of DRAM chips, namely the 16K, the 64K, the 256K, the 1MB and the 4MB generation. This selection relies primarily on the fact that not all generations were in the market for a long enough period

[17] The source for energy prices is OECD/IEA (1998), that for industry wages OECD (1998).

of time. Thus I do not consider generations which give me relatively fewer data points. This is of particular relevance concerning the estimation of the inverse demand equation. The generations 64K and 256K are of special interest as these generations were under dumping investigations by the US Commerce Department and the International Trade Commission (see, for example, Flamm (1993)).

Demand equation For estimating the demand relations of five DRAM generations, I use two-stage least square. The instruments in the inverse demand equation consist of the exogenous variables in the demand equation, like the general demand shifters and the time trend, and of summary measures from the supply side, like the number of firms in the industry, and cumulative world output. The substitute generations are also instrumented by the respective summary measures from their supply side and cumulative world output. The first stage equations for each DRAM generation and for each of its substitute generation are of good fit with adjusted R-squares above 0.80. The F-statistics always have a value much larger than 10, which has been recommended by Staiger and Stock (1997) as a concrete guideline for the power of instruments. The residuals of the second stage equations exhibit first order autocorrelation. Therefore the estimated standard errors are corrected by using the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix. The estimates of the five inverse demand equations and their respective t-statistics are reported in Table 3.[18] For estimation 36, 67, 56, 45, and 34 observations are used. All estimations have good fits with adjusted R-squares

[18] The time series in the inverse demand equations are tested for a unit root. By using (Augmented) Dickey Fuller tests I can reject the null hypothesis of a unit root at a significance level of 10% for logarithmic prices and logarithmic outputs of the 16K, 64K, the 256K, the 1MB and the 4MB generation. However, the general demand shifter, the logarithm of GDP attributed to electronic and electrical equipment, has a unit root. I therefore use the first-differenced time series, which has no unit root.

ranging from 0.91 to 0.99.

Table 3 about here

Each generation's own demand elasticity is negative and significant, indicating that higher industry output decreases prices. The estimates across generations with respect to their own inverse demand elasticity have estimated values of 0.430, 0.368, 0.334, 0.683 and 0.214 for 16K, 64K, 256K, 4MB and 1MB, respectively. These correspond to demand elasticities of 2.325, 2.481, 2.584, 1.464 and 4.672 and are in line with the previous literature (see, for example, Brist and Wilson (1997) or Flamm (1993)). The cross elasticities to the previous generation are positive and significant for the 16K to the 1MB generation and significantly negative for the 4MB generation. The cross elasticities with respect to the following generations are negative and significant only for the 4MB generation. For the other generations they are insignificant. The (growth rate of the) nonprice demand shifter is positive and significant for the 256K and the 1MB generation, but proves to have no significant influence on the 16K, the 64K and the 1MB generation. The remaining demand determinant, the time trend, should be negative, suggesting that buyers substitute away from one generation to the next as time elapses. The estimated time trend exhibits the expected sign for all generations but the 1MB generation.

Pricing equation For estimating the pricing equations I again use single equation techniques. The dependent variable of equation (10) is the average industry price of the respective DRAM generation. Because of its endogeneity with the average industry output and with the firm-specific outputs at time t and $t+1$ two-stage least square estimations are used. The instruments in the pricing equations for a particular DRAM generation consist of exogenous variables in the respective demand equation, like the general demand shifter and the time trend, and summary measures from the supply side, like the number of firms in the industry and cumulative world output. Further instruments are lagged firm-specific outputs. In the case of the closed-loop specification for firm-specific outputs at time $t + 1$ the once and for firm-specific outputs at time t the twice lagged firm-specific outputs are used. In the case of the open-loop specification only the once lagged firm-specific outputs are used. The estimates of the first stage equations for each DRAM generation are significantly different from zero using a F-test. The adjusted R-squares range from 0.78 to 0.95.

For each of the five DRAM generations I estimate two specifications corresponding the closed-loop no memory and the open-loop equilibrium relation, respectively. The inverse demand effect β_1' is derived from the estimated inverse demand elasticity β_1 of the respective inverse demand equation (5). As the closed-loop equation nests the open-loop equation the significance of the intertemporal strategic parameters θ_0 and θ_1 can be used for model selection. The open-loop specification can be rejected, when these coefficients are jointly significant.[19] Afterwards I compare the two specifications with respect to the parameter estimates and the average price-cost margins.

Tables 4 and 5 contain the parameter estimates for the closed-loop no memory and the open-loop specification for the 16K, 64K, 256K, 1MB and 4MB generation. The number of observations is different in the two set-ups as the in the closed-loop specification not only once but also twice lagged variables are used as instruments. The fit of the five estimations is not as good as the fit for the demand equations with adjusted R-squares ranging from 0.25 to 0.70. The coefficients of the intertemporal strategic parameters θ_0 and θ_1 are significantly different from zero for all estimated generations, suggesting that firms take the intertemporal strategic effect of their con-

[19] The null hypothesis is open-loop, the alternative hypothesis is closed-loop.

temporaneous output decision on their rivals' future output decision into account.[20] By using a F-test to test the joint significance of θ_0 and θ_1 the null hypothesis of no influence can be rejected for the five generations under investigation. Thus, the null hypothesis of firms precommitting themselves to a production plan can be rejected. Firms take the intertemporal strategic nature of their current output decision on their rivals' future cost structure into account. The adjusted R-squared model selection criterion also favors the closed-loop no memory specification. Only in the case of the 64K generation this criteria would not allow for a distinction between the two specifications.

Table 4 about here

Table 5 about here

The negative sign of θ_0 suggests that firms view the future production of their rivals as a strategic substitute to their own current output. As there are both significant learning-by-doing and spillovers, this further indicates that the spillovers are not large enough relative to proprietary learning-by-doing to bring about intertemporal strategic complements. The positive sign of θ_1 means that the intertemporal strategic effect (in absolute terms) declines over time. The size of the intertemporal effect depends on a firm's position in the product cycle. The further in the product cycle the less firms regard their rivals' output tomorrow as a strategic substitute. That is a result such as one would expect. The gain of future cost savings due to accumulation of experience declines over time.

From definition (7) we can calculate the evolution of the average intertemporal strategic effect over time.[21] Table 6 shows one of the four values for each year,

[20] In fact, I estimated rather $\delta\theta_{it}$ than θ_{it}. However, as the discount factor δ is strictly positive, a significant negative (positive) sign of the estimate means that θ_{it} has to be negative (positive).

[21] It is also possible to calculate firm specific intertemporal parameters over time. However, the results do not exhibit much deviation across firms.

namely the value of the third quarter. In the course of time firms reconsider their rivals' future cost structure. For example, in the last two years of the 16K generation production, firms' intertemporal strategic behavior changes. Either the spillovers are then large enough to create intertemporal strategic complementarity between today's output and rivals' output tomorrow or the positive sign of θ_{it} recovers coordinated behavior among firms (Jarmin 1994, p. 448). In the latter case current output should be positively correlated with tomorrow's output. In contrast to the static conduct parameter the size of the intertemporal strategic parameter cannot be used to infer how large the impact of collusion would be. Towards the end of the product cycle firm-specific experience due to learning-by-doing and spillovers has been aggregated over the industry in such a way that a firm's learning-by-doing would benefit its rivals more than itself. The results across different DRAM generations are quite similar. Only in the case of the 64K generation the point of reconsideration takes place rather early in the product cycle. Therefore for this generation, the average over the product cycle of the intertemporal strategic effects is positive in contrast to a negative average for all other generations.

Table 6 about here

The consequence of neglecting the intertemporal strategic interaction can be an omitted variable bias, as the following description of the other estimates will show. Economies of scale are measured by the coefficient of current output. The coefficients of this variable are negative and significant for all generations but the 4MB generation in the closed-loop specification and negative and significant for all generations in the open-loop specifications, indicating increasing returns to scale. Economies of scale are overestimated (in absolute values) in the open-loop specification compared to the closed-loop specification and the differences between the estimates of the two specifications are significant for all but the 64K generation using a t-test.[22] In the case of the 64K generation we actually observe the opposite. Although the difference is not significant, the estimate in the open-loop specification would be underestimated.

Now consider the parameter that measures learning-by-doing. The parameter is always negative and significant in both the closed-loop and the open-loop setting. Only in the latter setting learning-by-doing is insignificant for the 4MB generation. Firms learn through their own past output, which contribute to firms' experience. The learning elasticities correspond to learning rates[23] of 17%, (6%, 24%, 13% and 15%) for the 16K (64K, 256K, 1MB and 4MB) generation in the closed-loop specification. If, for example, past cumulative production of the 16K generation doubles cost declines to 83% of its previous level. Comparing these values with those at the industry level (Table 1) we observe expected lower rates at the firm level. The respective learning rates in the precommitment specification are underestimated and have values of 6%, 8%, 14%, 10% and 0%. Again, only for the 64K generation the opposite holds with an overestimated learning rate. The differences between the learning rates of the two specifications are significantly different from zero for the 16K, the 256K and the 4MB generation.[24]

Spillovers are negative and significant for all generations in both specifications. Again, in the precommitment specification they are insignificant for the 4MB generation. Firms also learn through spillovers from other firms. Thus, a fraction of rivals' output add to firms' experience. The sign of the difference between the estimates of the two specifications shows no clear direction. In some cases spillovers

[22] The t-statistics with unknown variances are equal to 2.896 (16K), -1.291 (64K), to 1.852 (256K), to 3.108 (1MB) and to 2.251 (4MB).

[23] For the calculation of learning rates see Section 2 and 3.2.2.

[24] The t-statistics with unknown variances are equal to -3.025 (16K), to 0.349 (64K), to -3.164 (256K), to -1.272 (1MB) and to -3.111 (4MB).

are underestimated, in the other cases overestimated. Under the assumption of one learning curve for proprietary learning and for learning from spillovers, the fraction α that spills over from other firms can be derived from the ratio of γ_3 and γ_4 (see also Section 3.2.2). We gain reasonable values for α in the closed-loop specification. These are 0.111, 0.216, 0.052, 0.071 and 0.045 for the 16K, the 64K, the 256K, the 1MB and the 4MB generation. The respective values in the open-loop specification are 0.346, 0.104, 0.073, 0.078 and -0.075. The negative sign for the 4MB generation can correspond to raising rivals' cost. Although here, it is due to the insignificant learning-by-doing effects.

Concerning the results for input prices first should be noted, that both specifications exhibit the same signs and roughly the same magnitudes for each of the estimated coefficients. Dynamic marginal cost of firms producing the 16K, the 1MB and the 4MB generation are positively effected by the price of silicon, price of energy, price of labor and user cost of capital. For the 64K generation we find a positive sign for all input prices but the price of energy. It has a significant negative effect on dynamic marginal cost. The same is true for the 256K generation, which has an additional negative sign, although insignificant, for labor cost. The occurrence of a negative influence of particular inputs on prices can be due to substitution effects. Another explanation can lie herewith, that, for example, wages at an aggregated industry level are used for the price of labor and these probably do not reflect the true cost structure of individual firms. This is also true for the price of energy. Only the price of silicon and user cost of capital seem to be reliable, as the first is a worldwide price and the latter is derived from firms' business reports.

Average price-cost margins In terms of policy and antitrust, the results concerning the price-cost margins are the most interesting ones. In Table 7 Herfindahl indices, elasticities of demand, predicted and estimated price-cost margins of both specifications are reported. Further, the average intertemporal strategic effects are given. The predicted price-cost margins are calculated by the use of the Herfindahl indices and the estimated demand elasticities. We obtain values of 6%, 10%, 6%, 12% and 3% for the five DRAM generations in the precommitment specification. These values are the same as one would dereive from a static Cournot game. In the presence of a significant negative intertemporal strategic effect they are upper bounds for the predicted price-cost margins of the closed-loop specification. Those cannot be exactly calculated, as future dynamic effects and firm-specific cost effects are not separately identified. The same is true for the estimated price-cost margins, which can be calculated according to (11) and (12), respectively. However, if we attribute the firm-specific effects completely to dynamic marginal cost, we can obtain the estimated price-cost margins of the closed-loop specification. The calculations yield larger average price-cost margins in the closed-loop specification for all but the 64K generation. The later result is due to the fact, that the intertemporal strategic parameter, averaged over the product cycle, is positive for this DRAM generation. The difference between the two price-cost margins are, for example, in the case of the 256K generation 20%.

Table 7 about here

To observe the development over the product cycle, Figure 3 shows the price and estimated dynamical marginal costs in both settings for the 256K generation. The picture looks similar for all other generations. Only for the 64K generation no difference between dynamic marginal costs of the two set-ups can be noticed. In the first half of the product cycle we see a rather clear distinction between the two dynamic marginal cost functions. Neglecting the intertemporal strategic effect would underestimate dynamic marginal costs. In the second half of the product cycle the difference moves towards zero and we arrive at a situation where prices are nearly equal to dynamic marginal costs. Thus, we can reject the hypothesis of coordinated behavior among firms, but cannot reject the hypothesis of intertemporal strategic complementarity in the end of the product cycle. However, as Figure 3 shows, this latter effect is rather small, nearly zero. We also observe, that in the very beginning of the product cycle firms have some market power resulting in prices above dynamic marginal costs. Only later a period characterized with price dumping emerges. Market power is assessed lower and dumping margins are assessed larger in the closed-loop set-up. In particular the results show that dumping margins do not completely vanish. The additional consideration that firms behave strategically implies even larger dumping margins.

Figure 3 about here

5 Discussion and conclusions

In this article, I estimate a dynamic oligopoly model that incorporates the strategic implications of learning-by-doing and spillovers. From a theoretical game I derive a structural model for estimation. The first order conditions are set up in closed-loop no memory and in open-loop strategies. The contribution of this paper is then to test which strategies firms use and to compare the estimated parameters of the two specifications. Further, the influence of the equilibrium concept on learning-by-doing, spillovers, economies of scale and price-cost margins is investigated. The two models are estimated using firm-level data from the DRAM semiconductor industry. The difference between these two specifications can be captured by two parameters that describe the intertemporal strategic interaction. As the open-loop equation is nested in the closed-loop no memory specification the joint (in)significance of these parameter can be used for model selection.

The estimation results support the presence of economies of scale, learning-by-doing and spillovers and are in line with, for example, Irwin and Klenow (1994). The joint significance of the intertemporal strategic parameters shows that firms take the intertemporal strategic effect of their contemporaneous output decision on their rivals' future output decision into account. The null hypothesis of firms' precommitting themselves to a production plan can be rejected. The negative sign of the intertemporal effect suggests that firms view their rivals' future production as an strategic substitute for their own current output. In the course of time the intertemporal strategic effect diminishes. This indicates that in the beginning of the product cycle spillovers are not large enough relative to proprietary learning to bring about strategic complements. In the end of the product cycle prices are equal dynamic marginal cost. The inferred structural parameters, such as economies of scale, learning-by-doing and price-cost margins are significantly affected by the equilibrium concept. In particular, price-cost margins are overestimated, if one does not consider firms as acting strategically over time. This means that market power is actually lower in a dynamic context than estimates, based on a static framework such as the open-loop equilibrium, would imply. Dick (1991) argued that the dumping hypothesis for the DRAM industry can be rejected because firms have an incentive to sell products below their static marginal costs during the early periods of the product cycle. However, dumping margins do not completely vanish and intertemporal strategic considerations suggest even larger dumping margins.

In the DRAM industry firms' contemporaneous output decision can be interpreted as an investment into experience. Other industries are characterized through other investment decision like investments into a network. In a conceptual similar way one could implement a model of network competition in order to measure the intertemporal strategic effects there. The same is true for durable or experience good industries. On the other side the intertemporal strategic effect in the empirical model of the DRAM industry could measure strategic considerations not only due to learning-by-doing and spillovers but due to the durability of a DRAM chip. However, it is not possible to identify these effects within the proposed model.

Because of the significant intertemporal strategic effect, I consider the estimation results of the closed-loop no memory specification as the relevant ones. Ignoring that firms consider the intertemporal strategic effect of their current output decision on their rivals' future output decision leads to an incorrect assessment of a market. Actually, market power is lower and dumping margins are larger. The empirical results are robust over a number of different DRAM generations.

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Table 1: Industry learning curves

Variable	16K	64K	256K	1MB	4MB
Constant	9.779	9.261	8.511	7.864	8.560
	(24.53)	(51.69)	(33.699)	(27.15)	(34.55)
Learning	-0.434	-0.407	-0.347	-0.288	-0.294
	(-20.37)	(-45.08)	(-28.25)	(-19.82)	(22.43)
adjusted R^2	0.92	0.97	0.94	0.90	0.94
Number of observations	36	67	56	45	33

T-statistics in parenthesis.

Table 2: Summary statistics

Variable	16K	64K	256K	1MB	4MB
	At the industry level				
Price	13.019	26.562	16.975	19.177	79.279
	(19.63)	(67.83)	(43.12)	(31.91)	(160.80)
Output (in Mill.)	36.5	38.7	82.2	103.3	162.0
	(80.5)	(60.4)	(83.2)	(71.4)	(151.0)
Price of silicon	2271.8	1872.4	1673.1	1654.6	1562.2
	(472.3)	(472.2)	(251.7)	(273.5)	(255.9)
Number of observations	36	67	56	45	34
	At the firm level				
Output (in Mill.)	2.56	3.80	5.73	6.69	10.50
	(2.77)	(5.86)	(7.73)	(6.36)	(11.60)
Price of energy	-	7483.7	7521.6	4616.6	6717.6
	-	(15730)	(15371)	(9803)	(13241)
Price of labor (in Mill.)	-	936	1160	829	1290
	-	(1680)	(2160)	(1660)	(2350)
Price of capital	-	0.158	0.098	0.088	0.0812
	-	(0.131)	(0.084)	(0.077)	(0.077)
Number of observations	510	693	817	710	525

For the 16K generation as input price only the price of silicon is available.

Prices are in constant US Dollars.

Standard deviations in parenthesis.

Table 3: Inverse demand equation

Variable	16K	64K	256K	1MB	4MB
Constant	5.820	11.788	9.607	-19.715	29.128
	(2.29)	(8.87)	(11.79)	(-1.12)	(3.62)
Ln(4K Output)	0.313	-	-	-	-
	(3.91)	-	-	-	-
Ln(16K Output)	-0.430	0.005	-	-	-
	(-5.10)	(2.43)	-	-	-
Ln(64K Output)	0.007	-0.368	0.004	-	-
	(1.44)	(-8.09)	(2.30)	-	-
Ln(256K Output)	-	0.004	-0.334	1.374	-
	-	(0.95)	(-7.82)	(1.64)	-
Ln(1MB Output)	-	-	-0.002	-0.683	-1.052
	-	-	(-0.74)	(-2.39)	(-2.69)
Ln(4MB Output)	-	-	-	-0.002	-0.214
	-	-	-	(-0.58)	(2.12)
Ln(8MB Output)	-	-	-	-	-0.009
	-	-	-	-	(-7.08)
D(Ln(GDP))	4.334	-1.703	28.486	26.320	16.216
	(0.92)	(-0.31)	(2.63)	(1.72)	(1.18)
Time	0.120	-0.249	-0.162	0.537	-0.184
	(-4.06)	(-6.52)	(-6.83)	(1.23)	(1.35)
Adjusted R^2	0.98	0.97	0.96	0.91	0.99
Number of observations	36	67	56	45	34

T-statistics in parenthesis.

Table 4: Estimation results for the closed-loop pricing relation

Variable	16K	64K	256K	1MB	4MB
Constant	17.553	-88.309	13.100	5.741	-174.708
	(5.49)	(-10.25)	(0.78)	(2.22)	(-4.66)
Current Output*	-0.199	-0.198	-0.074	-0.100	-0.074
	(-2.54)	(-4.41)	(-1.63)	(-1.82)	(0.47)
Learning-by-doing*	-0.273	-0.092	-0.400	-0.203	-0.237
	(-7.03)	(-1.96)	(-9.49)	(-6.53)	(-3.02)
Spillovers*	-0.410	-0.287	-0.295	-0.236	-0.011
	(-7.58)	(-4.50)	(-5.03)	(-7.40)	(-3.76)
Price of silicon	0.008	0.051	0.005	0.007	0.107
	(0.93)	(20.04)	(0.24)	(4.93)	(6.35)
Price of energy**	-	-0.410	-0.177	0.785	0.121
	-	(-3.23)	(-1.87)	(4.24)	(0.10)
Price of labor**	-	0.276	-0.052	0.031	2.760
	-	(2.26)	(-0.93)	(0.30)	(2.99)
Price of capital	-	11.363	37.012	5.471	107.52
	-	(1.78)	(8.99)	(1.46)	(3.08)
θ_0	-35.009	-4.577	-24.363	-8.371	-31.923
	(-10.39)	(-2.21)	(-9.28)	(-5.37)	(-2.09)
θ_1	1.397	0.289	0.962	0.275	1.340
	(10.90)	(3.14)	(8.97)	(5.17)	(2.26)
Firm specific effects	yes	yes	yes	yes	yes
Adjusted R^2	0.70	0.63	0.50	0.66	0.32
Number of observations	435	588	709	608	429

T-statistics in parenthesis.

*The estimate is expressed as elasticity evaluated at the sample means.

**The estimate of the price of energy (labor) is multiplied with 10^3 (10^8).

Table 5: Estimation results for the open-loop pricing relation

Variable	16K	64K	256K	1MB	4MB
Constant	24.409	-90.528	-3.292	12.903	-37.621
	(5.68)	(-14.45)	(-0.58)	(4.58)	(-1.92)
Current Output*	-0.447	-0.152	-0.163	-0.283	-0.297
	(-12.55)	(-9.25)	(-9.40)	(-13.02)	(-6.21)
Learning-by-doing*	-0.095	-0.114	-0.208	-0.149	0.043
	(-2.130)	(-2.65)	(-5.44)	(-4.96)	(0.99)
Spillovers*	-0.446	-0.171	-0.219	-0.190	-0.055
	(-6.01)	(-3.16)	(-3.67)	(-4.57)	(-1.34)
Price of silicon	0.003	0.052	0.022	0.003	0.032
	(0.38)	(21.98)	(3.03)	(2.10)	(4.43)
Price of energy**	-	-0.494	-0.007	1.240	0.220
	-	(-4.82)	(-0.70)	(4.95)	(0.18)
Price of labor**	-	0.325	0.039	0.022	1.680
	-	(3.41)	(0.70)	(0.16)	(2.05)
Price of capital	-	13.586	38.371	6.125	128.519
	-	(2.31)	(9.09)	(1.19)	(3.93)
Firm specific effects	yes	yes	yes	yes	yes
Adjusted R^2	0.53	0.63	0.42	0.55	0.25
Number of observations	492	631	734	651	451

T-statistics in parenthesis.

*The estimate is expressed as elasticity evaluated at the sample means.

**The estimate of the price of energy (labor) is multiplied with 10^3 (10^8).

Table 6: Intertemporal strategic effects over time

Year	16K	64K	256K	1MB	4MB
1976	-33.611	-	-	-	-
1977	-30.468	-	-	-	-
1978	-28.721	-	-	-	-
1979	-24.652	-4.000	-	-	-
1980	-19.813	-3.519	-	-	-
1981	-15.364	-2.874	-	-	-
1982	-9.775	-2.460	-	-	-
1983	-4.186	-1.674	-22.851	-	-
1984	2.933	-0.696	-19.446	-	-
1985	8.191	0.254	-17.481	-8.096	-
1986	-	1.153	-15.825	-7.585	-
1987	-	2.747	-12.819	-6.789	-
1988	-	3.319	-11.199	-6.537	-30.583
1989	-	4.724	-7.351	-5.717	-27.401
1990	-	5.622	-3.503	-4.910	-24.220
1991	-	6.738	0.345	-3.810	-21.123
1992	-	7.892	4.336	-2.709	-17.038
1993	-	9.047	8.793	-1.870	-12.675
1994	-	9.278	13.376	-0.698	-6.694
1995	-	10.433	17.076	0.274	-2.876
1996	-	-	21.170	1.167	-1.357

Table 7: Average price-cost margins

	16K	64K	256K	1MB	4MB
Herfindahl index	0.147	0.246	0.149	0.173	0.145
Elasticity of demand	2.325	2.481	2.584	1.464	4.672
Predicted price-cost margins (open-loop)	0.063	0.099	0.058	0.118	0.031
Estimated price-cost margins (closed-loop)	0.209	0.818	0.603	0.477	0.710
Estimated price-cost margins (open-loop)	0.422	0.774	0.755	0.558	0.715
Average intertemporal strategic effect	-13.299	1.327	-3.330	-3.149	-12.656

Figure 1: Industry units shipped, 1974-1996

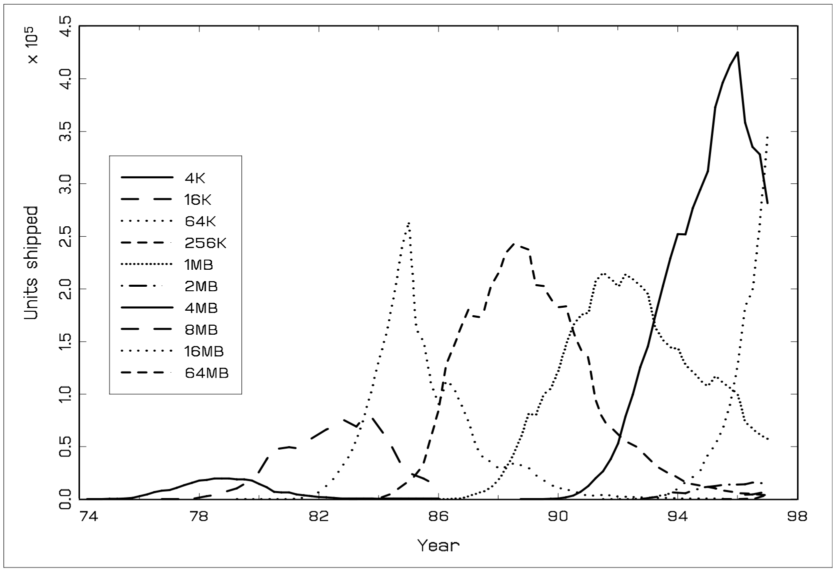

Figure 2: Average selling prices in USD, 1974-1996

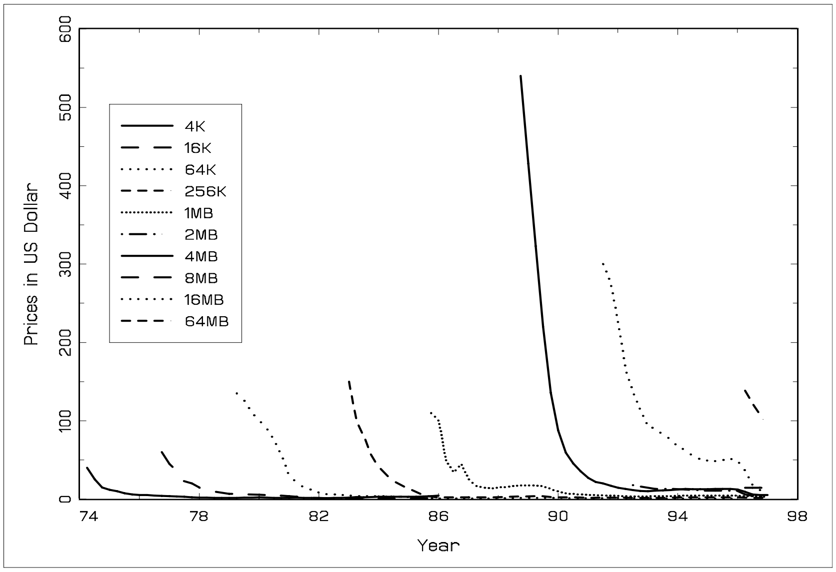

Figure 3: Price-cost margins of the 256K DRAM generation