The impact of market demand and innovation on market structure

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Abstract

We analyze why the number of firms in the dynamic random access semiconductor industry follows an inverse U-shape throughout different product generations. A dynamic oligopoly model with entry, exit, learning by doing and firm-specific productivity is estimated using the two-step estimator developed by Bajari, Benkard and Levin (2007). The estimator recovers investments into product specific innovation as a sunk cost derived from firms' equilibrium behavior. We find that the interdependence between product-specific innovation and market demand explains the change in market structure. Our results also confirm that a firm's investment into improved process technologies is an important factor that determines if firms are able to keep up with the competitive pressure in the market.

JEL: C1, L1, L6, O3.

Keywords: Dynamic random access memory industry, Dynamic oligopoly, Entry, Exit, Industry evolution, Innovation, Learning-by-doing, Market structure, Sunk costs.

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1 Introduction

Seminal contributions highlight the interdependence between innovation, growth, entry and exit and evaluate their impact on the competitiveness of markets.[1] The purpose of this study is to analyze the impact of innovation on entry and exit in the dynamic random access memory (DRAM) industry.[2] The industry is characterized by improved process technologies, which became increasingly complex over time, as recently developed electronic products imposed higher requirements for DRAM chips regarding the storage of information and the size of the chips requiring higher R&D investments. Moreover, life cycles became shorter and imposed higher pressure on firms to recoup R&D investments within a shorter time period. Firms may not be able to keep up with the increasingly required investments into new technologies and exit the market. Accounting for the fact that more innovative industries are characterized by higher exit rates (Geroski, 1995), it is surprising, however, that the number of firms in the DRAM industry did not decline over time, but rather followed an inverse U-shape throughout different generations. More specifically, the number of active firms increased from 15 in the 4K DRAM generation in 1978 to 30 in the 4MB generation in the mid 1990's, and declined to 8 firms in the 1 GB generation in 2004. We are especially interested in explaining why the number of firms in the DRAM industry follows an inverse U-shape.

One reason why the number of firms increased for early generations, might be given by the fact that demand for DRAM chips steadily increased over time as an input for electronic devices. Whereas the ongoing growth in demand for DRAM chips may explain the increase in the number of firms for early generations, it still remains unanswered why the number of firms declined for more recent generations.

Our study concentrates on evaluating the increase in development costs and market demand on market structure, i.e. firms' entry and exit. We are especially interested in estimating the increasingly required R&D investments throughout different generations. A challenging task is that we do not observe R&D investments into specific DRAM generations.[3] To overcome

[1] See Acs and Audretsch (1988), Griliches and Klette (1997), Klepper (2002), Klepper and Graddy (1990), Klepper and Simons (2000), Scherer (1998) and Sutton (2001) among many others for contributions in this area. Klepper (1996) provides an excellent overview of how entry, exit, market structure and innovation vary over the product life cycle.

[2] Dynamic random access memories are components within the family of semiconductors. They are designed for storage and retrieval of information in binary form and are classified into 'generations' according to their storage capacity. For more information on the industry, see Section 2.

[3] Potential proxies such as patents are available at the firm level and difficult to attribute to specific products or DRAM generations.

this missing data problem, we infer the product-specific investments as a sunk cost from firms' equilibrium behavior in different DRAM generations. Therefore, we exploit the fact that firms need to recoup their R&D investments into a new product generation in order to be able to survive in the market.

We formulate a dynamic oligopoly model in the tradition of Ericson and Pakes (1995) in which forward looking firms make entry, exit and production decisions. Firms account for learning-by-doing effects and firm-specific productivities in order to maximize their expected discounted sum of profits over the life cycle.

To obtain an estimate for generation-specific R&D investments, we apply the two stage estimator by Bajari, Benkard and Levin (2007) which allows us to incorporate continuous (production) as well as discrete choices (entry and exit) in dynamic games. Their estimator builds on the idea by Hotz, Miller, Saunders, and Smith (1993) and uses forward simulations to obtain the continuation values given optimal policies.[4] There are other studies that estimate a fully dynamic oligopoly model applying a two-step algorithm, see e.g. Beresteanu and Ellickson (2006), Collard-Wexler (2005), Gowrisankaran, Lucarelli, Schmidt-Dengler, and Town (2008), Hashmi and Van Biesebroeck (2008), Macieira (2006), Ryan (2006), and Sweeting (2006). One common feature in those studies is that state variables are commonly observed by the players and the econometrician. To date, few dynamic discrete choice models have been extended to accomodate unobserved heterogeneity, see Hu and Shum (2008a and 2008b) and Kasahara and Shimotsu (2008).[5]

A well known fact for the DRAM industry is that learning by doing is an important phenomenon. Through repetitions and fine tuning of production processes, firms are able to lower manufacturing costs.[6] Firms experience lowers (future) costs and enters the model as an observed state variable. Beyond industry-specific learning by doing effects which are usually assumed to be common across firms, we also account for firm-specific productivity, as potential

[4] Recent studies focus on reducing the computational burden in dynamic games by estimating instead of calculating the continuation values and apply two step algorithms, see Aguirregabiria and Mira (2007), Bajari, Benkard and Levin (2007), Pakes, Ostrovsky and Berry (2007), Pesendorfer and Schmidt-Dengler (2007). For further discussion and an description of the different methods, see also Ackerberg, Benkard, Berry and Pakes (2005).

[5] For more information about how to correct for serially correlated unobserved state variables, see also Bajari, Benkard, and Levin (2007), Ackerberg, Benkard, Berry and Pakes (2006), Ackerberg, Caves and Frazer (2005), Levinsohn and Petrin (2003), Olley and Pakes (1996) and Wooldridge (2005). For discussions on the problems caused by unobserved correlated state variables in dynamic models, see also Heckman (1981) and Pakes (1994).

[6] Contributions in estimating learning effects for the semiconductor industry are Gruber (1996), Irwin and Klenow (1994), Siebert (2007), and Zulehner (2003).

deviations from the common industry learning curve. Firm-specific productivity is stemming from the fact that firms invest differently into the development of new process technologies to reduce costs.[7] Firm-specific productivity may also last more than one period, as the development of new process technologies has longlasting impact on firms' profits. Therefore, we treat the firm-specific productivity as a serially correlated unobserved state variable. We assume that the firm-specific productivity enters the firms' cost function and follows a first order autoregressive process, such that it depends on the last period's productivity and an independent private shock every period.

One problem with unobserved serially correlated state variables in dynamic models is the fact that identification becomes a challenging task. In dynamic games and contrary to i.i.d. shocks, we explicitly need to account for the fact that players and the econometrician need to form beliefs over the distribution of their rivals' unobserved state variables. When solving this problem backwards, we get back to the initial condition problem. In our study, we can easily overcome the initial condition problem since every single DRAM generation starts from the same initial state, which is zero production. Another challenge is the fact that the unobserved serially correlated state variable causes a contemporanous correlation between firm-level productivity and learning by doing, leading to a potential simultaneity bias. Firms characterized by a higher productivity will further increase output which will enter next period's experience through learning by doing and lower costs. Different alternatives have been suggested to account for the simultaneity bias. Prominent studies in the production function literature apply a proxy variable approach, see e.g. Olley and Pakes (1996). One difficulty in applying a proxy variable approach is that the proxy variable needs to be monotonic in order to appropriately proxy for the firm-specific productivity.

Applying an instrumental variable approach is another alternative, e.g. searching for instruments that are highly correlated with the endogenous regressor (learning by doing), but not correlated with the productivity term.[8] In finding an appropriate instrument for learning by doing in a specific generation, we follow Thompson (2005). Using the fact that technologies are generation-specific. Firms need to establish new plants equipped with different technologies compared to those having been used in the previous generation. Given that firm-level produc-

[7] Other reason are differences in managerial abilities, technological (absorptive) capacities, organizational structure, or strategic alliances. However, we primarily focus on the development of new process technologies.

[8] The decision whether to apply a proxy or an instrumental variable approach gets back to finding appropriate proxies for the omitted variable (productivity) or finding appropriate instruments for the endogenous regressors, respectively. Also, the fact that we have firm-level data over a sufficiently long time series reinforces the decision to apply an instrumental variable approach.

tivity is generation-specific, it is only correlated with learning in the current generation, but not with learning in the previous generation. On the other hand, learning is a common phenomenon across generations and therefore correlated across generations. This feature enables us to use the production experience in the previous generation as an instrument for learning by doing in the generation under consideration.

In the first step of our estimation algorithm, the policy functions (i.e. production, entry and exit) are estimated. The policy functions describe what actions firms take at different states. We assume that the policy functions are determined by costs that are characterized by economies of scale, learning-by-doing, input prices and firm-specific productivity. The latter is incorporated into the cost function using as a serially correlated unobserved state variable. In our main specification, we directly control for the serially correlated unobserved productivity by applying a lagged dependent variable model and use a fixed effects estimator. To account for the dependence between the lagged and the current dependent variable and the unobserved heterogeneity, we use instruments for the lagged dependent variable and learning by doing. We also estimated two other instrumental variable models in order to check for robustness of our results. In the first alternative, we treat the unobserved productivity as an error term that follows a first-order autoregressive process and apply a Generalized Least Squares estimator allowing for fixed effects in order to control for unobserved heterogeneity.[9] In the second alternative, we use a first difference GMM estimator by Blundell and Bond (1998), which eliminates unobserved firm-specific effects using first-differences and instruments for the differenced learning variable.[10]

In the second stage, we estimate the structural parameters, i.e. the generation-specific cost of developing technologies, parameters from the cost functions and the distribution of private shocks. We rely on the fact that firms are rational and forward-looking, i.e. they compare their discounted profit streams given the evolution of the state vector and their policy functions. The discounted expected profits of entering at different states is simulated for many different paths. The distance between those calculated profit streams and the observed observed entry rates at those states is minimized, which allows us to recover the sunk cost distribution. We use a simulated minimum distance estimator and look for those parameters that provide the

[9]Note that a fixed effects estimator violates the strict exogeneity assumptions. Feedback effects resulting from contemporary production to future experience in production results in past experience being sequentially exogenous, which causes inconsistent estimates. We therefore use a GLS estimation.

[10]We also compared the results with the GMM estimator by Arellano and Bond (1991) which uses lagged levels as instruments. The problem with this estimator is that instruments are not strongly correlated as the series on production is highly persistent, so that lagged levels are only weakly correlated with first differences.

best fit to the data generated by the optimal policies representing the equilibrium outcomes of profit-maximizing firms, compared to the data generated from suboptimal policies.

We find that the estimator performs well in predicting firms policies as well as the product-specific sunk costs. Our estimates of sunk costs get close to the few reported establishment costs. They are increasing over different product generations, providing evidence for increasingly required investments for developing new technologies.

Related literature (e.g. Asplund and Nocke, 2006), emphasizes the impact of fixed costs and market size on entry and exit rates. They show that entry costs are negatively related to entry and exit rates and that the level of firm turnover increases in market size. Klepper (2002) investigates common patterns between industries in the evolution of the number of firms over time. Many industries are characterized by a increase in the number of firms, up to a 3 digit number at early stages. Afterwards, a sudden shake out lowers the number of firms to a handful of survivors. Prior literature also pointed out common regularities in firm survival patterns: earlier entrants have sharply higher survival rates due to higher R&D productivity, caused by production-scale economics (Jovanovic and MacDonald, 1994) or learning by doing (Dasgupta and Stiglitz, 1988). Geroski (1995) distills a series of "stylized facts and results" from the empirical literature on entry. He concludes that entry is less a mechanism for keeping prices down and more a mechanism for bringing about change associated with innovation. Moreover, it has been shown that exit rates are higher in more innovative industries.

The remainder of the paper is organized as follows. The next section gives an industry description providing insight into the development of new process technologies and the data. Section 3 introduces our dynamic oligopoly model and Section 4 presents the econometric model. In Section 5 we present the empirical results. We conclude in Section 6.

2 Industry description and data

DRAMs are one of the microelectronics industry's highest-volume parts and a key input for electronic goods, such as computers, workstations, communication systems and graphic subsystems. DRAMs store each bit of information in a memory cell consisting of one transistor and a capacitor. The capacitor stores data and the transistor transfers data to and from the capacitor. DRAM chips are produced in batches on silicon wafers. The process of manufacturing an integrated circuit involves building up a series of layers on a wafer of polycristalline silicon. The production process requires a complex sequence of photolithographic transfer of circuit patterns from photo masks onto the wafer and of etching processes. The wafer, once processed, is cut and the single chips are then assembled. DRAM products are typically classified by the number of bits per chip, their capacity of storing memory.

Permanent research effort is required in order to increase the memory of DRAM chips as new operating systems of electronic products impose a minmium requirement for memory capacity. According to Moore's Law, the number of transistors on an integrated circuit doubles every 12 months, resulting in a fourfold increase in bits per chip. The increase in transistors per chip is mainly due to three factors: reductions in cell size per bit, improved lithography processes and an increase in die size manufacturability.[11]

Reductions in cell size per bit increases the number of dies per wafer and is an important parameter for achieving cost reductions.[12] For example, the first generation Pentium used a 0.8 micron circuit size, and required 296 square milimeters per chip. The second generation chip had the circuit size reduced to 0.6 microns, and the die size dropped by 50% to 148 square milimeters. Investments into smaller die sizes became more relevant throughout generations in order to achieve further cost reductions. Whereas the die size for the 64K generation remained rather constant withing the generation, it shrank three to four times for the 4MB and 16MB generations. The die sizes in the 64MB, 256MB and 512MB generations shrank between seven to nine times. Every DRAM generation begins by scaling lithography by a factor of 0.7 in order to further reduce the die area, see also Table 1a. Lithography processes are permanently improved. For instance, traditional dry lithography uses air as the medium to image through masks. Immersion lithography uses water as the medium between the light source and wafer. The wavelength of light shrinks through water so it is able to project more precise and smaller images on the wafer.

In the late 90's further reduction in cell size became much harder to achieve because of the increased number and complexity of variables affecting cell structures: further improvements required the introduction of new cell structures in conjunction with lithography scaling and advances in doping, etching, planarization, and multilevel metallization. While the development of chips with faster speeds was important in order to meet increasing capacity requirements for storing memory, the reduction of power consumption became equally important. Table 1a

[11] For more details regarding the description of production processes, see also Gruber (1996a), Irwin and Klenow (1994) and Flamm (1993). Further information regarding the innovation process of new DRAM generations can be found at El-Kareh and Bronner (1997).

[12] On March 2nd, 2007, Samsung reported that it begins mass production using 60 nanometer (nm)–class process technology for its1 GB DRAM chip. Samsung confirmed that use of the new process technology is a significant milestone in that it increases production efficiency by 40 percent over the 80nm process technology deployed in DRAM fabrication since early 2006, and offers twice the productivity of 90nm general process technology. Samsung's continuous technology migration below 90nm has relied heavily on the company's extensive use of three-dimensional transistor technologies to build increasingly smaller chips.

shows the evolution of different parameters throughout different generations. Note that the cell size decreases by a factor of 40 from the 4MB to the 1GB chip.

The cost of technology development was estimated at half a billion dollars in the early 90's and exceeded a billion dollars in the late 90's. Required investments for a manufacturing facility are even larger. Table 1b shows that a plant with a capacity of 30,000 chips per month rose from US-$ 1/2 billion in 1985 to US-$ 2.5 billion in 1999, and reached about US-$ 5 billion in 2007.[13] Table 2 shows the increase in R&D activity in the DRAM and the semiconductor industry. The number of patent applications in the DRAM industry increased from 462 in 1989 to 1,214 in 1997.[14]

Table 3 shows the number of firms producing different generations. The number of firms increases from 15 firms in the 4K generation to 30 firms in the 4MB and 16MB generations. Afterwards, the number of firms declined to 20 firms in the 128MB generation and declined even further to 8 firms in the 1 GB generation, see also Figures 4 and 5 for the evolution of the number of firms throughout different generations.[15]

It is well known that the DRAM industry is characterized by learning-by-doing effects, resulting from the fine-tuning of production processes.[16] Despite the rapid reduction in defect densities, only a small fraction of manufactured DRAM chips will have entirely perfect cells and peripheral circuits. If all dice with one or more defective cells were to be discarded, the resulting yield would be too low and the cost per chip prohibitively high. The effective yield will increase substantially by repairing memories with a limited number of defective cells, mostly using laser blown fuses. Memory repair increases yield from <1 to $>50\%$ throughout the life cycle. Prior literature assumes that firms move down a cost curve, common to the industry, which illustrates efficiency effects achieved through learning-by-doing. Depending on firms' timing

[13] It is important to note that a firm transfers the intellectual property of its inventions to all its own plants. Therefore, the R&D investments into inventing a new technology at the plant level are equivalent to those at the firm-level.

[14] We would like to highlight the fact, that it is controversial whether patent counts is an appropriate proxy for representing higher R&D investments. As mentioned earlier, attributing patents to specific DRAM generations is difficult and causes the problem of retrieving generation-specific R&D investments. Therefore, we will estimate the development cost of new DRAM technologies as a sunk cost.

[15] Note that the maximum number of firms has been passed in the 1GB generation, as entry occurs within the first one or two year after a generation has been launched.

[16] Note that knowledge may depreciate over time (sometimes also termed forgetting) especially in labor-intensive industries, such as the aircraft industry, see e.g. Benkard (2000). The semiconductor industry, however, is a capital-intensive industry that is characterized by cumulative innovation and short life cycles. Forgetting is therefore not a common phenomenon in this industry.

to enter a generation they achieve different yield learning since they are at different locations on the learning curve.[17] In order to capture learning effects firms' experience is proxied using firms' past accumulated output. Hence, a firm's production rate enters costs through experience and becomes a state variable. Note that firms' contemporaneous production has an impact on current prices and profits, as well as an intertemporal impact on their profits through costs. This fact makes it difficult to separately estimate firms' static profits from their continuation values. Given the existence of learning effects our study will account for a dynamic model as firms follow a dynamic production strategy, i.e. firms' current production will have an instant impact on prices and profits, and will increase future experience resulting in future cost savings (see e.g. Dick, 1991; Fudenberg and Tirole, 1983 and 1986; Majd and Pindyck, 1989; Spence, 1981; and Wright, 1936). Learning-by-doing is an important phenomenon, as it explains the rapid price decline for DRAMs (see Figure 3).

Table 3 also shows the ordering of firms when they entered and exited a specific DRAM generation. As the table shows, the order of entering a specific DRAM generation is not closely related with the probability of surviving a specific generation. This observation is surprising, since prior literature found that early entry in industries such as the tire, auto, penicilin and tv industry increases the likelihood of firm survival. Moreover, this fact indicates that firm-specific deviations from the common industry learning curve plays an important role for explaining survival and productivity in the DRAM industry. Examples of firm-specific productivities in developing new technologies are the discovery of new lithography processes, the improvement of smaler cell sizes and the invention of new cell architectures.

Market demand must also be noted as one important factor having an impact on market structure. The reason is that in the late 80's and the early 90's, the PC market was the dominant market for DRAMs. Approximately 75% of DRAMs were sold to PC clients or servers. For most of that period, memory upgrades were a critical way to improve PC performance and to enable the use of new applications. By the end of the 90's, however, the sizes of operating systems and of applications were no longer growing as rapidly. Consequently, the dominant market for DRAM's did not demand as fast an increase in bits per chip and demand did not continue growing as much. In the late 90's the populartiy of mobile phones and playstations accelerated the demand for DRAMs again (see Figure 2 for the industry output cumulated over product generations).

Our study uses firm level and industry level information on prices and quantities for different

[17] The learning-by-doing aspect is generation-specific, as production takes place in specific plants using specific production processes. Irwin and Klenow (1994) confirmed this fact by finding only low, sometimes even nonexisting intergenerational spillovers.

DRAM generations which are compiled by Gartner Inc. The data cover firm and industry units shipped, the average selling price, and the number of firms in the market and run from January 1974 until December 2004 on a quarterly basis. The data set encompasses 12 product generations, namely the 4K, 16K, 64K, 256K, 1MB, 4MB, 16MB, 64MB, 128MB, 256MB, 512MB, and 1GB generation. Figure 1 shows the industry shipments (in mio.) across different generations, i.e. the 4K till the 1GB generation. The figure illustrates that every DRAM generation is characterized by a product life cycle, that lasts for approximately 5 years in the 80's and shortened to 3-4 years in the 90's. Recently developed products and a higher demand from downstream industries for more advanced chips is one reason why product cycles became shorter. Shorter life cycles also put higher pressure on firms to recoup research and development cost within a shorter time period.

We also use patent data taken from the NBER patent database established by Hall, Jaffe, and Trajtenberg (2001). The patent database includes patents that were applied for and subsequently granted in the U.S between 1963 and 2002. We use U.S. patents because the U.S. is the world's largest technology marketplace and it has become routine for non-U.S. based firms to patent in the U.S., see also Albert et al. (1991). The database holds detailed information on approximately 3 million utility patents. The patent data themselves were procured from the Patent Office. We identified the patents that each DRAM producer holds in the DRAM market. Table 4 provides summary statistics of some of our variables that we use in our empirical analysis.

In a first step of our empirical analysis, we investigate if learning effects are prevalent in our data set and if the magnitude of learning effects is comparable throughout different generations. We test for learning by doing accounting for economies of scale, using past cumulated and current industry output, respectively. We regress the average prices on a constant, cumulated industry output, current industry output, and a set of dummy variables for different generations. Table 5 shows the results when we specify learning effects to be identical across generations. We apply Ordinary Least Squares and Two Stage Least Squares regressions, in which we instrument for the current industry output using the price for material, which is the world market price of silicon compiled by Metal Bulletin. We also use summary statistics from the supply side such as the number of firms in the market. We are able to use more than 500 observations and get R squares higher than 80%. A negative sign for the cumulated industry output is consistent with learning by doing. The negative sign on current industry output relates to increasing economies of scale in the industry. Note that we also estimate the learning effects separately for every generation. Our results confirm significant learning effects, which are comparable in magnitude to earlier findings. We also tested and can confirm that the magnitude of learning effects are similar across generations. This result allows us to pool our data across different generations, which enables us to use a larger number of observations in our empirical analysis.

3 Dynamic oligopoly model

This section outlines a model of dynamic competition between oligopolistic firms in the DRAM industry. The model is formulated as a state game model. A firm's action in a given period influences not only its own and rival firms' current profits, but also its own and rival firms' future states. Besides market demand and market structure, an important state that affects current and future profits is a firm's cost structure.

The cost structure depends on produced output, input prices, a firm's experience in the production process, and on its productivity. Experience is determined by learning-by-doing and spillovers. The first component is usually modeled as own cumulated past output, and the second component is usually modeled as other firms' cumulated past output. A firm's output decision is therefore an investment into experience and influences its own and rival firms' cost structure.

We use a discrete-time infinite horizon model with time indexed by $t = 0, 1, \ldots, \infty$. There are I firms denoted by $i = 1, \ldots, I$. The set of firms includes potential entrants and incumbent firms. In each period, each firm i earns profits equal to $\pi_{it} = \pi(q_{it}, q_{-it}, s_t, v_{it})$, which are a function of own actions q_{it}, other firms' actions q_{-it}, a vector of state variables s_t describing the market conditions and a private shock v_{it} describing a firm's productivity which shifts marginal costs.

Relevant state variables are market demand d_t, input prices m_t, the set of producing firms n_t and a firm i's experience ex_{it}, i.e. $s_t = (d_t, m_t, n_t, ex_{it})$. Market demand d_t and input prices m_t are determined by a common shock. The number of firms in the market n_t is determined by the exit decision of incumbents and the entry decision of potential entrants. Incumbent firms decide whether to stay in the market and produce q_{it} or to exit and receive a fixed scrap value κ. Potential entrants decide whether to enter the market and to produce output q_{it} or to stay out of the market and produce no output. A firm i's experience ex_{it} has two components. The first component is a firm's proprietary experience x_{it} and the second component is spillovers x_{-it} that firm i receives from other firms. A firm i's proprietary experience x_{it} is its own cumulated past output, such that $x_{it} = \sum_{\tau=1}^{t-1} q_{i\tau}$. Or expressed differently, $x_{it} = x_{it-1} + q_{it-1}$ with $x_{i0} = 0$, where we assume there is no proprietary experience in the beginning of the product cycle. A firm i's spillovers x_{-it} are other firms' cumulated past output, such that $x_{-it} = \sum_{\tau=1}^{t-2} \sum_{j \neq i} q_{j\tau}$. Or again expressed differently, $x_{-it} = x_{-it-1} + \sum_{j \neq i} q_{-jt-2}$ with $x_{-i0} = 0$, where we assume there are no spillovers in the beginning of the product cycle. Potential entrants have no experience and receive no spillovers.

Before firms simultaneously set their action by choosing their output q_{it}, each firm i observes a private shock v_{it}, independently drawn from a distribution $G_i(.|s_t)$. The private shock may derive from variability in production costs, c_{it}. Firms productivity is modeled as a first order autoregressive process $\omega_{it} = \rho\omega_{it-1} + v_{it}$, where v_{it} is independently identically distributed with zero mean and a constant variance σ_v^2, ρ is the persistence or autocorrelation parameter. We assume a stationary first order autoregressive process, i.e. $|\rho| < 1$. The key difference between w and v is that the former is a state variable which influences firms decisions, and the latter is an independent contemporaneous shock. The autocorrelation reflects the fact that firms that are more productive today are more likely to be more productive tomorrow. Since a firm's productivity is correlated over time, it represents a serially correlated unobserved state variable.

Each potential entrant additionally observes a shock $u_{i\tau}$, independently drawn from a distribution $H_i(.|s_{\tau_i})$, where τ_i is the period firm i enters the market. Entering firms immediately start to produce. This means that a firm that enters the market observes two private shocks. As the shocks are private information firms solve for a Bayesian Nash equilibria.

Each firm i maximizes its future discounted payoffs conditional on the initial state s_0, the initial value of private shock v_{i0} and the initial value of sunk cost u_{i0}:

$$\mathrm{E}_{v,u} \sum_{t=0}^{\infty} \beta^t [\pi_i(q_{it}, q_{-it}, s_t, v_{it}, u_{it}) | s_0, v_{i0}, u_{i0}] \tag{1}$$

where $\beta \in (0, 1)$ is the discount factor, which is set equal to 0.95.

3.1 Profits in the product market

A firm i's per period profits in the product market are revenues minus cost

$$\pi_{it}(q_{it}, q_{-it}, s_t, v_{it}) = p_t(q_t, z_t, d_t)q_{it} - c(q_{it}, m_t, x_{it}, x_{-it}, \omega_{it-1}, v_{it})q_{it} \tag{2}$$

where $p(q_t, z_t, d_t)$ is the industry price as a function of the industry output $q_t = \sum_{i=1}^{n_t} q_{it}$, observable demand shifters z_t and a random shock d_t. $c(q_{it}, m_t, x_{it}, x_{-it}, \omega_{it-1}, v_{it})$ is firm i's marginal cost as a function of its output q_{it}, input prices m_{it}, proprietary experience x_{it}, spillovers x_{-it}, unobserved state ω_{it-1} and firm i's private shock v_{it}. We specify the inverse demand function p_t as follows:

$$p_t(q_t, z_t, d_t) = d_t q_t^{\delta_1} z_t^{\delta_z}, \tag{3}$$

where δ_1, the elasticity of the inverse demand, and δ_z are coefficients to be estimated. We assume there is no firm specific uncertainty about demand as this would not be identified from a private shock in marginal cost. We specify a firm i's marginal costs as a linear function of its arguments:

$$c(q_{it}, m_t, x_{it}, x_{-it}, \omega_{it-1}, v_{it}) = \theta_0 + \theta_1 q_{it} + \theta_2 m_t + \theta_3 x_{it} + \theta_4 x_{-it} + \rho\omega_{it-1} + v_{it}, \tag{4}$$

where we denote the vectors of coefficients with θ and ρ, and v_{it} is drawn from a standard normal distribution. The initial condition for ω_i is derived from the fact that firms do not produce output q_i before the product cycle starts.

3.2 Entry and exit cost

A potential entrant incurs entry cost when it enters the product market and its profits in the first period of market appearance are

$$\pi_i(q_{i\tau_i}, q_{-i\tau_i}, s_{\tau_i}, v_{i\tau_i}, u_i) = p_t(q_{\tau_i}, z_{\tau_i}, d_{\tau_i})q_{i\tau_i} - c(q_{i\tau_i}, m_{\tau_i}, v_{i\tau_i})q_{i\tau_i} - u_{i\tau_i}, \tag{5}$$

where τ_i is the period firm i enters the market and u_i is the privately observed random shock before entering the market. Learning-by-doing x_i, spillovers x_{-i}, the unobserved state ω_i are equal to zero at the time of entering the market.

The profits of an incumbent firm that leaves the market are

$$\pi_i(q_{iT_i}, q_{-iT_i}, s_{T_i}, v_{iT_i}) = p_t(q_{T_i}, z_{T_i}, d_{T_i})q_{iT_i} - c(q_{iT_i}, m_{T_i}, x_{iT_i}, x_{-iT_i}, \omega_{iT_i-1}, v_{iT_i})q_{iT_i} + k$$

where T_i is the period firm i leaves the market and k is the scrap value.

3.3 Transition of states

For a complete description of the state game, the transition between states has to be defined. Our state variable market demand d_t is determined by a common period-specific shock and therefore does not require any further assumptions on state transitions over time. However, our state variables experience x_{it} and spillovers x_{-it} are influenced by past actions. The laws of motion for those state variables are deterministic and described by cumulated past own output

$$x_{it+1} = x_{it} + q_{it} \tag{6}$$

and the second law of motion is cumulated past output of other firms

$$x_{-it+1} = x_{-it} + \sum_{j \neq i} q_{jt-1}. \tag{7}$$

For (6) and (7), the initial condition is that the respective state is equal to zero. There is no output production before the product cycle starts and no experience and no spillovers at the beginning of the product cycle.

This leaves us to define the transition of the number of firms in the market n_t from time t to time $t+1$. The number of firms in the market n_{t+1} is

$$n_{t+1} = n_t + ne_t - nx_t, \tag{8}$$

where ne_t is the number of entering firms and nx_t the number of exiting firms. The number of entering firms ne_t depends on the distribution of u_i. A firm i enters, when future expected profits are positive. The number of entering firms nx_t depends on the scrap value k. A firm i exits, when future expected profits are lower than the scrap value which is fixed but could be estimated in the second stage.

3.4 Firms' strategies

Firms use Markov strategies $q_{it} = \sigma_i(s_t, v_{it})$, i.e. a firm's output q_{it} is a function of the state variables s_t and the private shock v_{it}, generating Markov-perfect Nash equilibrium. Rival firms' strategies are denoted by $q_{-it} = \sigma_{-i}(s_t, v_{-it})$. If behavior is given by a Markov strategy profile $\sigma = (\sigma_i(s_t, v_{it}), \sigma_{-i}(s_t, v_{-it}))$, firm i's expected profits given the state variables s_t can be written recursively:

$$\begin{aligned} V_i(s_t;\sigma) = \mathrm{E}_{v,u}[&\pi_i(\sigma_i(s_t, v_{it}, u_i), \sigma_{-i}(s_t, v_{-it}, u_{-i}), s_t, v_{it}, u_i) \\ &+\beta \int V_i(s_{t+1};\sigma) dP(s_{t+1}|\sigma_i(s_t, v_{it}, u_i), \sigma_{-i}(s_t, v_{-it}, u_{-i}), s_t, v_{it}, u_i)|s_t], \end{aligned} \tag{9}$$

where $V_i(s_t;\sigma)$ is firm i's ex-ante value function. A strategy profile σ is a Markov perfect equilibria if, given the strategy profile of rival firms $\sigma_{-i}(s_t, v_{-it}, u_{-i})$, firm i does not want to deviate from its strategy profile $\sigma_i(s_t, v_{it}, u_i)$, i.e.

$$V_i(s_t;\sigma) \geq V_i(s_t;\sigma_i\prime, \sigma_{-i}), \tag{10}$$

where $\sigma_i\prime$ is an alternative strategy for firm i.

The structural parameters of our model are the discount parameter β, the profit functions $\pi_1, \ldots, \pi_I$, the distribution of private shocks G and H following a standard normal distribution. To obtain estimates of these parameters, we build on the estimation method developed by Bajari, Benkard and Levin (2007). This is a two-stage procedure. The first stage includes the estimation of the policy function σ_i, and the value functions V_i. The second stage estimates the profit function π_i and the distribution G_i. We assume that a firm's productivity is unobserved. We therefore extend their estimation method to allow for unobserved state variables.

4 Econometric model

In this section we present the econometric model. As mentioned above we follow the two step algorithm developed by Bajari, Benkard and Levin (2007).[18] The estimator relies on the fact that firms are rational and forward-looking, i.e. firms compare their discounted profit stream given the evolution of the state vector and their policy functions. In the first step, we estimate the policy functions and the value function. The second step assumes that the policy functions are parameterized by a finite vector that can be consistently estimated at the first step. This assumption permits a non-parametric first stage with discrete action and state variables or a parametric first stage with continuous action and state variables. As described above, our model allows for continuous action and state variables. To parameterize the first stage, we thus have to assume that the functional form of the policy functions is known or can be sufficiently approximated by polynomials. For the exposition of the estimation algorithm, we assume it is a linear function. The estimation algorithm is however equally applicable to more complicated functions of however known form. For the estimations, we try various higher order polynomials to approximate an arbitrary non-linear policy function and finally use the specification with the highest fit. Since some of the generations are not long enough in the market to generate a sufficiently large time series, we will not estimate the dynamic model for each generation separately, but rather pool the data and use dummy variables to account for generation-specific effects. We also would like to refer to our estimation results displayed in Tables A which provide support for learning effects. Moreover, the results confirm that the magnitude of learning effects are comparable throughout different generations. Note, however, that we also estimated the learning effects separartely for different generations.

4.1 Estimation of the first stage

In the first stage, we estimate various policy functions. We estimate the entry decision of potential entrants, the exit decision of incumbent firms and we also estimate the production decision of incumbents. For the incumbents' output function, it is necessary to obtain estimates for the demand (3).

[18] Note that we are interested in analyzing the competitive degree in the DRAM market and would like to estimate the entry and exit costs in a dynamic model allowing for observed and unobserved serially state variables. Examining responses to policy or environmental change, would be an interesting task as well, but goes beyond the scope of the paper.

4.1.1 Demand

We specify the demand function log-linearly as

$$\ln(q_t) = \delta_0 + \delta_1 \ln(p_t) + \delta_2 \ln(p_t^S) + \delta_3 \ln(GGDP_t) + \delta_4 time_t + \sum_{l=5}^{15} \delta_l D_l + d_t \tag{11}$$

where we denote the vector of coefficients with δ. q_t is the market output of the chip at time t. p_t is the average selling price of a chip at time t, and p_t^S is the average selling price of the closest substitute. For the price of the closest substitute we construct a price index. For each DRAM generation, we identify corresponding substitute DRAM generations and use the average weighted prices of these generations as the price of the closest substitute. $GGDP_t$ represents the growth rate of the GDP, which we use as an exogenous demand shifter. $Time$ is a time trend, D_l presents a dummy variables for every generation, where the 4K generation is used as the reference. d_t is a sequence of independently distributed normal variables with a mean of zero and a constant variance σ_d. We predict a negative sign for the own price elasticity of demand δ_1. The cross-price elasticity δ_2 is supposed to be positive (negative) if the respective products are substitutes (complements). We further await a positive sign for the demand shifter δ_3. The expected sign of the time trend coefficient δ_7 is supposed to be negative. It captures the effect of the time length that a particular generation has been in the market.

4.1.2 Incumbents' output policy function

Firm i's policy function σ_i is a function of the state variables s_t and the private shock v_{it} in marginal cost, i.e. $q_{it} = \sigma_i(s_t, v_{it}, u_i)$. If we assume that the policy function is log-linear in the state variables and in the private shock and if we implement the first order autoregressive process of the firm-level productivity, the policy function of incumbent firms is equal to

$$\begin{aligned}\ln(q_{it}) = \gamma_0 + \gamma_1 \hat{d}_t + \gamma_2 \ln(m_t) + \gamma_3 \ln(n_t) + \gamma_4 \ln(x_{it}) + \gamma_5 \ln(x_{-it}) + \gamma_6 time_t \\ + \gamma_7 w_{it-1} + \sum_{l=8}^{18} \gamma_l D_l + v_{it},\end{aligned} \tag{12}$$

where we denote the vector of coefficients with γ, q_{it} represents firm i's output at time t and $\hat{d}_t$ is the contemporary demand shock obtained as the residual of (11). The variable m_t represents the price of silicon in period t, n_t stands for the lagged number of firms, x_{it} and x_{-it} represents the cumulated past output of firm i and all other firms, respectively. The $time$ variable and the dummy variables are defined as in the demand equation. Note that we estimate a pooled regression in order to be able to use more observations for our variables of interest. Therefore, we assume that our right hand side variables have an equal impact on different generations. The dummy variables, however, will absorb any time invariant differences between the generations.

Finally, firms' productivity is modeled as a first order autoregressive process $\omega_{it} = \rho\omega_{it-1} + v_{it}$. As mentioned in the introduction, we will not account for time invariant unobserved heterogeneity as feedback effects occurring from contemporary production to future experience in production results in past experience being sequentially exogenous. Since the unobserved heterogeneity, or any contemporaneous error, determines the contemporaneous production, it will enter production experience in the next period. Hence, the contemporaneous error and experience in the future are correlated, which violates the strict exogeneity assumption and causes inconsistent estimates when we account for fixed effects. There are many models, including the AR(1) model, for which it is reasonable to assume that the contemporaneous error is uncorrelated with current and past values, but will be correlated with future values of the regressor (sequential exogeneity). To eliminate the unobserved heterogeneity, we also use other techniques than fixed effects, e.g. we estimate the equation in first differences.

We assume that a firm i's private shock v_{it} in marginal cost is uncorrelated with the state variables $s_t, s_{t-1}, \ldots, s_0$ such that

$$E[v_{it}|s_t, s_{t-1}, \ldots, s_0] = 0.$$

We estimate the first order autoregressive process applying a GLS estimator and using instruments for past production experience. We would expect positive signs for the coefficients γ_2, γ_4, and γ_5 and a negative sign for γ_7.

We also directly control for the serially correlated unobserved productivity by applying a lagged dependent variable model, or an AR(1) model. In this case the policy function looks as follows:

$$\begin{aligned} \ln(q_{it}) &= \widetilde{\gamma}_0 + \widetilde{\gamma}_1 \hat{d}_t + \widetilde{\gamma}_2 \ln(m_t) + \widetilde{\gamma}_3 \ln(n_t) + \widetilde{\gamma}_4 \ln(x_{it}) + \widetilde{\gamma}_5 \ln(x_{-it}) + \widetilde{\gamma}_6 time_t \\ &+ \widetilde{\gamma}_7 \ln(q_{it-1}) + \sum_{l=8}^{18} \widetilde{\gamma}_l D_l + c_i + v_{it}, \end{aligned} \tag{13}$$

where the vector of coefficients is denoted by $\widetilde{\gamma}$, and c_i denotes firm invariant unobserved heterogeneity. If $\widetilde{\gamma}_7 \neq 0$, then q_{it} exhibits state dependence, the current state depends on the last period's state. Note that we have a feedback structure as described above, such that strict exogeneity fails in this case as well. We instrument for the past dependent variable q_{it-1} as well as for firm-level past experience x_{it}, by using further lags of the variables. Hence, we use an IV estimator in levels. Note that firms are facing the same initial condition at the beginning of the very first generation, which is $q_{io} = 0$.

Finally, we also rewrite the policy function in first differences in order to eliminate the unobserved heterogeneity. This implies the orthogonality conditions $E[w_{is}' \Delta v_{it}] = 0$ for $s < t$, where w are the sequentially exogenous regressors conditional on the unobserved effect c. So at time t we can use w_{it-1}^0 as potential instruments for Δw_{it}, where $w_{it-1}^0 = (w_{i1}, ..., w_{it})$. The fact that w_{it-1}^0 is uncorrelated with Δv_{it} opens up a variety of estimation procedures. For example, a simple estimator uses lagged differences Δw_{it-n} (for $n > 1$) as the instruments for Δw_{it}, however we can also use lagged levels w_{it-n}.

We could apply the Arellano-Bond (1991) estimator for dynamic panel data. The estimator uses the Generalized Method of Moments (Hansen, 1982), and is called "difference GMM" estimator. It especially holds for small T and large N. If T is large, the dynamic panel bias becomes insignificant, and a fixed effects estimator works. If N is small, the Arellano-Bond autocorrelation test may become unreliable. As differentiating removes much of the variation in the explanatory variables, the Arellano-Bond (1991) estimator may exacerbate measurement errors in the regressors. In addition, the differentiated regressors need not be highly correlated with the instruments. We therefore apply the Blundell-Bond (1998) estimator, which uses the levels and differences of the lagged dependent variable in the set of instruments.

4.1.3 Entry and exit

To obtain estimates for the distribution of u_i and κ, we estimate probit models. Potential entrants make their decision to enter dependent on the state variables d_t and n_t, but not on x_{it} and x_{-it} as they have not gained either propriety experience or gained experience through spillovers:

$$\begin{aligned} P(\text{entry}_{\tau_i}) = {} & \alpha_0 + \alpha_1 \hat{d}_{\tau_i} + \alpha_2 \ln(m_{\tau_i}) + \alpha_3 \ln(n_{\tau_i}) + \alpha_4 \ln(x_{i\tau_i}) + \alpha_5 \ln(x_{-i\tau_i}) \\ & + \alpha_6 time_{\tau_i} + \sum_{l=7}^{17} \alpha_l D_l + u_{i\tau_i}, \end{aligned} \tag{14}$$

where we denote the vector of coefficients with α, and $\hat{d}$ is the demand shock obtained as the residual of (11).

Incumbent firms face the decision, whether to stay in the market or to exit. Their decision to exit the market depends on all state variables

$$\begin{aligned} P(\text{exit}_{T_i}) = {} & \lambda_0 + \lambda_1 \hat{d}_{T_i} + \lambda_2 \widehat{\omega}_{i\tau_i} + \lambda_3 \ln(m_{T_i}) + \lambda_4 \ln(n_{T_i}) + \lambda_5 \ln(x_{iT_i}) \\ & + \lambda_6 \ln(x_{-iT_i}) + \lambda_7 time_{T_i} + \sum_{l=8}^{18} \lambda_l D_l + \kappa_{T_i}, \end{aligned} \tag{15}$$

where we denote the vector of coefficients with λ and $\widehat{\omega}_{it} = \rho\widehat{\omega}_{it-1} + v_{it}$ is the productivity shock obtained as the residual of the output policy function.

Given (14) and (15), we calculate the number of firms in the market by assuming that when the predicted probability is larger than 0.5 the firm enters or exits the market, respectively.

4.1.4 Value functions

Estimation of the value functions is based on the estimated policy functions and the transition between states. From estimating (12), we obviously get $q_{it} = \hat{q}_{it} + v_{it}$, which we use to simulate a sample of optimal policies

$$q_{itl} = \hat{q}_{it} + v_{itl}, \tag{16}$$

where at each point in time $t = 0, 1, \ldots$, we draw a random sample of v_{itl} with $l = 1, \ldots, L$ from the distribution $G_i(.|s_t)$ and calculate simulated profits $\pi_{ilt}(q_{itl}, q_{-itl}, s_{tl}, v_{itl})$. We use (8) to move from one state to the other w.r.t. the number of firms and obtain for each simulation l

$$n_{t+1l} = n_{tl} + ne_{tl} - nx_{tl},$$

where ne_{tl} and nx_{tl} are determined by (14) and (15) and a random draw u_{itl} from $H_i(.|s_t)$ with $l = 1, \ldots, L$. We then use (6) and (7) to move from one state to the other w.r.t. proprietary experience and spillovers and obtain for each simulation l, $x_{it+1l} = x_{itl} + q_{itl}$ and $x_{-it+1l} = x_{-itl} + \sum_{j \neq i} q_{jt-1l}$. Finally, we use the specifications for demand (3) and the marginal cost function (4) and calculate simulated profits as

$$\pi_{itl} = \hat{p}_{tl} q_{itl} - (\theta_0 + \theta_1 q_{itl} + \theta_2 m_{tl} + \theta_3 x_{itl} + \theta_4 x_{-itl} + \rho\omega_{it-1l} + v_{itl})\, q_{itl},$$

where $\hat{\delta}_1$ is an estimate for the elasticity of demand obtained from (11). To obtain an estimate for the value function, we add up profits π_{itl} over t and take the mean of the simulated profits π_{il} over l such that

$$\begin{aligned} &\tilde{V}_i(s_t; \sigma_i, \sigma_{-i}, \delta, \gamma, \alpha, \lambda, \theta) = \\ &\qquad \frac{1}{L} \sum_{l=1}^{L} \sum_{t=0}^{\infty} \beta^t \{\hat{p}_{tl}\, q_{itl} - (\theta_0 + \theta_1 q_{itl} + \theta_2 m_{tl} + \theta_3 x_{itl} + \theta_4 x_{-itl} + \rho\omega_{it-1l} + v_{itl})\, q_{itl}\}, \end{aligned} \tag{17}$$

where we assume that for large enough t firms do not produce anymore.

4.2 Estimation of the second stage

To recover the structural parameters θ of the marginal cost function, we exploit the equilibrium condition (10). We construct alternative policies $k = 1, \ldots, K$ that are equal to

$$q_{itk\prime} = q_{it} + \epsilon,$$

where ϵ is a random draw from some arbitrary distribution function F. We calculate alternative profits given the alternative strategy $q_{itk\prime}$

$$\pi_{itk\prime} = \hat{p}_{tk}\ q_{itk\prime} - (\theta_0 + \theta_1 q_{itk\prime} + \theta_2 m_{tk} + \theta_3 x_{itk} + \theta_4 x_{-itk} + \rho\omega_{it-1k} + v_{itk})q_{itk\prime}.$$

An estimate for the value function given the alternative strategy is

$$\begin{aligned}&\widetilde{V}_i(s_t; \sigma_{i\prime}, \sigma_{-i}, \delta, \gamma, \alpha, \lambda, \theta) = \\ &\qquad \sum_{t=0}^{\infty} \beta^t \{\hat{p}_{tk}\ q_{itk\prime} - (\theta_0 + \theta_1 q_{itk\prime} + \theta_2 m_{tk} + \theta_3 x_{itk\prime} + \theta_4 x_{-itk} + \rho\omega_{it-1k} + v_{itk})q_{itk\prime}\}. \quad (18)\end{aligned}$$

This gives us $K \times \widetilde{V}_i(s; \sigma_{i\prime}, \sigma_{-i}, \delta, \gamma, \alpha, \lambda, \theta)$'s, i.e. K times profits from alternative strategies. When we can rewrite the equilibrium condition (10) as

$$V_i(s_t; \sigma_i, \sigma_{-i}, \delta, \gamma, \alpha, \lambda, \theta) \geq V_i(s_t; \sigma_{i\prime}, \sigma_{-i}, \delta, \gamma, \alpha, \lambda, \theta),$$

and exploit the linearity of θ in firm i's profit, we can define the function f as follows

$$f(y; \delta, \gamma, \alpha, \lambda, \theta) := [W_i(s_t; \sigma_i, \sigma_{-i}, \delta, \gamma, \alpha, \lambda) - W_i(s_t; \sigma_{i\prime}, \sigma_{-i}, \delta, \gamma, \alpha, \lambda)]\ \theta \geq 0.$$

We then define the function

$$Q(\delta, \gamma, \alpha, \lambda, \theta) := \int (\min\{f(y; \delta, \gamma, \alpha, \lambda, \theta), 0\})^2 dF(x),$$

where the inequality defined by y is satisfied at $(\delta, \gamma, \alpha, \lambda, \theta)$, if $f(y; \delta, \gamma, \alpha, \lambda, \theta) \geq 0$. When we define the function $\widetilde{f}(y; \hat{\delta}, \hat{\gamma}, \hat{\alpha}, \hat{\lambda}, \theta)$ as the empirical counterpart of $f(x; \delta, \gamma, \alpha, \lambda, \theta)$ computed by replacing the W_i terms with simulated estimates $\widetilde{W}_i$, we can define

$$Q_k(\delta, \gamma, \alpha, \lambda, \theta) := \sum_{k=1}^{K} \{\min\ [\widetilde{f}(y; \hat{\delta}, \hat{\gamma}, \hat{\alpha}, \hat{\lambda}, \theta), 0]\}^2.$$

By using the minimum distance estimator we obtain a value for θ.

In order to estimate the sunk cost we rely on the fact that the firms are rational and forward-looking. They are able to calculate their discounted profit stream given the evolution of the state vector and their policy functions. If a firm does not enter, even though the expected profits are positive, it implies that the draw on sunk cost exceeded the value generated in the market. Hence, the discounted expected profits of entering at different states is simulated for many different paths. Averaging those gives the theoretically expected profits of entering at different states. The distance between those calculated profit streams and the observed observed entry rates at those states is minimized, which gives allows us to recover the sunk cost distribution.

Finally, we calculate the sunk costs by calculating the expect discounted values at different states and compare them to entry observations at those states. If entry occurred at those states it indicates that sunk costs are lower than the generated discounted profits at this stage and vice versa.

5 Estimation results

This section discusses the estimation results. We start with the estimation results of the demand function. We then proceed with the incumbents' output policy function, and the entry and exit distribution. Finally, we describe the structural parameters.

Demand Equation To obtain estimates for the coefficient vector δ, we estimate industry demand (11) using ordinary least squares as well as two stage least squares. In the latter case, we instrument the average selling price in the demand equation summary measures from the supply side, like the number of firms in the industry, cumulated industry output, and the price of silicon – all variables in logarithm.

The estimation results of the demand equation are shown in Table A. The results using the ordinary least squares estimator as shown in column 1, whereas the results for the 2 stage least squares estimator as depicted in columns 2 and 3. Since the results of the two estimators are very similar, we only describe on the results using the instrumental variable estimator.

The first stage equation (column 2) represents a good fit with an adjusted R-square of about 0.94. A test for the joint significance of the instruments indicates that the number of firms in the industry, cumulated world output and the price of silicon are highly correlated with the average selling price. With a value of 73.41 for the F-statistics, we reject the null hypothesis that the estimated coefficients of these variables are equal to zero. A Hausman test indicates the necessity to instrument the average selling price in the demand equation. The value of the χ^2 distributed test statistic is equal to 60.55, which is larger than 18.31 – the 5% critical value with 11 degrees of freedom. Two of our three instruments are significantly different from zero. The negative sign on the cumulated industry output is meaningful as higher cumulated industry output lowers marginal costs in the presence of learning-by-doing, which shifts the supply curve downwards resulting in lower equilibrium prices. The positive sign on the price of silicon indicates that higher factor prices shifts the marginal cost curve upwards which results in higher equilibrium prices.

Turning to the second stage of the instrumental variable estimator (column 3), the R-square of about 0.71 confirms a high explanatory power of the estimation. All variables are significantly different from zero at least at the 5% level. The estimate of the average selling price of a chip is negative and significantly different from zero, indicating a negative own price elasticity of demand. The magnitude of -3.03 represents the fact the DRAM market is characterized by a highly elastic demand curve. The estimate of substitute DRAM chips, is significant and positive, indicating a positive cross-price elasticity and indicating that substitute DRAM chips represent substitutes. Moreover, the estimate of 1.85 also confirms that the price of substitute DRAM chips has a lower impact on the DRAM demand than the price of DRAM chips themselves. The demand shifter $GGDP_t$ is positive and significantly different from zero, providing evidence that a higher growth in GDP shifts the demand outwards. The negative time trend is consistent with previous findings that buyers substitute away from one generation to the next as time elapses. The dummy variables for the different generations are all highly significant and positive. The magnitude of the dummy variables is increasing throughout all the different generations, which underlines the increasing importance of using DRAM chips in application specific electronic products. Moreover, it is interesting to note that the increase in dummy variables increases by a magnitude of 3 to 4 up until 16 MB generation. Thereafter, however, the increase in the dummy variables diminishes to 1. This results emphasizes that the growth in market demand increased over different generations, but the growth in demand slowed down towards the more recent generations.

Policy function We estimate incumbents' output policy (12) with general least squares to obtain estimates for the coefficient vector γ. The results are shown in Table A.[19] We estimate equation (12) in by accounting for a first-order autocorrelation process, see column 1. We also estimate firm's output policy function by applying a lagged dependent variable model, or an AR(1) model, in order to control for the serially correlated unobserved productivity as shown in (13). Finally, we apply a first difference estimator accounting for a first-order autocorrelation process in the unobserved state variable ω_i (columns 3 and 4, respectively). Column 3 display the estimation results for the Arellano-Bond (1991) estimator which uses lagged dependent variables in levels. Column 4 displays the results for the Blundell-Bond (1998) estimator, which uses the levels and differences of the lagged dependent variable in the set of instruments.

[19]Table A shows first stage results for the output policy function.

Note that the last two estimators eliminate the unobserved heterogeneities by applying first differences.

Our pooled regression allows us to use approximately 3,500 observations. The regression estimations for the instrumental variable estimations illustrates a remarkably good fit, it has R-square of 0.89. The estimates for the instrumental variable regressions in differences performs quite poorly and also carries parameter estimates that are sometimes counterintuitive. The problem with the first difference estimators is that the instruments are not strongly correlated as the series on production is highly persistent, so that lagged levels are only weakly correlated with first differences. The instrumental variable estimator in levels (column 2) fits the expectations of our model the best. The observed serially correlated variable, cumulated past output, which captures the learning-by-doing effects is positive and significant. This result emphasizes the importance of learning-by-doing in this industry. More experience in production increases efficiency and increases output. The lagged output carries a positive significant sign which shows that a first-order autocorrelation process is present in the data. We can confirm that correcting for serially correlated unobserved state variable, e.g. firm-specific productivity is important to control for. It confirms our notion that firms are able to react according to the private shocks they receive in the short run. The positive demand shock indicates that firms are able to increase their production. The negative sign on the price of material confirms that higher factor prices increase marginal cost and lower firm level output. The positive sign of the number of firms in the market illustrates that more firms in the market increase the competitive pressure in the market. The dummy variables for the different generations as well as the time trend turn out to be highly significant.

Entry and exit distribution We estimate the entry distribution (14) and exit distribution (15) with probit models to obtain estimates for the coefficient vectors α and λ. The results are shown in Table A. The results for the entry regression are shown in the first column.

The positive coefficient on number of firms is insignificant. However, the sign indicates the fact that few early movers enter at the initial time periods, whereas the majority of firms enters when the life cycle approaches the matured phases. This entry pattern emphasizes the fact that firms need to come up with a new technology to enter a new technology, and only few firms are clearly ahead of others. This results reinforces the existence of spillovers in the market, which make it difficult to protect flows from research and development. The time trend shows that the number of entering firms increases over the life cycle of a generation, which is intuitive as we include the whole time span over the life cycle for most generations. An interesting results is that the dummy variables are negative and become even more negative throughout different generations. This result shows that entry became less likely over different generations given generation-specific fixed effects, which is an indication that entry costs increased throughout different generations. An increase in sunk costs would be supported by the engineering literature. Slightly surprising is the negative sign of the demand shock.and the positive coefficient on the price of silicon.

Turning to the results for the exit equation (columns 2-4), the demand and productivity shock carry negative signs. The results confirm that negative productivity shocks foster firm's exit.

Structural parameters Finally, we are interested in recovering the structural parameters θ and ρ from the marginal cost function (4) as well as estimating the sunk cost in the different generations. As described above, we exploit the equilibrium condition (10) and construct for each simulated policy (16) an alternative policy. We compared the simulated value functions based on optimal strategies with the simulated values based on alternative non-optimal strategies and minimize the deviations of those to recover the structural parameters. We use 10,000 simulations and without firm-specific and product-specific fixed effects in the marginal cost function.

As shown in Table A, the estimation results are plausible. We are able to use 304 observations and our structural parameters are all highly significant at the 1% level. We find that the cost function is characterized by increasing economies of scale. Moreover, we can confirm significant learning-by-doing effects and spillovers being prevalent in the industry which lower the marginal costs. Our estimate for sunk costs over all generations are about 1.3 billion US-dollars and get close to what has been reported in business reports. The standard deviation is about 2.2 billion US-dollars, which indicates that sunk cost over different generations do fluctuate a lot. We can also confirm increasing sunk cost over the first part of the different generations. However, we are currently facing the problem that some estimated sunk costs for the latest generations are decreasing. We think that we may not have enough data to accurately estimate the sunk costs for the latest generations. The expected discounted profits are not accurate in this case as the life cycles did not even reach the peak yet. Since the discounted profits are compared to the entry probabilities we may get distorted sunk cost estimates. We contemplate to possibly correct for this truncation problem.

6 Conclusion

This paper contributes to empirical regularities on market structure. Seminal contributions highlight the interdependence between innovation, growth, entry and exit. The main interest of our study is to analyze the impact of innovation on firms' entry and exit in R&D intensive industries, such as the DRAM industry. We are especially interested in explaining why the number of firms in the DRAM industry follows an inverse U-shape throughout generations. This study concentrates on examining to what extent increasingly required investments for the exploration of new technologies may drive firms' entry and exit. The challenging task is the difficulty to find data for product- or generation-specific investments in research and development. We overcome this problem by treating the investment into a new technology as a sunk cost and infer those from firms' equilibrium behavior in different DRAM generations. We estimate a dynamic model accounting for firms' entry, exit, and intertemporal production decisions in an oligopolistic market structure, using the estimator by Bajari, Benkard and Levin (2007). A serially correlated unobserved state variable, i.e. firm-specific productivities, is incorporated into the production policy and estimated using different instrumental variable estimators.

Our sunk costs estimates are getting close to the reported establishment plant costs. We find that the exploration of new technologies became increasingly expensive throughout different generations. We also find that the growth in market demand increased throughout different generations, but at a declining rate. The increase in demand attracts more firms to enter the market, especially for early generations when it dominated the increase in investments in research and development. For more recent generations, however, the investment in new technologies became increasingly expensive such that it dominated the increase in demand. Firms were not able to cover the required investment from the generated profit stream and decided to exit the market. Consequently, the inverse U-shape in the industry can be explained by the interdependence between the growth in market demand and the investments into new technologies, which became increasingly expensive.

Our study confirms the importance to account for serially correlated firm specific productivity. We find that deviations from the common learning curve captured by firm-specific productivities explain firms survival in the market and the likelihood to enter new DRAM generations. Therefore, the likelihood to stay in the DRAM market is not entirely due to first mover advantages by entering the product market and moving down an industry learning curve. Firms being characterized by low investment into improving lithography processes, reducing cell sizes etc, are more likely to not being able to keep up with their competitives and not be able to enter the next DRAM generation.

For future research it would be interesting to further investigate the impact of entry and exit on the competitiveness of markets. This would be especially interesting with respect to evaluating different firm size distributions in the market, the reallocation of output between incumbents and the impact on the competitiveness and performance in the product market. These questions, however, would be beyond the scope of the paper.

References

Acs, Z.J. and D. Audretsch, 1988, "Innovation in Large and Small Firms," American Economic Review, Vol. 78, No. 4, pp. 678-690.

Ackerberg, D., L. Benkard, S. Berry and A. Pakes, 2006, *Econometric Outcomes for Analyzing Market Outcomes,* in: The Handbook of Econometrics, J. J. Heckman (ed.).

Ackerberg, D., K. Caves and G. Frazer, 2005, "Structural Identification of Production Functions," Mimeo, UCLA.

Aguirregabiria, V. and P. Mira, 2007, "Sequential Estimation of Dynamic Games," Econometrica, Vol. 75, No. 1, pp. 1-53.

Albert, M., D. Avery, F. Narin and P. McAllister, 1991, "Direct Validation of Citation Counts as Indicators of Industrially Important Patents," Research Policy, Vol. 20, pp. 251–259.

Arellano, M. and S. Bond, 1991, "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," Review of Economic Studies, Vol. 58, No. 2, pp. 277-297.

Asplund, M. and V. Nocke, 2006, "Firm Turnover in Imperfectly Competitive Markets," Review of Economic Studies, Vol. 73, No. 2, pp. 295-327.

Bajari, P., L. Benkard and J. Levin, 2007, "Estimating Dynamic Models of Imperfect Competition," Econometrica, Vol. 75, No. 5, pp. 1331–1370.

Benkard, L., 2000, "Learning and Forgetting: The Dynamics of Aircraft Production," The American Economic Review, Vol. 90, No. 4, pp. 1034-1054.

Benkard, L., 2004, "A Dynamic Analysis of the Market for Wide-Bodied Commercial Aircraft," Review of Economic Studies, Vol. 71, No. 3, pp. 581-612.

Beresteanu, A. and B. Ellickson, 2006, "The Dynamics of Retail Oligopoly," Mimeo, Duke University.

Blundell, R. and S. Bond, 1998, "Initial conditions and Moment Restrictions in Dynamic Panel Data Models," Journal of Econometrics, Vol. 87, No. 1, pp. 115-143.

Collard-Wexler, A., 2005, "Plant Turnover and Demand Fluctuations in the Ready-Mix Concrete Industry," Mimeo, Northwestern University.

Dasgupta, P. and J.E. Stiglitz, 1988, "Learning-by-Doing, Market Structure and Industrial and Trade Policies," Oxford Economic Papers, Vol. 40, pp. 246-268.

Dick, A.R., 1991, "Learning by Doing and Dumping in the Semiconductor Industry," Journal of Law and Economics, Vol. 34, pp. 133-159.

Duflo, E., R. Hanna and S.P. Ryan, 2007, "Monitoring Works: Getting Teachers to Come to School," Mimeo, Massachusetts Institute of Technology.

El-Kareh, B. and G.B. Bronner, 1997, "Evolution of DRAM cell technology", http://www.solid-state.com/display_article/5462/5/none/none/Dept/The-evolution-of-DRAM-cell-technology.

Ericson, R. and A. Pakes, 1995, "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," Review of Economic Studies, Vol. 62, No. 1, pp. 53-83.

Flamm, K., 1993, *Measurement of DRAM Prices: Technology and Market Structure*, in: M. Foss, M. Manser, and A. Young, eds. Price Measurement and their Uses, University of Chicago Press.

Fudenberg, D. and J. Tirole, 1983, "Learning-by-doing and Market Performance," The BELL Journal of Economics, Vol. 140, No. 2, pp. 522–530.

Geroski, P.A., 1995, "What Do We Know About Entry?," International Journal of Industrial Organization, Vol. 13, pp. 421-440.

Gowrisankaran, G., C. Lucarelli, P. Schmidt-Dengler and R.J. Town, 2008, "Policy and the Dynamics of Market Structure: The Critical Access Hospital Program," mimeo.

Griliches, Z. and T. Klette, 1997, "Empirical Patterns of Firm Growth and R&D Investment: A Quality Ladder Model Interpretation," Discussion Paper No. 188, Statistics Norway.

Gruber, H., 1996a, "Trade Policy and Learning by Doing: The Case of Semiconductors," Research Policy, Vol. 25, pp. 723-739.

Gruber, H., 1996b, "The Semiconductor Industry: Review of the Sector and Financing Opportunities," European Investmentbank, Luxembourg.

Hall, B.H. and A. Jaffe, and M. Trajtenberg, 2001, "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools," NBER Working Papers 8498, National Bureau of Economic Research, Inc.

Hansen, L.P., 1982, "Large Sample Properties of Generalized Method of Moments Estimators," Econometrica, Vol. 50, No. 4, pp. 1029-1054.

Hashmi, A.R. and J. Van Biesebroeck, 2008, "Market Structure and Innovation: A Dynamic Analysis of the Global Automobile Industry," No. 1787, Munich Personal RePEc Archive.

Heckman. J., 1981, "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process," Chapter 4 in C. Manski and D. McFadden eds. *Structural Analysis of Discrete Data and Econometric Applications*, MIT Press.

Hotz, V., R. Miller, S. Sanders and J. Smith, 1993, "A Simulation Estimator for Dynamic Models of Discrete Choice," Review of Economic Studies, Vol. 60, pp. 397-429.

Hu, Y. and M. Shum, 2008a, "Identifying Dynamic Games with Serially-Correlated Unobservables," mimeo.

Hu, Y. and M. Shum, 2008b, "Nonparametric Identication of Dynamic Models with Unobserved State Variables," mimeo.

Irwin, D. and P. Klenow, 1994, "Learning by Doing Spillovers in the Semiconductor Industry," Journal of Political Economy, Vol. 102, pp. 1200-1227.

Jovanovic, B. and G.M. MacDonald, 1994, "The Life Cycle of a Competitive Industry," Journal of Political Economy, Vol. 102, pp. 322-347.

Kasahara, H. and K. Shimotsu, 2008, "Nonparametric Identification of Finite Mixture Models of Dynamic Discrete Choices," Econometrica, Vol. 77, No. 1, pp. 135-176.

Keane, M.P. and K.I. Wolpin, 1994, "The Solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence," The Review of Economics and Statistics, Vol. 76, No. 4, pp. 648-672.

Klepper, S., 1996, "Entry, Exit, Growth, and Innovation over the Product Life Cycle," American Economic Review, Vol. 86, No. 3, pp. 562-584.

Klepper, S., 2002, "Firm Survival and the Evolution of Oligopoly," The RAND Journal of Economics, Vol. 33, No. 1, pp. 37-61.

Klepper, S. and E. Graddy, 1990, "The Evolution of New Industries and the Determinants of Market Structure," RAND Journal of Economics, Vol. 21, No. 1, pp. 27-44.

Klepper, S. and K. Simons, 2000, "The Making of an Oligopoly: Firm Survival and Technological Change in the Evolution of the U.S. Tire Industry," Journal of Political Economy, Vol. 108, pp. 728-760.

Levinsohn, J. and A. Petrin, 2003, "Estimating Production Functions Using Inputs to Control for Unobservables," The Review of Economic Studies, Vol. 70, No. 2, pp. 317-341.

Macieira, J., 2006, "Measuring the Effects of Innovation Subsidies: The Case of Supercomputers," Mimeo, Northwestern University.

Majd, S. and R.S. Pindyck, 1989, "The Learning Curve and Optimal Production under Uncertainty," RAND Journal of Economics, Vol. 20, No. 3, pp. 331-343.

Olley, S. and A. Pakes, 1996, "The Dynamics of Productivity in the Telecommunications Equipment Industry," Econometrica, Vol. 64, No. 6, pp. 1263-1298.

Pakes, A. 1994, "The Estimation of Dynamic Structural Models: Problems and Prospects, Part II. Mixed Continuous-Discrete Control Models and Market Interactions," J.J. Laffont and C. Sims eds, *Advances in Econometrics: Proceedings of the 6th World Congress of the Econometric Society*, Chapter 5.

Pakes, A., M. Ostrovsky and S. Berry, 2007, "Simple Estimators for the Parameters of Discrete Dynamic Games (with Entry/Exit Examples)," RAND Journal of Economics, Vol. 38, No. 2, pp. 373-399.

Pesendorfer, M. and P. Schmidt-Dengler, 2007, "Asymptotic Least Squares Estimators for Dynamic Games," forthcoming in Review of Economic Studies.

Ryan, S., 2006, "The Costs of Environmental Regulation in a Concentrated Industry", Mimeo, Massachusetts Institute of Technology.

Salant, S.W. and G. Shaffer, 1999, "Unequal Treatment of Identical Agents in Cournot Equilibrium," American Economic Review, Vol. 89, No. 3, pp. 585-604.

Scherer, F.M., 1998, "The Size Distribution of Profits from Innovation," Annales d'Economie et de Statistique, No. 49/50, pp. 495-516.

Siebert, R., 2007, "Learning by Doing and Multiproduction Effects over the Life Cycle: Evidence from the Semiconductor Industry," Mimeo, Purdue University.

Spence, A.M., 1981, "The Learning Curve and Competition," Bell Journal of Economics, Vol. 12, No. 1, pp. 49-70.

Stinebrickner, T.R., 2000, "Serially Correlated Variables in Dynamic, Discrete Choice Models," Journal of Applied Econometrics, Vol. 15, No. 6, pp. 595-624.

Sutton, J., 2001, *Technology and Market Structure*, MIT Press.

Sweeting, A., 2006, "The Costs of Product Repositioning: The Case of Format Switching in the Commercial Radio Industry," Mimeo, Northwestern University.

Thompson, P., 2005, "Selection and Firm Survival: Evidence from the Shipbuilding Industry, 1825-1914," The Review of Economics and Statistics, Vol. 87, No. 1, pp. 26-36.

Thornton, R.A. and P. Thompson, 2001, "Learning from Experience and Learning from Others: An Exploration of Learning and Spillovers in Wartime Shipbuilding," American Economic Review, Vol. 91, No. 5, pp. 1350-1368.

Wooldridge, J., 2005, "On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables," Mimeo, Michigan State University.

Wright, T. P., 1936, "Factors Affecting the Cost of Airplanes," Journal of Aeronautical Sciences, Vol. 3, pp. 122-128.

Zulehner, C., 2003, "Testing Dynamic Oligopolistic Interaction: Evidence from the Semiconductor Industry," International Journal of Industrial Organization, Vol. 21, No. 10, pp. 1527-1556.

A Appendix: Tables

Table 1a: DRAM trend from 4MB to 1GB

	4MB	16MB	64MB	256MB	1GB	Scaling Factor
Year of Introduction	1988	1991	1995	1999	2003	
Design Rules (μm)	0.80	0.50	0.35	0.25	0.18	~0.7
Chip Size (mm^2)	87	130	200	300	450	~1.5
Cell Size (mm^2)	11	4.0	1.6	0.6	0.25	~0.4
Internal Power Supply (V)	3.3-5.0	3.3	2.5	2.0	1.5	~0.8

Table A presents the evolution of DRAM technology from the 4MB until the 1GB DRAM chip. Source: El-Kareh and Bronner (1997).

Table 1b: Number of patents

Time	DRAM Patents	Semiconductor Patents	Total Patents
1989	462	4,063	78,619
1990	526	4,521	81,302
1991	571	5,276	82,939
1992	581	5,313	86,548
1993	636	5,688	89,572
1994	826	7,554	102,553
1995	901	9,250	122,127
1996	1,009	10,390	122,552
1997	1,214	13,507	143,109
1998	1,026	13,080	136,905
1999	868	12,624	125,063
2000	439	9,299	90,591
2001	169	4,443	32,694
2002	22	243	1,397

Table A presents the number of patents for the DRAM industry and semiconductor industry as well as the total number of patents over time. Source: NBER patent database. The data are described in detail in Hall, Jafee, and Trajtenberg (2001).

Table 2: Reported establishment costs

Company	Country	Products	Year	Wafers/Month	Cost (US-$)
n.a.	n.a.	16K DRAM	1985	30,000	0.5b
Fujitsu	England	64MB DRAM	1999	15,000	1.4b
IBM	France	16/64MB DRAM	1997	20,000	1.0b
Siemens	Germany	256MB DRAM	1999	25,000	1.9b
n.a.	n.a.	64MB DRAM	1999	30,000	2.5b
Siemens	England	Memory	1997	25,000	1.6b
Texas Instr	Italy	16MB DRAM	1995	15,000	1.0b
LG	Wales	256MB DRAM	1998	n.a.	1.3b
n.a.	n.a.	1GB DRAM	2007	30,000	5.0b

Table A presents reported establishment costs at the plant-level. Prices are in current US Dollars. Sources: Shin-Etsu (Interview), Gruber (1996b).

Table 3: Number of firms and entry and exit ranking in different DRAM generations

Firm (HQ*)	4K	16K	64K	256K	1MB	4MB	16MB	64MB	128MB
AMD (US)	7,7	8,7	13,3	.	.	.	.	.	.
Alliance(US)	.	.	.	.	.	16,13	11,11	.	.
AMS (US)	6,1	.	.	.	.	.	.	.	.
AT&T (US)	.	.	.	3,3	2,1	.	.	.	.
Fairchild (US)	5,2	4,5	11,1	.	.	.	.	.	.
Fujitsu (JAP)	8,6	3,7	2,8	2,11	3,9	2,7	1,12	3,10	3,2
Hitachi (JAP)	10,4	5,7	5,7	1,11	2,9	1,5	1,4	5,4	1,1
Hyundai (SK)	.	.	16,7	12,8	11,9	10,5	6,4	3,4	2,1
IBM (US)	.	.	.	.	14,3	13,5	4,4	1,4	.
Intel (US)	1,4	2,7	7,10	6,6	9,2	.	.	.	.
Intersil (US)	6,5	8,1	.	.	.	.	.	.	.
LG (SK)	.	.	.	13,8	13,8	9,3	7,2	3,3	.
Matsushita (JAP)	.	10,3	11,13	7,11	6,9	4,13	1,8	8,3	.
Micron (US)	.	.	9,12	6,7	7,8	8,10	5,12	6,10	3,4
Mitsubishi (JAP)	.	7,5	6,9	3,10	4,8	3,5	2,3	3,4	2,1
Mosel Vitelic (US)	.	.	15,3	10,11	12,8	12,9	9,12	7,7	5,4
Mostek (US)	3,11	1,7	.	4,2	.	.	.	.	.
Motorola (US)	5,9	4,7	.	7,5	8,4	5,2	4,1	4,1	.
Ntl. Semic. (US)	5,8	5,7	12,2	6,1	.	.	.	.	.
NEC (JAP)	4,5	3,7	4,5	3,11	5,9	1,5	1,4	1,4	2,1
Nippon (JAP)	.	.	.	10,6	8,8	6,3	8,2	9,3	.
OKI (JAP)	.	.	5,13	3,11	4,9	2,14	1,12	7,8	.
Ramtron Int. (US)	.	.	.	.	.	15,1	.	.	.
Samsung (SK)	.	.	14,13	8,9	7,8	7,5	3,10	5,10	2,4
Seiko Epson (JAP)	.	.	.	.	.	18,3	12,2	.	.
Siemens (EU)	.	5,7	8,4	9,6	7,7	4,6	4,5	2,6	4,4
Signetics (US)	9,3	6,2	.	.	.	.	.	.	.
Texas Instr. (US)	2,4	2,6	1,11	5,11	3,6	5,2	3,1	2,2	.
Toshiba (JAP)	.	5,7	3,5	3,9	1,8	1,4	1,6	3,5	2,4
Vanguard (US)	.	.	.	.	.	14,5	7,7	11,9	7,3
Winbond (CH)	.	.	.	.	.	.	14,12	10,10	3,4
Zilog (US)	.	5,2	.	.	.	.	.	.	.
# of Firms	15	20	22	23	22	30	30	28	21

Table A presents the order of firms' entry and exit for the different DRAM generations. * HQ abbreviates headquarter with CH=China, EU=European Union, JAP=Japan, SK=South Korea, TA=Taiwan, and US=United States. Source: Gartner Inc. Note that we only reported those firms that were among the first three firms to enter or exit at least one of the generations.

Table 4: Summary statistics over product generations

	4K	16K	64K	256K	1Mb	4Mb	16Mb	64Mb	128MB	256MB
market size (avg shipments)	24,531	131,347	129,351	293,231	337,862	466,018	726,045	756,966	845,398	1,232,064
change in %	.	4%	-2%	127%	15%	38%	56%	4%	12%	46%
market size (avg revenues)	60,287	296,361	378,206	839,090	1,924,650	3,879,964	5,420,886	4,909,546	4,237,914	6,844,068
change in %	.	392%	28%	122%	129%	102%	40%	-9%	-14%	61%
avg number of firms	8	13	9	13	14	13	14	12	10	7
change in %	.	63%	-31%	44%	8%	-7%	8%	-14%	-17%	-30%
avg shipments per firm	3,066	10,104	14,372	22,556	24,133	35,848	51,860	63,081	84,540	176,009
change in %	.	229%	42%	57%	7%	49%	45%	22%	34%	108%
avg revenues per firm	7,536	22,797	42,023	64,545	137,475	298,459	387,206	409,129	423,791	977,724
change in %	.	203%	84%	54%	113%	117%	30%	6%	4%	131%
new entry	15	6	7	5	1	10	3	0	0	0
change in %	.	-60%	17%	-29%	-80%	900%	-70%	-300%	0%	0%
exit	15	21	23	28	27	28	20	17	5	3
change in %	.	40%	10%	22%	-4%	4%	-29%	-15%	-71%	-40%

Table A presents industry-specific averages. Standard errors are shown in parentheses. Prices are in constant US Dollars as of 2000.

Table 5: Learning effects in the DRAM industry

	Ordinary least squares		Two-stage least squares	
			First stage	Second stage
Variable	(1)	(2)	(3)	(4)
Constant	6.3308	5.9383	0.1026	5.7870
	(55.83)***	(53.73)***	(0.84)	(51.11)***
Log(Cumulated industry output)	-0.3988	-0.4723	1.0017	-0.5007
	(-53.34)***	(47.01)***	(86.98)***	(47.30)***
Log(Qutput)		0.1545		0.2140
		(9.95)***		(12.71)***
First difference of Log(GDP)			15.4986	
			(2.79)**	
Time trend			-0.1396	
			(57.83)***	
Dummy variable for 16K	0.0965	-0.1702	2.2818	-0.2731
	(0.83)	(1.55)	(20.55)***	(2.45)*
Dummy variable for 64K	0.1591	0.1560	3.3861	0.1548
	(1.57)	(1.69)	(30.17)***	(1.65)
Dummy variable for 256K	0.5406	0.3627	5.6540	0.2940
	(5.15)***	(3.73)***	(44.67)***	(2.97)**
Dummy variable for 1MB	0.9161	0.6457	7.6786	0.5414
	(8.65)***	(6.45)***	(53.48)***	(5.30)***
Dummy variable for 4MB	0.9177	0.6686	9.6323	0.5725
	(8.88)***	(6.86)***	(56.75)***	(5.76)***
Dummy variable for 16MB	1.1400	0.7991	11.2193	0.6677
	(10.65)***	(7.74)***	(60.36)***	(6.32)***
Dummy variable for 64MB	0.8624	0.4687	12.7763	0.3169
	(7.20)***	(4.04)***	(60.80)***	(2.67)**
Dummy variable for 128MB	0.7302	0.2861	13.9123	0.1149
	(5.59)***	(2.25)*	(61.19)***	(0.88)
Dummy variable for 256MB	0.9084	0.4122	14.9150	0.2208
	(6.50)***	(3.02)**	(61.72)***	(1.58)
Dummy variable for 256MB	0.9084	0.4122	14.9150	0.2208
	(6.50)***	(3.02)**	(61.72)***	(1.58)
Dummy variable for 1GB	0.0845	-0.1255	17.4191	-0.2065
	(0.36)	(0.59)	(49.07)***	(-0.95)
Number of observations	488	488	488	488
R-squared adjusted	0.86	0.89	0.96	0.88

Table A presents learning effects for the DRAM industry. The dependent variable is average selling price. In column 1, the explanatory variable are a constant and cumulated past output. In columns 2 and 4, the explanatory variable are a constant, the cumulated past output and contemporaneous output. In the reduced form equation (column 3), the dependent variable is the average industry output. Explanatory variables are a general demand shifter, and a time trend. All specifications are estimated in logarithms and with product-specific dummy variables. Absolute values of t-statistics are shown in parentheses below the parameter estimates. *** (**, *) denotes a 99% (95%, 90%) level of significance.

Table 6: Estimation results for the demand function

	Ordinary least squares	Two-stage least squares		
		First stage		Second stage
Variable	(1)	(2)	(3)	(4)
Constant	15.6122	-5.7424	-11.6827	17.3926
	(19.49)***	(-4.09)***	(-6.29)***	(18.54)***
Log(Average selling price)	-3.0359			-3.4870
	(19.80)***			(18.96)***
Log(Price index	1.5320			1.8492
of substitute DRAM generations)	(6.70)***			(5.58)***
Log(Number of firms)		0.0531	0.0529	
		(0.42)	(0.50)	
Log(Number of firms		0.2350	-0.2459	
in substitute DRAM generations)		(1.25)	(1.18)	
Log(Cumulative industry output)		-0.3340	-0.0787	
		(10.75)***	(2.88)**	
Log(Cumulated industry output		0.1840	0.0253	
in substitute DRAM generations)		(3.88)***	(0.55)	
Log(Price of silicon)		1.0334	1.5406	
		(6.29)***	(7.41)***	
Log(Average SRAM selling price)	0.1214	0.1716	0.2882	0.0376
	(0.95)	(4.36)***	(5.96)***	(0.25)
First difference of Log(GDP)	28.4178	7.4937	6.0783	30.8773
	(2.12)*	(1.72)	(1.14)	(2.04)*
Time trend	-0.0650	-0.0066	-0.0346	-0.0816
	(3.59)***	(1.19)	(5.74)***	(3.98)***
Dummy variable for 16K	2.7912	-0.0006	-0.1691	2.9007
	(8.05)***	(0.00)	(1.13)	(6.26)***
Dummy variable for 64K	5.5337	0.1573	-0.8989	6.5387
	(10.97)***	(0.88)	(5.10)***	(10.58)***
Dummy variable for 256K	9.6048	0.5597	-1.4110	11.1869
	(14.83)***	(2.03)*	(5.97)***	(13.36)***
Dummy variable for 1MB	13.6247	0.9714	-2.0703	15.9609
	(15.82)***	(2.95)**	(6.15)***	(13.73)***
Dummy variable for 4MB	16.8203	1.3763	-2.5274	19.7769
	(15.01)***	(3.49)***	(6.48)***	(13.41)***
Dummy variable for 16MB	19.7173	1.7459	-3.1330	23.2995
	(14.61)***	(3.92)***	(6.57)***	(13.02)***
Dummy variable for 64MB	21.7587	1.6960	-3.7892	25.8033
	(14.12)***	(3.55)***	(7.82)***	(12.59)***
Dummy variable for 128MB	23.5801	1.8698	-4.4855	28.0229
	(15.12)***	(3.86)***	(9.12)***	(12.98)***
Dummy variable for 256MB	25.7931	2.0193	-4.6228	30.1895
	(15.86)***	(4.29)***	(9.55)***	(13.37)***
Dummy variable for 512MB	26.9809	1.9876	-5.2215	32.1104
	(14.77)***	(3.51)***	(9.08)***	(12.74)***
Dummy variable for 1GB	25.0113	2.5328	-4.7983	31.3587
	(12.55)***	(3.82)***	(7.30)***	(12.26)***
Number of observations	424	417	417	417
R-squared adjusted	0.83	0.93	0.98	0.81

Table A presents ordinary least squares and two-stage least squares estimation results for the demand equation. In the demand equation (columns 1 and 4), the dependent variable is industry output. Explanatory variables are the average selling price, a price index of substitute DRAM generations, average SRAM selling price, a general demand shifter, and a time trend. In the reduced form supply equations (columns 2 and 4), the dependent variables are the average selling price and a price index for substitute DRAM generations. Explanatory variables are the number of firms, number of firms in substitute DRAM generations, cumulated industry output, cumulated industry output in substitute DRAM generations, and price of silicon. All specifications are estimated in logarithms and with product-specific dummy variables. Absolute values of heteroscedasticity and autocorrelation robust t-statistics are shown in parentheses below the parameter estimates. *** (**, *) denotes a 99% (95%, 90%) level of significance.

Table 7: Estimation results for incumbents' output policy function

Variable	OLS-FE (1)	IV-FE (2)	IV-FE II (3)	IV-FD (4)
Constant	792.1619	575.9142	373.5527	-0.1673
	(80.42)***	(1.90)	(5.03)***	(9.41)***
Demand shock	0.0353	0.0485	0.0329	-0.0145
	(4.59)***	(4.59)***	(2.69)**	(0.84)
Log(Price of silicon)	-0.3929	-0.3902	-0.3578	-0.2878
	(6.58)***	(4.84)***	(3.77)***	(2.25)**
Log(Lagged number of firms)	0.3432	0.6564	0.4347	0.3242
	(8.00)***	(6.94)***	(3.70)***	(3.01)**
Log(Cumulated past output)	0.8451	1.1448	0.4701	0.1905
	(54.54)***	(28.29)***	(3.83)***	(2.12)**
Log(Cumulated past output of other firms)	0.0336	-0.1765	-0.1546	0.6395
	(2.51)**	(4.92)***		(2.70)**
Time trend	-0.1512	-0.0692	0.6788	-0.1452
	(57.67)***	(4.32)***	(4.39)***	(7.89)***
AR(1)	0.8699	0.7926		0.0439
	(42.96)***	(27.42)***		(1.19)
Lagged output			0.5989	
			(6.87)***	
Dummy variable for 64K	3.1258	1.8804	0.8547	0.0093
	(62.47)***	(34.28)***	(4.79)***	(0.27)
Dummy variable for 256K	4.8971	3.5872	1.6698	0.0159
	(69.74)***	(49.17)***	(5.22)***	(0.79)
Dummy variable for 1MB	6.8288	5.4853	2.4519	0.0394
	(79.27)***	(59.53)***	(5.14)***	(1.66)*
Dummy variable for 4MB	8.5079	7.2406	3.1786	0.0425
	(86.53)***	(59.35)***	(5.04)***	(1.67)*
Dummy variable for 16MB	9.9598	8.9356	3.8632	0.0493
	(83.22)***	(62.83)***	(5.03)***	(1.61)
Dummy variable for 64MB	11.2759	10.5943	4.6017	-0.0124
	(91.63)***	(70.76)***	(5.08)***	(0.42)
Dummy variable for 128MB	11.7451	11.2063	4.9174	-0.0875
	(86.74)***	(65.27)***	(5.05)***	(1.83)*
Dummy variable for 256MB	13.2375	12.7171	5.6182	0.0230
	(100.89)***	(83.23)***	(5.23)***	(0.47)
Dummy variable for 512MB	14.9492	14.6396	6.5041	0.0751
	(76.05)***	(66.85)***	(5.23)***	(0.46)
Dummy variable for 1GB	14.9185	14.8611	6.4012	0.1000
	(60.07)***	(53.59)***	(4.99)***	(0.63)
Number of observations	5,051	3,857	4,031	3,669
R-squared adjusted	0.93	0.91	0.90	0.18

Table A presents estimation results for the incumbents' policy function. The dependent variable is firm-specific output. Explanatory variables are the demand shock, price of silicon, lagged number of firms in the market, firm-specific past cumulated output, cumulated past output of all other firms, and a time trend. All specifications are estimated in logarithms and with product-specific and firm-specific dummy variables. The specification in column (1) is estimated with ordinary least squares, columns (2) and (3) with instrumental variables, and column (4) in first differences. In columns (2) to (4), we instrument cumulated past output with cumulated past output in the previous product generation.Absolute values of heteroscedasticity and autocorrelation robust t-statistics are shown in parentheses below the parameter estimates. *** (**, *) denotes a 99% (95%, 90%) level of significance. The first stage results are available from the authors upon request.

Table 8: Estimation results for first stage of incumbents' output policy function

Variable	IV-FE (1)	IV-FE II (2)	IV-FD (3)
Constant	-13.5490	-485.1445	0.0163
	(7.51)***	(34.08)***	(2.98)**
Log(Cumulated past output in previous generation)	0.3333	0.1366	0.3905
	(14.37)***	(8.86)***	(9.63)***
Log(lagged cumulated past output)			0.1488
			(2.68)**
Demand shock	-0.0126	-0.0234	-0.0067
	(0.77)	(2.15)**	(1.08)
Log(Price of silicon)	-0.1433	0.2100	0.0250
	(1.52)	(3.40)***	(1.13)
Log(Lagged number of firms)	-0.1384	-0.5003	0.0313
	(0.93)	(6.10)***	(0.61)
Log(Cumulated past output of other firms)	0.6869	0.2779	0.3896
	(30.38)***	(15.33)***	(10.09)***
AR(1)	-0.0880		0.2395
	(3.72)***		(5.16)***
Lagged output		0.6089	
		(33.35)***	
Dummy variable for 64K	-1.4270	-1.5538	0.0365
	(15.22)***	(28.53)***	(4.02)***
Dummy variable for 256K	-1.9919	-2.6946	0.0088
	(18.33)***	(36.69)***	(1.67)
Dummy variable for 1MB	-2.6434	-3.9979	0.0056
	(17.65)***	(40.44)***	(1.01)
Dummy variable for 4MB	-3.2277	-5.1547	0.0190
	(18.25)***	(42.38)***	(2.31)*
Dummy variable for 16MB	-3.6488	-6.2432	0.0033
	(18.20)***	(43.18)***	(0.46)
Dummy variable for 64MB	-4.1629	-7.4043	-0.0041
	(17.86)***	(44.82)***	(0.56)
Dummy variable for 128MB	-4.3254	-7.8776	-0.0071
	(16.77)***	(42.08)***	(0.34)
Dummy variable for 256MB	-4.1750	-8.6265	-0.0029
	(15.73)***	(42.52)***	(0.24)
Dummy variable for 512MB	-4.8786	-9.9434	0.0092
	(14.41)***	(39.14)***	(0.28)
Dummy variable for 1GB	-4.4377	-9.8920	-0.0169
	(10.46)***	(37.39)***	(0.19)
Number of observations	3,857	4,031	3,669
R-squared adjusted	0.87	0.95	0.78

Table A presents the estimation results for the first stage of the incumbents' policy function. The dependent variable is firm-specific past cumulated output. Explanatory variables are the past cumulated output in the previous generation, demand shock, price of silicon, lagged number of firms in the market, firm-specific past cumulated output, cumulated past output of all other firms, and a time trend. All specifications are estimated in logarithms and with product-specific and firm-specific dummy variables. Absolute values of heteroscedasticity and autocorrelation robust t-statistics are shown in parentheses below the parameter estimates. *** (**, *) denotes a 99% (95%, 90%) level of significance.

Table 9: Estimation results for entry and exit distribution

	Entry	Exit	Exit	Exit
Variable	(1)	(2)	(3)	(4)
Constant	-396.6066	-551.3873	-507.7130	-524.0555
	(7.43)***	(9.96)***	(9.38)***	(9.30)***
Unobserved productivity (IV-FE I)		-0.1532		
		(5.65)***		
Unobserved productivity (IV-FE II)			-0.1647	
			(5.81)***	
Unobserved productivity (IV-FD)				-0.1903
				(2.60)**
Demand shock	-0.0699	-0.0269	-0.0135	-0.0243
	(1.67)	(0.53)	(0.27)	(0.47)
Log(Cumulated past output)		-0.2728	-0.1591	-0.2683
		(5.70)***	(3.35)***	(5.24)***
Log(Cumulated past output of other firms)		0.1903	0.2184	0.2903
		(2.43)*	(2.87)**	(3.23)**
Log(Price of silicon)	0.3307	0.3137	0.3044	0.2669
	(1.39)	(1.40)	(1.37)	(1.17)
Log(Number of firms)	0.4574	0.0859	0.1414	-0.0708
	(4.50)***	(0.46)	(0.76)	(0.37)
Dummy variable for 64K	-1.2539	-2.1075	-1.9352	-2.0477
	(4.79)***	(8.32)***	(7.78)***	(8.09)***
Dummy variable for 256K	-1.8893	-4.0028	-3.7000	-3.6072
	(5.89)***	(10.13)***	(9.65)***	(9.46)***
Dummy variable for 1MB	-2.5216	-4.9318	-4.4344	-4.5532
	(6.50)***	(9.92)***	(9.19)***	(9.33)***
Dummy variable for 4MB	-3.3885	-5.4639	-4.8210	-5.0011
	(6.98)***	(9.97)***	(9.04)***	(9.29)***
Dummy variable for 16MB	-3.9182	-5.9904	-5.1391	-5.3870
	(7.12)***	(9.86)***	(8.74)***	(9.07)***
Dummy variable for 64MB	-4.2407	-6.1441	-5.1236	-5.4298
	(6.68)***	(9.66)***	(8.35)***	(8.72)***
Dummy variable for 128MB	-4.1343	-6.6994	-5.6035	-5.8728
	(5.96)***	(9.68)***	(8.43)***	(8.67)***
Dummy variable for 256MB	-4.2562	-6.6247	-5.3688	-5.8503
	(5.77)***	(9.59)***	(8.07)***	(8.62)***
Dummy variable for 512MB	-5.1172	-6.0430	-4.7532	-4.6977
	(5.78)***	(7.07)***	(5.80)***	(5.39)***
Dummy variable for 1GB	-4.0845	-5.1972	-4.2237	
	(4.33)***	(4.74)***	(4.20)***	
Number of observations	2,526	4,808	5,020	4,576
Pseudo R-squared	0.23	0.28	0.28	0.27

Table A presents the estimation results from the probit models of the entry and exit distribution. In the entry model (column 1), the dependent variable is an indicator variable, which is equal to one when a firm enters the market and zero before. Explanatory variables are the demand shock, price of silicon, number of firms, and a time trend. In the exit models (columns 2 to 4), the dependent variable is an indicator variable, which is equal to one when a firm exits the market and zero before. Explanatory variables are the demand shock, productivity shock (from the estimation of incumbents' policy function), price of silicon, number of firms, cumulated past output, and cumulated past output of other firms. All specifications are estimated in logarithms and with firm-specific and product-specific dummy variables. Absolute values of t-statistics are shown in parentheses below the parameter estimates. *** (**, *) denotes a 99% (95%, 90%) level of significance.

Table 10: Estimation results for the structural parameters

Variable	(1)	(2)
Constant	θ_0	4.699499
		(7.06)***
Economies of scale	θ_1	-1.031769
		(215.52)***
Learning effects	θ_3	-0.0049591
		(2.83)***
Spillovers	θ_4	-.0004025
		(2.66)***
Number of observations		304

Table A presents the structural parameters in the (marginal) cost function. Absolute values of t-statistics are shown in parentheses below the parameter estimates. *** (**, *) denotes a 99% (95%, 90%) level of significance.

Table 11: Ranking of firms' unobserved productivity by generation

Firms	**HQ**	**16K**	**64K**	**256K**	**1Mb**	**4Mb**	**16Mb**	**64Mb**	**128MB**
Adv. Micro Dev.	US	6, 2	9, 9	16,.	.	.	.	.	.
Alliance	US	.	.	.	.	17,.	25, 11	.	.
Elite	CH	.	.	.	.	20,.	18, 22	21, 2	14, 2
Elpida	JAP	.	.	.	.	.	26	15, 11	6, 10
Etron	TAIW	.	.	.	.	26,.	28, 1	16, 20	11, 13
Fairchild	US	14, 1	20, 12	.	.	.	.	.	.
Fujitsu	JAP	4, 3	5, 2	4, 1	5, 14	11, 10	13, 9	14, 14	20, 14
Hitachi	JAP	6, 11	3, 8	3, 9	., 12	2, 7	9, 7	12, 22	19,.
Hynix	SK	.	.	.	.	27, .	4, 23	2, 1	3, 3
Hyundai	SK	.	18,.	11, 11	10, 16	4,.	3, 5	5, 7	16
IBM	US	.	.	.	20,.	13, 3	17, 12	19, 16	.
Inmos	US	.	12,.	21,.	.	.	.	.	.
Integr Circuit Sol	US	.	.	.	.	24,.	21, 20	20, 4	12, 5
Integr Silicon Sol	US	.	.	.	.	23,.	22, 16	18, 5	13,.
Intel	US	10,.	13, 3	18, 14	19, 17	.	.	.	.
LG	SK	.	.	17,.	15, 18	9, 1	8, 8	17, 9	.
Matsushita	JAP	16,.	9, 10	12, 12	17, 4	15, 16	20, 2	27,.	.
Micron	US	.	8,.	8, 2	9, 5	6, 14	2, 14	1, 12	1, 6
Mitsubishi	JAP	15,.	4, 7	5, 4	3, 12	10, 9	12, 14	11, 18	17,.
Mosel Vitelic	US	.	19,.	16, 5	16, 13	14, 18	24, 17	8,.	7, 7
Mostek	US	1, 8	x	22,.	.	.	.	.	.
Motorola	.	.	x	15,.	11, 1	18, 5	23, 19	28,.	.
Nan Ya Techn.	US	.	.	.	.	.	14,.	9, 21	8,.
Ntl. Semic.	US	5, 4	15, 6	23,.	.	.	.	.	.
NEC	JAP	2, 6	1, 1	1, 8	6, 9	3, 11	5, 10	6, 10	15,.
Nippon	JAP	.	.	10,.	14, 3	16, 8	27, 21	25,.	.
OKI	JAP	.	7,.	7, 6	7, 2	5, 2	6, 15	23, 15	.
Samsung	SK	.	6,.	6, 13	2, 8	1, 4	1, 6	3, 8	2, 8
Sanyo	JAP	.	.	20,.	13, 6	21, 13	.	.	.
SGS-Thompson	EU	17, 7	.	.	.	.	.	.	.
Sharp	JAP	.	14,.	13,.	18, 15	25, 15	.	.	.
Siemens	EU	11,.	11, 4	14, 10	8, 10	12, 12	7, 3	4, 3	4, 9
STC	US	8, 5	17, 5	.	.	.	.	.	.
Texas Instr.	US	3, 9	2,.	2, 7	4, 7	7, 17	15, 18	26, 6	.
TM Tech	US	.	.	.	.	.	., 24	., 13	., 1
Toshiba	JAP	12,.	10, 11	9, 3	1, 11	8, 6	11, 13	10, 19	5, 11
Vanguard	US	.	.	.	.	19,.	10,.	13 23	10, 12
Winbond	CH	.	.	.	.	.	16,.	7, 17	9, 4

Table A shows the ranking in shipments and the ranking in the calculated firm-level unobserved productivity, respectively, for the different DRAM generations.

B Appendix: Figures

Figure 1: Industry units shipped, 1974-2004

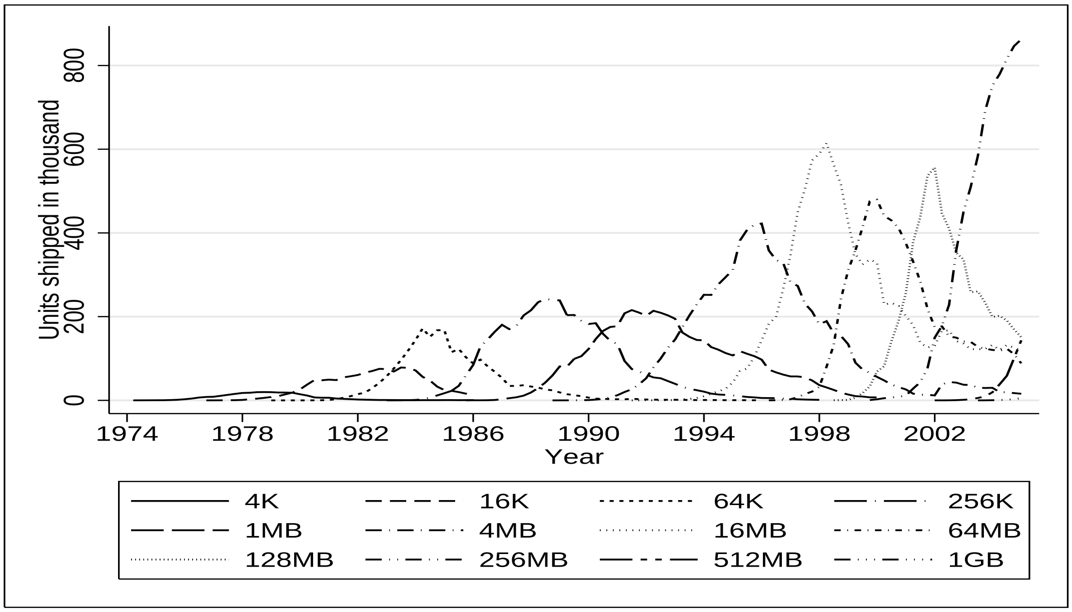

Figure 2: Cumulated industry units shipped, 1974-2004

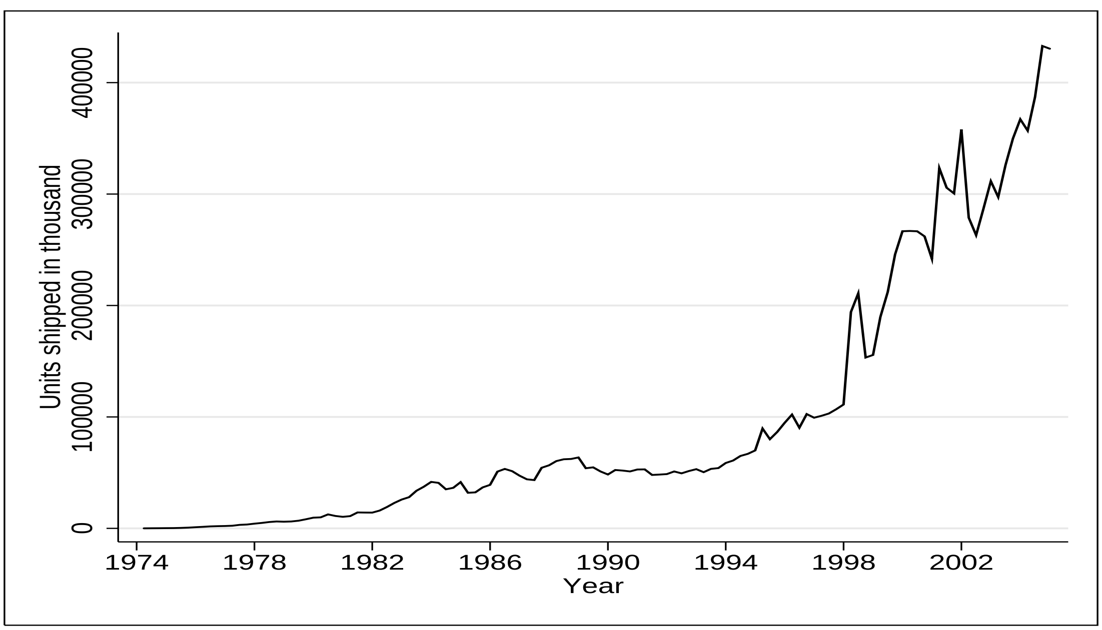

Figure 3: Average DRAM selling prices in USD, 1974-2004

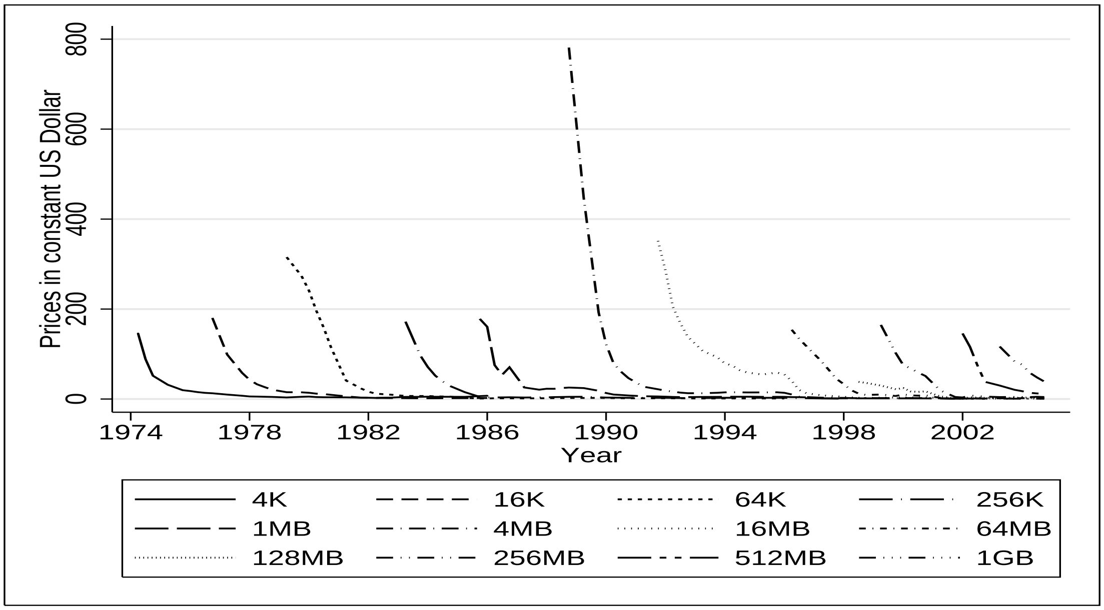

Figure 4: Number of firms in the DRAM market, 1974-2004

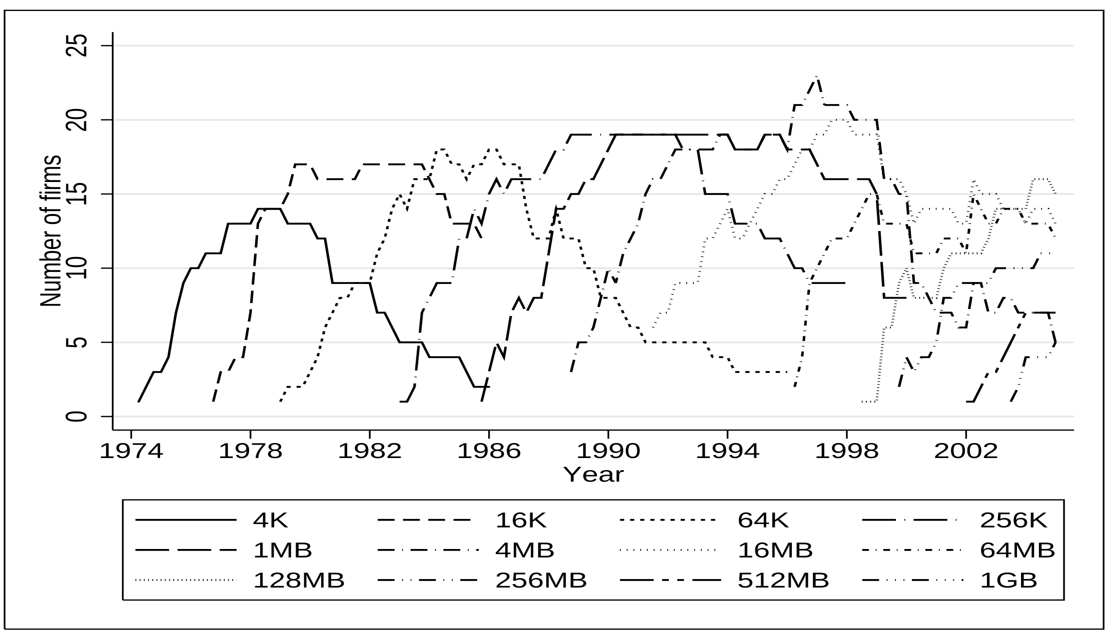

Figure 5: Number of firms in different DRAM markets, 1974-2004