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 firms' 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 firms' presence in the market is better explained by their investments into intangible assets than by their timing of entering into product markets.

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

Many policy debates target on evaluating the competitiveness of markets, especially in the context of innovation. The main interest is to analyze the impact of innovation on entry, exit in R&D intensive industries. Seminal contributions highlight the interdependence between innovation, growth, entry and exit, in order to evaluate the competitiveness in those markets.[1]

Entry and exit have important consequences on the efficiency of an industry. Entry may increase the competitive pressure in the product and technology markets having a positive effect on efficiency and market performance. A higher degree of innovation, however, may also drive firms out of the market leading to an increased market concentration. Exit may, on the other hand, also lead to efficiency gains, as the output formerly produced by the extinguished firms will be reallocated to more efficient survivors. On the other hand, fewer survivors will lead to an increased market concentration and a lower degree of competition, see also Salant and Shaffer (1999). [**I think we should be using the paragraph for our other paper, since we do not evaluate the competiveness of markets here**]

Asplund and Nocke (2006) emphasize the effect 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 in the evolution of the number of firms over time, which frequently resembles a product life cycle. In many industries, the number of firms drastically increases to a 3 digit number at early stages and then the industry experiences a sudden shake out, such that only a handful of firms survive. He finds 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 dynamic random access memory (DRAM) industry is characterized by a high degree of innovation that leads to bringing new product generations onto the market and high entry and exit rates.[2] The purpose of this study is to contribute to empirical regularities on the

[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. Klepper (1996) provides an nice overview of how entry, exit, market structure and innovation vary over the product life cycle.

[2] Dynamic random access memories are components within the semiconductor industry. They are designed for storage and retrieval of information in a binary form and are classified into 'generations' according to their

evolution of market structure in new industries. We focus on the question why the number of firms in the DRAM industry follows an inverse U-shape throughout different generations. The number of firms present in a product generation increased from 14 firms in the 4K DRAM generation in 1978 to 24 firms in the 4MB generation in the mid 1990's, and declined to 16 firms in the 128 MB generation in 2004.[3] The inverse U-shape in the number of firms is surprising because the 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 quite well, it is still unclear why the number of firms declines for more recent generations. One explanation might be that technologies became increasingly complex throughout different generations. For DRAM chips higher requirements are imposed regarding the storage of information and the size of the chip, which requires higher investments, and may induce firms to gradually exit the market. The artificial fiber industry, for example, was highly R&D intensive in the 1950s to the 1970s, and R&D competition and learning effects were important influences on concentration. Accounting for the fact that more innovative industries are characterized by higher exit rates (Geroski, 1995), it is surprising to observe an increase in the number of firms in early DRAM generations.

The focus of our study is to examine the impact of the increase in sunk costs from investments in product-specific innovation and market demand on market structure, i.e. firms' entry and exit. A challenging task in our study is that we do not observe product-specific innovation. Therefore, proxies such as R&D investments or patents are difficult to attribute to specific products or DRAM generations. To overcome the missing data problem, we exploit the fact that firms recoup their R&D investments into a new product generation. We infer the product-specific innovation as a sunk cost from firms' equilibrium behavior in different DRAM generations. We concentrate on estimating the evolution of investments in product-specific innovation over time, and 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 and firm-specific productivity in order to maximize their expected discounted sum of profits over the life cycle. A well known fact for the DRAM semiconductor industry is that learning by doing is an important phenomenon. Through repetitions and fine tuning of production processes, they are able to lower manufacturing costs.[4]

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storage capacity. For more information on the industry, see Section 2.

[3]Note that the 16MB, 64MB, and 128 MB DRAM generations have already passed the maximum of industry production at the time we are referring to.

[4]Contributions in estimating learning effects for the semiconductor industry are Gruber (1996), Irwin and Klenow (1994), Siebert (2007), and Zulehner (2003). For other industries, see Benkard (2004) and Thornton and Thompson (2001).

The number of discarded chips declines and the cost for the input -semiconductor wafers- declines. Production increases firms' experience which lowers (future) costs. Experience is proxied by past cumulated output which 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 deviations from the common learning curve.[5] Firm-specific productivity is stemming from the fact that firms differ in quality or have different capabilities to learn. Those quality differences may result from different firm-specific investments into intangible assets that establish different capabilities to learn and may occur e.g. through differences in managerial abilities, technological (absorptive) capacities, innovation ability, organizational structure, or strategic alliances. Firm-specific productivity may also last more than one period. Firms that have been more productive in the past are more likely to be more productive today. We assume that the time variant 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. In this way, the firm-specific productivity becomes a serially correlated unobserved state variable.

To obtain an estimate for sunk costs, we apply the two stage estimator by Bajari, Benkard and Levin (2007) which allows us to incorporate continuous as well as discrete choices in dynamic games. Their estimator builds on the idea by Hotz, Miller, Saunders, and Smith (1993) to use forward simulations to obtain the continuation values given optimal policies.[6] As of now there are only few studies that estimate a fully dynamic oligopoly model applying a two-step algorithm, exceptions are 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 Kasahara and Shimotsu (2008).[7]

[5]Learning-by-doing effects could be understood as long run or more persistent efficiency effects which reduce the marginal costs, whereas the firm-level productivity differences would represent short run efficiency effects that capture the firm-level variation around the long run effects.

[6]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).

[7]See also Heckman (1981) and Pakes (1994) for discussions on the problems caused by unobserved correlated state variables in dynamic models.

In the first step, the policy functions (production, entry and exit) are estimated. The policy functions describe what actions firms take given the state variables. We assume that firms' cost function is characterized by observed and unobserved state variables, i.e. economies of scale, learning-by-doing, spillovers, input prices and firm-specific productivity.[8]

To account for the serially correlated unobserved state variable we apply three different instrumental variable estimators in the production policy. First, 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] Second, we directly control for the serially correlated unobserved productivity by applying a lagged dependent variable model, or an AR(1) model and use a fixed effects estimator. To account for the dependence between the lagged and the current dependent variable and for time invariant unobserved heterogeneity, we use instruments for the lagged dependent variable and learning by doing. Finally, we use a first difference GMM estimator by Blundell and Bond (1998), which eliminates unobserved firm-specific effects by taking differences and using random effects and using instruments for the differenced learning variable. This estimator uses instruments for the differenced learning variable.[10]

One problem with unobserved serially correlated state variables in dynamic models is the contemporanous correlation between firm-level productivity and learning by doing, leading to a potential simultaneity bias. Different alternatives have been suggested to account for the simultaneity bias. Prominent studies in the production function literature account for time variant firm-specific productivity, or serially correlated unobserved state variables, by applying a proxy variable approach, see e.g. Olley and Pakes (1996). The problem with applying a proxy variable approach in our case is that we do not have sufficient data in order to appropriately

[8] Applying an instrumental variable approach is another alternative, e.g. searching for instruments that are highly correlated with the endogenous regressors, but not correlated with the productivity term. Note that the instrumental variable approach relies on find an instrument that is correlated with our learning by doing variable and not with the productivity term. It is easier in our case to find an appropriate instrument that is correlated with learning by doing compared to finding a proxy variable that is monotonic in the firm-level productivity. Having firm-level data over a sufficiently long time series reinforces this decision.

[9] Note, however, that applying a fixed effects estimator would violate the strict exogeneity assumptions while accounting for unobserved heterogeneity. Feedback effects resulting from contemporary production to future experience in production results in past experience being sequentially exogenous, which causes inconsistent estimates.

[10] Note that we also compared the this estimator with the standard 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.

proxy for the firm-specific productivity.[11]

We apply an instrumental variable approach in order to control for the potential simultaneity problem.[12] When searching for an appropriate instrument for learning by doing in a specific generation, we build on the fact that technologies are generation-specific. Firms interested in introducing a new chip generation, need to establish new plants equipped with different technologies. Firms charcterized by higher quality or productivity will determine production according to the steepness of their cost curve and learning by doing effects. Hence, more productive firms were more likely to be more productive in the past generations. This characteristic enables us to use the production experience in the previous generation as an instrument for learning by doing in the generation under consideration.[13]

Another problem with unobserved serially correlated state variables in dynamic models is the fact that identification becomes a challenging task.[14] Up to date, very little is known about the treatment of serially correlated unobservables in dynamic games. 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. One alternative of how to solve this problem is to try different initial draws, or assuming a functional form for the unobserved characteristic. Some studies estimate dynamic models, but not games, allowing for autocorrelated errors, see e.g. Keane and Wolpin (1994) and Stinebrickner (2000). Duflo, Hanna and Ryan (2007) estimate a structural dynamic labor supply model that allows for serial correlation in the opportunity cost of attending school. Their solution to the problem of serially correlated errors is to integrate out over the unknown distribution of the error term. To overcome the "initial condition" problem they make the assumption that agents receive an idiosyncratic draw from an unconditional error distribution. 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.

[11] Moreover, the proxy variable also needs to be monotonic in productivity, which makes it even more difficult finding an appropriate proxy variable.

[12] 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. Since we face difficulties in finding a good proxy for firm-level productivity, we apply the instrumental variable approach.

[13] See also Thompson (2005) for a related argument.

[14] 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), Hu and Shum (2008), Levinsohn and Petrin (2003), Olley and Pakes (1996) and Wooldridge (2005).

In the second stage, we estimate the structural parameters, such as generation-specific investments as a sunk costs, parameters from the cost functions and the distribution of private shocks. The discounted expected profits of entering at different states is simulated for many different paths. We rely on the fact that the firms are rational and forward-looking, i.e. they compare their discounted profit stream given the evolution of the state vector and their policy functions. 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 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 by Bajari, Benkard and Levin (2007) performs very well in predicting firms policies as well as the product-specific sunk costs. Our estimates of sunk costs get very close to the few reported establishment costs. They are increasing over different product generations, providing evidence for increasingly required investments throughout generations.

We provide evidence that the interdependence between pace of innovation of product generations, and market demand explains the inverse U-shape of the number of firms in the DRAM industry throughout different product generations. For early product generations, the increasing market demand had a higher impact than the increasingly required investments into new product technologies. For more recent product generations, however, the investments into new product technologies became increasingly expensive relative to the growth in demand such that less profitable firms would not have been able to cover their expenditures in research and development and exited the market.

Our estimates confirm the importance to account for serially correlated firm specific productivity. We find that firms investment into intangible assets is an important factor that determines whether firms stay in the market and is even more important than the order of entering into product markets. The latter result confirms, that first mover advantages for sliding down the learning curve early are dominated by the firm-specific productivity. Hence, firms characterized by a low investment in their productivities will not continue investing in the next technology and drop out.

The remainder of the paper is organized as follows. The next section gives an industry description providing insight into the production technology as well as into 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

Semiconductors are a key input for electronic goods, such as computers, consumer electronics, and communications equipment. The semiconductor industry is considered to be important as it has a significant impact on downstream industries and on growth of the economy. The semiconductor market consists of memory chips, micro components, and other components such as logic devices. DRAMs chips memory devices that are differentiated by their capacity of storing memory. The DRAM industry is an R&D intensive industry, which is characterized by innovation that either improves existing technologies, or leads to introducing new product generations into the market. The technologies for DRAM chips became increasingly complex over time. More 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. Table A 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 to about US-$ 5 billion in 2007.[15] Table A shows the increase in R&D activity in the DRAM and the semiconductor industry. For example, the number of patent applications in the DRAM industry increased from 462 in 1989 to 1,214 in 1997. However, it is controversial whether patent counts is an appropriate proxy for representing higher R&D investments. Moreover, it is difficult to attribute patents to specific generations in order to retrieve generation-specific R&D investments.

Table A shows the number of firms active in producing different generations. The number of firms increases from 15 in the 4K DRAM generation to 22 firms in the 64K, and 30 firms in the 4 MB DRAM as well as the 16MB generation. Afterwards, the number of firms starts declining to 28 and 20 firms in the 64MB and 128MB generation, respectively. See also Figure B and Figure B for the evolution of the number of firms over different generations.[16] Moreover, our data set shows that firms enter new generations at latest two years after the generation has been launched. Firms exit close to the time when the life cycle becomes obsolete. One explanation for finding only little entry and exit within a DRAM generation is given by the fact that learning effects are prevalent in the market and late entrants will not be sufficiently efficient to compete with firms that are further down the cost function due to learning effects.

DRAM chips are produced in batches on silicon wafers. The process of manufacturing an integrated circuit involves builiding up a series of layers on a wafer of polycristalline silicon.

[15] 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 at the plant level to the firm-level investments into inventing a new technology.

[16] Note that the number of firms for these generations is not due to a truncation problem or the fact that life cycles just started as for 64MB and the 128MB generations the peak of the life cycle has been reached.

Builiding up each layer invoves a sequence of steps. The production process requires a complex sequence of photolithographic transfer of circuit patterns from photo masks onto the wafer and of etching processes. Regarding the manufacturing process within a generation, it has to be very precise in terms of temperature, dust, vibration levels and other determinants. It is of fundamental importance that this process occurs in clean rooms, as even tiny dust particles on the wafer surface interrupt the connecting pattern and thus the chip useless. The wafer, once processed, is cut and the single chips are then assembled.[17] A permanent effort in increasing the wafersize is required in order to achieve higher productivity for every generation. These requirements are associated with exploring new technologies and became increasingly costly throughout different generations.

The DRAM industry is characterized by extensive learning-by-doing effects, resulting from the fine-tuning of production processes.[18] The yield rate, which is measured by the ratio of usable chips to the total number of chips on the wafer increases through learning over time. Through repetitions and fine tuning of production processes, they lower their manufacturing costs. It is assumed that firms slide down the (industry) learning curve which illustrates efficiency effects that firms achieve in the long run through learning-by-doing. Learning-by-doing is highest at the beginning of the life cycle and slow down over time. Given a decreasing rate of learning within a generation cost differences between firms become smaller throughout the life cycle which toughens price competition towards the end of the life cycle for a generation. Past accumulated output is usually used to proxy firms' experience.[19] 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. Depending on their past experience firms are at different locations on the industry learning curve. Production enters firms' costs through experience and, therefore, becomes a state variable. Firms' production has a contemporaneous impact on prices and profits, as well as an intertemporal impact on firms profits through their costs. Hence, quantities and prices are not solely determined in static equilibrium, but also through intertemporal production plans. 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.

[17] More detailed descriptions of the production processes can be found in e.g. Gruber (1996a), Irwin and Klenow (1994) and Flamm (1993).

[18] See for example, Gruber (1996a), Irwin and Klenow (1994), Siebert (2007), and Zulehner (2003).

[19] Note that for some industries such as the aircraft, or biotechnology industry the learning process might involve forgetting as well, see Benkard (2000). However, since the semiconductor industry is a very capital-intensive industry and represented by cumulative innovation and short life cycles, we abstract from forgetting.

firms' current production will increase future experience which results in future cost savings (see e.g. Dick, 1991; Fudenberg and Tirole, 1983 and 1986; Majd and Pindyck, 1989; Spence, 1981; and Wright, 1936).

We have firm level and industry level information on prices and quantities of different DRAM generations which are compiled by Gartner Inc. The data cover firm units shipped, industry units shipped, the average selling price, and the number of firms in the market from January 1974 to 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 B shows the industry shipments (in mio.) across different generations, i.e. the 4K till the 1GB generation from the years 1974 to 2004 on a quarterly basis. The figure illustrates that every DRAM generation is characterized by a product life cycle, that lasts for approximately 5 years in the in 1980's to 3-4 years in the late 1990's. A higher pace of innovation in downstream industries and higher demand for more advanced chips is one reason why product cycles became shorter. Shorter life cycles put higher pressure on firms to recoup research and development cost within a shorter time period. Figure B shows the industry output cumulated over product generations. It illustrates the upward trend in shipments over time and emphasizes a continuing market growth.

Learning-by-doing is frequently used to explain the rapid price decline of the different generations (see Figure B). The price decline is an important aspect in the industry and even more so as it is transmitted to many other downstream industries having an impact on economic growth. Note that the price decline looks quite similar across different generations, giving some indication that the learning effects are of comparable magnitude. Table A shows the ordering of firms when they entered and exited a specific DRAM generation. As the table shows, the ordering of entering and exiting a specific DRAM generation is not closely related with the probability of surviving a specific generation. The reason that we do not find a correlation between entry and survival may show that beyond learning by doing other factor such as firm-specific productivities might be important to account for. This fact is even more interesting as Klepper (2002) finds that the ordering of entry in the tire, auto, penicilin and tv industry is an important factor which explains firm survival.

Table A provides summary statistics of some of our variables that we use in our empirical analysis later on. 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 U. S. 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.

In a first step, we are primarily interested in investigating if learning effects are prevalent in our data set and if they are 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 A shows the results when we specify learning effects to be identical across generations. We are able to use more than 500 observations and get R squares higher than 80%. We apply Ordinary Least Squares and Two Stage Least Squares regressions, in which we instrument for the current industry output by 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. 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 that learning effects are similar across different generations with parameter estimates in front of the cumulated industry output ranging from -0.15 to -0.47.

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:

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

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:

$$c(q_{it},m_t,x_{it},x_{-it},\omega_{it-1},v_{it})=\theta_0+\theta_1q_{it}+\theta_2m_t+\theta_3x_{it}+\theta_4x_{-it}+\rho\omega_{it-1}+v_{it}, \tag{4}$$

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:

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

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.

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

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).[20] 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

[20] 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.

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. Note that we also estimated the learning effects separartely for different generations. We find that the estimates of the learning effects are comparable throughout 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).

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

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

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:

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

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^0_{it-1} as potential instruments for Δw_{it}, where $w^0_{it-1} = (w_{i1}, ..., w_{it})$. The fact that w^0_{it-1} 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:

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

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

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

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

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

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 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

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

where $k = 1, \ldots, K$. 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.[21] 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. 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

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

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

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. We rely on the fact that firms are rational and forward-looking, i.e. they compare their discounted profit stream given the evolution of the state vector and their policy functions.

The results of our study contribute to empirical regularities on market structure. 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. Interestingly, our study also show that the order of entry into product markets is not a good indicator for surviving in the DRAM industry. We rather find that deviations from the common learning curve captured by firm-specific productivities explain firms survival in the market and the adoption of new technologies.

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 and their impact on the competitiveness and market performance. These questions, however, would be beyond the scope of the paper.

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A Appendix: Tables

Table 1: 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

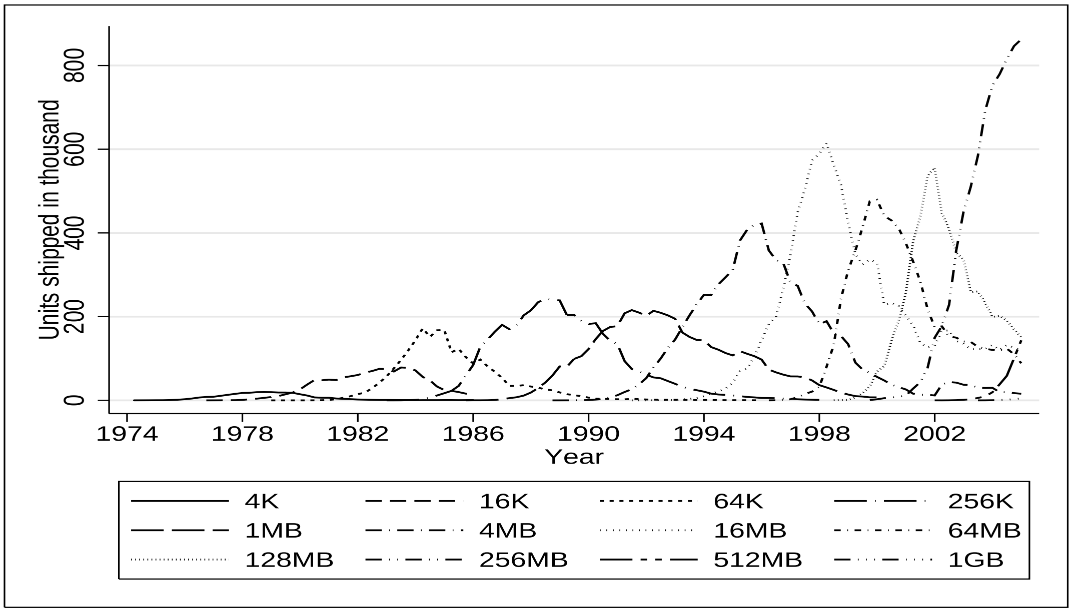

Figure 2: Cumulated industry units shipped, 1974-2004

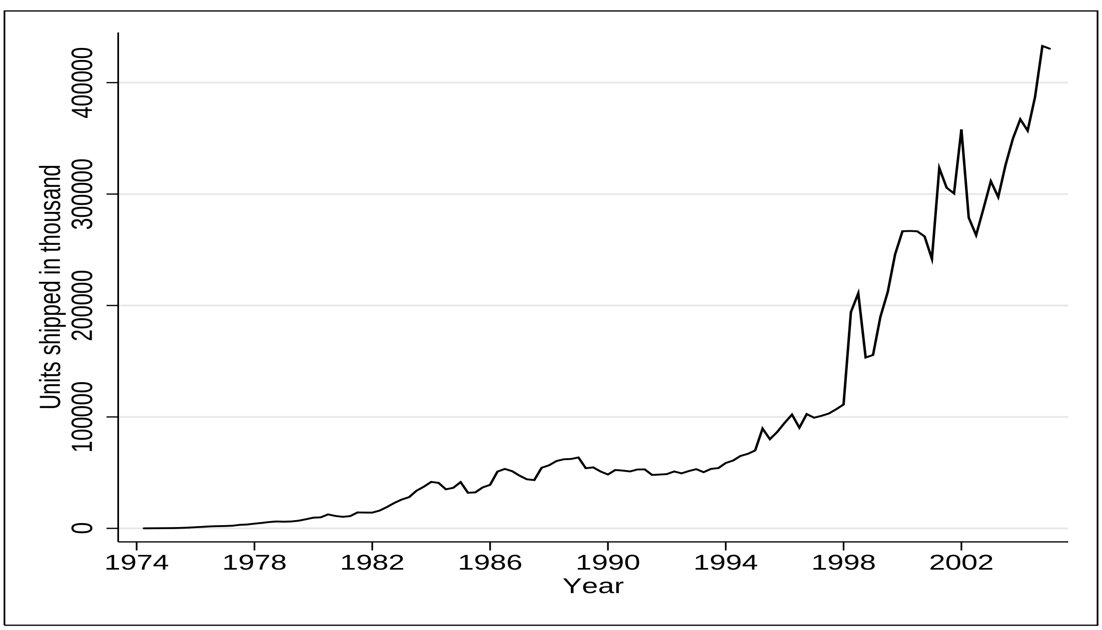

Figure 3: Average DRAM selling prices in USD, 1974-2004

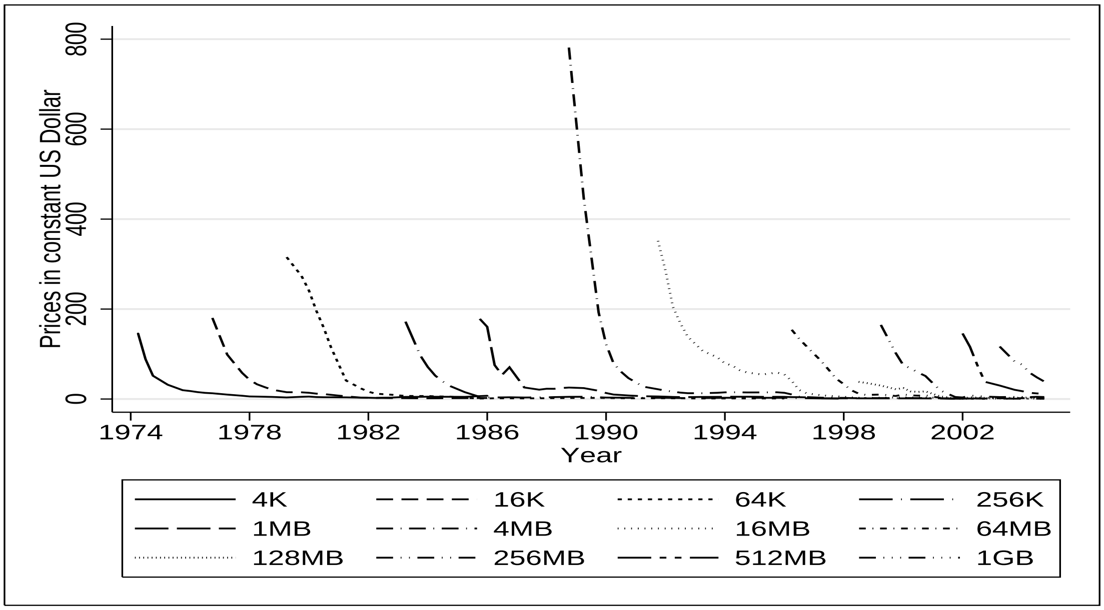

Figure 4: Number of firms in the DRAM market, 1974-2004

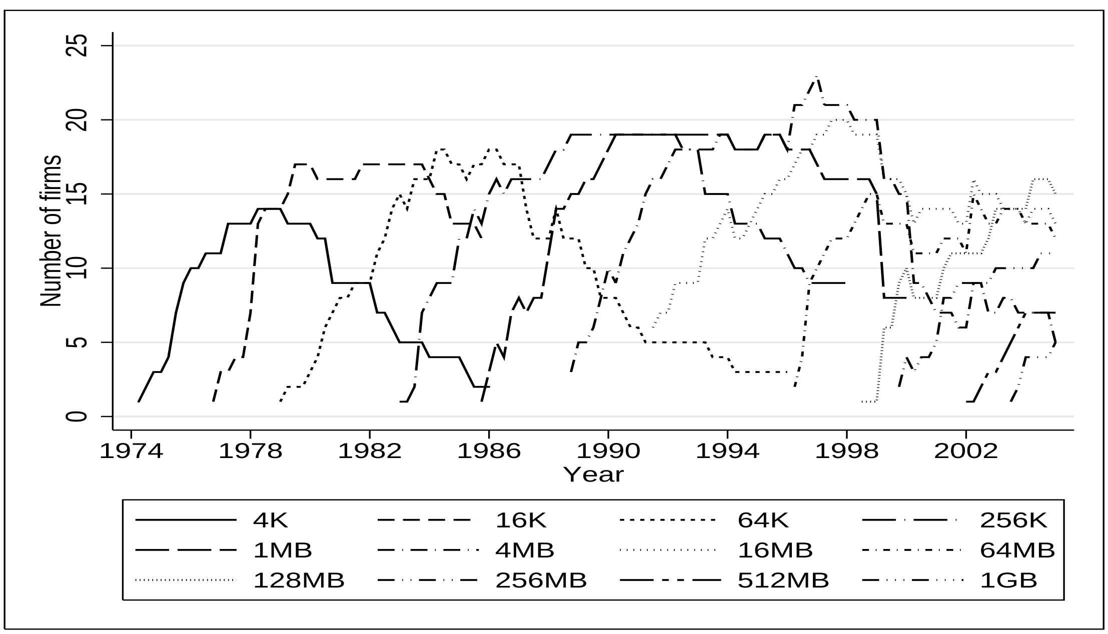

Figure 5: Number of firms in different DRAM markets, 1974-2004