The impact of market demand and entry costs on market structure^{*}

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Abstract

Our study contributes to the literature on industry and firm dynamics. We focus on the question why the number of firms in the semiconductor market follows an inverse U-shaped pattern throughout different product generations. We pay special attention to the fact that the number of firms declined after the mid 1990's. We disentangle the impact of changes in market demand and changes in entry costs on the number of firms in the market. We estimate a dynamic model in which firms make production, entry and exit decisions applying the two-step estimator developed by Bajari, Benkard and Levin (2007). A counterfactual experiment provides evidence that increasing entry costs (rather than diminishing growth in demand) is the main reason why the semiconductor industry experience a shake out in mid 1990's.

JEL: C1, L1, L6, O3.

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1 Introduction

Seminal studies in the area of industry and firm dynamics concentrate on the link between market structure and market performance.¹ Dunne, Roberts and Samuelson (1988) and Klepper and Graddy (1990) highlight the fact that many industries follow a similar pattern in the evolution of the number of firms: it is increasing up to a point when a sudden shake out process drastically reduces the number of firms. There are several explanations in the literature that aim to explain industry dynamics.

One strand of literature on industry dynamics considers market growth to be a major driving force that explains market entry and exit.² One established finding is that the number of firms is positively correlated with market size. Another strand of literature on industry dynamics emphasizes that higher entry costs provide a disincentive for market entry. The escalation in entry costs is considered to constitute a barrier to entry.³ Moreover, Asplund and Nocke (2006) have shown that higher entry costs are negatively related to entry rates. Entry costs are related to the cost of capital required to enter a market, i.e., the investments required to establish new plants equipped with advanced production machinery, and to the technological progress. Jovanovic and MacDonald (1994a and 1994b) emphasize that technology-based mechanisms contribute to shake outs and explain life cycles. Along this vein, Klepper and Simons (2000) provide an explanation for the sudden shake out process in the tire industry. In line with Utterback and Suarez (1993), they explain the shake out process by technological progress and argue that a major innovation was the cause for the drastic decline in the number of firms. Unproductive firms which did not adopt a new production technology exited the market.

The goal of our study is to explain why the number of firms in one of the semiconductor markets evolves according to an inverse U-shaped pattern over time, or throughout different product generations. More specifically, the dynamic random access memory (DRAM) market is characterized by an interesting pattern of market dynamics.⁴ The DRAM industry was characterized by a significant market growth. The number of firms increased from 15 in the 4K

¹Prominent studies in this area are Dasgupta and Stiglitz (1980), Shaked and Sutton (1987), Klepper and Simons (2000), Mueller and Tilton (1969), Acs and Audretsch (1988), Griliches and Klette (1997), Klepper (2002), Klepper and Graddy (1990), Klepper and Simons (2000), Scherer (1998) and Sutton (2001).

²See e.g., Schmalensee (1989), Scherer and Ross (1990), Shaked and Sutton (1987), Sutton (1991 and 1998), Dasgupta and Stiglitz, (1980), Bresnahan and Reiss (1991) and Asplund and Sandin (1999).

³See e.g. Baumol, Panzar, and Willig (1982, pp. 291), Hopenhayn (1992), Martin (2002) and Geroski (1995). ⁴Dynamic random access memories are components within the family of semiconductors. They are designed for storage and retrieval of information in binary form and are classified into generations according to their storage capacity. For more information on the industry, see Section 3.

generation in 1978 to over 30 in the 4MB generation in the late 1990's when market demand experienced a boom due to the increased sales of personal computers. After the 4 MB generation, growth in demand slowed down and the number of firms declined to 21 in the 128MB generation and 14 in the 256MB generation in 2004, and it declined even further to under 10 firms in successive generations.

We are interested in analyzing the causes of the inverse U-shaped pattern in the number of firms, especially those which determined the decline in the late 1990's. While in our study a growth in demand may well explain the increase in the number of firms for early generations, it still remains unclear why the number of firms declined for more recent generations. Using a fully dynamic oligopoly model, we aim to explain to what extent the evolution of market structure is driven by changes in market growth and entry costs.

Throughout product generations, the production of DRAM chips became increasingly complex. More advanced production techniques and lithographic processes required higher investments into more advanced equipment and machinery. Consequently, entry costs increased throughout different product generations. One challenging task in our study is to identify entry costs as they are product-specific and not observed. We thus estimate entry costs and exploit the fact that firms have to recoup their entry costs from their generated profits.

Our model is formulated in the tradition of Ericson and Pakes (1995) in which forward looking firms make entry, exit and production decisions. Firms maximize their expected discounted sum of profits over the product life cycle accounting for learning-by-doing and firm-specific productivities. The model is estimated using the two stage estimator by Bajari, Benkard and Levin (2007).⁵ In the first step, we estimate the policy functions (production, entry and exit); in the second step, we estimate the structural parameters, i.e., generation-specific entry cost.

Our results show that the entry cost drastically increased from approximately USD 18 million for the 4MB generation to USD 65 million and USD 118 million for the 16MB and 64MB generation, respectively. Our entry cost estimates are close to the establishment costs for new DRAM generations that are occasionally reported in the engineering literature. This confirms the reliability of our entry cost estimates. Our estimations also return reasonable results for the production, entry and exit policies. We also find that the share of entry costs on profits

 $^{{}^{5}}$ Ryan (2012) was the first who applied the BBL estimator to a fully dynamic structural model. While we concentrate on the industry dynamics, he studied the costs of environmental regulation on firms' profits in the cement industry.

is relative low (around 25%) for early generations and increased to 37%, 58% and 44% for the latter generations in our sample. This results confirms the fact that part of the entry costs on profits was increasing throughout generations, such that it was more difficult to recover the entry costs from the profit streams.

We also perform a counterfactual experiment to separately identify, whether the decline in the number of firms was primarily caused by the diminishing growth in demand or the increasing entry costs. Our counterfactual builds on the assumption that market growth did not decline after the 4MB generation, but continued growing at the same rate as before. Hence, we isolate the market growth from the increase in entry costs. Our counterfactual generates predictions for firms' profits, exit probabilities, and the shares of entry costs on profits for every generation. The results provide evidence that the share of entry costs on profits only marginally declines from 58% to 54% for the 64MB generation. This share is about 25% higher than in previous generations, indicating that diminishing growth in demand has a minor impact on the shake out process. The main impact on the decline in the number of firms is explained by the increasing entry costs. A similar results applies to the 128MB generation.

To summarize, our results show that the increase in entry costs in combination with diminishing growth in demand explains the inverse U-shaped pattern in the number of firms across generations. For early generations, the growth in demand dominated the accelerated entry costs such that more firms were attracted to enter the market. A slowdown in growth of demand in conjunction with substantial increase in entry costs in the late 90's caused a main shake out for the 16MB generation and thereafter. Most interestingly, our study provides evidence that the main reason for the shake out is driven by the increasing entry costs after the 4MB generation.

The remainder of the paper is organized as follows. In the next section we discuss the relevant literature. Section 3 describes the industry and provides insights into the development of new process technologies. This section also describes the data and presents summary statistics. Section 4 introduces our dynamic oligopoly model and Section 5 illustrates the econometric model. In Section 6 we discuss the empirical results. We conclude in Section 7.

2 Literature Review

A large strand of the literature on industry dynamics focuses on explaining the evolution of market structure. Klepper (2002) studies the evolution of market structure in the automobiles,

tires, televisions, and penicillin markets, which initially grew and then experienced a sharp decline or shakeout. Firms invest in R&D to lower their average cost. Since the total return from lowering average cost is scaled by the output of the firm, larger firms earn a greater return from R&D and are more likely to survive. Smaller firms earn a lower return from R&D and exit disproportionately, contributing to a shakeout. Gort and Klepper (1982) analyze the evolution of the number of firms in 46 industries characterized by shake out patterns. Klepper and Simons (2005) investigate the shake out processes in four different industries which are characterized by many firms entering the market. Jovanovic and MacDonald (1994b) explicitly focus on the DRAM industry in which firms introduce cost reducing technological improvements within generations, and explained the expansion in industry output and the decline in prices. Jovanovic and MacDonald (1994a) analyze the U.S. automobile tire industry and provide a technologybased explanation on sudden shake out processes, which drastically reduced the number of firms in the U.S. automobile tire industry. They explain the shake out process in the 1910-20 period by an exogenous technological invention developed outside the industry. Those firms that implemented the innovation staved in the industry and increased their output as the optimal scale increased. Technological laggards exited the market.

To investigate how the evolution of entry costs and the growth in demand throughout different product generations affect market structure, we estimate a dynamic game. Recent studies on the estimation of dynamic games focus on reducing the computational burden by simulating instead of calculating the continuation values and apply two step estimation algorithms.⁶ The estimator by Bajari, Benkard and Levin (2007) builds on the idea by Hotz, Miller, Saunders, and Smith (1994) and uses forward simulations to obtain the continuation values given optimal policies.⁷ Prominent studies that estimate a fully dynamic oligopoly model while applying a two-step algorithm are, e.g. Beresteanu, Ellickson and Misra (2010), Collard-Wexler (2010), Gowrisankaran, Lucarelli, Schmidt-Dengler, and Town (2008), Van Biesebroeck and Hashmi (2007), Macieira (2009), Ryan (2010), and Sweeting (2007).⁸ Ryan (2010) evaluates the welfare

⁶See e.g., Aguirregabiria and Mira (2007), Bajari, Benkard and Levin (2007), Pakes, Ostrovsky and Berry (2007), Pesendorfer and Schmidt-Dengler (2008) for more detailed information.

⁷For further discussion and a description of the different methods, see also Ackerberg, Benkard, Berry and Pakes (2005).

⁸One common feature in these studies (similar to our study) is that state variables are commonly observed by the players and the econometrician. Studies on dynamic discrete choice models which accommodate unobserved heterogeneity are Hu and Shum (2008 and 2010) and Kasahara and Shimotsu (2008). For more information about how to correct for serially correlated unobserved state variables, see also Bajari, Benkard, and Levin (2007), Ackerberg, Benkard, Berry and Pakes (2006), Ackerberg, Caves and Frazer (2005), Levinsohn and Petrin (2003), Olley and Pakes (1996), Rust (1994) and Wooldridge (2005). For discussions on the problems caused by

costs of the 1990 Amendments to the Clean Air Act on the US Portland cement industry. He estimates the distributions of sunk entry costs and capacity adjustment costs and finds that the Amendments have significantly increased the sunk cost of entry. Hashmi and Van Biesebroeck (2007) focus on the automobile industry and apply a two-step estimation method to simulate the effects of mergers on innovative activity. They find that the effect on innovation depends on the original level of concentration. If the industry is (not) originally concentrated, consolidation may reduce (increase) the innovation incentives.

3 Industry and data description

In this section, we present the data sources and provide descriptive statistics, especially with regard to the number of firms in the market throughout different product generations. We also describe the manufacturing process of DRAM chips as well as the process of entering new DRAM generations.

3.1 DRAMs

DRAMs are one part of the microelectronics industry and a key input for electronic goods, such as computers, workstations, communication systems and graphic subsystems. DRAM products are typically classified by the number of bits per chip, their capacity of storing memory. DRAMs store each bit of information in a memory cell consisting of one transistor and a capacitor. The capacitor stores data and the transistor transfers data to and from the capacitor. New operating systems of electronic products impose a minimum requirement for memory capacity. Thus, permanent research effort is required to increase the memory, reduce the size and cost, and increase the density and speed of DRAM chips. Moore's law is usually used to describe the growth pattern of the number of transistors on an integrated circuit over time. Moore predicted that the number of transistors per chip doubles every 24 months, resulting in a fourfold increase in bits per chip. The increase in transistors per chip is mainly due to three factors: reductions in cell size per bit, improved lithography processes and an increase in die size manufacturability.⁹

unobserved correlated state variables in dynamic models, see also Heckman (1981) and Pakes (1994).

⁹For example, improved nm process technologies are associated with improved lithography, improved substrate materials and metalization as well as device architecture optimization. The cost of developing the 90 nm process is estimated to be around USD 400 million, while the 45 nm process is estimated to cost USD 600 million. For more details regarding the description of production processes, see also Gruber (1996a), Irwin and Klenow (1994), Flamm (1993) and El-Kareh and Bronner (1997).

3.2 Data

Our study uses firm level and industry level information on prices and quantities for different DRAM generations which are compiled by Gartner Inc. The data set encompasses 12 product generations, namely the 4K, 16K, 64K, 256K, 1MB, 4MB, 16MB, 64MB, 128MB, 256MB, 512MB, and 1GB generation. It entails quarterly data from January 1974 until December 2004. The data set covers firm and industry units shipped, the average selling price, and the number of firms in the market. Figure 1 shows the industry shipments across different generations, i.e., the 4K till the 1GB generation. This figure illustrates that every DRAM generation is characterized by a product life cycle that lasts for approximately 10 years.

3.3 Number of firms in the market

Table 1 shows that firms introduce new generations in a subsequent manner. Hence, once firms exited one generation, they will not reenter into a subsequent generation. Figure 2 shows the evolution of the number of firms throughout different product generations. We observe similar patterns across product cycles and overall we note that the number of firms increased for the early generations and decreased for latter generations. Table 2 shows the number of firms and the number of new entrants in the different generations. The number of firms increases from 15 firms in the 4K generation to 30 firms in the 4MB and 16MB generations. Afterwards, a shake out took place in the industry and the number of firms declined to 20 firms in the 128MB generation and even further to 11 firms in the 256MB generation and 5 firms in the 1GB generation. We observe that early generations and the 4MB and 16 MB generation attracted a lot of first time entrants. After the 4MB generation the number of first time entrants slowed down. The number of permanent exitors increased drastically in the 4 MB and 16 MB generations.

We are aware of the fact that the latter generations may suffer from a lack in the number of observations.¹⁰ We thus compare the number of firms per product generation with the other summary measures such as the number of firms in the beginning of the product cycle (first four and first eight quarters), completeness of the product cycle and whether the output peek had been reached. Table 2 also provides these figures. We observe that only half of the generations had finished their product cycle (column 8). However, most of the product generations had reached their output peek; only the last three had not (column 9). Therefore, we calculate the

 $^{^{10}\}mathrm{The}$ maximum number of firms has already been passed for the 256MB, but not the 1GB generation.

number of firms for the first four and eight quarters (columns 6 and 7). We observe that the number of firms that had entered in first four quarters was highest in the 64MB generation. Afterwards this number fell. We thus decided to exclude the last three generations from our analysis, since their presence in the market might have been too short. We therefore include only generations in our study whose number of firms passed the peak.¹¹

3.4 Growth in market demand

Market demand is considered to be one important factor having an impact on market structure. The increase in demand is explained by the growth of markets using DRAM chips as an input in electronic devices. Figure 3 shows the total number of DRAM chips being sold summed over all generations. In the late 1980's and the early 1990's, the PC market was the primary target for DRAMs. Approximately 75% of DRAMs were sold to PC clients or servers. For most of that period, memory upgrades were a critical way to improve PC performance and to enable the use of new applications. By the end of the 1990's, however, the sizes of operating systems and applications were no longer growing as rapidly as before. Consequently, the demand for DRAMs did slowed down. Figure 3 illustrates the era in which demand remained relatively stable. The number of shipments in the mid 90's remained about constant. From the mid 90's onwards, the popularity of mobile phones and playstations increased the demand for DRAMs again. Figures 1 and 3 show that demand eventually declined again for the 16MB and 64MB generations. Table 3 provides summary statistics on the growth of market size, firm average shipments and revenues throughout the different generations. For example, the growth of market size declined from 54%in the 16MB to only 2% in the 64MB generation. The market revenues increased by 27% in the 16MB generation and suffered from a 17% decline in the 64MB generation.

3.5 Production process and learning by doing

The production processes determine the cost to enter a new DRAM generation. Throughout different DRAM generations the production processes became increasingly complex, which increased the cost to enter new generations. In the following, we describe the details how production processes became more advanced throughout generations. DRAM chips are produced in

¹¹Our sample also includes observations from a period for which several firms in the industry pled guilty to price fixing. The alleged cartel lasted from April 1, 1999 to June 15, 2002. In our empirical analysis we account for this period using yearly dummy variables.

batches on silicon wafers. The process of manufacturing an integrated circuit involves building up a series of layers on a wafer of polycristalline silicon. The production process requires a complex sequence of photolithographic transfer of circuit patterns from photo masks onto the wafer and of etching processes. The wafer, once processed, is cut and the single chips are then assembled. Lithography processes are permanently improved to achieve better printing procedures, to increase the density per transistor and to reduce the size of the chips. For instance, traditional dry lithography uses air as the medium to image through masks. Immersion lithography uses water as the medium between the light source and wafer. The wavelength of light shrinks through water so it is able to project more precise and smaller images on the wafer. In general, lithography processes determine costs, size, performance and yield.

In the late 90's further reduction in cell size became much harder to achieve because of the increased number and complexity of variables affecting cell structures. Major advancement in cell innovation is shown in Figure 4. It is interesting to note that the introduction of 64MB capacitors represented a milestone for different types of cell architectures. Further improvements required the introduction of new cell structures in conjunction with lithography scaling and advances in doping, etching, planarization, and multilevel metalization. While the development of chips with faster speeds was important in order to meet increasing capacity requirements for storing memory, the reduction of power consumption became equally important. Table 4 shows the evolution of different parameters throughout different generations. For example, the cell size decreases by a factor of 40 from the 4MB to the 1GB chip.

Every DRAM generation begins by scaling lithography by a factor of 0.7 to further reduce the die area, see also Table 4. A continuous effort is required to shrink the die size throughout generations. While the die size shrank only three to four times for the 4MB and 16MB generations, it shrank between seven to nine times in the 64MB, 256MB and 512MB generations.

The DRAM industry is characterized by learning-by-doing effects, resulting from the finetuning of the above explained production processes. Despite the rapid reduction in defect densities, only a small fraction of manufactured DRAM chips will have entirely perfect cells and peripheral circuits. If all dice with one or more defective cells were to be discarded, the resulting yield would be too low and the cost per chip prohibitively high. The effective yield will increase substantially by repairing memories with a limited number of defective cells, mostly using laser blown fuses. Memory repair increases yield from <1% to >50% throughout the life cycle. Learning-by-doing is considered to be an important phenomenon that explains the rapid price decline for DRAMs (see Figure 5).

Learning-by-doing is usually modeled as firms moving down a cost curve, common to the industry, which illustrates efficiency effects achieved through learning-by-doing. Depending on firms' timing to enter a generation they achieve different yield learning since they are at different locations on the learning curve.¹² Thus, higher requirements for later DRAM chip generations require higher investments and increase the cost to enter subsequent generations.

Finally, it should be noted that firms introduce several plants for producing memory chips. Once they plan on investing a new plant, firms already have accurate predictions on how much they are planning on producing in each plant. One example mentions: "On April 21, 2011, Intel officials mentioned that Intel and Micron Technology opened a 3 billion US dollar factory to make NAND flash memory in Singapore. The factory is planned to produce 25,000 wafers per week." This example emphasizes the fact that the production rate in the memory industry is highly predictable. This fact stands in contrast to other industries, i.e., the cement industry, in which future production is more difficult to predict. One reason for the difficulty in predicting future production is that the industry is characterized by strong seasonal effects throughout the year. Consequently, marginal cost in those industries are significantly high once the production rate is getting close to the capacity limit. The concern of facing increasing marginal costs is not much of a concern in the memory chip industry, as the semiconductor industry is rather characterized by significantly decreasing marginal costs due to learning effects.

4 Dynamic oligopoly model

This section outlines a model of dynamic oligopolistic competition between firms in the DRAM industry. The model is formulated as a state space game. A firm's action in a given period determines not only its own and rival firms' current profits, but also its own and rival firms' future states. Firms are rational and forward-looking, i.e. they derive their discounted profit streams given the evolution of the state vector and their actions.

We use a discrete-time infinite horizon model with time indexed by $t = 0, 1, \ldots, \infty$. There are

 $^{^{12}}$ Note that knowledge may depreciate over time (sometimes also termed forgetting) especially in labor-intensive industries, such as the aircraft industry, see e.g. Benkard (2000). The semiconductor industry, however, is a capital-intensive industry that is characterized by cumulative innovation and short life cycles. Forgetting is therefore not a common phenomenon in this industry. Further contributions in estimating learning effects for the semiconductor industry are Gruber (1996a), Irwin and Klenow (1994), Siebert (2010), and Zulehner (2003).

I firms denoted by i = 1, ..., I. The set of firms includes potential entrants and incumbent firms. In each period, each firm *i* earns profits equal to $\pi_{it} = \pi(q_{it}, q_{-it}, s_{it}, v_{it})$, which are a function of own actions, i.e., output q_{it} , other firms' actions or output q_{-it} , a vector of state variables s_{it} and a private shock v_{it} . The private shock may derive from variability in productivity shifting marginal costs c_{it} .¹³

The state variables are market demand d_t , input prices m_t , the set of producing firms n_t , and a firm *i*'s production experience ex_{it} , i.e. $s_{it} = (d_t, m_t, n_t, ex_{it})$. 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 . Each potential entrant observes an entry cost u_i drawn from a distribution F(.|s). The entry cost is an iid shock which is private information. The potential entrants decide whether to enter the market and to immediately produce output q_{it} or to stay out of the market and to produce no output. We assume that potential entrants are short-lived and may disappear once they decided not to enter.

Firm *i*'s experience ex_{it} has four components. The first two components represent a firm's own production experience gained in the current and the previous generation x_{it}^c and x_{it}^p , respectively. The third and the forth components x_{-it}^c and x_{-it}^p indicate the experience in the current and previous generation that firm *i* gains from its rivals' past production through spillovers in the current and in the previous generation.¹⁴ Potential entrants have no own experience in the current generation, but may benefit from spillovers in the current generation, and own experience and spillovers in the previous generation. The vector $s_t = (s_{it}, s_{-it})$ denotes the state of the commonly observed state variables in the industry at period *t*.

Before firms simultaneously choose their output q_{it} , each firm *i* observes a private shock v_{it} , independently drawn from a distribution $G(.|s_t)$. The shocks v_{it} and u_i are private information and firms solve for a Markov perfect equilibrium, where each firm *i* maximizes its future discounted payoffs conditional on the initial state s_0 , the vector of the initial value of the private shocks v_0 and the entry cost u_i :

$$E_{v,u} \sum_{t=0}^{\infty} \beta^t [\pi_{it}(q_{it}, q_{-it}, s_t, v_{it}) | s_0, v_{i0}, u_i]$$
(1)

¹³All variables are referring to a single generation. In order to simplify the notation we will abstract from using subscripts for different production generations.

¹⁴If a firm did not produced the previous generation, own experience x_{it}^p and spillovers x_{-it}^p are set equal to zero.

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

4.1 Profits in the product market

Firm i's per period profits in the product market are revenues minus cost plus a scrap value, which a firm receives once it leaves the market,

$$\pi_{it}(q_{it}, q_{-it}, s_t, v_{it}) = p_t(q_t, z_t, d_t) \ q_{it} - c_{it}(q_{it}, x_{it}^c, x_{-it}^c, x_{it}^p, x_{-it}^p, w_t, v_{it}) \ q_{it} + \kappa \ exit_{it}, \tag{2}$$

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 demand shock d_t . Firm *i*'s marginal costs c_{it} is a function of its output q_{it} , proprietary experience x_{it}^c and spillovers x_{-it}^c in the current generation, proprietary experience x_{it}^p and spillovers x_{-it}^p from the previous generation, observable cost shifters w_t and productivity v_{it} . We assume that firm *i*'s fixed costs of production are equal to zero. The scrap value κ depends on firm *i*'s exit decision $exit_{it}$, which is one if firm *i* leaves the market and zero otherwise. The scrap value is realized in the first period after production of q_{it} has ended.

4.2 Transition of states

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

$$x_{it+1}^m = x_{it}^m + q_{it}^m, \ m = c, p \tag{3}$$

with $x_{i0}^m = 0$, m = c, p, assuming that there is no experience from own production in the beginning of each product cycle, and

$$x_{-it+1}^m = x_{-it}^m + \sum_{j \neq i} q_{jt-1}^m, \ m = c, p \tag{4}$$

with $x_{-i0}^m = 0$, m = c, p, assuming that there is no experience from others via spillovers in the beginning of each product generation. We define the transition of the number of firms in the market n_t from time t to time t + 1 also to be deterministic. The number of firms in the market

$$n_{t+1} = n_t + ne_t - nx_t, (5)$$

where ne_t is the number of entering firms and nx_t is the number of exiting firms.

4.3 Firms' strategies

Firms use Markov strategies $q_{it} = \sigma_i(s_t, v_{it}, u_i)$, i.e., a firm's production q_{it} is a function of the state variables s_t , and a Markov-perfect Nash equilibrium is generated by the private shocks u_i and v_{it} . Rivals' production is determined by their strategies denoted by $q_{-it} = \sigma_{-i}(s_t, v_{-it}, u_{-i})$.¹⁵ If behavior is given by a Markov strategy profile $\sigma = (\sigma_i(s_t), \sigma_{-i}(s_t))$, firm *i*'s expected profits, given the state variables s_t , can be written recursively:

$$V_{i}(s_{t};\sigma) = \mathbb{E}_{v,u}[\pi_{i}(\sigma_{i}(s_{t}), \sigma_{-i}(s_{t}), s_{t}) + \beta \int V_{i}(s_{t+1};\sigma)dP(s_{t+1}|\sigma_{i}(s_{t}), \sigma_{-i}(s_{t}), s_{t})|s_{t}],$$
(6)

where $V_i(s_t; \sigma)$ is firm *i*'s ex-ante value function and *P* is the transition probability for nondeterministic states. Firms maximize (6) with respect to their output $q_{it} = \sigma_i(s_t)$.

A firm i will decide to enter the market, if

$$u_{i} \leq \mathcal{E}_{v,u}[\pi_{i}(\sigma_{i}(s_{t}), \sigma_{-i}(s_{t}), s_{t}) + \beta \int V_{i}(s_{t+1}; \sigma) dP(s_{t+1} | \sigma_{i}(s_{t}), \sigma_{-i}(s_{t}), s_{t}) | s_{t}].$$
(7)

Hence, the draw on entry cost has to be sufficiently low, such that entry becomes profitable.

A firm *i* will decide to produce $q_{it} \ge 0$, if

$$p_{t}(q_{t}, z_{t}, d_{t})q_{it} - c_{it}(q_{it}, x_{it}^{c}, x_{-it}^{c}, x_{it}^{p}, x_{-it}^{p}, w_{t}, v_{it}) q_{it} + \kappa \ exit_{it}$$

$$+\beta \int V_{i}(s_{t+1}; \sigma) dP(s_{t+1} | \sigma_{i}(s_{t}), \sigma_{-i}(s_{t}), s_{t}) \ge \beta \int V_{i}(s_{t+1}; \sigma) dP(s_{t+1} | \sigma_{i}(s_{t}), \sigma_{-i}(s_{t}), s_{t}).$$
(8)

The draw on firms' productivity has to be sufficiently high to provide sufficient incentives to produce.

A strategy profile σ is a Markov perfect equilibrium if, given the strategy profile of rival firms $\sigma_{-i}(s_t)$, firm *i* has no incentive to deviate from its strategy profile $\sigma_i(s_t)$, i.e.

$$V_i(s_t;\sigma) \ge V_i(s_t;\sigma_{i'},\sigma_{-i}),\tag{9}$$

¹⁵For simplicity, we abbreviate $q_{it} = \sigma_i(s_t, v_{it}, u_i)$ to $q_{it} = \sigma_i(s_t)$ and $q_{-it} = \sigma_{-i}(s_t, v_{-it}, u_{-i})$ to $q_{-it} = \sigma_{-i}(s_t)$ from now on.

where σ_i is an alternative strategy for firm *i*.

5 Econometric model

In this section we present the econometric model, which builds on a fully dynamic game accounting for continuous (production) as well as discrete (entry and exit) choices.

The structural parameters of interest are the discount parameter β , the profit functions π_1, \ldots, π_I , the distribution of entry costs (drawn from a standard normal distribution F) and firms' productivity which is drawn from a normal distribution G. To obtain estimates for these parameters, we build on the two-stage estimation method developed by Bajari, Benkard and Levin (2007) which allows us to explain a mix of continuous (production) as well as discrete (entry and exit) choices. The estimator relies on the fact that firms are rational and forwardlooking, i.e., firms calculate their discounted profit stream given the evolution of the state vector and their policy functions. The first stage includes the estimation of the policy functions σ_i (entry, exit, production), which describe what actions firms take at different states. Based on the policy functions, the value functions V_i are simulated. The second stage estimates the profit function π_i and the distributions F and G. The second stage assumes that the policy functions are parameterized by a finite vector that can be consistently estimated at the first stage. 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, hence, we therefore specify parametric functional forms for the first stages.

5.1 Estimation of the first stage

In the first stage, we estimate the production and exit decisions of incumbents, and the entry decision of potential entrants. For estimating the incumbents' output function, it is necessary to first obtain estimates for the demand, in order to be able to retrieve the demand shock which enters firms' production policy. To parameterize the first stage, we assume that the functional form of the production policy is known, or can be sufficiently approximated by polynomials. For the exposition of the estimation algorithm, we assume it is a log-linear function. The estimation algorithm is, however, equally applicable to more complicated functions of whichever known form. In fact, we also applied and tested for different functional forms, such as linear and polynomials of higher orders.

Demand We specify the demand function log-linearly as

$$\ln(q_t) = \delta_0 + \delta_1 \ln(p_t) + \delta_2 \ln(p_t^S) + \delta_3 \ln(GGDP_t) + \delta_4 time_t + \sum_{g=5}^{15} \delta_g D_g + d_t,$$
(10)

where q_t is industry output and p_t the average selling price. The average selling price of the closest substitute at time t is p_t^S , which is established as a price index. For each DRAM generation, we identify corresponding substitute DRAM generations and use the average weighted prices per kilobyte 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 that captures the effect of the time length that a particular generation has been in the market, D_g presents dummy variables for each generation using the 4K generation as the base category, and d_t is an independently distributed normal variable with a mean of zero and a constant variance σ_d^2 . In addition, we estimate a second specification in which we explicitly allow the own-price elasticity of demand to be generation-specific by interacting the average selling price p_t with dummy variables for each product generation.

Incumbents' output policy Firm *i*'s output policy σ_i is a function of the state variables s_t and the private shock v_{it} entering marginal costs, i.e. $q_{it} = \sigma_i(s_t, v_{it})$. If we assume that the policy function is log-linear in the state variables and the private shock, the policy function of incumbent firms is given by¹⁶

$$\ln(q_{it}) = \gamma_0 + \gamma_1 \hat{d}_t + \gamma_2 \ln(m_t) + \gamma_3 \ln(n_t) + \gamma_4 \ln(x_{it}^c) + \gamma_5 \ln(x_{-it}^c) + \gamma_6 \ln(x_{it}^p)$$
(11)
+ $\gamma_7 \ln(x_{-it}^p) + \gamma_8 time_t + \sum_{g=9}^{19} \gamma_g D_g + \zeta_i + v_{it},$

where we denote the vector of coefficients as γ , and \hat{d}_t is the contemporary demand shock obtained as the residual from (10). The variable m_t and n_t represent the price of silicon and the lagged number of firms (both in period t-1), respectively. In addition to the variables $ex_{it} = (x_{it}^c, x_{-it}^c, x_{it}^p, x_{-it}^p)$ that measure the direct cost reducing effect of experience, we include

 $^{^{16}}$ We tested for robustness with regard to the chosen functional form, and estimated various specifications. We applied higher order polynomials to approximate an arbitrary non-linear production policy and finally used the specification with the highest fit.

a time trend in our regressions to account for the dynamic strategic interaction introduced by experience.¹⁷ D_g are again dummy variables for each product generation.

We also account for time-invariant unobserved firm heterogeneity denoted by ζ_i . In the production policy equation, we have to account for the potential contemporaneous correlation between productivity and output which enters learning-by-doing. We need to account for this feedback structure, as firms characterized by a higher productivity will further increase output which will enter next period's experience through learning-by-doing and lower costs.¹⁸

We apply different estimation procedures. First, we apply an ordinary least squares estimator with fixed effects in order to control for unobserved heterogeneity.¹⁹ In addition, we use instruments for learning-by-doing, because of its potential correlation with firm-specific productivity. As instruments we use the two and three period lagged learning-by-doing variables. Finally, we also control for potential remaining serial correlation in the productivity term and apply a lagged dependent variable model, using a fixed effects instrumental variable estimator.²⁰

Entry and exit To obtain estimates for the distribution of u_i and predicted values for $exit_{it}$, we estimate probit models with generation-specific fixed effects D_g . Potential entrants make their entry decision dependent on the state variables d_t , n_t , x_{-it}^c , x_{it}^p and x_{-it}^p , but not on x_{it}^c as

 $^{^{17}}$ Not all firms have produced previous generations. If this is the case, we replace a zero cumulative output with a value of 0.01 to be able to take the logarithm.

¹⁸Estimating industry learning curves, we find significant learning effects which magnitudes are similar across generations. This allows us to pool the data across generations when estimating the production policy function. In addition, since some of the generations are not long enough in the market to generate a sufficiently long time series, pooling the data allows us to use more observations and returns more efficient estimates. We use dummy variables to account for generation-specific effects. The results of the industry learning curves are described and depicted in Appendix C.

¹⁹There are many models for which it is reasonable to assume that the contemporaneous error is uncorrelated with current and past values of the regressors, but will be correlated with future values of the regressor (sequential exogeneity). Accounting for time invariant unobserved heterogeneity causes feedback effects occurring from contemporary production to future experience in production. Since the unobserved heterogeneity, or any contemporaneous error, determines the contemporaneous production, it will enter production experience in the next period. The contemporaneous error and experience in the future are correlated, which violates the strict exogeneity assumption (past experience is sequentially exogenous) and causes inconsistent estimates when we estimate fixed effects.

²⁰We also applied the Arellano-Bond (1991) estimator for dynamic panel data and the results are not significantly different. The estimator uses the generalized method of moments (Hansen, 1982) and especially holds for small T and large N. 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. One could therefore apply the Blundell-Bond (1998) estimator, which uses the levels and differences of the lagged dependent variable in the set of instruments. If, however, T and N are large as is in our case, the dynamic panel bias becomes insignificant, and a fixed effects estimator is applicable (Alvarez and Arellano, 2003).

they have not accumulated propriety experience in the current generation:

$$P(entry_{it}) = \Phi(\alpha_0 + \alpha_1 \hat{d}_t + \alpha_2 \ln(m_t) + \alpha_3 \ln(n_t) + \alpha_4 \ln(x_{-it}^c) + \alpha_5 \ln(x_{it}^p)$$
(12)
+ $\alpha_6 \ln(x_{-it}^p) + \alpha_7 time_t + \sum_{g=8}^{18} \alpha_g D_g),$

where we denote the vector of coefficients by α .

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 and is specified as follows,

$$P(exit_{it}) = \Phi(\lambda_0 + \lambda_1 \hat{d}_t + \lambda_2 \hat{v}_{it} + \lambda_3 \ln(m_t) + \lambda_4 \ln(n_t) + \lambda_5 \ln(x_{it}^c) + \lambda_6 \ln(x_{-it}^c)$$
(13)
+ $\lambda_7 \ln(x_{it}^p) + \lambda_8 \ln(x_{-it}^p) + \lambda_9 time_t + \sum_{g=10}^{20} \lambda_g D_g),$

where we denote the vector of coefficients with λ and v_{it} is the productivity shock obtained as the estimated residual of the output policy function.

Marginal cost function We back out (static) marginal costs using the Lerner index and specify firm i's marginal costs c_{it} such that

$$\ln c_{it} = \theta_0 + \theta_1 q_{it} + \theta_2 q_{it}^2 + \theta_3 x_{it}^c + \theta_4 x_{-it}^c + \theta_5 x_{it}^p + \theta_6 x_{-it}^p + \theta_7 m_t + \sum_{g=8}^{18} \theta_g D_g + v_{it},$$
(14)

where we denote the vector of coefficients with θ . We define firm *i*'s marginal cost c_{it} as an exponential function of its output q_{it} , proprietary experience x_{it}^c and spillovers x_{-it}^c in the current generation, proprietary experience x_{it}^p and spillovers x_{-it}^p from the previous generation, material prices m_t , and dummy variables D_g for each generation, where the 4K generation is used as the reference category and productivity v_{it} .²¹

Value function Estimation of the value functions is based on the estimated policy functions and the transition between states. From estimating equation (11), we get $q_{it} = \hat{q}_{it} + v_{it}$, which we use to simulate a sample of optimal output policies

$$q_{itl} = \hat{q}_{it} + v_{itl},\tag{15}$$

²¹Backing out static marginal cost from the Lerner index does not imply that the dynamic effects of quantity choices are ignored. These are incorporated in the firms' profit maximization by defining the output policy function depending on a time trend.

where at each point in time t = 0, 1, ..., we draw a random sample of v_{itl} with l = 1, ..., Lfrom the distribution $G(.|s_t)$ and calculate simulated profits $\pi_{ilt}(q_{itl}, q_{-itl}, s_{tl}, v_{itl})$. We use (5) to move from one state to the other with regard to the number of firms. We then use (3) and (4) to move from one state to the other regarding experience and spillovers and obtain for each simulation $l, x_{it+1l}^m = x_{itl}^m + q_{itl}^m$ for m = c, p and $x_{-it+1l}^m = x_{-itl}^m + \sum_{j \neq i} q_{jt-1l}^m$ for m = c, p. Next, we back out marginal costs from our policy and demand estimation using the Lerner index. We regress the retrieved marginal costs onto the marginal cost function (14) to obtain estimates for the static marginal costs. Finally, we calculate simulated profits as

$$\pi_{itl} = \hat{p}_{tl}q_{itl} - \exp(\theta_0 + \theta_1 q_{itl} + \theta_2 q_{itl}^2 + \theta_3 x_{itl}^c + \theta_4 x_{-itl}^c + \theta_5 x_{itl}^p + \theta_6 x_{-itl}^p + \theta_7 m_t + \theta_8 time_t + \sum_{g=9}^{19} \theta_g D_g + v_{itl}) q_{itl} + \kappa exit_{itl},$$
(16)

where \hat{p}_{tl} are the simulated prices obtained from (10). The scrap value κ is obtained by regressing the (backed out) static profits on a dummy variable that is equal to one when a firm exits a product generation and zero, otherwise. This gives us $L \times \pi_{itl}$'s, i.e. L times profits based on optimal strategies. To obtain an estimate for the value function, we add up profits π_{itl} over tand take the mean of the simulated profits π_{il} over l such that

$$\tilde{V}_i(s_t;\sigma_i,\sigma_{-i},\delta,\gamma,\alpha,\lambda,\theta,\kappa) = \frac{1}{L} \sum_{l=1}^L \sum_{t=0}^\infty \beta^t \pi_{itl},\tag{17}$$

where we simulate over the actual observation horizon.

5.2 Estimation of the structural parameters

In the second step, we estimate the generation-specific cost of developing technologies. We exploit the equilibrium condition (9) and construct alternative policies k = 1, ..., K given by

$$q_{itk}\prime = q_{it} + \epsilon_k,\tag{18}$$

where ϵ_k is a random draw from some arbitrary distribution function H. We calculate alternative profits using alternative strategies,

$$\pi_{itk} \prime = p_t \ q_{itk} \prime - \exp(\theta_0 + \theta_1 q_{itk} \prime + \theta_2 q_{itk}^2 \prime + \theta_3 x_{ik}^c \prime + \theta_4 x_{-ik}^c \prime + \theta_5 x_{itk}^p \prime + \theta_6 x_{-itk}^p \prime + \theta_7 m_t$$

$$+\theta_8 time_t + \sum_{g=9}^{19} \theta_g D_g + v_{itk}\prime) q_{itk}\prime + \kappa \ exit_{itk}\prime.$$
⁽¹⁹⁾

An estimate for the value function given the alternative strategy is

$$\tilde{V}_i(s_t;\sigma_i\prime,\sigma_{-i},\delta,\gamma,\alpha,\lambda,\theta,\kappa) = \sum_{t=0}^{\infty} \beta^t \pi_{itk}\prime.$$

This gives us $K \times \tilde{V}_i(s; \sigma_i, \sigma_{-i}, \delta, \gamma, \alpha, \lambda, \theta, \kappa)$'s, i.e. K times profits from alternative strategies. When we rewrite the equilibrium condition (9) as

$$V_i(s_t; \sigma_i, \sigma_{-i}, \delta, \gamma, \alpha, \lambda, \theta, \kappa) \ge \tilde{V}_i(s_t; \sigma_i', \sigma_{-i}, \delta, \gamma, \alpha, \lambda, \theta, \kappa),$$

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

$$f(y;\delta,\gamma,\alpha,\lambda,\theta,\kappa) := [W_i(s_t;\sigma_i,\sigma_{-i},\delta,\gamma,\alpha,\lambda) - \tilde{W}_i(s_t;\sigma_i\prime,\sigma_{-i},\delta,\gamma,\alpha,\lambda)] \times (\theta,\kappa) \ge 0,$$

where $W_i(\cdot) = V_i(\cdot) \times (\theta, \kappa)$ and $\tilde{W}_i(\cdot) = \tilde{V}_i(\cdot) \times (\theta, \kappa)$ and the inequality defined by y is satisfied at $(\delta, \gamma, \alpha, \lambda, \theta, \kappa)$, if $f(y; \delta, \gamma, \alpha, \lambda, \theta, \kappa) \ge 0$. We then define the function

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

where we replace the function $f(y; \delta, \gamma, \alpha, \lambda, \theta, \kappa)$ by its empirical counterpart $\tilde{f}(y; \hat{\delta}, \hat{\gamma}, \hat{\alpha}, \hat{\lambda}, \theta, \kappa)$ computed by replacing the W_i terms with simulated estimates \widetilde{W}_i . This results in

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

Using the simulated expected discounted values we retrieve the distribution of entry costs at different states and compare those to the entry probabilities at the corresponding states.

Hence, firm i will enter the market, if the draw of the entry cost is sufficiently small, such that

$$P(Entry; s) = P(u_{i} \le EV(s)) = \phi(\mathbb{E}_{v,u}[\pi_{i}(\sigma_{i}(s_{t}), \sigma_{-i}(s_{t}), s_{t}) + \beta \int V_{i}(s_{t+1}; \sigma) dP(s_{t+1} | \sigma_{i}(s_{t}), \sigma_{-i}(s_{t}), s_{t})]; \mu_{u}, \sigma_{u}),$$
(20)

where μ_u and σ_u are the mean and standard deviation of the cumulative density function F. The probability of entry and the expected discounted values are calculated at different states using our forward simulation estimator from above. Averaging over those simulations gives the theoretically expected profits of entering at different states. **Identification** The identification of the parameters entering the marginal costs and static profit function follows from the optimization of profits and functional form assumptions. To calculate entry cost, we compare the expected profits to firms' entry decisions at different states. If entry occurred, it indicates that entry costs are lower than the generated discounted profits at this state and vice versa. Using this rationale, we are able to recover and identify the entry cost distribution for every product generation. The identification of the entry cost therefore follows directly from the functional form assumptions and profits generated at different states.

6 Estimation results

This section presents our estimation results. First, we discuss the estimation results of the demand function, incumbents' output policy, and firms' entry and exit policies. We then proceed with the results of the marginal cost function, the scrap value and firms' static profits. Finally, we describe firms' actual and counterfactual cumulated profits and the estimates for the entry cost.

6.1 First stage estimates

Demand Equation To obtain estimates for the coefficient vector δ , we estimate industry demand (10) using ordinary least squares as well as two stage least squares methods. In the latter case, we instrument the prices of the current product generation using summary measures from the supply side such as the number of firms in the current and substitute generations, cumulated industry output of the current and substitute generations, and the price of silicon – all variables are specified in logarithms and with product-specific dummy variables.

The estimation results of the demand equation are shown in Table 5. The results from using the ordinary least squares estimator are shown in columns 1 and 2, and the results for the two stage least squares estimator are shown in columns 3 and 4. For each method we estimate two specifications. While the first specification applies the same demand elasticities for different generations, the second specification allows for product-specific demand elasticities. Since the results of the two estimators are very similar, we concentrate on describing the two stage least squares results.

A test for the joint significance of the instruments indicates that the instruments are highly correlated with the average selling price. A value of 389.48 for the F-statistics of the first specification and a range of values between 68.31 and 800.13 for the F-statistics of the second specification, allow us to reject the null hypothesis that the estimated coefficients of the instruments are equal to zero. The first-stage estimation results support a good fit with adjusted R-squares of about 0.95 for the first specification and between 0.96 and 0.99 for the second specification. In all specifications, the instruments in the first stage regressions are also individually significantly different from zero. We observe a negative sign on the cumulated industry output which 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. Cumulative industry output of the substitute generations has a positive effect, indicating that higher cumulated industry output reduces marginal costs through spillovers. The positive sign on the price of silicon indicates that higher factor prices shift the marginal cost curve upwards resulting in higher equilibrium prices.

To test for potential endogeneity of our instruments, we calculate the Sargan statistic and test for overidentification of all instruments. For the first specification, we get a value of 2.179 with a p-value of 0.337. Assuming that at least one instrument is exogenous, this result allows us to reject the endogeneity of the other instruments. For the second specification, we obtain a value of 187.313 with a p-value of 0.0000. In contrast to the first specification, we cannot reject the endogeneity of our instruments. Furthermore, we calculated the Hausman test. This test indicates the necessity to using instruments for the prices of the current generation in the first specification, but not in the second one. The value of the χ^2 distributed test statistic is equal to 178.59 for the first specification, which is larger than 18.31 – the 95% critical value with 11 degrees of freedom. For the second specification, the test statistic is equal to 16.13 with a p-value of 0.933. We conclude from these results that the two-stage least squares results are the preferred ones for at least the first specification.

We now turn to the second stages of the instrumental variable estimation (columns 3 and 4). We find all variables to be significantly different from zero at least at the 95% significance 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 -3.062 represents the fact that the DRAM market is characterized by a highly elastic demand curve. If we interact the average selling price with the product-specific dummy variables, we again obtain highly elastic values. However, the 4K, 512MB and 1GB generation are even more

elastic with values ranging from -4.431 to -5.605. The estimate of substitute DRAM chips is significant and positive. The positive cross-price elasticity confirms the conjecture that different DRAM generations are substitutes. Moreover, the estimate of 1.543 shows that the price of a substitute DRAM generation has a lower impact on the DRAM demand than the own price of that specific DRAM generation under consideration. 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 indicating a persistent growth in market demand throughout different generations. The magnitude of the dummy variable estimates is increasing throughout generations, which emphasizes an increase in market size and the increasing relevance of using DRAM chips in application specific electronic products. Moreover, we observe that the increase in market size is quite steep until the 16 MB generation; market demand increased more drastically for early generations. Thereafter, growth in market demand slowed down.

From the demand estimations, we retrieve the residuals and allow them to enter the output policy as well as the entry and exit policy.²²

Policy function We estimate incumbents' output policy (11) using different estimation methods to obtain estimates for the coefficient vector γ . The results are shown in Table 6. All specifications are estimated in logarithms and with product-specific and firm-specific dummy variables. Columns (1) and (2) show the ordinary least squares results, columns (3) and (4) show the two stage least squares results. We instrument cumulative past output in the current generation with its twice and tree times lagged values. In columns (1) and (3) we use the residual from specification (2) in Table 5 as demand shock, and in columns (2) and (4) the residual from specification (4) in Table 5.

Our pooled regression allows us to use approximately 5,500 observations. All regression estimations illustrate a remarkably good fit, with an R-square of 0.67 and higher. The estimates for the least square regressions (columns 1 and 2) as well as the two-stage least square regressions (columns 3 and 4) are highly significant and carry the expected signs. The demand shock has

²²To reduce the number of specifications we have to estimate for the policy functions, we use the residuals from the second specification. Our robustness checks using the residuals from the first specification show no substantial differences to the ones we used.

a positive effect on firm level output. The negative sign on the price of material confirms that higher factor prices increase marginal cost and lower firm level output. The negative sign of the number of firms in the market indicates that more firms in the period before decreases firmspecific output today. Cumulated past output 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 positive sign of the cumulative past output by other firms indicates that spillovers within a generation are important. Learning effects between generations, however, are significant only between firms. The negative estimate on the time trend illustrates that subsequent generations replace the output for earlier generations. The results for the dummy variables for the different generations turn out to be highly significant and increase throughout different generations. This results indicate that production increases throughout generations, reconfirming the fact that market demand grows over time. Again, it is interesting to see that the magnitude of the estimated market growth is higher for early generations and begins slowing down for the 16MB generation. We also used the lagged dependent variable as an additional regressor. The estimations returned a significantly positive estimate for this term. which shows that a first-order autocorrelation process is present in the data.

Entry and exit distribution We estimate the entry (12) and exit (13) decisions using probit models to obtain estimates for the coefficient vectors α and λ . The results are shown in Table 7. We estimate two entry models, both including product-specific dummy variables. The first model, column (1), includes the residual from specification (2) in Table 5 as the demand shock; the second model, column (2), the residual from specification (4) in Table 5 as the demand shock. Regarding the exit policy function, the first (second) model includes the residuals from specification (2) ((4)) in Table 5 as the demand shock and the residuals from specification (2) ((4)) in Table 6 as the productivity shock. Both models are estimated with firm-specific and product-specific dummy variables. The results are shown in columns (3) and (4).

In both entry models, we find that the cumulative past output in the previous generation is positively significant. This result confirms that firms subsequently enter different generations. If a firm was present in the previous generation, it is more likely to enter the next generation. Once a firm exits the market, it is less likely to reenter in subsequent generations. The coefficient of the time trend shows that the number of entering firms increases over the life cycle of a generation. The generation-specific fixed effects are negative and become even more negative throughout different generations. This result indicates that entry became less likely over different generations and reflects increasing entry costs throughout different generations. We discuss this fact in more detail in the next section when we present the estimation results for the entry costs.

Turning to the results for the exit equation, columns (3) and (4), we observe that negative productivity shocks drive firms' exit. The positive coefficient on the number of firms shows that firms are more likely to exit if more firms are present in the market. The positive estimate on the time trend reconfirms that firms exit at later periods of the life cycle. The estimates for the dummy variables are negative and become more negative throughout subsequent generations.

Marginal cost Table 8 shows the estimation results for the parameters entering the marginal cost function (equation (14)). The dependent variable is the logarithm of marginal cost. All specifications are estimated with product-specific fixed effects, and the specifications in columns (3) and (4) also include firm-specific fixed effects. We report the results of two specifications. One specification includes own intergenerational learning and intergenerational learning via spillovers. Another specification excludes those learning effects. All estimations return highly significant learning estimates. Own learning effects and learning via spillovers carry a negative sign, indicating that an increase in own and other firms' cumulated past output decreases marginal costs. All specifications confirm decreasing returns to scale, i.e., a 1% increase in output increases marginal costs by 1.6%, see column (4). The positive estimate of the price of silicon indicates that higher factor prices result in higher marginal costs.

Actual and predicted outcomes In the following, we are interested to see how well our policy functions and our model specification predict our data. This comparison is especially important as our structural estimates (entry costs) are based on our policy functions estimated in the first-stage. Hence, we compare the average prices, outputs, revenues, market shares, marginal costs, static profits and profit margins for every generation from the data, with those predicted by our model. The averages based on the observed data are shown in Panel A of Table 9. We observe that the average industry price sharply declines after the 16MB generation. This decline in demand growth after the 16MB generation explains the lower industry equilibrium price. Firm revenues are increasing until the 16MB generation and remain at about the same level for the next two successive generations. We also observe that market shares are increasing

after the 16MB generation. This is due to the fact that many firms dropped out after the 16MB generation which increased the market shares of the surviving firms. Static profits increased up to the 64MB generation and only slightly decreased in the 128MB generation. It seems to be surprising that static profits increased even after a shake out process occurred in the 16MB generation. This is explained by the fact that price competition diminished due to massive exit. Moreover, firms' output steadily increased, even after the 16MB generation, which contributes to increasing profits. An increase in profits also supports the fact that entry cost increased throughout generations. Higher profits are required to cover the increase in entry costs.

In addition to the actual outcomes, we calculate the outcomes predicted by our model, see Panel B. Overall, we observe that actual and predicted outcomes are qualitatively in line, i.e., firm specific output, revenues, profits and market shares are well predicted. Table 10 presents the estimated actual and counterfactual scrap value averaged over product generations. It is derived from regressing the per period profits on the exit dummy variable (and no constant).²³

6.2 Structural estimates and counterfactual results

Based on our first-stage results, we recover the entry costs for the different product generations. To evaluate the plausibility of the estimated entry cost, we compare them with predicted average cumulated firm profits, which are obtained by summing up the predicted static profits over the product cycle for each firm and each product generation. We would expect that on average the estimated entry cost do not exceed cumulated profits. Finally, we perform a counterfactual analysis to assess the impact of demand growth and entry costs on exit and the evolution of market structure.

Entry costs To obtain estimates for the entry costs, we exploit the equilibrium condition (9) as described above. For the simulated policies (15), we construct the alternative policies (18). Using 300,000 simulations and 1,000 alternative strategies, we compare the simulated value functions based on optimal strategies with the simulated values based on alternative non-optimal strategies. Column (1) in Table 11 shows the estimated entry cost for the specific product generations. Entry costs are increasing for early generations and even more drastically increasing after the 4MB generation. They reach its maximum of around 118 million USD for

 $^{^{23}}$ We also tested whether the scrap value is different across product generations, but the estimation results rejected the inequality of the coefficients.

the 64MB generation. 24

Column (2) in Table 11 presents the predicted average cumulated firm profits. Comparing these to the estimated entry cost reveals that on average entry cost are covered by cumulated profits. Moreover, we observe that the ratio of entry cost over firm profits is increasing over product generations (column (4)). For the 4K generation, the entry cost amount for 17% of cumulated profits. This ratio sharply increases for the 16MB generation and reaches its maximum of 58% for the 64MB generation. It slightly declines to 44% for the 128MB generation. Firms pay an increasing share of their profits to enter new technology generations, especially after the 4MB generation. Hence, it became more difficult to recover the entry costs from their profit streams. This fact may explain why the number of firms started declining after the 4MB generation.

Separating the effect of entry cost and demand growth on market structure To assess the effect of increasing entry cost and diminishing market growth on the evolution of the number of firms in more detail, we perform a counterfactual experiment. In particular, we are interested to disentangle the impact on market structure originated by the increasing entry costs and diminishing market growth on exiting the market. Our counterfactual builds on the assumption that market growth did not decline after the 4MB generation, but continued growing at the same rate as before (see also Figure 1). Hence, for the 64MB and 128MB generations, we expose our industry to positive demand shocks and increase the firm specific output in product generations by 10%. This change induces a change in industry output, industry prices, firm profits, entry and exit, and thus a change in the entire evolution of the market structure. Column (3) in Table 11 reports the cumulated firm profits for every generation based on the counterfactual. We observe that, while the cumulated profits in the early generations are similar to the predicted profits, see column (2), the cumulated profits for the 64MB and 128MB generations increase by 6% and 7%. As a consequence, firms share of entry costs related to their profits, see column (5), declines. Firms have to attribute a lower share of their profits for entering new generations. However, the share of entry costs only marginally declines from 58% to 54% for the 64MB generation. Even though the share for the 64MB generation slightly decreased, it is still

 $^{^{24}}$ The 128MB shows considerably lower entry costs of about 28 million USD. A reason for this number could be that the 128MB generation is a side product. It is only the double value of 64MB and not the quadruple as any other generation is. In addition, the estimated entry costs for this generations may suffer from a truncation problem in the time series data. Although the output peak has been reached, the data on shipments are still at earlier stages of the life cycle and did not yet exceed their maturity stage.

significantly higher than the share of the earlier generations, which are between 15 and 37%. Similar results apply to the 128MB generation, indicating that diminishing growth in demand has a minor impact on the shake out process. The main impact on the decline in the number of firms is explained by the drastically increasing entry costs. A similar results applies to the 128MB generation.

This result therefore confirms that the significant increase in entry costs from the 16MB (65 mio.) to the 64MB (118 mio.) significantly contributes to the shake out in the DRAM industry. In fact, as mentioned in our industry description, the 64MB generation faced many innovative challenges such as improving lithography processes, reducing cell sizes and lowering energy consumption. This is interesting to note, since the share of the entry cost went down to 33% in the 128MB generation. Hence, the increase in entry costs had the highest impact on the 64MB generation.

Finally, we report the predicted exit probabilities for our model and our counterfactual, as shown in columns (6) and (7), respectively. The exit probabilities of our model range from 2.25-6.54% depending on the particular product generation, see column (6). Remarkable is the increase to 5.9% for the 64MB generation and 6.54% for the 128MB generation. Those exit probabilities reconfirm the fact that our model is able to capture the increase in exit due to the increase in the entry costs. The exit probabilities based on our counterfactual experiment for the 64MB and the 128MB generations, see column (7), are still above the exit probabilities of the early generations, which confirms the fact that growth in demand did not have a significant impact on firm exit for the later generations.

We summarize that the increase in entry costs in combination with diminishing growth in demand explains the inverse U-shaped pattern in the number of firms across generations. For early generations, the growth in demand dominated the accelerated entry costs such that more firms were attracted to enter the market. A slowdown in growth of demand in conjunction with substantial R&D costs in the late 90's caused a main shake out for the 16MB generation and thereafter. Most interestingly, however, our study provides evidence that the main reason for the shake out is driven by increasing entry costs after the 4MB generation. The increase in entry costs was especially detrimental for the 64MB generation, according to the entry cost to profit share, shown in column (5).

7 Summary and concluding remarks

This paper contributes to empirical regularities on market structure. Our study concentrates on the evolution of market structure in the DRAM industry which is described as follows: the number of firms steadily increased throughout generations until the mid 1990's, when it experienced a sudden shake out and the number of firms drastically declined. We are interested in explaining why the number of firms in the DRAM industry follows an inverse U-shape throughout generations. We put special attention to demand side and technology related arguments that might explain the shake out process. More specifically, the main interest of our study is to disentangle to what extent a decline in demand growth and an increase in entry cost throughout different generations might have caused the shake out in the mid 1990's.

Based on a fully dynamic oligopoly model, in which firms make entry, production and exit decisions, we estimate the evolution of entry cost throughout different generations. Our results show that entry cost continuously increased throughout generations and experienced a sharp increase in the 64MB generations due to improving lithography processes and reducing cell sizes. This result is consistent with our observation that the shake out process took place after the 16MB generation. Our results also show that a higher share of entry costs on profits increased firms' burden to recover the entry costs from the generated discounted profit streams after the 16MB generation.

In a next step, we apply a counterfactual experiment which eliminates the decline in the demand growth for the last two generations. This counterfactual allows us to test to what extent the shake out process was caused by increasing entry cost and the decline in market growth. Using the counterfactual, we predict the profits, the share of entry costs and the predicted exit probability. The results show that the increase in entry costs explains most of the shake out process.

To summarize, in the early generations the increase in entry costs was dominated by an increase in market growth which attracted more firms to enter the markets. From the mid 90s, a significant increase in entry costs dominated the market growth. Consequently, firms exited the market.

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A Appendix: Tables

$Firm (HQ^*)$	4K	16K	64K	256K	1MB	4MB	$16 \mathrm{MB}$	64MB	128MB
AMD (US)	x	x	x						
Alliance (US)						x	x		
AMS (US)	х								
AT&T (US)				х	x				
Fairchild (US)	х	x	x						
Fujitsu (JAP)	х	x	x	x	x	x	х	х	x
Hitachi (JAP)	х	x	x	x	x	x	х	х	x
Hyundai (SK)			x	х	x	x	х	х	x
IBM (US)					x	х	х	х	
Intel (US)	х	х	x	х	x				
Intersil (US)	x	х							
LG (SK)				х	x	х	x	х	
Matsushita (JAP)		х	x	х	x	х	x	х	
Micron (US)			x	х	x	x	x	х	х
Mitsubishi (JAP)		х	х	х	x	х	х	х	х
Mosel Vitelic (US)			x	x	x	х	x	х	х
Mostek (US)	х	х		х					
Motorola (US)	х	х		х	x	x	x	х	
Ntl. Semic. (US)	х	x	x	x		•			
NEC (JAP)	х	х	х	х	x	x	x	х	х
Nippon (JAP)				x	x	x	x	x	
OKI (JAP)			x	x	x	x	x	x	
Ramtron Int. (US)						x			
Samsung (SK)			x	x	x	x	x	x	x
Seiko Epson (JAP)						x	х		
Siemens (GER)	•	х	x	х	x	х	х	х	х
Signetics (US)	х	х							
Texas Instr. (US)	х	х	х	х	x	х	х	х	
Toshiba (JAP)	•	х	x	х	x	х	х	х	х
Vanguard (US)	•					x	х	х	х
Winbond (CH)							х	х	х
Zilog (US)		х	•			•	•	•	
# of Firms	15	20	22	23	22	30	30	28	21

Table 1: Firms' entry and exit patterns in different DRAM generations

Table 1 shows firms' presence in different DRAM generations. * HQ abbreviates headquarter with CH=China, GER=Germany, JAP=Japan, SK=South Korea, TA=Taiwan, and US=United States. Note that we only reported those firms that were among the first three firms to enter or exit at least one of the generations. Source: Gartner Inc.

		Number of firms First quarters							Output peek reached
	Max	Total	Δ in %	New	Δ in %	four	eight	Yes/No	Yes/No
Product generation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
4K	14	15		15		3	10	Yes	Yes
16K	17	20	33	6	-60	4	14	Yes	Yes
64K	18	20	0	7	17	2	7	Yes	Yes
256K	19	23	15	5	-29	7	9	Yes	Yes
1MB	19	22	-4	1	-80	5	8	Yes	Yes
4MB	23	30	36	10	900	6	11	Yes	Yes
16MB	20	30	0	3	-70	9	12	No	Yes
64MB	15	28	-7	0	-300	10	12	No	Yes
128MB	16	21	-25	0	0	6	10	No	Yes
256MB	11	14	-33	0	0	4	8	No	No
512MB	7	7	-50	0	0	3	6	No	No
1GB	5	5	-29	0	0	4	5	No	No

Table 2: Summary statistics for different product generations

Table 2 presents descriptive statistics on the number of firms in the market across product generations.

Table 3:	Summarv	statistics	for	different	product	generations
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		Mark	et size		Per firm			
	Shipn	nents	Reve	nues	Shipr	nents	Revenues	
Product generation	Average	Δ in $\%$	Average	Δ in $\%$	Average	Δ in $\%$	Average	Δ in $\%$
4K	6 133		38 609		757		4 764	
16K	34,565	464	154,973	301	2,555	238	11,457	140
64K	33,744	-2	$155,\!899$	1	3,667	43	16,721	46
256K	76,913	128	309,437	98	$5,\!533$	51	22,259	33
1MB	87,378	14	639,563	107	5,839	6	42,736	92
4MB	120,035	37	1147,902	79	8,812	51	84,273	97
16MB	184,811	54	1454,847	27	12,867	46	101,287	20
64MB	189,241	2	1205,404	-17	15,734	22	100,218	-1
128MB	219,177	16	1030,970	-14	21,441	36	100,856	1
256MB	336,018	53	1677,750	63	42,002	96	209,719	108
512MB	29,253	-91	368,180	-78	6,338	-85	79,772	-62
256MB	1,533	-95	60,998	-83	447	-93	17,791	-78

Table 3 presents industry-specific averages. Prices are in constant US-\$ as of 2000. Shipments are shown in 1,000 units and revenues are shown in 1,000 US Dollar.

	4MB	$16 \mathrm{MB}$	64MB	$256 \mathrm{MB}$	1GB	Scaling factor
Year of introduction	1988	1991	1995	1999	2003	
Design rules (μm)	0.80	0.50	0.35	0.25	0.18	$^{\sim}0.7$
Chip size (mm^2)	87	130	200	300	450	~1.5
Cell size (mm^2)	11	4.0	1.6	0.6	0.25	~0.4
Internal power supply (V)	3.3 - 5.0	3.3	2.5	2.0	1.5	~0.8

Table 4: Progress of DRAM technologies from 4MB to 1GB

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

Dependent variable: Log(Industry output)	Ordinary le	east squares	Two-stage least squares		
Variable	(1)	(2)	(3)	(4)	
Constant	16.082	17.540	18.016	20.206	
Log(Average selling price)	$(42.60)^{**}$ -3.015 $(28.05)^{**}$	$(17.58)^{**}$	$(41.22)^{**}$ -3.787 $(34.05)^{**}$	$(14.27)^{**}$	
$Log(Average selling price) \times 4K$	(-20.35)	-3.911	(-04.00)	-5.430	
$Log(Average selling price) \times 16K$		(-5.68) -3.345		(-5.80) -3.652	
$Log(Average selling price) \times 64K$		$(-24.68)^{**}$ -2.923		$(-24.57)^{**}$ -3.323	
$Log(Average selling price) \times 256K$		$(-20.22)^{**}$ -3.132		$(-20.40)^{**}$ -3.606	
$Log(Average selling price) \times 1MB$		$(-24.95)^{**}$ -3.326		$(-23.71)^{**}$ -3.694	
$Log(Average selling price) \times 4MB$		$(-19.55)^{**}$ -3.196		$(-18.34)^{**}$ -3.617	
Log(Average selling price) × 16MB		$(-25.60)^{**}$		$(-23.37)^{**}$	
		$(-20.86)^{**}$		$(-21.83)^{**}$	
Log(Average selling price) × 64MB		$(-11.90)^{**}$		$(-13.35)^{**}$	
$Log(Average selling price) \times 128MB$		-3.414 $(-9.99)^{**}$		-3.769 $(-10.48)^{**}$	
Log(Price index of substitute DRAM generations)	$(0.08)^{**}$	1.518	2.091	1.920	
Time trend	(0.077)	(0.079)	(12.09) -0.087 (7.00)**	(10.03) -0.079 (.0.70)**	
First difference of Log(GDP)	(-6.61) 24.717	(-6.45) 31.625	(-7.20) 30.773	(-6.50) 36.983	
Dummy variable for 16K	$(2.17)^{**}$ 2.846	$(2.59)^{**}$ 2.099	$(2.30)^{**}$ 3.305	$(2.88)^{**}$ 0.423	
Dummy variable for 64K	$(12.42)^{**}$ 5.781	$(2.23)^{**}$ 4.421	$(9.35)^{**} \\ 7.509$	(0.34) 3.624	
Dummy variable for 256K	$(17.50)^{**}$ 9.923	$(4.89)^{**}$ 8.959	$(16.97)^{**}$ 12.494	$(3.21)^{**}$ 8.739	
Dummy variable for 1MB	$(24.39)^{**}$ 14 023	$(9.65)^{**}$ 13.570	$(22.93)^{**}$ 17 716	$(7.83)^{**}$ 13.803	
Dummy variable for IMP	$(27.11)^{**}$	$(14.05)^{**}$	$(26.47)^{**}$	$(12.12)^{**}$	
Durinity variable for 400D	$(26.31)^{**}$	$(17.16)^{**}$	$(26.51)^{**}$	$(15.48)^{**}$	
Dummy variable for 16MB	$(26.62)^{**}$	$(19.05)^{**}$	$(26.97)^{**}$	$(17.54)^{**}$	
Dummy variable for 64MB	22.247 $(25.41)^{**}$	20.771 (19.71)**	28.486 $(26.57)^{**}$	22.310 $(18.12)^{**}$	
Dummy variable for 128MB	24.213 (25.40)**	24.195 (20.85)**	31.138 $(27.13)^{**}$	$(19.40)^{**}$	
First-stage F-Test (joint significance of instruments)	/	/	**	**	
Number of observations R-squared adjusted	$\begin{array}{c} 433\\ 0.82 \end{array}$	$\begin{array}{c} 433 \\ 0.83 \end{array}$	$\begin{array}{c} 426 \\ 0.76 \end{array}$	$426 \\ 0.81$	

Table 5: Estimation results for the demand function

Table 5 presents ordinary least squares and two-stage least squares estimation results for the demand equation(10). The dependent variable is industry output. The specification in columns (1) and (2) are estimated with ordinary least squares, and columns (3) and (4) with two stage least squares. We instrument industry prices with price of silicon, past cumulative output and number of firms. An F-test shows that these instruments are jointly significant at the 95% level. All specifications are estimated in logarithms and with product-specific dummy variables. Values of robust t-statistics are shown in parentheses below the parameter estimates. ** (*) denotes a 95% (90%) level of significance.

Dependent variable: Log(Firm output)	Ordinary le	east squares	Two-stage least squares		
Variable	(1)	(2)	(3)	(4)	
Constant	2.692	2.453	2.697	2.471	
Lagged demand shock (OLS)	$(4.45)^{**}$ 0.027 $(2\ 15)^{**}$	$(4.14)^{**}$	$(4.39)^{**}$ 0.047 $(3.63)^{**}$	$(4.10)^{**}$	
Lagged demand shock (2SLS)	(2.15)	-0.007	(0.00)	0.021	
Log(Lagged price of silicon)	-0.394	(-0.59) -0.371 $(-5.76)^{**}$	-0.430	$(1.77)^*$ -0.408	
Log(Lagged number of firms)	(-0.00) -0.129 $(-2.45)^{**}$	(-5.70) -0.124 $(-2.34)^{**}$	(-0.44) -0.235 $(-4.25)^{**}$	(-0.24) -0.226 $(-4, 10)^{**}$	
Current generation	(-2.43)	(-2.54)	(-4.20)	(-4.10)	
Log(Cumulative past output)	$(27.91)^{**}$	$(27.89)^{**}$	$(30.24)^{**}$	$(30.14)^{**}$	
Log(Cumulative past output of other firms)	$(19.68)^{**}$	$(19.78)^{**}$	$(21.14)^{**}$	$(21.29)^{**}$	
Previous generation Log(Cumulative past output)	0.005	0.005	0.003	0.003	
Log(Cumulative past output of other firms)	$(1.69)^*$ 0.014 $(4.22)^{**}$	$(1.65)^*$ 0.015 $(4.54)^{**}$	(0.90) 0.011 (2.20)**	(0.88) 0.011 (2.20)**	
Time trend	$(4.32)^{-0.127}$	(4.54) -0.127	$(3.20)^{-0.140}$	(3.38) -0.141	
Dummy variable for 16K	$(-57.46)^{**}$ 1.446	$(-56.33)^{**}$ 1.454	$(-61.48)^{**}$ 1.630	$(-60.22)^{**}$ 1.630	
Dummy variable for 64K	$(22.78)^{44}$ 2.620	$(22.93)^{**}$ 2.653	$(24.83)^{++}$ 2.908	$(24.88)^{**}$ 2.935	
Dummy variable for 256K	$(36.56)^{**}$ 4.263	$(37.25)^{**}$ 4.281	$(39.74)^{**}$ 4.757	$(40.35)^{**}$ 4.772	
Dummy variable for 1MB	$(40.16)^{**}$ 6.148	$(40.24)^{**}$ 6.172	$(43.35)^{**}$ 6.803	$(43.36)^{**}$ 6.824	
Dummy variable for 4MB	$(48.58)^{**}$ 7.684	$(48.50)^{**}$ 7.715	$(51.66)^{**}$ 8.494	$(51.50)^{**}$ 8.525	
Dummy variable for 16MB	$(53.03)^{**}$ 8.989	$(53.08)^{**}$ 9.027	$(56.19)^{**}$ 9.942	$(56.15)^{**}$ 9.983	
Dummy variable for 64MB	$(54.42)^{**}$ 10.231	$(54.37)^{**}$ 10.279	$(57.84)^{**}$ 11.222	$(57.72)^{**}$ 11.276	
Dummy variable for 128MB	$(56.62)^{**}$ 10.773	$(56.80)^{**}$ 10.824	$(59.48)^{**}$ 11.840	$(59.63)^{**}$ 11.896	
AR(1)	$(56.83)^{**}$ 0.698 $(33.06)^{**}$	$(56.78)^{**}$ 0.699 $(33.14)^{**}$	$(60.19)^{**}$ 0.669 $(31.51)^{**}$	$(60.07)^{**}$ 0.671 $(31.59)^{**}$	
Number of observations R-squared adjusted	$5,211 \\ 0.90$	$5,211 \\ 0.90$	$5,211 \\ 0.90$	5,211 0.90	

Table 6: Estimation results for incumbents' output policy function

Table 6 presents the estimation results for the incumbents' policy function, see equation (11). The dependent variable is firm-specific output. All specifications are estimated in logarithms, accounting for an autoregressive term of order one, and with product-specific and firm-specific dummy variables. Columns (1) and (2) are estimated with ordinary least squares, columns (3) and (4) with two stage least squares. We instrument cumulative past output in the current generation with its twice and tree times lagged values. In columns (1) and (3) we use the residual from specification (2) in Table 5 as demand shock, and in columns (2) and (4) the residual from specification (4) in Table 5. Values of robust t-statistics are shown in parentheses below the parameter estimates. ** (*) denotes a 95% (90%) level of significance.

Dependent variable: Firm entry and exit	Entry	Entry	Exit	Exit
Variable	(1)	(2)	(3)	(4)
Constant	-4.378	-3.642	-5.030	-4.938
Lagged demand shock (OLS)	(-2.28)**	$(-1.89)^*$	$(-2.46)^{**}$ 0.004 (0.06)	(-2.43)**
Lagged demand shock (TSLS)		-0.060	(0.00)	0.023
Log(Lagged price of silicon)	0.399	(-1.55) 0.337 (1.44)	0.115	(0.45) 0.101 (0.46)
Log(Lagged number of firms)	(1.74) -0.073 (-0.54)	(-0.119)	(0.32) 0.828 $(3.46)^{**}$	(0.40) 0.842 $(3.52)^{**}$
Current generation Log(Cumulative past output)	(0.01)	(0.00)	-0.235	-0.236
Log(Cumulative past output of other firms)	0.058	0.054	$(-5.15)^{**}$ 0.032 (0.42)	$(-5.18)^{**}$ 0.032 (0.42)
Previous generation Log(Cumulative past output)	0.087	0.087	-0.015	-0.015
Log(Cumulative past output of other firms)	$(11.75)^{**}$ -0.026 (1.20)	$(11.74)^{**}$ -0.028	(-1.18) -0.003	(-1.19) -0.003 (-0.25)
Productivity shock (OLS)	(-1.29)	(-1.41)	(-0.20) -0.211 $(-3.65)^{**}$	(-0.23)
Productivity shock (TSLS)			(0.00)	-0.209
Time trend	0.025	0.025	0.119	(-3.70) 0.119
Dummy variable for 16K	$(2.84)^{**}$ -0.506	$(2.75)^{**}$ -0.572	$(9.90)^{**}$ -1.067 $(2.20)^{**}$	$(10.03)^{**}$ -1.075
Dummy variable for 64K	-1.156	(-0.99) -1.292	(-3.29) -3.024	(-3.30) -3.041
Dummy variable for 256K	$(-1.89)^*$ -1.307	$(-2.13)^{**}$ -1.387	$(-7.89)^{**}$ -5.289	$(-8.00)^{**}$ -5.314
Dummy variable for 1MB	$(-1.93)^*$ -1.877	$(-2.05)^{**}$ -1.926	$(-8.33)^{**}$ -6.669	$(-8.43)^{**}$ -6.705
Dummy variable for 4MB	$(-2.54)^{**}$ -2.274	$(-2.58)^{**}$ -2.346	$(-8.41)^{**}$ -7.267	$(-8.53)^{**}$ -7.301
Dummy variable for 16MB	$(-2.75)^{**}$ -2.515 $(-2.50)^{**}$	$(-2.82)^{**}$ -2.613	$(-8.24)^{**}$ -7.847	$(-8.36)^{**}$ -7.881
Dummy variable for 64MB	(-2.78) -2.507	(-2.88) -2.678	(-7.98) -7.925	(-8.10) -7.966
Dummy variable for 128MB	$(-2.54)^{**}$ -2.658 $(-2.63)^{**}$	$(-2.72)^{**}$ -2.798 $(-2.77)^{**}$	$(-7.68)^{**}$ -8.542 $(-7.79)^{**}$	$(-7.81)^{**}$ -8.588 $(-7.94)^{**}$
Number of observations Pseudo R-squared	$2,399 \\ 0.23$	$2,399 \\ 0.28$	$4,983 \\ 0.28$	$4,983 \\ 0.27$

Table 7: Estimation results for entry and exit distribution

Table 7 presents the estimation results from the probit models of the entry and exit policy functions, see equations (12) and (13), respectively. In the entry model (columns (1) and (2)), the dependent variable is an indicator variable, which is equal to one when a firm enters the market and zero before. In the exit models (columns (3) and (4)), the dependent variable is an indicator variable, which is equal to one when a firm enters the market and zero before. The entry equations are estimated with product-specific dummy variables. The exit equations are estimated with firm-specific and product-specific dummy variables. Values of t-statistics are shown in parentheses below the parameter estimates. In columns (1) and (3) we use the residual from specification (2) in Table 5 as demand shock, and in columns (2) and (4) the residual from specification (4) in Table 5. In columns (3) and (4) we use the residuals from specifications (2) and (4) in Table 6 as productivity shock. ** (*) denotes a 95% (90%) level of significance.

Dependent variable: Log(Marginal cost)	Ordinary le	east squares	Fixed effects		
Variable	(1)	(2)	(3)	(4)	
Constant	-0.647 (-9.17)**	-0.856	-0.054	-0.259	
Output	$(22.56)^{**}$	$(15.62)^{+}$	-2.934	-2.188	
Output squared	(-22.36) 0.017 $(13.98)^{**}$	(-13.03) 0.012 $(9.66)^{**}$	(-24.17) 0.018 $(15.27)^{**}$	(-10.54) 0.013 $(11.05)^{**}$	
Current generation Cumulative past output	0.005 (0.97)	-0.007	-0.039 $(-6.50)^{**}$	-0.031 (-4.85)**	
Cumulative past output of other firms	-0.036	-0.030 $(-52.00)^{**}$	$(-51.52)^{**}$	-0.028 $(-41.43)^{**}$	
Previous generation Cumulative past output	()	0.007	(• - • • -)	-0.011	
Cumulative past output of other firms		(1.08) -0.011 $(-17.92)^{**}$		(-1.47) -0.009 $(-14.02)^{**}$	
Price of silicon	0.001	(-17.32) 0.001 $(43.10)^{**}$	0.001	(-14.02) 0.001 $(42.00)^{**}$	
Dummy variable for 16K	(33.37) 0.306 $(7.66)^{**}$	(43.13) 0.327 $(8.42)^{**}$	(33.13) 0.300 $(7.35)^{**}$	(42.03) 0.323 $(8.05)^{**}$	
Dummy variable for 64K	(7.00) 0.626 (15 51)**	(0.42) 0.647 $(16.47)^{**}$	(7.55) 0.661 (14.57)**	(0.03) 0.694	
Dummy variable for 256K	(15.51) 1.320 (22.00)**	(10.47) 1.409 $(25.04)^{**}$	(14.57) 1.335 (20.22)**	(15.58) 1.431 (21.59)**	
Dummy variable for 1MB	(33.09) 1.924 $(46.01)^{**}$	(35.94) 2.175 $(40.86)^{**}$	(29.23) 1.947 $(40.70)^{**}$	(31.58) 2.192 $(42.04)^{**}$	
Dummy variable for 4MB	(40.01) 2.764 $(61.51)^{**}$	(49.80) 2.918 $(64.04)^{**}$	(40.79) 2.797 $(55.40)^{**}$	(43.94) 2.957 $(52.00)^{**}$	
Dummy variable for 16MB	(01.31) 3.304 $(69.45)^{**}$	(04.94) 3.683 (70.00)**	(33.40) 3.344 $(62.47)^{**}$	(38.00) 3.691 (64.15)**	
Dummy variable for 64MB	(68.45) 2.852 (51.05)**	(70.90) 3.431 (52.71)**	(02.47) 2.952 $(47.57)^{**}$	(04.15) 3.464	
Dummy variable for 128MB	$(51.05)^{**}$ 2.651 $(43.31)^{**}$	$(53.71)^{+}$ 3.056 $(47.59)^{**}$	$(47.57)^{+}$ 2.818 $(41.07)^{**}$	(49.31) 3.164 $(43.78)^{**}$	
Number of observations R-squared adjusted	$5,\!651 \\ 0.78$	$5,\!651 \\ 0.79$	$5,\!651 \\ 0.79$	$5,\!651 \\ 0.80$	

Table 8: Estimation results for the marginal cost function

Table 8 presents ordinary least squares estimation results for marginal costs, equation (14), for the DRAM industry. The dependent variable is logarithm of marginal cost (backed out of the Lerner index). All specifications are estimated with product-specific fixed effects, specifications in columns (3) and (4) also include firm-specific fixed effects. Values of t-statistics are shown in parentheses below the parameter estimates. ** (*) denotes a 95% (90%) level of significance.

Product generation	Industry Price (1)	Firm output (2)	Firm revenue (3)	Market share (4)	Demand elasticity (5)	Marginal cost (6)	Static Profits (7)	Profit Margin (8)
Panel A. Actual								
4K	13.46	756	4.764	12.34	3.911	8.23	153	2.24
16K	21.62	2.555	11.457	7.39	3.345	9.97	370	2.02
64K	28.30	3.666	16,721	10.87	2.923	12.37	735	3.27
256K	17.33	5,532	22,259	7.19	3.132	6.68	694	2.00
1MB	17.38	5,838	42,735	6.68	3.326	9.57	1,255	1.81
4MB	46.72	8,812	84,273	7.34	3.196	22.97	1,996	2.02
16MB	48.32	12,866	101,286	6.96	3.012	32.78	3,348	2.03
64MB	24.13	15,733	100,218	8.31	2.670	16.20	5,949	2.84
128MB	11.82	21,441	100,855	9.78	3.414	6.94	$5,\!612$	2.58
Panel B. Predicted								
4K	4.91	762	4,522	11.70	3.911	5.30	121	2.16
16K	12.37	2,484	11,219	7.29	3.345	7.73	386	2.00
64K	24.12	3,514	12,068	10.77	2.923	9.85	514	3.24
256K	12.52	5,222	20,951	7.16	3.132	5.51	668	1.98
1MB	12.80	5,871	40,183	6.57	3.326	8.10	1,179	1.78
4MB	36.66	9,878	76,434	6.51	3.196	19.42	2,462	1.80
16MB	38.73	15,916	92,228	6.96	3.012	26.47	7,039	2.04
64MB	13.17	30,114	102,361	8.33	2.670	9.90	14,291	2.85
128MB	8.18	23,030	88,058	9.32	3.414	4.12	5,783	2.47

Table 9: Industry description by product generation

Table 9 presents actual and predicted average prices, average firm output, average firm revenues, average market shares, marginal cost, the Lerner index, static profits and profit margins per product generation. Shipments are shown in 1,000 units and revenues and profits are shown in 1,000 US Dollar.

Table 10: Estimated scrap value

	Actual		Predicted	1
Estimated scrap value averaged over product generations	1,133.225	$(2.33)^{**}$	656.707	$(2.95)^{**}$

Table 10 presents the estimated scrap value averaged over product generations in the DRAM industry. It is derived from regressing the actual and predicted per period profits on the exit dummy variable (and no constant). The value of the t-statistic is shown in parentheses besides the parameter estimate. ** (*) denotes a 95% (90%) level of significance.

	Entry costs	Average c firm p	umulated rofits	Ratio: er to prof	ntry costs its in %	Average exit probability	
			Counter-				Counter-
		Predicted	factual	(1)/(2)	(1)/(3)	Predicted	factual
Product generation	(1)	(2)	(3)	(4)	(5)	(6)	(7)
4K	521	3,119	3,148	17	17	4.43	4.43
16K	2,629	10,152	10,181	26	26	3.35	3.35
64K	4,867	16,321	16,350	30	30	2.97	2.97
256K	5,497	24,447	24,475	22	22	2.75	2.75
1MB	6,933	45,741	45,770	15	15	2.25	2.25
4MB	18,828	63,034	63,063	30	30	2.42	2.42
16MB	64,795	175,710	175,739	37	37	3.52	3.52
64MB	118,454	204,820	$218,\!052$	58	54	5.99	4.00
128MB	28,249	$64,\!553$	69,216	44	33	6.54	4.66

Table 11: Entry cost, cumulated profits and exit probabilities by product generation

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Table 11 presents average cumulated firm profits, average cumulated exit probabilities, average entry costs in 1,000 US Dollars, and entry costs in percent of average cumulated profits per product generations. Entry costs are estimated based on 300,000 simulations and 1,000 alternative strategies.

B Appendix: Figures



Figure 1: Industry units shipped, 1974-2004

Source: Gartner Inc.



Figure 2: Number of firms in the DRAM market

Source: Gartner Inc.





Source: Gartner Inc.





Source: Sunami (2008)





Source: Gartner Inc. Prices are in constant US-\$ as of 2000.

C Appendix: Industry learning

We apply a test to confirm the presence of learning effects in production. With regard to learning effects, firms follow a dynamic production strategy, as firm's production rate enters costs through experience and becomes a state variable. Firms' current production has an instant impact on prices and profits, and will increase future experience resulting in future cost savings (see e.g. Dick (1991), Fudenberg and Tirole (1983 and 1986), Majd and Pindyck (1989), Spence (1981) and Wright (1936)). This implies that firms' contemporaneous production has an impact on current prices and profits as well as an intertemporal impact on their profits through future costs.

We test if learning effects and economies of scale are prevalent in our data. We proxy learning using using past accumulated output and economies of scale using current production. We regress the average prices on a constant, past accumulated industry output, current industry output, and a set of dummy variables for different product generations. Table 12 shows the results when we specify learning effects to be identical across generations. We apply ordinary least squares (columns 1 and 2) and two stage least squares regressions (columns 3 and 4), as learning describes a predetermined variable. For the latter, we instrument for the current industry output using supply shifters, i.e., 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 as instruments such as the number of firms in the market. We are able to use 488 observations and get R-squares higher than 80%. A negative sign for the cumulated industry output is consistent with learning-by-doing. The calculated learning elasticities range from 24%-30%, meaning that if past cumulative production doubles cost declines to about 70%-76% of its previous level.²⁵ We also estimate the learning effects separately for every generation. Our results confirm significant learning effects, which are comparable in magnitude to earlier findings. We can also confirm that the magnitude of learning effects are similar across generations, which allows us to pool the data across generations when estimating the production policy function.

 $^{^{25}}$ Learning elasticities or learning rates are calculated by 1 - 2^(learning coefficient). For a detailed discussion see for example, Berndt (1991, pp. 66).

Dependent variable: Log(Industry price)	Ordinary least squares		Two-stage First stage	east squares Second stage
Variable	(1)	(2)	(3)	(4)
Constant	6.390	5.970	7.095	5.816
	$(66.14)^{**}$	$(53.84)^{**}$	$(21.86)^{**}$	$(48.31)^{**}$
Log(Cumulative industry output)	-0.404	-0.475		-0.501
	$(-51.41)^{**}$	$(-49.23)^{**}$		$(-42.75)^{**}$
Log(Industry output)		0.154		0.210
		$(10.31)^{**}$		$(10.62)^{**}$
First difference of Log(GDP)			-10.587	
			(-0.51)	
Time trend			0.162	
			$(20.12)^{**}$	
Dummy variable for 16K	0.098	-0.168	-0.546	-0.266
	(1.33)	$(-1.96)^*$	(-1.48)	$(-2.75)^{**}$
Dummy variable for 64K	0.167	0.160	-3.349	0.157
	$(3.00)^{**}$	$(2.15)^{**}$	$(-7.05)^{**}$	$(1.77)^*$
Dummy variable for 256K	0.554	0.370	-4.293	0.303
	$(8.25)^{**}$	$(4.39)^{**}$	$(-8.64)^{**}$	$(3.11)^{**}$
Dummy variable for 1MB	0.928	0.653	-6.017	0.552
	$(10.68)^{**}$	$(7.22)^{**}$	$(-11.20)^{**}$	$(5.63)^{**}$
Dummy variable for 4MB	0.931	0.677	-8.328	0.583
	$(9.46)^{**}$	$(7.17)^{**}$	$(-12.35)^{**}$	$(5.72)^{**}$
Dummy variable for 16MB	1.151	0.806	-9.649	0.680
	$(10.18)^{**}$	$(6.90)^{**}$	$(-13.44)^{**}$	$(5.38)^{**}$
Dummy variable for 64MB	0.875	0.477	-10.987	0.331
	$(8.51)^{**}$	$(4.48)^{**}$	$(-13.70)^{**}$	$(2.92)^{**}$
Dummy variable for 128MB	0.741	0.293	-12.054	0.129
	$(6.77)^{**}$	$(2.47)^{**}$	(-14.38)**	(1.01)
Number of observations	449	449	449	449
R-squared adjusted	0.86	0.89	0.65	0.88

Table 12: Learning effects in the DRAM industry

Table 12 presents ordinary least squares and two-stage least squares results of learning effects for the DRAM industry. In columns (1), (2), and (4), the dependent variable is average selling price. In the reduced form equation (column (3)), the dependent variable is the average industry output. All specifications are estimated in logarithms and with product-specific dummy variables. Values of t-statistics are shown in parentheses below the parameter estimates. ** (*) denotes a 95% (90%) level of significance.