The Competitive Effects of Declining Entry Costs over Time: Evidence from the Static Random Access Memory Market*

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Abstract

We focus on the estimation of market entry costs that are declining over time and evaluate their impact on competition and market performance. We employ a dynamic oligopoly model in which firms make entry, exit, and production decisions in the presence of declining entry costs and learning by doing effects. Focusing on the static random access memory industry, we show that entry costs drastically decline by more than 80 percent throughout the life cycle. This corresponds to entry cost reductions of $30 million per quarter. To show the relevance of declining entry cost, we perform three counterfactuals in which a social planner can (a) regulate entry, (b) charge a tax on entry, and (c) provide a subsidy to promote entry. Our simulations show that declining entry costs can lead to excessive entry costs that result from too early entries by firms. Tax and entry regulation policy can reduce the excessive entry problem having a positive effect on total surplus while reducing consumer welfare. In contrast, a subsidy policy intensifies the problem of excessive entry at early periods but it increases consumer welfare.

JEL: C1, L1, L6, O3.

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1 Introduction

A long-standing topic of interest among economists and policy makers has been the relationship between market entry, competition, and market performance. One established result is that a larger number of firms increases competition and surplus. In the presence of high fixed set-up costs, however, studies have shown that an excessive number of operating firms can cause inefficient production allocations and wasteful redundant entry cost payments (see also Bresnahan and Reiss (1987 and 1990), Berry (1992), Berry and Waldfogel (1999), and Pesendorfer (2005)).[1] Studies on market entry assume usually time-invariant fixed setup or entry costs and determine the number of firms that maximizes surplus. While the time-invariant setup cost assumption is appropriate for a variety of markets, it is critical for other markets. For example, one essential feature of the capital intensive high-tech industry, such as the semiconductor industry, is that the cost of capital and production machinery quickly depreciates over time. The costs of production equipment decline drastically over time due to high capital depreciation.[2]

Declining entry costs have strong implications on firms' optimal timing to enter markets. Against the background of declining entry costs over time firms have an additional option value to wait, which provides the following trade off: An early entry requires a higher capital investment in equipment and machinery, but it also provides the opportunity to earn higher profits (before net of entry costs) due to fewer firms being present in the market and lower competition. Waiting and entering at a later period requires lower capital expenditures, but diminishes profits due to higher competition. From a social perspective, an early entry incurs higher entry cost and generates the business stealing externality earlier, but rises competition and improves consumer welfare. Therefore, in the presence of declining entry costs over time, the optimal timing of entry is a further aspect that deserves attention when evaluating social welfare. Our study contributes to the estimation of declining entry costs over time, and it provides economic insights on welfare effects.

Our study employs a dynamic oligopoly model in which firms are forward-looking agents that maximize their discounted profits. Firms make their entry decisions (accounting for declining entry costs over time) and decide on exit and production. The consideration of declining entry

[1]For theoretical contributions in this area, see Chamberlin (1933), Spence (1976a, 1976b), Dixit and Stiglitz (1977), Mankiw and Whinston (1986), and Sutton (1991).

[2]Indicative evidence for declining entry costs is that used production machinery is offered on the market for lower prices.

costs over time implies that potential entrants are aware of an option value to wait and enter later. Therefore, potential entrants face a trade-off in determining their optimal timing of market entry: While an earlier entry requires a higher entry cost, it returns a higher discounted profit due to less competition and higher prices in early periods, a longer time span operating in the market. In determining the optimal time to enter, firms compare the time-specific entry cost with the discounted net profits while forming expectations about future market conditions.

We concentrate on the static random access memory (SRAM) market, which belongs to the family of semiconductors. The SRAM industry provides a natural setting for this empirical study for several reasons. First, the SRAM industry is characterized by high entry costs that drastically decline over time due to a high depreciation of production machinery. Second, the SRAM industry is characterized by successive entry. Figure 2 shows the entry pattern of an SRAM chip generation over time. Interestingly, firms continue to enter the market many years after the product generation has been launched. It is important to recognize that more than 50 percent of the firms still entered a product generation five years (or 20 quarters) after the first firm entered, which suggests that late entry is still profitable, and it supports the notion that entry costs decline over time. We also observe that demand already started to decrease for the SRAM chip generation (as shown in Figure 1) such that demand expansions would not explain the ongoing entry process. In general, Figure 2 shows that firms enter throughout the life cycle and pick different dates to enter a certain generation.[3] The fact that firms enter at different periods provides some indication of declining entry costs over time. Third, the SRAM industry is characterized by free entry. It should be noted that firms are not able to patent the information storage capacity of memory chips. The patents protect new architecture designs rather than new technologies that are related to the storage of information. Forth, cannibalization across generations is not a main concern in our entry study. In contrast to other electronic devices, the manufacturers' demand for SRAM chips is rather generation-specific, so firms produce in multiple generations in order to fulfill the demand from different customers. Moreover, this is supported by the fact that the firm identity of early entrants is persistent across different generations. If cannibalization were a concern, we would observe that an early entrant in one

[3] We focus in our study on the 64Kb generation for reasons that are explained later in detail. The same entry pattern also applies to other generations. For studies focusing on the timing of adopting new technologies, see also Genesove (1999), Gowrisankaran and Stavins (2004), Ackerberg and Gowrisankaran (2006), Schmidt-Dengler (2006), Sweeting (2006 and 2009), and Einav (2010).

generation would choose to enter a successive generation at a later date to avoid cannibalizing its previous product generation's demand.[4] Finally, the SRAM industry is characterized by fairly homogeneous chips within generations, which keeps the analysis tractable. To summarize, the rich data on the SRAM industry enables us to identify firms' policy functions, to evaluate discounted profit flows at different entry periods, and to identify the evolution of entry costs over time.

Our estimation procedure builds on the literature on dynamic games.[5] We adopt a two-stage algorithm and estimate firms' entry, exit, and output policies in the first stage. In the second stage, we perform forward simulations, calculate the discounted continuation values, and estimate the marginal cost and entry cost parameters. Our estimations return reasonable results for firms' policy functions, as well as demand, marginal cost, and entry cost parameters. For example, we find that entry costs decline by more than 80 percent throughout the life cycle, which corresponds to entry cost reductions of $30 million per quarter.

To show the relevance of declining entry cost, we perform several counterfactual simulations with an emphasis on dynamic efficiency gains and entry cost savings. Our simulation methodology closely relates to Das, Roberts, and Tybout (2007) and Blonigen, Knittel, and Soderbery (2017), among others.[6] First, we consider a welfare-maximizing social planner who evaluates the welfare effects of entry regulations. The government can protect the first entrant from subsequent entry for different numbers of periods. Entry protection of an incumbent can serve the purpose to prevent excessive entry during early periods and to prevent firms from paying excessive entry costs. In contrast, entry protection can reduce competition and elevate prices.[7] The social planner eventually compares the potential welfare gains from delaying excessive early entry with the potential welfare losses originated by delaying competition to later periods. The ultimate welfare impact of entry regulation is an empirical question and depends on factors—such as the duration of entry protection, the evolution of entry costs, learning and spillover effects, and other market characteristics that determine firms' profits and prices.

We consider different lengths of entry protection and evaluate their impact on entry, exit,

[4]For further information on cannibalization effects, see Siebert (2015).

[5]Prominent examples in this area are Aguirregabiria and Mira (2007), Aguirregabiria and Nevo (2013), Bajari, Benkard, and Levin (2007), Pakes, Ostrovsky, and Berry (2007), and Pesendorfer and Schmidt-Dengler (2008).

[6]More details will be provided in the model section.

[7]Gilbert and Shapiro (1990) remark that limitations on the length of entry protection are necessary to avoid the negative impact on consumer welfare.

production, prices, and welfare. Our simulation results show that a longer-lasting entry protection duration for the incumbent (or first entrant) monotonically reduces consumer welfare compared to the free entry case. The overall producer surplus declines for short protection periods, but increases after 11 quarters and eventually is greater than the producer surplus under free entry due to the prevention of excessive early entry and entry cost savings. The producer surplus gains can even dominate the losses in consumer surplus such that entry regulation can be total welfare enhancing for sufficiently long protection periods. Our welfare simulation results highlight that declining entry costs over time can cause inefficiencies where firms enter too early and pay an associated entry cost that is too high from a social welfare perspective. A sufficiently long entry protection period can eliminate these dynamic inefficiencies. Therefore, beyond the established insight by previous entry studies that entry regulation can serve as a mechanism to avoid excessive entry, our study provides additional insight—that entry regulation can prevent excessive "early" entry and spending an excessive amount on early entry costs. On a side note, it should be emphasized that the literature on research and development considers entry protection regulation as a mean to reward innovating firms. Firms that spend resources in research and development are entry protected (often with intellectual property rights such as patents) and have the opportunity to recoup their research investments. For further information on this topic, see also Hashmi and Van Biesebroeck (2016). Our study shows that even in the absence of research and development investments, entry regulation can generate socially beneficial effects and can serve as an instrument to avoid excessive entry costs and result in entry cost savings.

We also consider a simulation in which a social planner can charge a tax or subsidize entry costs. Similar to Blonigen, Knittel, and Soderbery (2017), the social planner can make entry more or less costly—by charging a tax or providing a subsidy—which influences entry and production decisions. In our case, upstream manufacturers of production machinery are charged a tax or receive a subsidy that changes the cost of purchasing production machinery (the entry cost) for SRAM producers. The entry cost changes have welfare implications since they affect the SRAM producers' optimal timing to enter the market, as well as their production and exit decisions. The results show that taxes (subsidies) decrease (increase) consumer surplus due to a smaller (larger) number of entering firms. A tax (subsidy) increases (reduces) total welfare as it diminishes (exacerbates) the problem of spending an excessive amount on early entry. Similar to entry regulation, taxes can serve as an instrument to prevent an excessive number of firms from entering too early at overly high entry costs. Our policy simulations show that the declining entry costs can result in excessive entry costs cause by too many firms entering too early and this can imply large welfare effects. Therefore, our study contributes to existing entry studies that assume invariant entry costs and reduce welfare due to too many firms entering the market overall.

Our study is most closely related to the following studies: Das, Roberts, and Tybout (2007) estimate time-invariant costs for entering export markets and use them to simulate the welfare effects of entry cost subsidies. Their simulations show that entry cost subsidies can stimulate firms' exports. Blonigen, Knittel, and Soderbery (2017) employ a dynamic oligopoly to study car redesigns in the U.S. automobile market. Based on their structural cost estimates, they perform welfare simulations and show that limited competition in car model redesigns can improve welfare by three percent. Suzuki (2013) considers how planning regulations in the lodging industry affect entry. Moreover, Schaumans and Verboven (2008) and Ferrari and Verboven (2010) address the optimal number of firms and market entry in the context of regulation.

Related studies on market structure show that entry has a significant impact on prices. Prominent examples are Carlton (1983), Bresnahan and Reiss (1987, 1991), Dunne, Roberts, and Samuelson (1988), Geroski (1989), Berry (1992), Mazzeo (2002), Toivanen and Waterson (2000, 2005), Campbell and Hopenhayn (2005), Davis (2006), and Seim (2006). Berry and Waldfogel (1999) estimate time-invariant fixed costs in the U.S. commercial radio broadcasting industry and derive policy conclusions regarding the socially optimal number of firms. Their study derives the socially optimal number of firms and finds that too many radio stations exist under free entry (on average, 19 per market, compared with a socially optimal number of five).

Barwick and Pathak (2015) consider a dynamic model of entry into the real estate brokerage market in Boston. They show that a 50 percent reduction in commission rates for real estate agents decreases entry by one-third and increases social welfare by 23 percent. Hsieh and Moretti (2003) show that a socially inefficient large number of real estate agents enter markets in which housing prices are high. Hashmi and Van Biesebroeck (2016) study the relationship between market structure and product quality in the global automobile industry. It should be recognized that entry studies usually assume time-invariant entry of fixed costs. Our study, however, considers declining entry costs over time where firms have an additional option value to wait and saving on entry costs by entering at later period.

The remainder of the paper is organized as follows: Section 2 describes the institutional features of the semiconductor industry and presents summary statistics. Section 3 introduces our dynamic oligopoly model, and Section 4 describes the econometric model. In Section 5, we discuss the estimation results and present welfare simulation results based on our dynamic model. We conclude in Section 6.

2 Institutional and industry background

In this section, we describe the SRAM industry in more detail, and provide a description of the data sources and summary statistics.

2.1 The SRAM industry

It is frequently highlighted that the semiconductor industry has a significant impact on productivity growth, since semiconductors serve as an input in computers and other electronic devices (such as digital cameras or cell phones, automotive products, and household appliances, among many others). Semiconductor devices consist of memory chips, microprocessors, and application-specific integrated circuits. SRAM chips are a type of memory chips; they are designed to store and retrieve information. SRAM chips are classified into generations according to their information storage capabilities. The increase in memory capacity per chip is determined by a constant technological relationship that relates to the growth pattern of the number of transistors on an integrated circuit over time, also referred to as Moore's Law.[8] While firms are not able to claim a patent on the capacity of information storage on memory chips, their patents rather protect process innovations. Hence, firms file patents mostly for new process technologies, not for new products. The production managers we interviewed confirmed that patents granted refers to new manufacturing processes, not memory capacity.[9] We interpret this as supportive evidence that the SRAM memory chip generations are characterized by free market entry.

A higher storage capacity SRAM chip often requires better machinery, which enables the

[8]According to Moore's Law, the memory storage capacity quadruples across chip generations.

[9]We conducted interviews with production managers from Siemens/Infineon and Micron Technology.

adoption of finer manufacturing technologies. New production machinery is required that coincides with changes in wafer sizes and cell architectures, smaller transistor and cell sizes, increases in die areas, lower temperatures for performing operations, lower energy consumption, etc. There are several semiconductor machinery and equipment manufacturers, such as Teradyne, Advantest, Advanced Dicing Technologies, Plasma-Therm, and Axcelis, among others.[10] These machinery manufacturers are different than the semiconductor chip manufacturers. Therefore, the development of semiconductor production machinery (and entry cost) can be considered exogenous to the semiconductor industry.

The installation of new fabrications plants with new production machinery and equipment requires a substantial amount of capital. The production equipment is costly and more than half of the cost is spent on the production equipment that converts the raw wafer to finished chips.[11] Interviews with experts and managers in the industry confirmed that cost of capital in equipment is the main determinant of entry. The cost of capital is significant and roughly amounts to half the production cost of a wafer. For example, in 2004, Samsung, Hynix, Toshiba, Intel, and Micron announced capital spending of around $5 billion or more.[12]

Interviewees also confirmed that the costs of production equipment decline drastically over time due to a high capital depreciation, such that older machines sell for less. With the intention to provide cost savings on entry and production machinery, a used semiconductor manufacturing equipment market has been established. According to *DigiTimes Report*, in 2003, Asian semiconductor manufacturers spent more than $1 billion on used semiconductor manufacturing equipment.[13] In fact, several companies specialize on the supply of used semiconductor equipment, such as LEL International and Fabsurplus.[14] These companies specialize on selling used semiconductor wafer production equipment, and test equipment.[15]

The manufacturing process of memory chips is highly complex. Advanced photolithographic

[10] For a list of the ten best semiconductor machinery suppliers (large and focused suppliers) see *https://www.vlsiresearch.com.*

[11] See also *https://www.forbes.com/sites/jimhandy/*2014/04/30/*why-are-chips-so-expensive/*.

[12] Note that these numbers are rarely reported and may also refer to different time periods of entry throughout the life cycle.

[13] The used equipment market allows late entrants to save on the cost of capital expenses.

[14] Their extensive inventories can be viewed at: *https://buy.lelinternational.com/used-semiconductors-for-sale* or *https://www.fabsurplus.com.*

[15] Examples include Ultrasonic Welders, manufacturer: Torsional; Screen Printers, manufacturer: Baccini; Vacuum Pumps, manufacturer: Busch; Dicing Saws, manufacturer: K&S; Air Dryers, manufacturer: Kaeser; Wafer Mounters, manufacturer: Lintec; Cluster Processing Tools, manufacturer: Octos; Tape Laminator Bubble Testers, manufacturer: Trio-Tech; Reflow Oven, manufacturer: Heller; Generators, manufacturer: Data Pulse; and Spectrum Analyzers, manufacturer: HP Agilent.

and chemical processes to etch electrical circuits onto the wafer surface are necessary to improve a chip's performance. Memory chips are cut from silicon wafers, which makes silicon the base material entering the manufacturing process. Prices of silicon can have a strong time-varying effect on marginal costs since silicon is the main material used as an input for wafer fabrication processes.

The chip production process is sensitive to the effectiveness of material handling, process control, and labor. Improved manufacturing processes and higher production yield rates (defined as the percentage of wafers that successfully pass all production stages) reduce the amount of material waste and manufacturing errors, thus reducing production costs. Firms are able to improve their yield rates from around 20 percent to more than 80 percent through learning from their own production experience (learning by doing). It is well established that learning by doing effects can have a sizable impact on production costs in memory chip markets.[16] With learning by doing, a firm has a higher incentive to increase production in order to achieve further cost reductions. Therefore, we need to incorporate this essential feature of the SRAM industry in our model.

2.2 Data description

The dataset is compiled by Gartner Inc., and includes quarterly data on the SRAM industry from January 1982 until December 2003. The dataset encompasses multiple product generations with firm-level and industry-level units produced, the average selling price, and the number of firms in the market. Figure 1 shows how industry shipments of one generation evolve over time.[17] It is interesting to relate the price declines (as shown in Figure 3) to the entry pattern (as shown in Figure 2). The figures suggest that prices decline as more firms enter a specific product generation. The impact of market entry on prices has an especially strong impact for the first 10 firms; a result that coincides with previous findings (see also Bresnahan and Reiss (1990 and 1991)). In general, the drastic price decline gives rise to the fact that the change in market structure and competition is a relevant feature in this industry, and it needs to be

[16] Learning by doing has a strong effect on the yield rate (as detailed later) and is one of the most important characteristics that determine the product costs of memory chips, see also Irwin and Klenow (1994), Zulehner (2003), and Siebert (2010), among many others.

[17] We concentrate on the 64Kb generation as this is the most recent generation with sufficiently long time series on prices and quantities. This allows us to identify the entry costs without facing truncation issues arising from incomplete observations (or time series) on price and quantity data.

accounted for.

3 Dynamic oligopoly model

In this section, we introduce our dynamic oligopoly model. We construct a discrete-time infinite horizon model with time indexed by $t = 0, 1, \ldots, \infty$. Firms, denoted by $i = 1, 2, \ldots, N$, maximize the sum of profits over all periods. The model is formulated as a state space game in which firms use Markov perfect strategies. Firms' actions in a given period determine not only their own and rival firms' current profits, but also their own and rival firms' future states. We build on the fact that firms are rational and forward looking, as they derive their discounted profit streams given the evolution of the state vector and their actions.

3.1 Output, Entry, and Exit Decisions

Firms make entry, production, and exit decisions. Regarding firms' entry decisions, potential entrants decide at the beginning of each period whether to enter the $k = 64Kb$ generation. An extension to more than one generation would make our model intractable and goes beyond the scope of this paper since it would require us to consider possible strategic incentives, such as preemption and deterrence effects, when determining the optimal timing to enter a specific generation. Firms would have the opportunity to preempt or deter other firms or even skip one generation to achieve an early head-start for the next generation.[18] We would like to emphasize that skipping generations is not observed in our data. Moreover, the consideration of one product generation in firms' objective function is justified by the fact that different product generations are usually produced at different fabrication plants. Therefore, firms' output decisions are usually made at the fabrication plant level. Even though preemption strategies are an interesting and important topic, they had to be left for future studies that concentrate on markets with fewer firms, as these allow researchers to explicitly solve for the value functions in a dynamic multi-agent setting.

Entering a product generation requires firms to incur an entry cost that reflects the necessity to invest in capital and machinery as described earlier. The entry cost is defined as sum of two parts, that is, $C_t + \phi^e_{it}$. The first part of the entry cost (C_t) is a deterministic part of the entry

[18] For an empirical study on preemption, see Schmidt-Dengler (2006)

cost, which is time-variant, monotonically declining over time, and the same for all firms. As mentioned in the industry description, these assumptions appropriately characterize the industry. Interviews with experts provide evidence that the cost of production equipment declines drastically over time due to older models selling for less and due to a high capital depreciation. Moreover, a used semiconductor manufacturing equipment market has been established with the intention to achieve cost savings on entry and production machinery. Institutional features –such as the establishment of the used semiconductor manufacturing equipment market, the fact that semiconductor manufacturing equipment producers post prices online, and price discrimination across purchasers not being prevalent– confirm that the evolution of entry costs over time is the same across firms, deterministic, and perfectly observed by all firms such that firms form correct beliefs on the evolution of entry costs over time. The fact that entry costs are allowed to decline implies that potential entrants consider an option value to wait and to enter at later periods.

The second part of the entry cost (ϕ_{it}^{e}) is a private firm- and time-specific entry shock that is distinguishable from the deterministic entry cost part. The entry cost shock describes an unforeseen deviation from the deterministic entry cost trend over time (C_t). Examples are variations in capital costs, such as unexpected changes in interest rates to finance production machinery and to establish production fabrications. It is a random draw from a normal distribution with mean 0 and standard deviation σ_e, independently and identically distributed across firms and across periods.

In each period, incumbents receive a private productivity shock (ν_{it})— drawn from a normal distribution function with zero mean and constant variance and independently and identically distributed across firms and across periods—and decide how much to produce, denoted by q_{it}.[19] Firms account for learning by doing effects and consider that their current production has a potential cost-reducing effect on their future marginal costs.[20] On a side note, one difficulty when estimating dynamic oligopoly models with learning by doing is that the model implementation of learning requires us to go beyond the traditional dynamic oligopoly model approach of estimating the product market stage in a static framework. So, they are able to separate firms' product

[19] Modeling the semiconductor firms as Cournot competitors is fairly established in empirical studies (see also Irwin and Klenow (1994), Zulehner (2003), and Siebert (2010), among many others).

[20] Note that we assume that firms are not capacity constrained. We impose this assumption in order to keep the model tractable and due to lack of data. Note, too, that the inclusion of capacity constraints would not cause fundamental changes since our model builds on imperfect competition and increasing marginal costs.

market choices from the remaining dynamic model.[21] In our study, firms make forward-looking production decisions while taking future cost reductions via learning into account. This requires us to embed the product market choices in a dynamic framework (see also Benkard (2004)). Hence, firms' product market choices and the marginal costs become part of the dynamic model.

Every period, incumbents decide whether to exit the market or not. As has been done in other studies, we assume that the resell or scrap value is zero.[22] This assumption is justified in our study, since the production of new generations requires generation-specific machineries, and existing machinery for a specific generation quickly becomes obsolete. We also assume incumbents that exit the market in the current period become permanently inactive in the market.[23]

State variables

The observable payoff relevant state variables to every firm at period t are denoted by s_t, which includes entry costs (C_t), factor price of silicon (P_t^{sil}), own learning (x_{it}), learning via spillovers (x_{-it}), the number of potential entrants (n_t^{pe}), and the number of firms (n_t) in the market, and a demand shifter — the price of a substitute (P_t^S).

We assume that firms' policy functions are stationary; that is, the problems faced by firms are identical in any two realizations of the state variables that are the same. One concern with this assumption could be that we do not explicitly observe the entry cost — an element of the state variable that we consider to be changing over time, which could cause non-stationarity. We follow Krusell (2004) and Sorger (2015) and proxy for this potential non-stationarity by including a time trend in our estimation of policy functions. We proxy for this potential non-stationarity by including a time trend in our estimation of policy functions. See, for example, Krusell (2004) and Sorger (2015) for a theoretical justification.[24]

[21] In common dynamic oligopoly models, firms' strategic product market choices, such as prices or quantities, have only a contemporaneous impact on profits. Hence, firms' choices are statically chosen in each period without the need to consider further effects on future cost savings.

[22] Other dynamic oligopoly studies set the scrap value to zero to avoid identification problems in the structural estimation (see also Aguirregabiria and Suzuki (2014), Aguirregabiria and Mira (2007), Snider (2009), Ellickson, Misra, and Nair (2012), Lin (2012), Collard-Wexler (2013), Dunne, Klimek, Roberts, and Xu (2013), Suzuki (2013), and Varela (2013), among others).

[23] The assumption that firms are not allowed to reenter is confirmed by our data. Moreover, the assumption enables us to condition the incumbent's value function on entry cost that has been incurred in the past and ensures that we have to consider the evolution of future entry costs for potential entrants.

[24] It should also be noted that the replacement of an unobserved state variable (here, declining unobserved entry costs as outlined in the industry section) with a proxy (here, the time trend) is commonly applied in economic studies. For example, Olley and Pakes (1996) replace unobserved productivity with investment under

Timing

The timing of our model can be summarized as follows. In each period t, events occur in the following order:

1. Firms observe the state s_t.

2. Each potential entrant observes its private entry cost shock (ϕ_{it}^e) and makes its entry decision. Each incumbent observes its private productivity shock (ν_{it}) and makes its output and exit decisions. We assume that entry and exit decisions take one period to be realized.

3. Incumbents collect their per-period profits $\pi_i(\sigma_i, \sigma_{-i}, s, \nu_i)$, where σ_i refers to firm $i's$ strategy (output, entry, and exit).

4. Entry, production, and exit are realized, and the state adjusts to s_{t+1}.

Strategy and private shock notation

We denote firm i's strategy by $\sigma_i(s, \epsilon_i)$, where ϵ_i represents firm i's private entry shock (ϕ_i^e) if firm i is a potential entrant. If firm i is an incumbent, then ϵ_i refers to the private productivity shock (ν_i), which has an impact on a firm's realized production. For potential entrants, $\sigma_i(s, \epsilon_i) = \chi^e(s, \phi_i^e)$, where $\chi^e(s, \phi_i^e) = 1$ indicates whether potential entrant i chooses to enter at state s given the private entry cost shock ϕ_i^e. For incumbents, $\sigma_i(s, \epsilon_i) = (\chi_i^{ex}(s), q_i(s, \nu_i))$, where $\chi_i^{ex}(s) = 1$ indicates that the incumbent decides to exit at state s.

3.2 Evolution of states

The transition of the endogenous state variables are defined in this subsection.

Number of firms

We assume that the number of firms is zero at the beginning of the life cycle. The transition of the number of firms n_t is represented as:

$$n_t = n_{t-1} + \sum_i \chi_{it}^e - \sum_i \chi_{it}^{ex}. \tag{1}$$

the assumption that investment is an increasing function in productivity. Hence, they treat the unobserved state variable as if it is observable.

The number of firms is supposed to capture the degree of competitiveness in the market.

Number of potential entrants

The number of potential entrants n_{pe} is defined as:

$$n_t^{pe} = n_{t-1}^{pe} - \sum_i \chi_{it}^{e}. \tag{2}$$

We assume that a fixed set of potential entrants exists at the beginning of the product life cycle. A potential entrant is defined as a firm that was either active in the previous generation or as a firm that was nonactive in the previous generation but entered the current generation at some period. The number of potential entrants declines as time elapses since some potential firms entered the generation.

Learning

Marginal cost of production is determined by learning from a firm's own experience and learning from other firms' experience via spillovers. A firm's own learning is measured by firm $i's$ accumulated production experience x_{it}, which consists of firm $i's$ past production experience x_{it-1} and its production in $t-1$:[25],[26]

$$x_{it} = x_{it-1} + q_{it-1}. \tag{3}$$

We assume that a firm's experience is zero before entry. Firm i's learning from spillovers is measured by the accumulated production experience of all other firms than firm i x_{-it-1} and their production in $t-1$. The accumulated production experience is set to zero at the beginning of the product cycle. Finally, we account for firm i's production experience in the previous generation (e_{it}^{k-1}), which follows the same law of motion as the own learning variable.

3.3 Profit

Each firm maximizes its future discounted per-period profits. The per-period profits of an incumbent firm i at state s, given strategy profile (σ_i, σ_{-i}), and private shock ν_i is (t subscripts

[25]This production is accumulated across all firms, which is similar to the accumulation process adopted in Ryan (2012).

[26]Note, equations (1) to (3) represent deterministic transition functions rather than transition probabilities.

are suppressed)

$$\pi_i^I(\sigma_i, \sigma_{-i}, s, \nu_i) = [P(s) - mc_i(s, \nu_i)]q_i,$$

where $P(s)$ refers to the SRAM price, which is a function of industry production and the exogenous demand shifter (the price of a substitute (P^S)). Finally, $mc_i(s)$ refers to firm i's marginal cost function. Hence, firm i's per-period profits depend on the actions of all firms, the state vector, and firm i's productivity shock. An inactive firm earns zero profit.

3.4 Equilibrium

An incumbent's problem

At the beginning of each period, an incumbent decides how much to produce and whether to exit the market. If the firm chooses to exit, it stops to collect profits starting from the next period onward. Let $0 < \beta < 1$ be the discount factor. The Bellman equation for an incumbent firm i can be written as:

$$\begin{aligned} V_i^I(s, \sigma, \nu_i) = \max\{&\max_{q_i}(P(s) - mc_i(s, \nu_i))q_i, \\ &\max_{q_i}(P(s) - mc_i(s, \nu_i))q_i + \mathbb{E}\big[V_i^I(s', \sigma, \nu_i') \mid s\big]\}. \end{aligned} \quad (4)$$

Note that the first argument refers to an incumbent firm's profits if it decided to exit. The second argument refers to an incumbent firm's discounted profits if it decided to stay in the market. In this case, the expectation is taken over the future states (s') and future productivity shocks (ν_i'). An incumbent firm chooses to exit if the expected discounted future profits are negative.

A potential entrant's problem

All potential entrants can choose to enter in each period. The Bellman equation of a potential entrant i can be written as:

$$V_i^E(s, \sigma, \phi_i^e) = \max\left\{-\phi_i^e - C + \beta\mathbb{E}\big[V_i^I(s', \sigma, \nu_i') \mid s\big],\ \beta\mathbb{E}\big[V_i^E(s', \sigma, \phi_i'^e)|s\big]\right\}. \quad (5)$$

A potential entrant compares the expected value of becoming an incumbent in the next period minus the entry cost payment this period (first argument) to the option value of waiting and having the opportunity to enter in the future (second argument). Note that the second argument includes the deterministic part of the future entry cost, C', which is included in the future state variable s'. Remember, that firms are informed about the evolution of entry costs over time and establish correct beliefs. Hence, a future entry cost, C', may be involved in the expected value of waiting, as the potential entrant may find it optimal to enter in the future. The recurrence of C_t, caused by an exogenous change in the costs of equipment, will lead firms to play the same Markov perfect equilibrium strategies, which supports the stationary assumption.

Markov perfect equilibrium

In a Markov perfect equilibrium, each firm's strategy is the best response to its rivals' equilibrium strategies. Therefore,

$$V_i(s, \sigma_i^*(s), \sigma_{-i}^*(s), \epsilon_i) \geq V_i(s, \tilde{\sigma}_i(s), \sigma_{-i}^*(s), \epsilon_i), \tag{6}$$

where σ^* is a Markov perfect equilibrium strategy profile. This inequality holds for all states s, private shocks ϵ_i and all possible suboptimal strategies $\tilde{\sigma}_i(s)$.

4 Econometric model

In this section, we describe our econometric model. We build on the two-step estimation method developed by Bajari, Benkard, and Levin (2007). This estimator is ideal in our case, as it allows for continuous actions and states. The first stage includes estimation of demand and policy functions. In the second stage, we apply forward simulations, calculate the continuation values, and estimate marginal cost and entry cost parameters that rationalize firms' policies. In estimating a model with an optional value of waiting, we use forward simulation to compute the value of waiting. Finally, we will conduct welfare evaluations that consider the impact of entry, tax, and subsidy policies on consumer, producer, and total surplus.

There are several technical or economic complications that require limitations for several reasons: First, entry into multiple generations would imply a necessity to consider additional strategic entry considerations such as preemption and deterrence motives, as mentioned above.

A second related reason is that a solution for the Bellman equation is problematic due to the curse of dimensionality, since we have more than 40 firms in our data, which is beyond the current computational feasibility of solving the Bellman equation. For example, Hashmi and Van Biesebroeck (2016) report that a consideration of more than four firms becomes technically impractical.[27] Third, we also account for learning by doing effects, which imposes constraints on marginal costs since they have to be embedded into the dynamic model. Fudenberg and Tirole (1983) and Ghemawat and Spence (1985) show that learning models become quickly complex, even in highly specified model frameworks assuming symmetric firms, two periods, and a few firms. Finally, time-invariant entry costs further complicates the estimation routine. The consideration of these arguments requires limitations on the supply side such as entry into one generation, namely, the 64Kb generation. This limitation is supported by institutional evidence that different product generations are usually produced at different fabrication plants. A final supportive argument is that the entry cost into one specific generation will be identified by the discounted values evaluated at different states of that specific generation only. Further related information follow in Section 5.3.

4.1 First stage

In the first stage, we estimate the demand and policy functions. All policy functions are assumed to be functions of payoff-relevant state variables (s_t).

Demand

In order to get an estimate for the own-price elasticity for the $64Kb$ generation, which will be needed for the supply relation, a demand model is estimated. The demand model is closely related to Ryan (2012), Zulehner (2003) and Siebert (2010), and is based on a constant elasticity of demand framework. We consider the fact that multiple generations ($k = 16Kb, 64Kb, 256Kb, 1Mb$) are offered on the market at the same time. Every generation is homogeneous in itself and we allow for substitution patterns across generations of SRAM chips. The consideration of multiple generations on the demand side serves the purpose to get an

[27] For other studies that estimate the value of waiting, see Ryan and Tucker (2012) and Fan and Xiao (2014). Ryan and Tucker (2012) solve the value of waiting using backward induction starting from a steady state. Fan and Xiao (2014) solve the value of waiting by applying the method developed by Pakes, Ostrovsky and Berry (2007).

unbiased estimate on the own-price elasticity for the $64Kb$ generation.[28]

A log-linear demand function is specified and estimated using industry-wide quantities (q_t^k) and prices for generations k:

$$\ln q_t^k = \beta_0 + \beta_0^k + \beta_1 \ln P_t^k + \beta_2 \ln P_{t-1}^{k,S} + \beta_3 time^k + d_t^k, \tag{7}$$

where we account for generation-specific demand shifters (β_0^k) to capture preferences for information storage across generations. The generation-specific fixed effects capture unobserved characteristics (such as design, energy consumption, and reliability characteristics). P_t^k is the price for generation k, and the own-price elasticity is denoted by the coefficient β_1. $P_{t-1}^{k,S}$ is the price for the adjacent generations from the last period, which serves as a demand shifter.[29] The cross-price elasticity is denoted by β_2. In following earlier studies on the semiconductor market, we include a time trend ($time$) that controls for unobserved time-variant effects, and d_t^k is the error term that is identically and independently distributed. We estimate equation (7) using an instrumental variable estimator, and the instruments are described in the results section.

Marginal Cost

The static marginal cost function is specified as:

$$mc_i(s_t) = \theta_0 + \theta_1 \hat{\gamma}_i + \theta_2 \ln P_t^{sil} + \theta_3 \ln x_{it} + \theta_4 \ln(\tilde{x}_{-it}). \tag{8}$$

It consists of a firm fixed effect (γ_i), the factor price of silicon (P_t^{sil}), and own past production (x_{it}) to proxy for own learning. To account for firm fixed effects in the marginal cost function, we include the estimated firm fixed effect $\hat{\gamma}_i$ from the output policy function estimation (equation (9)). The variable $\tilde{x}_{-it} = \frac{x_{-it}}{n_t - 1}$ measures learning from others. Here, we divide the other firms' accumulated output by the number of other firms in the market since the marginal cost is independent of the number of firms, opposed to the output policy. This ensures that learning via spillovers is defined at the industry average and moves along at the industry level. Moreover,

[28] It is important to note, while the inclusion of multiple generations into the demand equation does not cause technical or economic complications, it does create technical challenges on the supply side for reasons mentioned above.

[29] We consider both adjacent generations as potential substitutes and form an average price. Note, even though the generation-specific shocks should not be correlated with the prices of adjacent generations, we still lag this price by one period in order to avoid a potential bias.

accounting for the number of firms in the denominator provides additional variation in the spillover variable, which eliminates a potential concern that our accumulated output would be strongly correlated with industry output and, therefore, picking up mostly industry effects rather than spillovers. One may raise the concern that the experience measure for own learning by doing might simply absorb path dependency of output over time stemming from an omitted variable problem. However, output is increasing during the growth phase of the life cycle and decreasing thereafter. In contrast, the experience or learning by doing measure is monotonically increasing throughout the entire life cycle. Hence, cost reductions via learning by doing would be identified from the monotonically increasing experience over time.

Output policy

The output policy is a descriptor for firms' production choices given the states that firms find themselves in. The specification of the output policy does not reflect just a static Cournot game since we incorporate own learning by doing and spillover effects. Following the specifications by Irwin and Klenow (1994), Jarmin (1994), and Roberts and Samuelson (1988), firms set quantities according to dynamic marginal costs, which lie below static marginal costs.[30] Therefore, the output policy is determined by the set of state variables that enter the static and dynamic part of the marginal cost function as introduced in equation (8) and the demand function.

The dynamic component of the marginal costs captures intertemporal strategic effects and cost savings that are realized in future periods. It depends on firms' positions in the life cycle since an earlier position increases firms' incentives to further increase output in anticipation of achieving future cost savings. The dynamic component is measured by a time trend ($time$). As a demand shifter, we include the substitute price (P^S_{t-1}).[31] Finally, since we consider a dynamic model in which the number of firms and the degree of competition in the market can change over time, we include the state variable number of firms (n_{t-1}) into the output relation.[32] The

[30]Other related production specifications in the context of learning by doing are shown in Fudenberg and Tirole (1983), Zulehner (2003), and Siebert (2010).

[31]To be consistent with the demand estimation, we lag the substitute price by one period.

[32]We assume that the output policy is determined by actual competition in the market, measured by the actual number of firms in the market. Therefore, we abstract from potential competition (potential entrants) having an effect on production in the market itself. Note, however, that potential entrants have an indirect effect via the entry policy, which is dependent on potential entrants. Hence, potential entrants have an effect on expected value function via firms' beliefs on the expected evolution of future market structure.

output policy is specified as:

$$\ln q_{it} = \gamma_i + \gamma_1 \ln P_t^{sil} + \gamma_2 \ln n_{t-1} + \gamma_3 \ln x_{it} + \gamma_4 \ln x_{-it} + \gamma_5 time + \gamma_6 \ln P_{t-1}^{S} + u_{it}, \tag{9}$$

where the error term u_{it} is i.i.d. normally distributed.

Entry and exit policies

We define entry as the first time we observe a positive output in our dataset for the specific generation under consideration. We estimate the following entry model using probit:

$$Pr(\chi_{it}^{e} = 1; s) = \Phi\Big(\lambda_0 + \lambda_1 \ln n_{t-1} + \lambda_2 \ln n_{t-1}^{pe} + \lambda_3 \ln e_{it}^{k-1} + \lambda_4 \ln x_{-it} + \lambda_5 time\Big), \tag{10}$$

where the entry policy depends on the number of active firms (n_{t-1}), the number of potential entrants (n_{t-1}^{pe}), firm i's production experience in the previous generation (e_{it}^{k-1}), other firms' past production (x_{-it}), and the evolution of entry costs (which is deterministic and known by the firms) is captured by the time trend. The parameters in the entry policy function (including the entry cost parameter) are identified by using multiple firm-level entry observations at given states. In case the entry costs approach zero, entry is explained by the remaining state variables, which include firm-level marginal costs such that existence of entry equilibria in pure strategies holds. Note that we are not able to include firm fixed effects in the entry and exit policies since not all firms have exited the generation at the end of the data period.

The exit policy is also estimated using probit and specified as follows:

$$Pr(\chi_{it}^{ex} = 1; s) = \Phi\Big(\psi_0 + \psi_1 \ln n_{t-1} + \psi_2 \ln x_{it} + \psi_3 \ln x_{-it} + \psi_4 time\Big), \tag{11}$$

where exit is a function of the same variables as in the entry policy, with the following exceptions: learning from own experience (x_i) enters the exit policy, as firms' decisions to exit might depend on their learning effects. Moreover, since the decision to exit is not affected by the number of potential entrants (n^{pe}), we exclude this variable from the exit policy. Finally, firm i's production experience from the previous generation (e_i^{k-1}) is excluded from the exit policy.

4.2 Second stage

In the second stage, we estimate the structural parameters in two steps. In the first step, we exploit the incumbent firms' policies to recover the marginal cost parameters. In the second step, we recover the entry cost using the potential entrants' optimality conditions.

Step one: Recovering marginal cost parameters

Incumbent $i's$ discounted expected profit given (s, σ) is:

$$V_i^I(s,\sigma;\theta) = E\left[\sum_{t=0}^{\infty} \beta^t (P(s) - mc_i(s;\theta)) q_i^*(s) \middle| s_0 = s, \sigma_{-i}\right] = W_i(s,\sigma)\cdot\theta, \tag{12}$$

where $W_i(s, \sigma)$ is a function independent of parameters derived from the fact that the value function is linear in parameters. The expectation is taken over the distribution of all future states s_t and productivity shocks ν_t, and q_i^* refers to firms' optimal output. Note that the incumbent's expected profit is independent of the entry cost and the private entry cost shock since entry costs are sunk for incumbents and we assume that a firm can enter a generation only once. Since the marginal cost function is linear in the parameters, the incumbents' value functions are also linear in the parameters. The function $W_i(s, \sigma)$ and θ can be defined as:

$$W_i(s_t,\sigma) = \mathbb{E}\sum_{t'=0}^{\infty} \beta^{t'} q_i^*(s_t)\Big[P(s_{t+t'}) \quad 1 \quad \hat{\gamma}_i \quad \ln P_{t+t'}^{sil} \quad \ln x_{i,t+t'} \quad \ln(\tilde{x}_{-it'})\Big] \tag{13}$$

and $\theta = [1 \quad -\theta_0 \quad -\theta_1 \quad -\theta_2 \quad -\theta_3 \quad -\theta_4]$.

In a Markov perfect equilibrium, each firm's strategy (σ_i^*) is the best response to its rivals' equilibrium strategies (σ_{-i}^*). For any suboptimal strategy $\tilde{\sigma}_i$, we must have:

$$W_i(s,\sigma_i^*,\sigma_{-i}^*)\cdot\theta \geq W_i(s,\tilde{\sigma}_i,\sigma_{-i}^*)\cdot\theta. \tag{14}$$

Next, we consider a minimum distance estimator defined as:

$$\hat{\theta} = \arg\min_{\theta} \frac{1}{N_I}\sum_{l=1}^{N_I}(\min\{0, g(\tilde{\sigma}_i^l;\theta)\})^2, \tag{15}$$

where $g(\tilde{\sigma}_i^l;\theta) = W_i(s,\sigma_i^*,\sigma_{-i}^*) - W_i(s,\tilde{\sigma}_i^l,\sigma_{-i}^*)$, and N_I is the number of alternative strategies we consider in the estimation. The estimator is defined such that a loss incurs when the incumbent's optimality condition (14) is violated. We search for the marginal cost parameters that minimize the sum of the squared losses. The marginal cost parameters are identified based on the incumbents' value function, as shown in equation (4). The identification depends on firms' policy functions, which will be used to forward simulate the discounted present values.[33] Finally, the standard errors are obtained using bootstrap.

Step two: Recovering entry costs

We recover the entry costs based on evaluating the incumbent's expected value (V_i^I) and the expected value of not entering and waiting (V_i^E) at state s. The observed entry time in combination with their discounted net profits enables us to characterize the evolution of entry costs over time. From the potential entrants' Bellman equation (5), we can derive the following condition:

$$\begin{aligned} Pr(\chi_i^e = 1; s) &= Pr\Big(-\phi_i^e - C + \beta\mathbb{E}\big[V_i^I(s')\big|s, \sigma, \chi_i^e = 1\big] > \beta\mathbb{E}\big[V_i^E(s')\big|s, \sigma, \chi_i^e = 0\big]\Big) \\ &= \Phi\Big(-C + \beta\mathbb{E}\big[V_i^I(s')\big|s, \sigma, \chi_i^e = 1\big] - \beta\mathbb{E}\big[V_i^E(s')\big|s, \sigma, \chi_i^e = 0\big]\,; 0, \sigma_e^2\Big), \end{aligned} \tag{16}$$

where $V_i^I(s)$ and $V_i^E(s)$ are the expected values from equations (4) and (5), respectively, involving the expectation of private shocks (ϵ_i). The first line in equation (16) follows from equation (5), and the second line accounts for the fact that the private entry shock ϕ_i^e is normally distributed. The unknown parameters left to be estimated are C and σ_e^2. Using our marginal cost estimates, we can compute the incumbent's expected value (V_i^I) conditional on entering at state s. The expected value of not entering and waiting at state s (V_i^E) can be forward simulated using the estimated policy functions and the marginal cost function estimates.

To forward simulate the value of waiting, we first write down the per-period profit for a potential entrant as:

$$\mathbb{E}_{\epsilon_i}\pi_i^E(s,\sigma) = \begin{cases} -C - \tilde{\phi}_i^e, & \text{if } \chi_i^e = 1,\ h_i = 0; \\ \pi_i^I(\sigma_i, \sigma_{-i}, s), & \text{if } \chi_i^{ex} = 0,\ h_i = 1; \\ 0, & \text{otherwise,} \end{cases} \tag{17}$$

[33] The firm-fixed effect (γ_i) entering the output policy is included in the forward simulations. In out of sample simulations, we do not have the observations of exogenous variables, therefore, we predict exogenous demand and cost shifters using a first-order autoregressive process.

where $h_i \in \{0, 1\}$ indicates if firm i is active in the product market, the expectations are taken over the private shocks, and $\tilde{\phi}_i^e$ is the conditional mean of the entry shock given entering. Following Ryan (2012), we use a linear b-spline function to replace the conditional mean, $\tilde{\phi}_i^e = \theta^E \cdot bs(p^e(s))$, where $bs(\cdot)$ is the b-spline function, $p^e(s)$ is the probability of entry at state s and θ^E contains parameters of the b-spline function.[34] Our goal is to recover the entry costs of the first 30 periods of the $64Kb$ generation, which is the time span when most firms chose to enter in our data (see Figure 2). Let $C_1, C_2, ..., C_{30}$ be the entry costs for these 30 time periods. Moreover, we assume that the entry cost changes at a constant per-period rate ζ_1. Thus, the entry cost can be written as $C_\tau = \zeta_0 + \zeta_1 \tau$, where τ refers to the entry periods $1, ..., 30$, ζ_0 is the initial entry cost at period 1, and $\zeta_1 \tau$ reflects the evolution of entry costs over time. The potential entrants' value function can be written as:

$$\begin{aligned} V_i^E(s, C = C_\tau, \sigma) =& \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t \mathbb{E}_{\epsilon_i} \pi_i^E(s, \sigma, \epsilon_i)\right] \\ =& \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t \mathbf{1}(h_{i,\tau+t} = 1)\big[P(s_{\tau+t}) - mc_i(s_{\tau+t})\big] q_i(s_{\tau+t})\right] \\ -& \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t p^e(s_{\tau+t})\big[\theta^E \cdot bs(p^e(s_{\tau+t})) + \zeta_0 + \zeta_1(\tau + t)\big]\right]. \end{aligned} \tag{18}$$

where $\tau + t$ refers to an index that counts the periods t following the period of entry denoted by τ. With the expected values of V_i^I (from equation (12)) and V_i^E (from equation (18)), we can recover the entry costs by minimizing the difference of the two sides in equation (16):

$$\min_{\zeta_0, \zeta_1, \sigma_e} \frac{1}{N_0} \sum_{\tau=1}^{30} \sum_{i=1}^{n_\tau^{pe}} \Big[Pr(\chi_i^e = 1; s) - \Phi\big(-\zeta_0 - \zeta_1 \tau + \beta \mathbb{E} V_i^I(s') - \beta \mathbb{E} V_i^E(s', C_\tau'); 0, \sigma_e^2\big)\Big]^2, \tag{19}$$

where N_0 is the total number of observations. For each of the first 30 periods, we consider each potential entrant as an observation. Then, for each observation, we can forward simulate its value of entry and value of waiting.[35] We search for the ζ_0, ζ_1 and σ_e that minimize the difference in the probabilities of entering.[36] The initial entry cost, ζ_0, can be identified since some potential entrants did not enter in our forward simulations. We can identify the changing

[34]We apply a clamped cubic b-spline with 10 knots.

[35]For simulating the value of waiting, some simulated timing of entry may be greater than 30. We simply drop these observations in order to increase the precision of estimation of the entry cost changes over time.

[36]Note that the value of waiting is a function of ζ_0, ζ_1, and σ_e.

rate, ζ_1, since the simulated timing of entry given waiting is different from τ.

In our model, there are two sets of parameters that need to be identified: marginal costs and entry costs. First, the marginal cost parameters are identified in the incumbents' revenues. As we assume that firms can only enter a generation once, incumbents' value functions are independent of entry costs. We are able to identify marginal cost parameters by considering the incumbents' output policy. Second, the entry cost parameters are identified in the potential entrants' revenues. We use forward simulation to compute the potential entrants' values of entering and waiting by using the marginal cost estimates obtained in the first step. Note that the one-time entry assumption is crucial that it allows us to identify the two sets of parameters separately.

5 Estimation results and welfare simulation

In this section, we describe our estimation results. We begin with discussing the first-stage results for the demand and the output, entry, and exit policies. We then turn to the second stage of the estimation routine and discuss the estimation results for firms' marginal costs. Finally, we present the results for the entry costs and discuss the results of our policy experiments.

5.1 First-stage results

Demand

The estimation for the industry demand is based on ordinary least squares and instrumental variable estimation techniques. Regarding the instrumental variable estimation, we account for a potential correlation between the price and the error term. We use several instruments for price. First, industry facts show that memory chip generations are imperfect substitutes due to space constraints in the electronic appliances for which memory chips are used. Hence, our identifying argument is that consumer taste shocks are not correlated across generations, and we use the prices of the other memory chip generations as an instrument. Similar identifying assumptions and instruments have been used in other demand models such as Berry, Levinsohn, and Pakes (1995). Second, we use the number of product generations offered on the market to capture the negative relation between the number of memory chips offered on the market and markups. A similar instrument has been used by Berry, Levinsohn, and Pakes (1995). Relatedly, we use the (lagged) number of firms to capture the negative relationship between competition and prices. Third, we use a factor price as a traditional supply-side cost shifter, here, the price of silicon (P_t^{sil}) (see also Zulehner (2003), Siebert (2010), and Ryan (2012)). As mentioned earlier, silicon is the main material used in the production of SRAM devices. However, silicon is by far not constrained to memory chip production, but also widely used in glass, bricks, pottery, steel, solar energy, aluminum alloys, and computer products such as different chips (SRAM, DRAM, Flash, among others), microprocessors, and many other computer parts. The wide use of silicon qualifies makes its price an appropriate instrument for the estimation of SRAM demands since it is rather unlikely that SRAM shocks entering the demand side have an impact on the silicon world price. Moreover, we use the cumulative industry output for the generation under consideration ($(\sum_{t'=1}^{t-1} q_{t'}^k)$) as a proxy for industry wide learning by doing to capture downward shifts in marginal costs over time (see also Zulehner (2003) and Siebert (2010)). Finally, we use the (lagged) GDP in electronics to control for shifts in downstream market demand.

In comparing the estimation results in Columns 1 and 2 of Table 1, the instrumental variable estimator returns more elastic price elasticities of demand than the ordinary least squares estimator. As expected, this result indicates an upward bias of the ordinary least squares estimates. To test for endogeneity, we conduct a Durbin-Wu-Hausman test. The test statistics is $F = 619.99$ for the first specification, and it is $F = 6.40$ for the second specification. We, therefore, reject the exogeneity of prices in both specifications. The estimated own price elasticity is -3.345, confirming a highly elastic market demand in the SRAM industry. Our estimations return positive cross-price elasticities, and the magnitude of the cross-price elasticities is smaller than the own-price elasticities, which confirms the fact that the quantity of a current generation is more responsive to a price change of the same generation compared to a price change of a substitute generation. The generation-specific intercepts are significant and increase across generations, emphasizing increasing prices throughout different generations due to larger market size and higher willingness to pay for more information storage. Finally, the time trend ($time$) is significantly negative, indicating that consumers substitute away from purchasing a specific generation as time elapses. We use the estimation results in Column 2 for our subsequent estimations.

Output policy

We now discuss the results of the output policy, as shown in equation (9). Even though a potential simultaneity bias for the parameters on past experience is unexpected, we still apply a robustness check and instrument past experience using the twice and three times lagged variables of own cumulative output. We also instrumented for the price of the adjacent generations using the same instruments as mentioned earlier. The differences between the estimated coefficients from the instrumental variable and the ordinary least squares estimations are negligible. In addition, the Hausman test fails to reject the consistency of the ordinary least squares estimates. Moreover, the Hausman test statistic of 97.76 rejects the random effects specifications. The estimation results are shown in Table 2. The results indicate that an increase in the price of silicon (P^{sil}) increases marginal costs and, hence, reduces output. The coefficient of the number of firms (n) is negative. A more competitive market (a larger number of firms in the market) reduces firms' output. These two parameter estimates are close to being significant at the 10 percent level. Our estimation results confirm highly significant own learning effects. The positive estimate supports the argument that a firm's own past accumulated output (x_i) reduces marginal costs and increases production. We also find highly significant spillover effects, that is, other firms' experience spills over and results in lower marginal costs and higher production. The coefficient of the price of adjacent generations (P^S) carries the expected sign, since firms' quantity supplied increases if the price of a substitute increases. The coefficient on the time trend is significantly negative, which indicates that dynamic marginal costs are further below static marginal costs at the early stages of the life cycle, which supports the notion that firms more drastically increase output during the early stages of the life cycle to further benefit from future cost savings. The fact that firms at earlier periods further increase output is also consistent with fewer firms operating in the market.

Entry and exit policy

We estimate the entry policy, as shown in equation (10), and the exit policy, as shown in equation (11), using probits. Similar to the output policy, we instrumented for past accumulated output in the entry and exit equation using the same set of instruments. The results are shown in Table 3. The first column reports the results of the entry policy. The results show that firms are more likely to enter if other potential entrants (n^{pe}) already entered the market in the past.

The significant and positive estimate of cumulative output in the previous generation (e_i^{k-1}) shows that a firm's production experience in the previous generation enhances productivity and increase the likelihood to enter. The estimate provides support for the notion that firms offer generations successively and do not skip generations. Firms are also more likely to enter when their forerunners have gained more experience (x_{-i}). This result highlights the fact that spillovers increase the likelihood of entry. The positive and significant time trend provides evidence that firms choose to enter in a later period in order to save on entry costs. This result provides a first insight that entry costs are decreasing over time.

Column 2 in Table 3 shows the results for the exit policy. Firms are more likely to exit the generation if many other firms compete in the market (n). Moreover, the likelihood of exit increases if firms missed out on gaining sufficient production experience (x_i), which translates into a competitive disadvantage due to lower learning effects and higher marginal costs. Moreover, firms are less likely to exit if other firms' cumulative output (x_{-i}) is higher, such that firms are able to benefit from higher spillovers.

5.2 Second-stage results

Marginal cost

The marginal cost function parameters (as shown in equation (8)) are estimated using the minimum distance estimator (as defined in equation (15)). We adopt 2,000 forward simulations and 2,000 alternative strategies that are carried out for 120 periods. The results are shown in Table 4. All coefficients carry the expected signs. As the estimate of the positive and significant constant indicates, marginal costs start at a relatively high level. The firm fixed effects have a significant impact on marginal costs, which explains heterogeneities across firms and different firm-level discounted values. A more productive firm (represented by a higher firm fixed effect in the output policy) has lower marginal costs, which is confirmed by the significantly negative parameter estimate (θ_1). The negative parameter estimate (θ_3) provides evidence for own learning effects. Marginal costs decline as a firm's production experience (x_i) increases. Moreover, the parameter estimate (θ_4) reflects spillover effects that are about one-third in magnitude of the own learning effects—a result that is consistent with previous studies. The estimate of learning via spillovers, however, is insignificant.

Entry cost

The estimation results for entry costs are shown in Table 5 and Figure 4.[37] All estimates, including the initial entry cost (ζ_0), the changing entry cost rate (ζ_1), and the standard deviation of entry cost shocks (σ_e), are significant. Our results provide evidence that entry costs decline rapidly over time. Entry costs decline by 80 percent or by more than $30 million per period throughout the 30 periods. The result of drastically declining entry costs over time provides evidence that firms can experience huge entry cost savings by entering at a later period. Hence, firms consider an option value of waiting and decide on an optimal timing to enter a market characterized by the trade-off we mentioned earlier: Enter early and earn higher net profits due to lower competition or wait and enter later to achieve entry cost savings but sacrifice on high per-period profits at the initial periods when only a few firms entered and the market is less competitive. The variation of entry cost shocks (σ_e) supports the fact that part of the entry costs are well characterized by a firm-specific random component, which contributes to explaining different entry times.

5.3 Welfare simulations

To verify the importance of considering declining entry cost, we conduct two sets of counterfactual simulations in this section. In the first counterfactual, we assume that a social planner can enforce entry regulation policies that keep the first entrant protected from other entrants for a limited number of periods. After the period of entry protection elapses, other firms can enter freely. In the second counterfactual, we assume that the social planner can either charge a tax on entry costs or provide a subsidy on entry costs.

We apply a similar counterfactual approach to Das, Roberts, and Tybout (2007) and Blonigen, Knittel, and Soderbery (2017). That is, rather than to solve for a full equilibrium in the counterfactual, our counterfactual exercise uses our estimated parameters to simulate the welfare effects of a social planner who engages in entry regulation, tax, and subsidy policies.[38] We are not aiming for solving for a socially efficient timings of entry as this is not feasible in our study, which includes a large set of heterogeneous firms. Our simulations should be rather understood

[37] We normalized the entry costs presented in the figure by setting the entry cost of the 30^{th} period to 0.

[38] Hashmi and Van Biesebroeck (2016) mention that the computation of a Markov perfect equilibrium in infinite-horizon dynamic games with simultaneously moving firms becomes impractical in their case if more than four firms are involved. We have more than 40 firms entering the industry.

as a numerical comparative statics exercise on welfare. Therefore, we use these counterfactuals to show that declining entry costs can substantially affect welfare.

Welfare simulation results of entry regulation policy

We begin with the entry regulation policy and evaluate the welfare of a social planner who can protect the first entrant from subsequent entry for different numbers of periods. We formulate the policy experiment as follows: The social planner grants an exclusive right to the first firm entering the 64Kb SRAM chip generation to sell SRAMs for a specific time period.[39] The right expires after a certain number of periods which is specified by the social planner. Once the entry regulation ends, potential entrants have the opportunity to enter the market, pay the corresponding entry costs, and decide how much to produce.

Evaluating the impact of entry protection on total welfare is not a straightforward exercise, as a longer protection period delays entry and reduces the entry costs for successive entrants. Hence, entry protection has a significant impact on firms' discounted values and their optimal timing to enter the market, as well as their quantity choices and the resulting prices that need to be simulated. Our approach is disregarding R&D innovation benefits of entry protection. Thus, our results address the trade-off between savings on entry cost and marginal cost savings via learning and spillover effects, but we abstract away from any effects that relate to R&D innovations.

Based on different entry protection durations and using the estimated marginal costs, entry costs, demand, and policy functions, we simulate firms' entry, exit, and outputs to evaluate welfare effects. The results are illustrated in Figures 5 and 6. The base case is our estimated free entry model, and all changes in welfare are evaluated relative to the free entry case.

Focusing on the impact of entry protection on consumer surplus (see Figure 5), a longer entry protection period preserves a monopoly position for an extended period, which increases market power for the first entrant, elevates prices, causes output to fall, and results in a lower consumer surplus (compared to free entry). Therefore, the consumer surplus monotonically declines with the duration of entry protection. This result provides evidence that the market power effect

[39]Note that the social planner is able to determine the protection period of only the first entrant. We are aware that other configurations related to an optimal timing of market entry are possible, but constrain our experiment to the one introduced here since we believe this is most closely related to real-world situations such as granting intellectual property rights or licensing agreements to firms.

and the associated price increase overcompensate own learning effects (via the concentration of all industry output on the entry protected monopolist). It should be noted that consumer surplus declines at a diminishing rate and does not decline much further after approximately 25 quarter periods of entry protection when a sufficient large number of firms entered.[40] This is explained by the fact that the impact on prices via competitive entry effects quickly diminishes (see Bresnahan and Reiss (1990 and 1991)).

Turning to the impact on producer surplus, we find a steady decline for entry protections that last less than 11 quarters. As a result, total surplus also declines, which emphasizes that entry regulation can be severely harmful to social welfare if the protection period lasts for only a short period of approximately 11 quarters. After 11 periods of regulation, producer surplus begins to rise and even dominates the producer surplus under free entry if the protection period exceeds 25 quarters. The total surplus under entry protection approaches the surplus under free entry if entry protection is sufficiently long.

To better understand the changes in producer and total surplus, we decompose the producer surplus change into changes in the monopolist's profits (i.e., the profits of the protected firm), other firms' profit changes, and the savings in entry costs (see Figure 6). As the length of entry protection increases, the protected monopolist's profits slightly decline (relative to the free entry case), which is explained as follows: Under free entry, only a limited number of firms are able to enter the market in early periods, and these are the most efficient firms since they were able to pay high entry costs (see Figure 2). Since firms learn from other firms' experience via spillovers, and those firms are highly efficient, the industry profits are relatively higher than those earned by a protected monopolist who does not have the benefit of learning from other firms' experience via spillovers. Figure 6 also shows that entry cost savings strongly increase with the length of entry protection, which is explained by longer entry protection delaying successive entry and reducing entry costs. Since firms under free entry care only about their own profits, while a welfare maximizer accounts for the overall industry profits, entry regulation can generate entry cost savings. It should be noted that entry cost savings increase more drastically after 10 periods of entry protection. The reason is that under free entry, many firms entered at around period 10 (see Figure 2), which generates large entry cost savings under entry protection. The large entry

[40] We acknowledge the fact that long-lasting entry protection might imply inaccuracies in predicting firms' choices, and they should be carefully interpreted. For that reason, we consider a maximum patent protection duration of 30 quarters.

cost savings are the reason that producer surplus starts to increase after 11 periods of regulation. The savings of entry cost even outweigh the loss from preventing other firms from entering the market. For sufficiently long-lasting entry regulations (more than 25 periods), producer surplus is larger compared to the free entry case.

In sum, the somewhat counterintuitive result that entry regulation can harm the protected incumbent firm results from large spillover effects in the SRAM industry. Theoretical entry studies have shown that entry can be insufficient when spillover effects are large (see Haruna and Goel (2011) and Hattori and Yoshikawa (2016)). In our case, however, the combined losses for the monopolist and other firms from entry regulation is dominated by the savings of entry costs. Hence, the declining entry cost savings is sufficiently large especially after 11 periods.

Welfare simulation results of tax and subsidy policies

We now consider a social planner who has the opportunity to charge a tax on entry costs or to subsidize entry costs. The purpose is to simulate the impact of these policy instruments on entry, exit, output, and welfare (net of tax and subsidy). Remember that the entry cost derives from purchasing production machinery that is developed and offered by firms in the upstream market, such that entry costs are changed exogenously. Therefore, upstream manufacturers are charged a tax or receive a subsidy, which is passed on to the cost of production machinery and changes the potential entrants' entry costs and their optimal timing to enter, as well as their production and exit decisions.

In accordance with Blonigen, Knittel, and Soderbery (2017), our policy experiment relates to a social planner who can decide on a tax or subsidy—which corresponds to making entry more or less costly—and this affects the probability of entry. We incorporate the tax (subsidy) policy by increasing (decreasing) the entry cost, and we multiply the entry cost in the policy functions with a scalar that runs from zero to two. A value equal to one corresponds to the status quo of free entry, which serves as the base case. As the value becomes smaller than one, the tax imposed on entry costs increases, which increases entry costs and delays firm entry. Increasing values above one reflect larger subsidies to firms, which decreases entry costs and facilitates entry.

The simulation results are illustrated in Figure 7. The base case relates to the point where the value on the horizontal axis is one. At this point, the evaluated changes in consumer, producer, and total surplus are zero (compared to our free entry case or base case).

Focusing on a tax charged on entry, as shown in the left panel of Figure 7, a further increase in the tax (corresponding to lower values on the horizontal axis), slightly diminishes the consumer surplus. This is explained by increasing entry costs providing fewer incentives for potential entrants to eventually enter (see also the lower dotted line in Figure 8). Consequently, marginal costs increase due to lower learning and spillover effects, which reduces output and increases prices, which reduces consumer surplus. The producer surplus drastically increase as taxes increase (and the tax value declines to 0.6). This is explained by higher entry costs and fewer firms entering early, which reduces the excessive entry cost problem. Figure 7 shows strong entry cost savings for tax values around 0.6. If the tax increases further (illustrated as tax values below 0.6), few firms will enter which results in few entry cost savings.

Turning to a subsidy (see the right panel of Figure 7), a higher subsidy (values on the horizontal axis exceed 1) increases consumer surplus since more firms enter (see the upper dashed line in Figure 8). As a consequence, firms produce more, which lowers price and increases consumer surplus. Interestingly, while the government provides a subsidy on entry costs, more firms enter earlier, which exacerbates the problem of spending an excessive amount on entry costs. Therefore, producer surplus monotonically declines with the amount of subsidy provided.

Both counterfactual simulations show that changes in total surplus are primarily driven by entry costs savings (see Figure 6 and Figure 7). Hence, excessive early entry in the SRAM industry dominates other welfare components, such as consumer surplus and firms' profits (net of entry cost). This result supports the relevance of accounting for time-variant entry costs. Remember, we are using these two policy simulations to point out welfare implications and to emphasize the importance of time-varying entry costs rather than finding the optimal socially efficient timings of entry.

6 Conclusion

This paper studies market entry with declining entry costs over time and provides economic insights into dynamic efficiency gains. Declining entry costs add an additional option value to potential entrants that pertains to the optimal timing of entry. Potential entrants consider a trade-off in determining their optimal timing of market entry. Entering at early periods requires higher entry costs, but allows firms to extract higher rents due to low initial competition in the market. Later entry requires lower entry costs, but returns lower net profits.

We build on a dynamic oligopoly model in which firms choose their optimal time to enter a market (accounting for declining entry costs over time), followed by production and exit decisions. Our estimation results return reasonable estimates for the output, entry, and exit policies as well as firms' marginal costs and entry costs. We find that entry costs decline by 80 percent throughout the product life cycle. We also perform welfare simulations in which a social planner evaluates governmental interventions such as entry regulation, tax, and subsidy policies. The simulation exercise is similar to Das, Roberts, and Tybout (2007) and Blonigen, Knittel, and Soderbery (2017) but it is extended to declining entry costs.

Our results on entry regulation show that consumer surplus is monotonically declining in the entry protection duration. Producer surplus first declines, but increases after 11 quarters and eventually dominates the producer surplus under free entry. The significant increase in producer surplus at later periods is explained by the fact that excessive entry is prevented, which results in cost savings and higher producer surplus. If the entry protection duration is sufficiently long the increase in producer surplus from entry cost savings compensates the losses in consumer welfare, and total welfare eventually increases.

Similar to entry regulation, our results on the tax policy simulations show that tax policies can serve as an instrument to prevent an excessive number of firms from entering too early at overly high entry costs. Finally, our subsidy simulation results show that higher subsidies trigger more entry at early stages and increase consumer surplus, but reduce total welfare due to firms spending excessive amounts on entry costs. The provision of subsidies increases consumer welfare as opposed to the entry regulation and tax policies. We show that declining entry costs over time have strong implications on firms' optimal timing to enter markets, total surplus, and governmental policies.

To conclude, our study shows that declining entry costs over time can have drastic implications on total welfare. Beyond the established insight by previous entry studies (that entry regulation can serve as a mechanism to avoid excessive entry), our study provides additional insight, that is, entry and tax regulations can serve as instruments to avoid excessive "early" entry at overly high entry costs; this increases producer surplus but it diminishes consumer surplus. Governmental interventions in the form of entry regulation and taxation can be total surplus enhancing since they prevent firms from paying a socially undesirable amount on entry costs.

On a final note, it is worth emphasizing that declining entry costs over time are also a significant feature in many other high-tech markets, such as pharmaceuticals, automotives, and electronics, as well as capital-intensive markets. Our study provides the underlying mechanics to be applied to other industries and further economic insight is needed on whether government regulations would generate similar welfare results as in our study.

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7 Appendix: Tables

Table 1: Demand Estimation Results

Variable	OLS	IV
	(1)	(2)
Constant	14.768***	18.405***
	(1.033)	(1.103)
$\ln(P)$	-2.516***	-3.345***
	(0.122)	(0.173)
$\ln(P^S)$	1.384***	1.517***
	(0.209)	(0.162)
Dummy $64Kb$	1.842***	2.128***
	(0.163)	(0.172)
Dummy $256Kb$	3.183***	3.836***
	(0.233)	(0.232)
Dummy $1Mb$	4.128***	5.426***
	(0.390)	(0.418)
time	-0.066***	-0.104***
	(0.010)	(0.011)
Number of observations	314	310
(Adjusted) R-squared	0.774	0.669

The dependent variable is the logarithm of industry output ($\ln q_t^m$). As instruments, we use the price of silicon and cumulative total industry output for the corresponding generations. The standard errors are shown in parentheses below the parameter estimates, and *** (**, *) denotes a 99% (95%, 90%) level of significance.

Table 2: Output Policy Estimation Results

Variable	Output
Constant	3.121**
	(1.356)
$\ln P^{sil}$	-0.242
	(0.154)
$\ln n$	-0.062
	(0.038)
$\ln x_i$	0.471***
	(0.037)
$\ln x_{-i}$	0.293 ***
	(0.040)
$\ln P^S$	0.293 ***
	(0.098)
time	-0.064 ***
	(0.005)
Firm fixed effect	Yes
Number of observations	1,697
Adjusted R-squared	0.778

The table shows the estimation results of equation (9). The dependent variable is the logarithm of firm-level output ($\ln q_{it}^k$) for generation $k = 64Kb$. The standard errors are shown in parentheses, and *** (**, *) denotes a 99% (95%, 90%) level of significance.

Table 3: Entry and Exit Policy Estimation Results

Variable	Entry	Exit
	(1)	(2)
Constant	-8.935***	-2.657***
	(2.825)	(0.734)
$\ln n$	-0.014	1.104*
	(0.034)	(0.577)
$\ln n^{pe}$	1.054**	
	(0.48)	
$\ln e_i^{k-1}$	0.078***	
	(0.016)	
$\ln x_i$		-0.139***
		(0.031)
$\ln x_{-i}$	0.100**	-0.395*
	(0.049)	(0.231)
time	0.046*	0.051**
	(0.024)	(0.019)
Number of observations	3,195	1,701
Pseudo R-squared	0.229	0.058

Table 3 shows the results for the entry and exit policies, as shown in equations (10) and (11). The entry and exit policies are estimated using probit models. The dependent variable in the entry model takes on a value of one when a firm chose to enter and zeros before entry occurred. In the exit model, the dependent variable takes on a value of one if a firm exits the generation and zero between the firm's entry and exit decisions. The standard errors are shown in parentheses, and *** (**, *) denotes a 99% (95%, 90%) level of significance.

Table 4: Marginal Cost Estimation Results

Parameters	Estimates
Constant (θ_0)	33.163***
	(13.434)
Firm fixed effect (θ_1)	-2.464***
	(0.802)
Price of silicon (θ_2)	0.195
	(1.055)
Learning (θ_3)	-1,808***
	(0.758)
Spillover (θ_4)	-0.741
	(1.922)

Table 4 shows the estimation results of the marginal cost function, as shown in equation (8). The standard errors shown in parentheses are based on subsampling, and *** (**, *) denotes a 99% (95%, 90%) level of significance. In our estimation, firms' outputs are forward simulated for 120 periods and value functions are computed by taking the average of $2,000$ forward simulations. We randomly select $2,000$ alternative output strategies in the marginal cost estimation.

Table 5: Entry Cost Estimation Results

Parameters	Estimates
ζ_0	11.50×10^8 ***
	(142.461×10^3)
ζ_1	-3.084×10^7 ***
	(1.029×10^7)
σ_e	2.944×10^7 ***
	(8.718×10^6)

Table 5 shows the estimation results of entry cost. The standard errors shown in parentheses are based on subsampling, and *** (**, *) denotes a 99% (95%, 90%) level of significance. Monetary values are measured in U.S. dollars.

8 Appendix: Figures

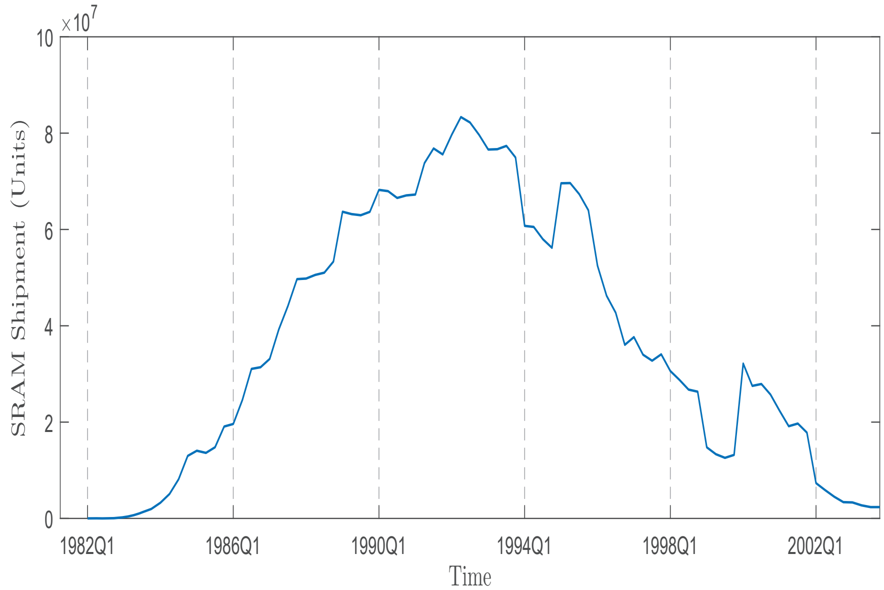

Figure 1: Industry units shipped for the 64Kb generation, 1982-2003.
Source: Gartner Inc.

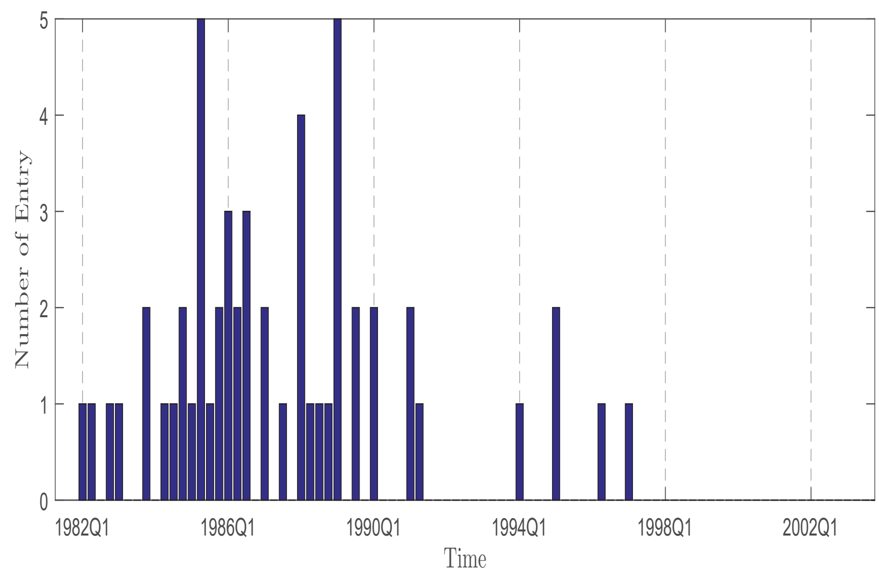

Figure 2: Distribution of Entry in the 64Kb Generation
Source: Gartner Inc.

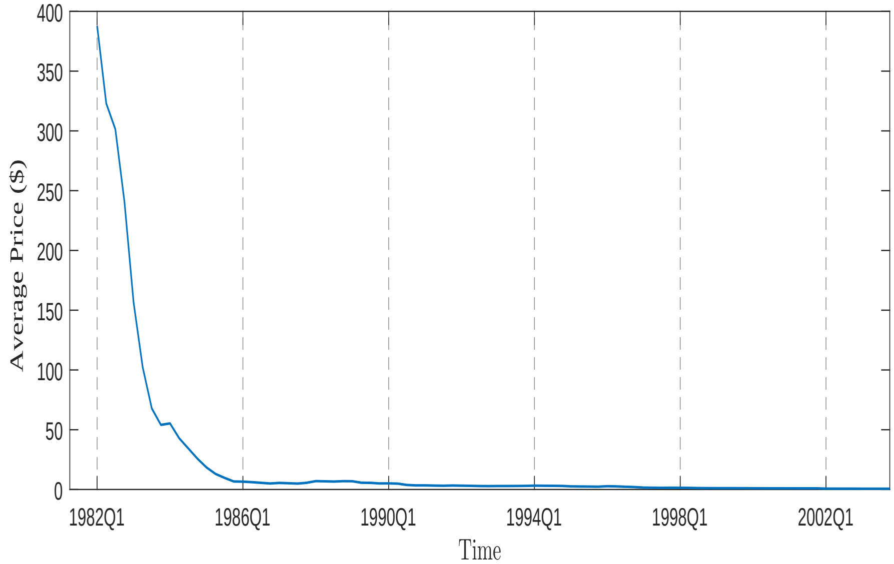

Figure 3: SRAM prices for the 64Kb generation, 1982-2003.
Source: Gartner Inc.

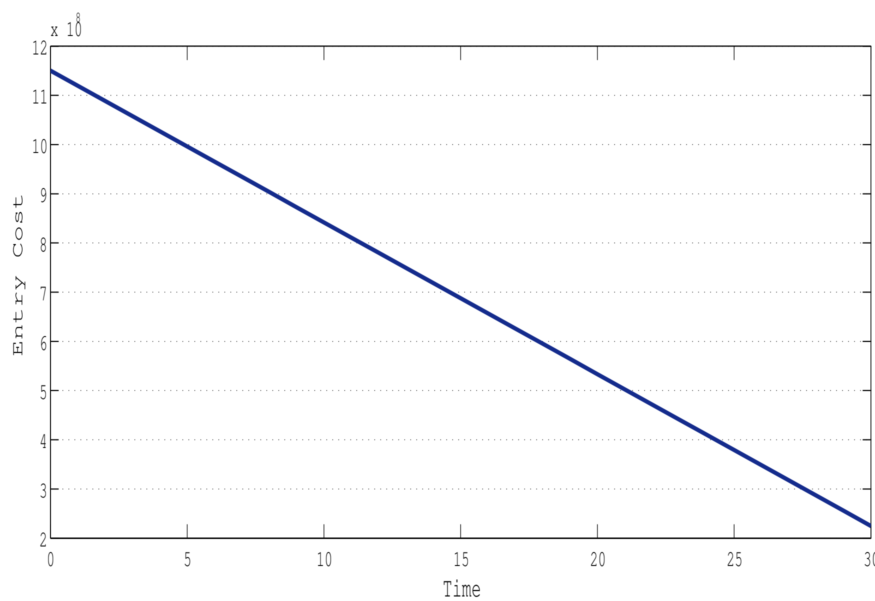

Figure 4: Entry Costs

All values are the discounted values at the timing of the first entry in U.S. dollars.

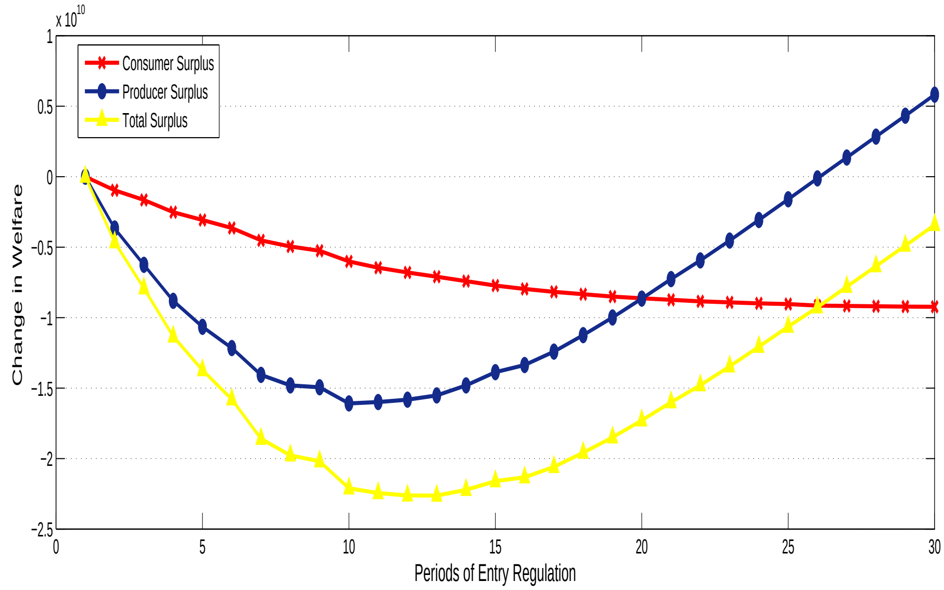

Figure 5: Change in Welfare

All values are the discounted values at the timing of the first entry in U.S. dollars.

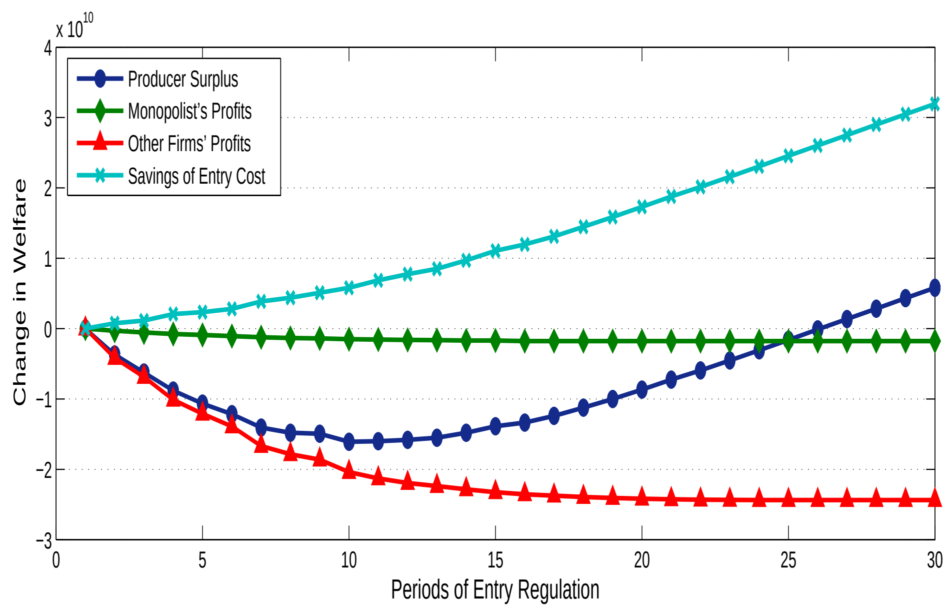

Figure 6: Change in Producer Surplus

All values are the discounted values at the timing of the first entry in U.S. dollars.

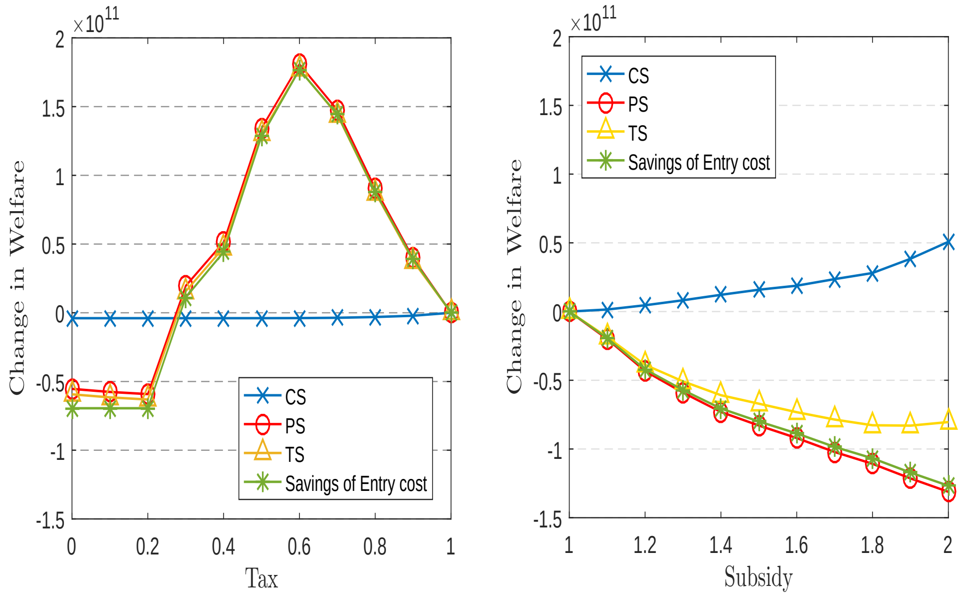

Figure 7: Change in Welfare

All values are the discounted values in U.S. dollars.

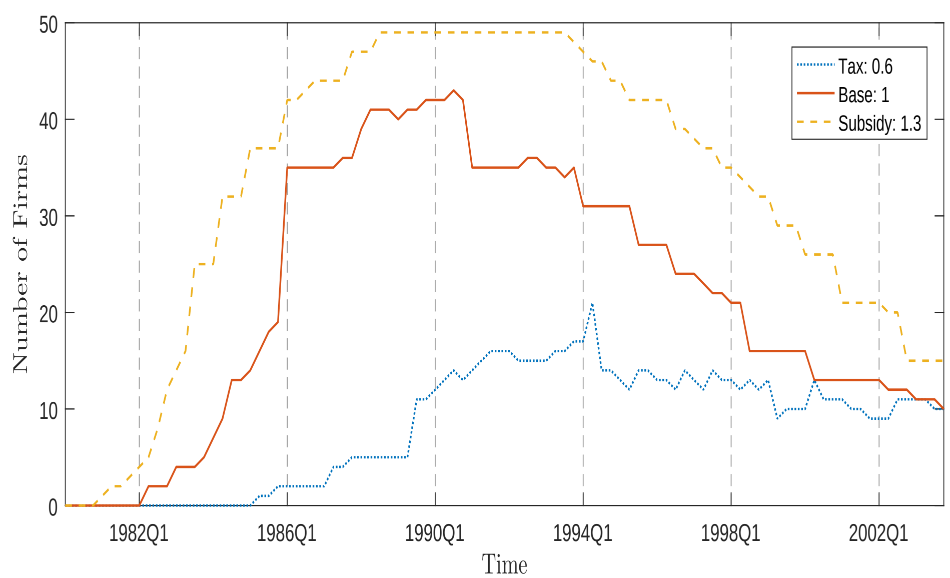

Figure 8: Number of Firms with a Tax and a Subsidy