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 decline drastically by approximately 2 percent or $40 million per quarter. We conduct a simulation exercise in which a social planner can protect an incumbent from subsequent entrants for different lengths of time. Based on declining entry costs over time, our results show that entry regulation can increase producer and total surplus since regulation can prevent firms from entering too early at overly high entry costs. If own learning and spillover learning are eliminated, total welfare gains are realized already for short lengths of entry protection. We also show that tax (subsidy) policies of entry costs have positive (negative) effects on total surplus while reducing (improving) consumer welfare. Finally, once we assume constant entry costs over time, we find that entry regulation reduces consumer, producer, and total 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 structure and market performance. A well-established fact in the economics literature is that free entry can result in an "excessive" number of firms entering the market (see Berry and Waldfogel (1999), Dixit and Stiglitz (1977), Mankiw and Whinston (1986), Perry (1984), Pesendorfer (2005), Spence (1976), and von Weizsaecker (1980), among others). Most empirical studies consider markets that are characterized by constant entry costs over time. In contrast, our study concentrates on technology markets, where entry costs are declining over time, as explained by production machinery becoming more inexpensive and the existence of secondary machinery markets. Beyond declining entry costs, technology markets are frequently characterized by declining production costs caused by learning-by-doing effects. In the presence of learning by doing, firms learn from their production experience and achieve future savings in production costs.[1]

Our study evaluates the impact of declining entry costs and declining production costs caused by learning by doing on market performance and economic welfare. As our research question, we focus on whether a social planner has opportunities to improve economic welfare while engaging in entry regulation such as optimizing the timing of entry. This welfare evaluation is especially useful for regulatory authorities since entry policies are a common instrument in technology markets (more details are provided later). Furthermore, our study contributes to the literature on entry by estimating declining entry costs over time when entry costs are unobserved.

Declining entry costs over time have strong implications on firms' optimal timing to enter markets since firms have an option value to delay entry. This implies the following trade-off: An early entry requires a high entry cost, but it provides the opportunity to collect profits for a longer time period due to prolonged market presence. An early entry also provides an opportunity to earn higher discounted profits due to low competition in early periods. While firms consider only their private benefits from entering, a social planner considers that firms may enter too early, which results in excessive entry costs incurred at early periods. Furthermore, social inefficiencies of entry can arise from business-stealing effects since an entrant imposes a negative externality while "stealing" output from incumbent firms (see Mankiw and Whinston

[1] See, for example, Fudenberg and Tirole (1983), Ghemawat and Spence (1985), Irwin Klenow (1994), Lieberman (1984), Spence (1981), and Zimmerman (1982).

(1986)). Therefore, entry is often more desirable to the entrant than it is to society such that private and social incentives are misaligned. A social planner has the opportunity to improve economic welfare by imposing entry regulations that prevent firms from entering too early and paying overly high entry costs. The entry regulation, however, comes at an economic cost, as it reduces competition and increases prices.[2]

This study also considers the effects of declining production costs caused by learning by doing on market structure and performance. It has been shown that learning by doing provides incentives for firms to enter the market early, as it allows firms to achieve a head start in production, move down the learning curve quickly, and achieve a comparative cost advantage versus their competitors (see Cabral and Riordan (1997), Dasgupta and Stiglitz (1988), Fudenberg and Tirole (1983), Ghemawat and Spence (1985), Scherer (1980), and Spence (1981)). Studies have also shown that the learning curve can erect entry barriers for potential later entrants (see Scherer (1980) and Spence (1981)). In the presence of learning by doing, a social planner might consider protecting the first entrant from subsequent entrants, which allows the incumbent to move down the learning curve quickly and achieve high cost efficiencies (see Dasgupta and Stiglitz (1988)). In contrast, entry protection reduces competition and increases markups. The welfare assessment becomes more complex once we consider learning spillovers—that is, once firms achieve production cost savings by learning from their competitors (see Irwin and Klenow (1994)). Spillovers can substantially attenuate the barriers to entry erected by proprietary learning and provide further incentives for firms to enter (see Ghemawat and Spence (1985) and Spence (1981)).

Overall, the impact of entry protection on social welfare is ambiguous and ultimately becomes an empirical question. Our study focuses on static random access memory (SRAM) chips, which belong to the semiconductor family. The semiconductor industry is often cited as a "strategic" industry, and it has frequently been the target of competition and antitrust policies (see Irwin and Klenow (1994) and Siebert (2010)). The SRAM market is well suited for our research purposes for several reasons. First, the SRAM industry is a high-technology market characterized by high entry costs that decline drastically over time.[3] Second, the SRAM industry is characterized by

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

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

free entry.[4] Third, the SRAM industry is characterized by successive entry where firms continue to enter the market many years after the product generation has been launched. Fourth, learning by doing is a well-known feature in memory chip industries such as the SRAM industry. Finally, the SRAM industry is characterized by fairly homogeneous chips within generations, which keeps the analysis tractable.

We employ a dynamic oligopoly model characterized by firms' entry, exit, and production decisions. Our empirical analysis puts special attention on the estimation of unobserved declining entry and production costs. 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. Our estimation procedure builds upon the literature of dynamic games.[5] We adopt a two-stage algorithm and estimate firms' entry, exit, and production 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 approximately 60 percent throughout the evaluation period, which corresponds to entry cost reductions of $40 million per quarter. Our estimation results also return substantial learning-by-doing and spillover effects.

To show the economic impact of declining entry costs and learning effects, we perform several simulations with an emphasis on dynamic efficiency gains. We begin with a social planner who compares the welfare effects of entry regulations with free entry (see also Ferrari and Verboven (2010) and Schaumans and Verboven (2008)). We consider entry regulations of different lengths of time and evaluate their impact on entry, exit, production, prices, and welfare. The social planner can protect the first entrant from subsequent entry for different lengths of time to prevent excessive entry during early periods and to prevent firms from paying excessive entry costs.

Our simulation results show that a longer-lasting entry protection duration for the incumbent firm monotonically reduces consumer surplus compared to the free entry case. Regarding the

[4]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.

[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).

impact of the entry regulation on producer surplus, we find that producer surplus declines for short protection periods, begins to increase after six quarters, and eventually is greater than the producer surplus under free entry due to the prevention of excessive entry cost spendings from early entry. The entry regulation can generate gains in producer surplus that 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 due to too many firms entering too early and paying an associated entry cost that is too high from a social welfare perspective. A sufficiently long duration of entry protection increases entry cost savings, which overcompensate the consumer welfare losses from entry regulation. Therefore, beyond the existing insight that entry regulation can serve as a mechanism to avoid excessive entry, our study provides additional insights, that is, entry regulation can prevent excessive "early" entry and reduce the associated excessive entry costs.

A further simulation exercise assumes constant entry costs over time and evaluates the impact of the same entry protection regulation lasting for different lengths of time. Our results show that entry protection again reduces consumer welfare. In contrast to the results with time-variant entry costs, however, producer and total surplus monotonically decline in the length of entry protection. The simulation result is different when entry costs vary over time since constant entry costs over time do not provide opportunities for entry cost savings when delaying subsequent entry, that is, firms pays the same entry cost independent of the entry time. Hence, our study shows that entry regulation under time-variant entry cost can be welfare improving due to postponing entry and generating entry cost savings.

We conduct further simulations in which we allow for time-variant entry costs but eliminate own learning and learning via spillovers. Our results show that entry regulation is not as harmful to consumer surplus and less harmful to other firms that faced delayed entry. We find that entry protection can improve producer and total welfare already for short lengths of entry protection.

Similar to Blonigen, Knittel, and Soderbery (2017), we also consider a simulation in which a social planner can make entry more or less costly. The social planner can charge a tax or provide a subsidy, both of which are commonly applied regulatory instruments in technology markets (see Das, Roberts, and Tybout (2007), Dasgupta and Stiglitz (1988), and Krugman (1984); further details are provided later). In our case, upstream manufacturers of production machinery are charged a tax or receive a subsidy, which changes the cost of purchasing production machinery (the entry cost) for SRAM producers. The changes of entry costs 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 attenuates (exacerbates) the problem of spending an excessive amount on early entry. Similar to entry regulation, taxes reduce consumer welfare, but they can serve as a total welfare-improving instrument (with declining entry costs) to prevent an excessive number of firms from entering too early at overly high entry costs.

The remainder of the paper is organized as follows: Section 2 provides a literature review. Section 3 describes the institutional features of the semiconductor industry and presents summary statistics. Section 4 introduces our dynamic oligopoly model, and Section 5 describes the econometric model. In Section 6, we discuss the estimation results and present welfare simulation results based on our dynamic model. We conclude in Section 7.

2 Literature Review

Several studies on market structure show that entry can drastically reduce prices. Prominent examples are Bresnahan and Reiss (1987, 1991), Campbell and Hopenhayn (2005), Carlton (1983), Davis (2006), Dunne, Roberts, and Samuelson (1988), Geroski (1989), Mazzeo (2002), Seim (2006), and Toivanen and Waterson (2000 and 2005). Studies also find that markets with free entry conditions can result in an excessive number of firms entering the market, which leads to inefficient production allocations and excessive entry cost payments (see also Barwick and Pathak (2015), Berry (1992), Berry and Waldfogel (1999), Hsieh and Moretti (2003), and Pesendorfer (2005)).[6] In contrast to previous studies, our study considers declining entry costs such that the timing of entry becomes an important aspect. In this regard, we not only consider whether too many firms enter the industry, but also whether too many firms enter too early.

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

Our research is closely related to several other 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 3 percent. Suzuki (2013) considers how planning regulations in the lodging industry affect entry. Moreover, Ferrari and Verboven (2010) and Schaumans and Verboven (2008) address the optimal number of firms in the context of regulation.

Turning to learning by doing, previous studies have shown that learning effects can exert strong effects on market structure and performance (see Benkard (2004), Fudenberg and Tirole (1983), Ghemawat and Spence (1985), and Spence (1981)). Learning provides a motive for a firm to increase production in order to gain experience and future cost savings. In regard to learning, firms will have to balance the following effects: (1) increase production to benefit from learning and cost savings; and (2) diminish production to limit price reductions via demand effects. In the presence of learning by doing, business-stealing effects can have welfare-reducing effects since an entrant steals output from an incumbent, slowing down its learning effect. An implication of the business-stealing effect is that learning curves can result in situations in which a concentration of production on one firm might result in larger cost savings and lower prices (see Dasgupta and Stiglitz (1988)). Learning can also erect entry barriers, reduce the number of operating firms, and increase the cost differentials among firms, resulting in higher markups (see Scherer (1980), and Spence (1981)). Learning-by-doing effects are especially high at the beginning of a life cycle, which provides firms with additional incentives to enter early and learn quickly (see Cabral and Riordan (1997)). Consequently, a social planner can increase total welfare by concentrating production on the first entrant—that is, protecting the first entrant from subsequent entry (see Dasgupta and Stiglitz (1988)). The fact that a social planner has the opportunity to improve economic welfare by restricting entry forms the basis of conducting entry simulations in our study.

Firms not only learn from their own experience, but also benefit from their competitors' experience spilling over through information transfers (see Irwin and Klenow (1994)). Ghemawat and Spence (1985) show that learning curve spillovers can have drastic effects on market structure and performance. For example, due to the public good character of spillovers, firms may underproduce relative to what is socially efficient (see also Roeller, Siebert, and Tombak (2007)). Spence (1981) has shown that spillovers can substantially attenuate entry barriers (erected by proprietary learning) and result in an increase in the number of firms entering the market (see Ghemawat and Spence (1985)).

Entry regulations can be socially desirable (see Schaumans and Verboven (2008)). Governments enact entry policies that grant firms the right to exclusively serve a market for a limited period of time. For example, the government grants innovators intellectual property rights that temporarily protect them from entrants (see Nordhaus (1969) and Lerner (2002)). Other policies require firms to acquire licenses for entering markets (such as the mobile spectrum (see Klemperer (2002)) and medical provider markets, among many others). In general, a large number of markets—including airlines, telecommunications, petroleum, pharmaceutical, railroads, and utility services (gas, electricity)—face entry regulations. Policy debates often center on the impact of entry regulations on economic welfare. Proponents argue that entry regulations help prevent excessive entry and wasteful duplication of entry costs. This especially applies to high-tech industries that are characterized by high entry costs. Opponents are concerned that entry restrictions reduce competition and result in higher prices.

Markets characterized by learning effects (such as aircraft, semiconductors, and shipbuilding) are often subsidy recipients. The aim is to establish national champions while concentrating production on a few established firms. Examples are the support of consortia (such as SEMATECH), production joint ventures (as formulated in the National Cooperative Research and Production Act from 1993), and the introduction of entry taxes (see Dasgupta and Stiglitz (1988) and Krugman (1984)).

3 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.

3.1 The SRAM Industry

It is frequently highlighted that the semiconductor industry has a significant impact on productivity growth, since semiconductors serve as an input for 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.[7] Firms are not able to claim patents on the capacity of information storage on memory chips; rather, their patents protect process innovations. Hence, firms file patents mostly for new process technologies, rather than for new products. The production managers we interviewed confirmed that patents granted refers to new manufacturing processes rather than memory capacity.[8] We interpret this as supportive evidence that SRAM memory chip generations are characterized by free market entry.

SRAM chips with higher storage capacities often require better manufacturing technologies. They require new production machinery 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. It is also worth noting that the production of memory chip generations is plant-specific, as every generation requires a specific production machinery. The new production machinery is developed and manufactured in upstream markets by companies such as Advanced Dicing Technologies, Advantest, Axcelis, Plasma-Therm, and Teradyne, among others.[9] These machinery manufacturers are different than the semiconductor chip manufacturers. Therefore, SRAM producers consider the development of semiconductor production machinery (and entry cost) as exogenous.

The installation of new fabrication plants with new production machinery and equipment requires a substantial amount of capital. Production equipment is costly, and more than half of

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

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

[9]For a list of the 10 best semiconductor machinery suppliers (large and focused suppliers), see *www.vlsiresearch.com*.

the cost is spent on the production equipment that produces memory chips.[10] Our interviews with experts and managers in the industry confirmed that cost of capital in equipment is the main determinant of entry, and that cost of capital is very high. For example, in 2004, Hynix, Samsung, Intel, Micron, and Toshiba each announced capital spending of around $5 billion or more.[11]

Interviewees also confirmed that the cost of production equipment declines drastically over time due to a depreciation in the value of the capital stock over time, such that older machines sell for less. With the intention of providing 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.[12] In fact, several companies, such as Fabsurplus and LEL International, specialize in supplying used semiconductor equipment.[13] These companies specialize in selling used semiconductor wafer production equipment.[14]

Institutional features—such as the establishment of the used semiconductor manufacturing equipment market, semiconductor manufacturing equipment producers posting prices online, and the nonexistence of price discrimination across purchasers—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 enter at later periods.

The memory chip manufacturing process is highly complex. To improve a chip's performance, it is necessary to use advanced photolithographic and chemical processes to etch electrical circuits onto the wafer surface. Memory chips are cut from silicon wafers, which makes silicon the main material that enters the wafer fabrication processes. Silicon prices can have a strong time-varying effect on marginal costs.

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

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

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

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

[14]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.

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. It is well established that learning by doing effects can have a sizable impact on production costs in memory chip markets.[15] With learning by doing, firms have higher incentives to further increase production in order to achieve future cost reductions. Therefore, we need to incorporate this essential feature of the SRAM industry in our model. Manufacturers in the downstream market consider learning by doing when determining their production, as higher production leads to future cost reductions, and this is endogenously accounted for by SRAM manufacturers. This is different than entry costs that evolve exogenously, as they stem from the development of production machinery in upstream markets. Therefore, the evolution of production costs and entry costs can be considered independent processes.

3.2 Data Description

Our dataset is compiled by Gartner Inc., and includes quarterly data on the SRAM industry from January 1982 until December 2003, where time periods refer to quarters. The dataset encompasses product generations with firm-level and market-level units produced, the average selling price at the market level, and the number of firms in the market. Figure 1 shows how industry shipments of one generation evolve over time.[16] It is interesting to relate the price decline (as shown in Figure 2) to the entry pattern (as shown in Figure 3). 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 changes in market structure and competition are relevant in this industry and need to be accounted for. A further potential reason for the drastic price

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

[16] 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.

decline could be that firms experience large cost reductions over time due to learning effects.

Figure 3 shows the entry pattern of the 64Kb SRAM chip generation over time. The SRAM industry is characterized by successive entry. 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 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 3 shows that firms enter throughout the life cycle and pick different dates to enter a certain generation.[17]

Table 1 demonstrates annual descriptive statistics. It shows that the maximum number of firms (34 firms) is reached in 1989 (see column (1)), which is consistent with the number of entrants that peaks between 1985 and 1989 (see column (2)). Firms start exiting the product generation in 1986 (see column (3)). The average firm-level production (column (4)) has a bell shape and reaches its maximum in 1995. In years when many firms enter (1985, 1986, 1988, and 1989), the average firm-level production rates increase more slowly. This is explained by the fact that new entrants usually start with low production volumes and also cannibalize demand of incumbent firms. This argument is also reflected in the evolution of the maximum production over time (column (7)). The large number of entering firms in 1988 and 1989 causes the largest firm to reduce production, an observation that supports the existence of strategic interactions between firms in the industry. Interestingly, the large number of entering firms in 1985 and 1986 is associated with a production increase of the largest firm. One reason for the post-entry firm-level production growth might be that entry occurred at the early stage of the product life cycle when the market expanded rapidly. During the second part of the life cycle (after 1995), the average firm-level production monotonically declines, while the minimum production (column (6)) is larger compared to the one in the first part of the data period. This indicates that entrants in later periods are able to choose larger production volumes, which could be explained by large learning effects from other firms via spillovers. Moreover, smaller firms exit the market.

[17] 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 Ackerberg and Gowrisankaran (2006), Einav (2010), Genesove (1999), Gowrisankaran and Stavins (2004), Schmidt-Dengler (2006), and Sweeting (2006 and 2009).

The average cumulative firm-level production increases rapidly until 2001 (see column (8)). The significant drop in the average cumulative production in 2002 and 2003 indicates that some of the largest firms exited the product generation. The large values of the minimum cumulative production (see column (10)) during the second part of the data periods show that mostly smaller firms exited the product generations. The increasing maximum cumulative production throughout the life cycle (column (11)) indicates that some of the largest firms continue to operate in the product market.

4 Dynamic Oligopoly Model

In this section, we introduce our dynamic oligopoly model. We construct a discrete-time infinite horizon model.[18] Time is indexed by $t = 0, 1, \ldots, \infty$ and firms are denoted by $i = 1, 2, \ldots, N$.

The model is formulated as a state space game in which firms use Markov perfect strategies. Firms maximize the sum of profits over all periods. 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. Each decision period is one quarter. We build on the fact that firms are rational and forward looking, as they derive their discounted profits given the evolution of the state vector and their actions.

4.1 Production, Entry, and Exit Decisions

Firms make entry, production, and exit decisions. As mentioned in the industry section, the production of a chip generation requires specific production machinery. We therefore concentrate on firms' production choices for the $k = 64Kb$ generation (generation k subscripts will be suppressed for most parts) and operate under the assumption that firm behavior in this generation is representative also for other generations.[19] An extension to more than one generation

[18]Note that the assumption of an infinite time horizon is well suited in our context due to the following market characteristics: First, the market is characterized by large learning effects that imply strong cost savings and price reductions over time, see Figure 2. The dramatic price reductions narrow price-cost margins and drive firm values close toward zero in the long run. This implies that the infinite time horizon assumption would not cause large differences compared to assuming a finite time horizon. Relatedly, Figure 3 shows that the industry is characterized by a large number of firms successively entering the market, which puts downward pressure on price and reduces markups and profits. Finally, newly launched (successive) generations of memory chips attract customers imposing further downward pressure on the price of the current generation and reduces firm value.

[19]Our industry description introduces several facts that support this assumption. We would not able to test this assumption due to data constraints and leave this for future research.

would make our model intractable and goes beyond the scope of this paper since it requires 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.[20] We would like to emphasize that skipping generations is not observed in our data. Moreover, as mentioned earlier, the consideration of one product generation in firms' objective function is justified by the fact that different product generations are produced at different fabrication plants. Therefore, firms' output decisions are usually made at the fabrication plant level.[21]

Regarding firms' entry decisions, potential entrants decide at the beginning of each period whether to enter the $64Kb$ generation. Entering a product generation requires firms to incur an entry cost that reflects the necessity to invest in production machinery as described earlier. The entry cost is defined as the sum of two parts, that is, $C_t + \phi^e_{it}$. The first part of the entry cost (C_t) is a deterministic part, 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.[22] The second part of the entry cost (ϕ^e_{it}) 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, independently and identically distributed across firms and across periods—and decide how much to produce, denoted by q_{it}.[23] Firms account for learning by doing effects and consider that their current production has a po-

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

[21]Note, even though the examination of preemption strategies is an interesting and important topic, is has to be left for future studies that concentrate on markets with fewer firms.

[22]Remember, the new production machinery is developed in upstream markets (outside the SRAM market) such that the evolution of entry costs is considered exogenous.

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

tential cost-reducing effect on their future marginal costs.[24] On a side note, one difficulty when estimating dynamic oligopoly models with learning by doing is that the model implementation of learning requires that firms' production decisions have an intertemporal impact on costs. This requires us to embed the product market choices into a dynamic framework (see also Benkard (2004)). In our study, firms make forward-looking production decisions while taking future cost reductions via learning into account. Learning by doing implies that firms determine their production according to dynamic marginal costs which lie below static marginal costs (see also Harris and Siebert (2017)).[25] Hence, firms' production choices and the marginal costs become part of the dynamic model.

Every period, incumbents decide whether to exit the market or not. Exit incurs a scrap value, κ, that is constant and identical to all firms. We also assume that exiting incumbents remain permanently inactive in the market.[26]

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}), 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, firms' decisions depend on the realizations of the state variables. 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 raise concerns about 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. See, for example, Krusell (2004) and Sorger (2015) for a theoretical justification.[27]

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

[25]In most 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.

[26]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.

[27]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^e_{it}) and makes its entry decision. Each incumbent observes its private productivity shock (ν_{it}) and makes its production and exit decisions. Exiting firms collect a scrap value κ. 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 (production, 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^e_i) 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, $\sigma_i(s, \epsilon_i) = \chi^e(s, \phi^e_i)$, where $\chi^e(s, \phi^e_i) = 1$ indicates whether potential entrant i chooses to enter at state s given the private entry cost shock ϕ^e_i. For incumbents, $\sigma_i(s, \epsilon_i) = (\chi^{ex}_i(s), q_i(s, \nu_i))$, where $\chi^{ex}_i(s) = 1$ indicates that the incumbent decides to exit at state s.

4.2 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:

$$n_t = n_{t-1} + \sum_i \chi^e_{it} - \sum_i \chi^{ex}_{it}. \tag{1}$$

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

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 time. 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 $t-1$, that is, q_{it-1}:[28]

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

We assume that a firm's experience is zero before entry.

Firm i's learning from spillovers (x_{-it}) is measured as follows:

$$x_{-it} = x_{-it-1} + q_{-it-1}, \tag{4}$$

where x_{-it-1} represents the accumulated production experience (until $t-1$) of other firms than firm i divided by the number of other firms in the market The same rationale applies to the industry output (q_{-it-1}). Hence, learning via spillovers are defined at the industry average. The accumulated production experience is set to zero at the beginning of the product cycle.

[28]This production is accumulated across all firms, which is similar to the accumulation process adopted in Ryan (2012). Note, equations (1) to (3) represent deterministic transition functions rather than transition probabilities.

Finally, we account for firm i's production experience in the previous generation (x_{it}^{k-1}), which follows the same law of motion as the own learning variable.

4.3 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 are suppressed)

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

where $P(s)$ refers to the SRAM price, which is a function of industry production and the demand shifter (the price of a substitute (P^S)), and $mc_i(s)$ refers to firm i's marginal cost function. Hence, firm i's per-period profit depend on the actions of all firms, the state vector, and firm i's productivity shock. An inactive firm earns zero profit. A firm exiting the market receives a scrap value, κ, which is assumed to be constant across firms.

4.4 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 collects the scrap value and 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:

$$\begin{aligned} V_i^I(s, \sigma, \nu_i) = \max\{&\max_{q_i}(P(s) - mc_i(s, \nu_i))q_i + \kappa, \\ &\max_{q_i}(P(s) - mc_i(s, \nu_i))q_i + \mathbb{E}\big[V_i^I(s', \sigma, \nu_i') \mid s\big]\}. \end{aligned} \tag{5}$$

Note that the first argument refers to an incumbent firm's profit if it decided to exit. The second argument refers to an incumbent firm's discounted profit 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 profit is 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:

$$V_i^E(s,\sigma,\phi_i^e) = \max\left\{-\phi_i^e - C + \beta\mathbb{E}\big[V_i^I(s',\sigma,\nu_i') \mid s\big],\ \beta\mathbb{E}\big[V_i^E(s',\sigma,\phi_i'^e)|s\big]\right\}. \tag{6}$$

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,

$$V_i(s,\sigma_i^*(s),\sigma_{-i}^*(s),\epsilon_i) \geq V_i(s,\tilde{\sigma}_i(s),\sigma_{-i}^*(s),\epsilon_i), \tag{7}$$

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 $\tilde{\sigma}_i(s)$.

5 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 simulations to compute the value of waiting. Finally, we will conduct welfare evaluations that consider the impact of entry regulation, taxes, and subsidies on consumer, producer, and total surplus.

A valid alternative method to Bajari, Benkard, and Levin (2007) would be the oblivious equilibrium concept of Weintraub, Benkard, and Roy (2008). One advantage with this method is that it more easily deals with the relatively larger number of firms. The drawback with adopting this method specifically in our case, however, is that it would ignore strategic interactions in production. Strategic production interactions are an important feature in our study due to the presence of learning by doing. The strategic aspect of learning-by-doing requires that each firm anticipates how its own current production affects its own future costs and other firms' costs and production, see Fudenberg and Tirole (1983).[29] Therefore, we eventually decided using the method by Bajari, Benkard, and Levin (2007), while accounting for strategic interactions in learning and production.

There are several technical and economic complications that require us to impose restrictions on the supply side such as entry into one generation, namely, the $64Kb$ generation.[30] First, the consideration of multiple generations would imply a necessity to consider additional strategic entry considerations such as preemption and deterrence motives, as mentioned above. This would render the algorithm intractable. Second, even a focus on one generation causes difficulties to solve the Bellman equation 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. Third, we also account for learning by doing effects, which implies that firms set their optimal production according to dynamic marginal costs which lie below static marginal costs and this further complicates the estimation routine. Finally, time-variant entry costs further complicates the estimation routine as firms experience a value of waiting.[31] Further related information follow in Section 6.3.

[29] Note that the earlier description of Table 1 supports the notion of strategic interdependencies in the SRAM industry.

[30] The limitation to one generation is supported by institutional evidence that different product generations are usually produced at different fabrication plants.

[31] 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).

5.1 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

We estimate a demand model which will help us to predict prices when simulating value functions. The demand model is closely related to Ryan (2012), Siebert (2010), and Zulehner (2003), and is based on a constant elasticity of demand framework. Note, for tractability reasons, we adopt a static demand and assume myopic consumers. 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 unbiased estimate on the own-price elasticity for the $64Kb$ generation.[32]

A log-linear demand function is specified and estimated using industry-wide quantities (q_t^k) and prices (P_t^k) for generation k in period t:

$$\ln q_t^k = \beta_0 + \beta_0^k + \beta_1 \ln P_t^k + \beta_2 \ln P_{t-1}^{k,S} + \beta_3 time^k + d_t^k, \tag{8}$$

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.[33] The cross-price elasticity is denoted by β_2. Remember that price evolutions follow a non-stationary process (see Figure f-price) and drastically decline over time. Potential reasons for the price decline could be: (1) large cost reductions over time due to learning effects, and (2) a change in market structure due to successively entering firms (see Figure 3). We account for those

[32] 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 earlier.

[33] 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.

alternative explanations using instruments (further information is provided below). Moreover, we include a time trend (*time*) that controls for customer switching toward recently introduced successive memory chip generations as they become increasingly attractive over time. The instruments and the time trend allow prices to follow a stationary process. The error term d_t^k is assumed to be identically and independently distributed.

We estimate equation (8) using an instrumental variable estimator as 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 prices of the other memory chip generations as an instrument. Similar identifying assumptions and instruments have been used in other demand models. 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, similar to Berry, Levinsohn, and Pakes (1995). Relatedly, we use the (lagged) number of firms to capture the change in market structure, that is, the successive entry imposing downward pressure on prices. Third, we use the cumulative industry output for the generation under consideration ((x_t) as a proxy for industry wide learning by doing to capture downward shifts in marginal costs over time (see also Siebert (2010) and Zulehner (2003)). Moreover, we use a factor price as a traditional supply-side cost shifter, here, the price of silicon (P_t^{sil}) (see also Ryan (2012), Siebert (2010), and Zulehner (2003)). 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 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. Finally, we use the (lagged) GDP in electronics to control for shifts in downstream market demand.

Marginal Cost

The static marginal cost function for the $k = 64Kb$ generation is specified as (k subscripts are suppressed):

$$mc_{it} = \theta_0 + \theta_1 \hat{\gamma}_i + \theta_2 \ln P_t^{sil} + \theta_3 \ln x_{it} + \theta_4 \ln x_{-it}. \tag{9}$$

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 (10)). The variable x_{-it} measures learning from others.

Production Policy

The production policy is a descriptor for firms' production choices given firms' states. 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.[34] Therefore, the production policy is determined by the set of state variables that enter the static marginal costs (see equation (9)) and a component that captures the dynamic part of marginal cost pricing (beyond the state variables that enter the demand function). The dynamic component of the marginal costs is measured by time trends ($time$ and $time^2$) that capture intertemporal strategic effects and cost savings that will be 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. As a demand shifter, we include the substitute price (P_{t-1}^S).[35] 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 number of firms (n_{t-1}) as a state variable into the production relation.[36]

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

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

[36]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 do have an effect on the expected value function via firms' beliefs on the expected evolution of future market structure.

The production policy is specified as:

$$\ln q_{it} = \gamma_i + \gamma_1 \ln P_t^{sil} + \gamma_2 \ln n_{t-1} + \gamma_3 \ln n_t^{pe} + \gamma_4 \ln x_{it} + \gamma_5 \ln x_{-it} + \gamma_6 \ln P_{t-1}^S$$
$$+ \gamma_7 time + \gamma_8 time^2 + u_{it}, \quad (10)$$

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

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.

Entry and Exit Policies

We define firm entry as the first period a positive production is registered in our dataset. We estimate the following entry model using probit:

$$Pr(\chi_{it}^e = 1; s) = \Phi\Big(\lambda_0 + \lambda_1 \ln n_{t-1} + \lambda_2 \ln n_{t-1}^{pe} + \lambda_3 \ln x_{it}^{k-1} + \lambda_4 \ln x_{-it}$$
$$+ \lambda_5 \ln P_y^{sil} + \lambda_6 P_t^S + \lambda_7 time + \lambda_8 time^2\Big) \quad (11)$$

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 (x_{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 trends. 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 by the end of the data series.

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

$$Pr(\chi_{it}^{ex} = 1; s) = \Phi\Big(\psi_0 + \psi_1 \ln n_{t-1} + \psi_2 \ln n_t^{pe} + \psi_3 \ln x_{it} + \psi_4 \ln x_{-it} \\ + \psi_5 \ln P_t^{sil} + \psi_6 \ln P_t^S + \psi_7 time + \psi_8 time^2\Big), \quad (12)$$

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' exit decisions are dependent to what extent firms were able to benefit from own learning. Finally, firm i's production experience from the previous generation (x_i^{k-1}) is excluded from the exit policy.

Similar to the production policy, we instrumented for past accumulated output in the entry and exit equations using the same set of instruments.

5.2 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 costs using the potential entrants' optimality conditions.

Step one: Recovering marginal cost parameters

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

$$V_i^I(s, \sigma; \theta) = E\left[\sum_{t=0}^{\infty} \beta^t (P(s) - mc_i(s; \theta)) q_i^*(s) + \kappa \chi_i^{ex} \middle| s_0 = s, \sigma_{-i}\right] = W_i(s, \sigma) \cdot \theta, \quad (13)$$

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:

$$W_i(s_t,\sigma) = \mathbb{E}\sum_{t'=0}^{\infty}\beta^{t'}\Big[q_i^*(s_t)\Big[P(s_{t+t'}) \quad 1 \quad \hat{\gamma}_i \quad \ln P_{t+t'}^{sil} \quad \ln x_{i,t+t'} \quad \ln x_{-it'})\Big] \quad \chi_{it}^{ex}\Big] \tag{14}$$

and $\theta = [1 \quad -\theta_0 \quad -\theta_1 \quad -\theta_2 \quad -\theta_3 \quad -\theta_4 \quad \theta_5]$.

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:

$$W_i(s,\sigma_i^*,\sigma_{-i}^*)\cdot\theta \geq W_i(s,\tilde{\sigma}_i,\sigma_{-i}^*)\cdot\theta. \tag{15}$$

Next, we consider a minimum distance estimator defined as:

$$\hat{\theta} = \arg\min_{\theta}\frac{1}{N_I}\sum_{l=1}^{N_I}(\min\{0,g(\tilde{\sigma}_i^l;\theta)\})^2, \tag{16}$$

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 (as shown in equation (15)) is violated. We search for the marginal cost parameters that minimize the sum of the squared losses. 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 entrant's Bellman equation (6), we can derive the following condition:

$$\begin{aligned} Pr(\chi_i^e=1;s) &= Pr\Big(-\phi_i^e - C + \beta\mathbb{E}\big[V_i^I(s')\big|s,\sigma,\chi_i^e=1\big] > \beta\mathbb{E}\big[V_i^E(s')\big|s,\sigma,\chi_i^e=0\big]\Big) \\ &= \Phi\Big(-C + \beta\mathbb{E}\big[V_i^I(s')\big|s,\sigma,\chi_i^e=1\big] - \beta\mathbb{E}\big[V_i^E(s')\big|s,\sigma,\chi_i^e=0\big]\,;0,\sigma_e^2\Big), \end{aligned} \tag{17}$$

where $V_i^I(s)$ and $V_i^E(s)$ are the expected values from equations (5) and (6), respectively, involving the expectation of private shocks (ϵ_i).[37] The first line in equation (17) follows from equation (6), 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. Equation (17) shows that a potential entrant enters the product generation when the value of entry is greater than the value of waiting. Using our marginal cost estimates, we can compute the incumbent's expected value (V_i^I) conditional on entering at state s.[38] 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:

$$\mathbb{E}_{\epsilon_i}\pi_i^E(s,\sigma) = \begin{cases} -C - \tilde{\phi}_i^e, & \text{if } \chi_i^e = 1,\ h_i = 0; \\ \pi_i^I(\sigma_i, \sigma_{-i}, s), & \text{if } \chi_i^{ex} = 0,\ h_i = 1; \\ 0, & \text{otherwise,} \end{cases} \tag{18}$$

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, $\tilde{\phi}_i^e = \theta^E \cdot bsPr(\chi_i^e = 1; s)$, where $bs(\cdot)$ is the b-spline function, $Pr(\chi_i^e = 1; s)$ is the probability of entry at state s and θ^E contains parameters of the b-spline function.[39] 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 3).[40] Let $C_1, C_2, ..., C_{30}$ be the entry costs for these 30 time periods. 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

[37] That is, $V_i^I(s) = \mathbb{E}_\epsilon V_i^I(s,\epsilon)$ and $V_i^E(s) = \mathbb{E}_\epsilon V_i^E(s,\epsilon)$.

[38] 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.

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

[40] Our simulations cover the first 30 data periods from 1982, first quarter to 1989, second quarter (see Figures 1-3).

potential entrants' value function can be written as:

$$\begin{aligned} V_i^E(s, C = C_\tau, \sigma) =& \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t \mathbb{E}_{\epsilon_i} \pi_i^E(s, \sigma, \epsilon_i)\right] \\ =& \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t \mathbf{1}(h_{i,\tau+t} = 1)\big[P(s_{\tau+t}) - mc_i(s_{\tau+t})\big] q_i(s_{\tau+t})\right] \\ -& \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t Pr(\chi_i^e = 1; s_{\tau+t})\big[\theta^E \cdot bs(Pr(\chi_i^e = 1; s_{\tau+t})) + \zeta_0 + \zeta_1(\tau + t)\big]\right]. \end{aligned} \tag{19}$$

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 (13)) and V_i^E (from equation (19)), we can recover the entry costs by minimizing the difference of the two sides in equation (17):

$$\min_{\zeta_0, \zeta_1, \sigma_e} \frac{1}{N_0} \sum_{\tau=1}^{30} \sum_{i=1}^{n_\tau^{pe}} \Big[\hat{Pr}(\chi_i^e = 1; s) - \Phi\big(-\zeta_0 - \zeta_1 \tau + \beta \hat{V}_i^I(s') - \beta \hat{V}_i^E(s', C_\tau')\,; 0, \sigma_e^2\big)\Big]^2, \tag{20}$$

where N_0 is the total number of observations, $\hat{Pr}(\chi_i^e = 1; s)$ is the estimated probability of entry from the estimation of equation (11), and $\hat{V}^I$ and $\hat{V}^E$ are the estimated value functions obtained from forward simulations. For each of the first 30 periods, we consider each potential entrant as representing an observation. Then, for each observation, we can forward simulate its value of entry and value of waiting.[41] We search for the ζ_0, ζ_1 and σ_e that minimize the difference in the probabilities of entering.[42]

5.3 Discussion on Identification

Since we do not observe the marginal costs of production and the entry costs, we have to retrieve those from the data using our model. Our model describes a dynamic game that is estimated in two stages using the estimation method as proposed by Bajari, Benkard, and Levin (2007). In the first stage, we estimate firms' policy functions (entry, production, and exit) that describe firms' behavior at different states. In the second stage, we estimate marginal costs and entry costs using forward simulated discounted profits.

We begin with discussing the identification of the marginal costs of production and the learning effects. We assume that a firm's marginal cost is determined by own learning and

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

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

learning from others via spillovers, among other arguments (see equation (9)). Own learning is measured by a firm's accumulated past production, which is standard practice in the literature (see, for example, Zulehner (2003) and Siebert (2010)). One may raise the concern that the experience measure for own learning 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.

A firm's learning from spillovers is proxied by the accumulated production experience of all other firms divided by the number of other firms in the market (see also Irwin and Klenow (1994)). Hence, learning via spillovers is defined at the industry average. 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. Note that equation (9) contains the past experience and, therefore, describes the static part of the marginal costs. The production policy (equation (10)) includes the static part of the marginal costs as well as a dynamic component as captured by the time trends. The dynamic components account for the fact that firms rationalize future cost savings from learning effects since an earlier position in the life cycle increases firms' incentives to further increase output in anticipation of achieving future cost savings. Hence, firms set quantities according to dynamic marginal costs, which lie below the static marginal costs. The marginal cost parameters are identified using firms' rational profit-maximizing behavior. Based on firms' optimally chosen strategies, we forward simulate the incumbents' value function, as shown in equation (5), and we compare those with firms' simulated discounted profits based on suboptimal strategies. The marginal cost parameters are identified by minimizing the sum of squared losses (that is, marginal cost parameters are chosen such that firms' optimal policies generate the highest discounted profits). The identification of marginal costs is, therefore, strongly dependent on the production policy. The large number of firms and the large coverage of states in the data improves the identification of marginal cost parameters. Note, we assume that firms can enter a generation only once, such that incumbents' value functions are independent of entry costs.

Turning to the identification of entry costs, we assume that the first part of the entry cost (C_t) is deterministic, time variant, monotonically declining over time, and the same for all firms. 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. We identify entry costs by building on the fact that firms are rational and forward looking; they make their optimal entry decisions based on maximizing their discounted profits, as shown in equation (5). We then compare those discounted profits to the forward-simulated discounted profits when firms waited and entered at a later time period (see equation (6)). Rational profit-maximizing behavior implies that the discounted profit under the observed entry time is optimized and, therefore, higher than the profits associated with a later entry time. Based on this argument, we search over the set of entry cost parameters that rationalizes this argument using a minimum distance estimator (see equation (20)). 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 rate, ζ_1, since the simulated timing of entry given waiting is different from τ. Note that the assumption—exiting firms cannot reenter a generation—is necessary to avoid cases where incumbent firms would exit and reenter at a later point of time with zero entry costs as their entry costs were incurred already in the past. Hence, our identification strategy would not allow for reentry at zero costs. This assumption is not much of a concern since we do not observe any exiting firms in our dataset that reenter at a later point of time.

6 Estimation Results and Welfare Simulation

In this section, we describe our estimation results. We begin with discussing the estimation results for the demand and the production, 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 simulations.

6.1 First-Stage Results

Demand

The estimation of industry demand (equation (8)) is based on ordinary least squares and instrumental variable estimation techniques. In comparing the estimation results in Columns (1) and (2) of Table 2, the instrumental variable estimator returns more elastic price elasticities of demand than does 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 statistic returns an F-value of 619.99 for the first specification, and an F-value of 6.40 for the second specification. We, therefore, reject the exogeneity of prices in both specifications. The estimated own price elasticity is -3.35, 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 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 coefficient on the time trend ($time$) is significantly negative, indicating that consumers substitute away from purchasing a specific generation as time elapses. The significant time coefficient provides support for prices following a stationary process. We use the estimation results in Column (2) for our subsequent estimations.

Production Policy

We now discuss the estimation results of the production policy, as shown in equation (10). We estimate the production policy using an instrumental variable and an ordinary least squares method. The differences between the estimated coefficients from the instrumental variable and the ordinary least squares estimations are negligible. We also adopt a Hausman test that fails to reject the consistency of the ordinary least squares estimates. Moreover, the Hausman test statistic of 97.76 rejects the random effects specifications. Table 3 reports the estimation results. 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 coefficient estimates are significant at least at the 5 percent level. Our estimation results also return 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 on the price of adjacent generations (P^S) carries the expected sign, since firms' quantity supplied increases as the price of a substitute increases. The negative coefficients on the time trends indicate that dynamic marginal costs lie further below static marginal costs at the early stages of the life cycle. This supports the notion that firms more drastically increase output during the early stages of the life cycle to further benefit from future cost savings.

Entry and Exit Policy

We estimate the entry policy, as shown in equation (11), and the exit policy, as shown in equation (12), using probits. The results are shown in Table 4. 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}) have already entered the market. The significant and positive estimate of cumulative output in the previous generation (x_i^{k-1}) shows that a firm's production experience in the previous generation enhances productivity and increases 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 confirms theoretical findings (as mentioned in the literature review) 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 some intuition that entry costs are decreasing over time.

Column (2) of Table 4 shows the results for the exit policy. Firms are more likely to exit the generation if more 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, since firms are able to benefit from higher spillovers.

6.2 Second-Stage Results

Marginal Cost

We estimate the parameters of the marginal cost function (see equation (9)) using the minimum distance estimator (as defined in equation (20)). We adopt 50,000 forward simulations and 2,000 alternative strategies that are carried out over 120 periods. Table 5 shows that all coefficients carry the expected signs. Factor price and learning effects are the most significant factors in explaining the marginal cost of production. The negative coefficient estimate on learning (θ_3) provides evidence that marginal costs decline as a firm's production experience (x_i) increases. The estimate of learning via spillovers, however, is insignificant.

Entry Cost

The estimation results for the entry costs are shown in Table 6 and Figure 4. The first column of Table 6 shows the results if we assume a linear decline of entry costs. Our results provide evidence that entry costs decline rapidly over time. They decline by approximately 2.15 percent each year or by $40 million per quarter. The result of drastically declining entry costs over time provides evidence that firms can experience large entry cost savings by entering at a later period. Hence, firms consider an option value of waiting and decide on an optimal entry time as characterized by the trade-off: Enter early and earn high net profits due to lower competition or 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 was 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.

To test whether the linear entry cost is a good approximation, we conduct a robustness check and allow the entry cost to be characterized by two different slopes. The estimation results are illustrated in column (2) of Table 6. The decreasing rate of the first 15 quarters is slightly higher and that of the last 15 quarters is slightly lower than the rate in the linear specification. This finding confirms that machinery prices are relatively higher in the early periods of the product life cycle.

6.3 Welfare Simulations

To verify the economic importance of considering declining entry costs, we conduct several simulation exercises. In the first simulation, we consider time-variant entry costs and assume that a social planner can enforce entry regulation policies that protect the first entrant from other entrants for a limited number of periods. After the period of entry protection elapses, other firms can enter freely. In the second simulation, we consider the same entry regulation but assume time-invariant entry costs. In the third simulation, we again consider time-variant entry costs and eliminate learning and spillover effects and compare the results on consumer, producer, and total welfare with the unrestricted results. In the last simulation, we assume that the social planner can either charge a tax or provide a subsidy on the time-variant entry costs.

We apply a simulation approach similar to that of Blonigen, Knittel, and Soderbery (2017) and Das, Roberts, and Tybout (2007). That is, based on our structural cost estimates, we conduct welfare simulations under the assumption that the estimated policies properly describe firms' policies in the simulation exercises. We adopt this approach for the following reasons: First, Hashmi and Van Biesebroeck (2016) have shown 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. In studies like Hashmi and Van Biesebroeck (2016) and Ryan (2012), a solution of equilibria was feasible since only small markets with at most four firms have been considered. One possibility could be to limit the number of firms in our study to around four firms. While this could be a reasonable strategy for the microprocessor market (which is highly concentrated), it is not appropriate in our context. The SRAM market is not strongly concentrated, and it encompasses a large number of relatively similarly sized firms. The 64Kb SRAM generation encompasses more than 40 firms entering the industry, which involves a high computational burden to solve for equilibria; this renders it impractical for the generation. Hence, a limitation to a handful of firms would describe a substantial intervention into market structure that may cause drastic distortions when evaluating economic welfare.

It should also be noted that our model is more complex than the models by Hashmi and Van Biesebroeck (2016) and Ryan (2012), such that further challenges arise when solving the model. For example, our model includes learning by doing. Previous studies on learning have shown that concentration can have drastic implications on market performance. (We addressed those arguments in the literature review.) Therefore, we do not want to impose strong assumptions on the number of firms. A further complication arises with learning by doing since firms price according to dynamic marginal costs. Therefore, optimal policies not only have to account for production experience, but must also capture future potential cost savings. Several theoretical studies on learning (e.g., Fudenberg and Tirole (1983) and Ghemawat and Spence (1985)) show that analytical expressions quickly become impracticable, even in highly constrained model frameworks—such as symmetric firms, two periods, time-invariant entry costs, and linear demand. Moreover, declining entry costs over time further complicate the Markov Perfect Equilibria solution.[43]

We would also like to address another point: Entry costs are determined by the development of production machinery in upstream markets, so they are assumed exogenous for memory chip producers in the downstream market. This implies that our considered policy changes are unlikely to affect downstream memory chip producers, and we would not expect an adjustment in the development of production machinery. Hence, the evolution of entry costs follows an exogenous process from the perspective of the SRAM producers. This is different from Ryan (2012), where the Clean Air Act Amendments require firms to adopt advanced production processes having an impact on entry costs and fixed costs. The author, therefore, recovers parameters before and after the 1990 Amendments to reflect these changes.[44]

We are not aiming to solve for a socially (first best) entry timing; this is not feasible due to the large number of firms. Rather, our simulations should be understood as numerical comparative statics exercises on welfare that is tied to a structural model. We use these simulations to provide an understanding of how declining entry costs can affect welfare.

Welfare Simulation Results of Entry Regulation Policy

We begin with the entry regulation policy based on time-variant entry costs. We 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.[45] The right expires after a certain number of periods, as specified by the social planner. Once the entry regulation ends, potential entrants have the opportunity to enter

[43] As it does not require solving for the equilibrium, we adopt the two-step estimation strategy by Bajari, Benkard, and Levin (2007).

[44] Note that our simulations are still very complex and time intensive, as they run for several days on the supercomputer at Purdue University.

[45] 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 we constrain our simulation exercise to the one introduced here since we believe it is most closely related to real-world situations (such as granting intellectual property rights or licensing agreements to firms).

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, their optimal timing to enter the market, their production choices, and the resulting prices.[46]

To evaluate welfare effects, we simulate firms' entry, exit, and production decisions based on different entry protection durations. 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, consumer surplus monotonically declines with the duration of entry protection. This result provides evidence that the market power effect dominates own learning effects (via the concentration of all industry output on the entry protected monopolist). We should note that consumer surplus declines at a diminishing rate and does not decline much further after approximately 25 quarters of entry protection (when a sufficient large number of firms have entered).[47] This is because the impact on prices via competitive entry effects quickly diminishes (see Bresnahan and Reiss (1990 and 1991)).

Turning to the impact on producer surplus, Figure 5 shows a steady decline for entry protections that last less than six 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 six quarters. After six quarters of regulation, producer surplus begins to rise and even dominates the producer surplus under free entry if the protection period exceeds 14 quarters. With an entry protection of more than 23 quarters, entry protection can enhance total surplus compared to free entry.

To better understand the changes in producer and total surplus, we decompose the change in producer surplus into changes in the monopolist's profits (i.e., the profits of the protected firm), other firms' profit changes, and entry cost savings (see Figure 6). As the length of entry

[46] Our approach disregards the R&D innovation benefits of entry protection.

[47] We acknowledge that long-lasting entry protection might imply inaccuracies in predicting firms' choices, and they should be carefully interpreted.

protection increases, the protected monopolist's profit increases slightly (relative to the free entry case), but it is much smaller compared to other firms' losses, 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 3). Since firms learn from other firms' experience via spillovers, and those firms are highly efficient, 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 the fact that a longer entry protection period delays successive entry and reduces 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. The large entry cost savings explain that producer surplus starts to increase after six quarters of regulation. The entry cost savings even outweigh the loss from preventing other firms from entering the market. For sufficiently long-lasting entry regulations (more than 17 quarters), producer surplus is larger versus the free entry case.

In sum, the somewhat counterintuitive result that entry regulations 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 are dominated by the entry cost savings. Hence, the declining entry cost savings are sufficiently large, especially after six quarters.

Welfare Simulation Results for Time-Invariant Entry Costs

In the following simulation, we keep the entry cost constant over time and evaluate entry regulation effects on consumer, producer, and total welfare changes, relative to the realized welfare effects under free entry. Constant entry costs over time are a natural simulation since earlier studies usually assume time-invariant entry costs. As shown in Figure 7, a longer lasting entry protection period results in monotonically declining consumer, producer, and total surplus. Noteworthy is the fact that the producer surplus monotonically declines, which is different to the earlier simulation with time-variant entry costs where producer surplus increased after a certain length of entry protection. The monotonic reduction in the producer surplus results from the profit loss experienced by firms that were prohibited to enter; those profit losses dominate the profit gains earned by the protected monopolist (see Figure 8). (Note that time-invariant entry costs do not provide opportunities for entry cost savings from delaying subsequent entry since every firm pays the same entry cost independent of the timing of entry.) Hence, non-existent entry cost savings is the main reason why producer surplus monotonically declines as the length of entry protection increases. The monotonically declining producer and consumer surplus eventually result in monotonically declining total surplus as the length of entry protection increases.

Overall, our simulation shows that entry protection with time-invariant entry costs diminishes consumer, producer, and total surplus. This result is different to the simulation with time-variant entry costs where producer and total surplus can increase due to the fact that entry protection delays subsequent entry at high entry cost, and this saves on entry costs. Hence, our study shows that the assumption on the evolution of entry costs over time can result in rather differential outcomes and imply differential entry protection policies.

Welfare Simulation Results without Learning and Spillovers

The next simulation eliminates learning and spillover effects but considers declining entry costs over time. Figure 9 illustrates the effects of entry protection on consumer, producer, and total welfare changes relative to the free entry case. (Note, the figure corresponds to Figure 5 in the original simulation.) Noteworthy are the following findings: First, without learning and spillover effects, consumer welfare declines as the length of entry protection increases (see also Figure 11)). The reduction in consumer surplus is explained by diminished competition and price increases. The reduction in consumer welfare, however, is much smaller in this simulation compared to the first simulation (compare Figures 9 and 5, respectively). The reason is that there is an additional counteracting effect at work in this simulation where spillover effects are eliminated. Without spillovers, firms ignore negative competitive externalities and overcome production reductions due to a firm's concern that competitors would learn from its own production via spillovers. Consequently, without spillovers firms are encouraged to further increase production, which results in price reductions and improves consumer welfare. This counteracting effect explains why consumer welfare eventually diminishes at a slower rate compared to the first simulation.

A second noteworthy finding is that producer surplus monotonically increases in the length of entry protection, see Figure 9. This is different to the basic simulation (see Figure 5) where producer surplus declined for short periods of entry protection and then increased only after about six quarters. Remember, in the first simulation the reduction of producer surplus in early periods was mostly driven by the reduction of other firms' profits, that is, their foregone profits from not being able to enter (see Figure 6). When eliminating learning and spillover effects, however, the foregone profits of other firms are not as large (see Figure 11). Other firms experience smaller foregone profits here since they are not able to learn from others via spillovers, which lowers their profits.

Finally, it should be noted that entry cost savings in this simulation is somewhat comparable to the first simulation (see Figures 10 and 6). One difference, however, is that entry cost savings here have to compensate only smaller amounts of foregone profits. Consequently, producer surplus is monotonically increasing in the duration of entry protection; and this also applies to short protection periods.

Welfare Simulation Results of Tax and Subsidy Policies

We now consider a social planner who has the opportunity to charge a tax on the time-variant entry costs or to subsidize the time-variant entry costs. The purpose is to simulate the impact of these policy instruments on entry, exit, production, and welfare (net of tax and subsidy). In accordance with Blonigen, Knittel, and Soderbery (2017), a social planner can decide on a tax or subsidy that corresponds to making entry more or less costly, and this affects the probability of entry. 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. This changes the potential entrants' entry costs and their optimal timing to enter, as well as their production and exit decisions.

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 entry. Values above one reflect subsidies to firms, which reduce entry costs and facilitate entry.

The simulation results are illustrated in Figure 12. At the base case (where the value on the horizontal axis is one), the evaluated changes in consumer, producer, and total surplus are zero. The left panel of Figure 12 shows that an increase in the tax (corresponding to lower values on the horizontal axis) slightly diminishes 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 13). Consequently, production declines, prices rise, and consumer surplus diminishes. Producer surplus increases drastically as taxes increase (i.e., the tax value declines to 0.6). This is explained by higher entry costs and fewer firms entering early, which reduces excessive entry cost payments. Figure 12 shows strong entry cost savings for tax values around 0.6. If the tax increases further (i.e., the tax values fall below 0.6), few firms will enter, which results in few entry cost savings.

Turning to a subsidy (see the right panel of Figure 12), a higher subsidy (i.e., values on the horizontal axis exceed one) increases consumer surplus since more firms enter (see the upper dashed line in Figure 13). As a consequence, firms produce more, which lowers price and increases consumer surplus. Interestingly, when the government provides a subsidy on entry costs, 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 simulations show that changes in total surplus are primarily driven by entry costs savings (see Figure 6 and Figure 12). 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 further supports the relevance of accounting for time-variant entry costs.

7 Conclusion

This research examines 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, which 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.

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 production, entry, and exit policies as well as firms' marginal costs and entry costs. We find that entry costs decline by around 60 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.

With declining entry costs over time, our simulation results on entry regulation show that consumer surplus declines monotonically (compared to the free entry case) as the length of entry protection increases. Entry regulation can improve producer and total welfare if the length of protection is sufficiently long. This reason is that entry regulation can serve as a mechanism to prevent entry at early periods when entry costs are high. When eliminating learning and spillover effects, producer and total surplus gains are registered already for short lengths of entry protection. Hence, our welfare simulation results highlight that entry regulation can serve as a total welfare-improving instrument when entry costs decline over time.

In contrast, when entry costs are assumed time-invariant, the entry cost savings argument from postponing the timing of entry time does not apply such that regulation diminishes consumer, producer and total surplus. Hence, our study shows that the assumption on the evolution of entry costs over time can result in rather differential outcomes and imply differential entry protection policies.

Similar to entry regulation with declining entry costs over time, our results on the tax policy simulations show that tax policies can serve as an instrument to prevent excessive entry cost payments. Finally, our subsidy simulation results show that higher subsidies reduce total surplus as they trigger more entry at early stages where firms spend excessive amounts on entry costs. In contrast, the provision of subsidies increases consumer welfare as opposed to entry regulations and tax policies.

In sum, our study shows that declining entry costs over time can have drastic implications when evaluating the effect of entry regulation on total welfare. Our study provides the insight that entry regulation can serve as an instrument to avoid excessive "early" entry at overly high entry costs; this regulation can increase producer surplus, but it diminishes consumer surplus.

It should be noted that our time series ends in 2003. Given the rapid developments of technology markets, it is unclear whether the identified behavioral aspects and entry cost reductions also apply to more recent SRAM chip generations. Due to limited data availability, we will have to leave this aspect for future research.

Relatedly, it should be emphasized that the literature on research and development considers entry protection regulation as a way to reward innovating firms. Firms that spend resources on research and development are entry protected (e.g., with intellectual property rights such as patents) and have the opportunity to recoup their research investments. For further information on this topic, see Hashmi and Van Biesebroeck (2016). Our study shows that even in the absence of research and development investments, entry regulations can generate socially beneficial effects, and they can serve as an instrument to avoid excessive entry costs and contribute to entry cost savings.

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, electronics, and other capital-intensive markets. The question remains whether government regulations in those industries generate welfare results similar to those in our study, which we leave for future research.

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8 Appendix: Tables

Table 1: Descriptive Statistics

Year	Number of Firms	Number of Entry	Number of Exit	Avg. Firm Production Mean	Std.	Min.	Max.	Avg. Cumulative Firm Production Mean	Std.	Min.	Max.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1982	3	3	0	52	44	10	110	52	44	10	110
1983	6	3	0	692	862	10	2,450	718	902	10	2,560
1984	10	4	0	2,948	3,644	5	11,525	3,378	4,369	5	14,085
1985	19	9	0	3,238	5,556	1	18,920	5,016	9001	1	33,005
1986	25	8	2	4,266	8,752	15	32,815	8,075	16,783	15	65,820
1987	25	3	3	7,224	12,434	27	40,030	15,468	29,663	27	105,850
1988	30	7	2	7,060	10,619	5	39,413	19,239	37,291	5	145,263
1989	34	7	3	7,455	9,989	3	33,610	23,619	44,085	4	178,710
1990	31	2	5	8,703	9,528	2	33,136	33,993	53,636	47	211,846
1991	32	3	2	8,892	9,032	38	34,160	40,823	59,866	91	241,096
1992	30	0	2	11,203	12,690	100	56,440	56,702	70,636	191	263,326
1993	29	0	1	10,537	12,093	95	52,870	67,234	78,512	286	282,096
1994	28	1	2	8,409	9,102	76	40,280	77,303	85,938	362	299,646
1995	26	2	4	11,272	12,524	200	52,310	97,007	96,042	6,000	315,261
1996	25	1	2	7,099	8,707	119	33,147	98,723	100,855	800	339,073
1997	23	1	3	6,021	7,545	63	28,352	110,325	106,991	1,365	362,973
1998	17	0	6	6,615	8,537	266	36,173	120,173	113,877	4,355	399,146
1999	15	0	2	3,849	3,458	24	11,332	141,425	119,625	17,095	407,146
2000	13	1	3	8,717	11,502	133	43,389	141,126	138,158	540	428,746
2001	11	0	2	7,902	9,840	343	35,437	165,175	150,188	883	435,746
2002	11	0	0	2,110	1,494	21	3,987	137,980	147,990	4,870	439,146
2003	7	1	5	1,194	1,271	115	3,831	117,518	134,113	625	440,546

The table shows summary statistics for the 64Kb SRAM generation on the number of firms, entry, exit, average production, and average cumulative production.

Table 2: 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 table shows the estimation results of equation (8). 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 3: Production Policy Estimation Results

Variable	Output
Constant	4.306
	(3.034)
$\ln P^{sil}$	-0.335**
	(0.161)
$\ln n$	-1.104***
	(0.291)
$\ln n^{pe}$	-0.277
	(0.480)
$\ln x_i$	0.471***
	(0.038)
$\ln x_{-i}$	0.482 ***
	(0.069)
$\ln P^S$	0.211 *
	(0.121)
time	-0.008
	(0.031)
time^2	-0.00051 ***
	(0.00017)
Firm fixed effect	Yes
Number of observations	1,697
Adjusted R-squared	0.780

The table shows the estimation results of equation (10). 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 4: Entry and Exit Policy Estimation Results

Variable	Entry	Exit
	(1)	(2)
Constant	-26.169**	-22.939*
	(10.941)	(13.319)
$\ln n$	1.740**	4.473***
	(0.717)	(1.245)
$\ln n^{pe}$	4.573**	3.229 *
	(1.828)	(1.972)
$\ln x_i^{k-1}$	0.063***	
	(0.015)	
$\ln x_i$		-0.132***
		(0.033)
$\ln x_{-i}$	-0.269	-0.552
	(0.172)	(0.694)
$\ln P^{sil}$	-0.203	0.264
	(0.549)	(0.405)
$\ln P^{S}$	0.644 *	-0.489
	(0.347)	(0.385)
time	0.081**	-0.048
	(0.034)	(0.019)
time^2	0.00009	0.0011 *
	(0.0005)	(0.0006)
Number of observations	2,235	1,701
Pseudo R-squared	0.092	0.088

Table 4 shows the results for the entry and exit policies, as shown in equations (11) and (12). 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 5: Marginal Cost Estimation Results

Parameters	Estimates
Constant (θ_0)	6.892
	(15.137)
γ_i, Firm fixed effect (θ_1)	-0.116
	(0.1578)
$\ln P^{sil}$, Price of silicon (θ_2)	9.012^{***}
	(3.513)
$\ln x_i$, Learning (θ_3)	-5.678^{***}
	(1.871)
$\ln x_{-i}$, Spillover (θ_4)	-0.0078
	(0.019)
κ, Scrap Value (θ_5)	$2.156 \times 10^{6\ ***}$
	(8.837×10^{5})

Table 5 shows the estimation results of the marginal cost function, as shown in equation (9). 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 $50,000$ forward simulations. We randomly select $2,000$ alternative output strategies in the marginal cost estimation.

Table 6: Entry Cost Estimation Results

Parameters	(1)	(2)
ζ_0	$1.901 \times 10^{9\ ***}$	$1.841 \times 10^{9\ ***}$
	(5.721×10^{8})	(4.699×10^{8})
ζ_1	$-4.09 \times 10^{7\ ***}$	$-5.019 \times 10^{7***}$
	(4.739×10^{6})	(8.960×10^{6})
ζ_2		-3.596×10^{7}
		(3.200×10^{7})
σ_e	$1.230 \times 10^{7\ ***}$	$3.124 \times 10^{7***}$
	(2.268×10^{6})	(1.995×10^{6})

Table 6 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.

9 Appendix: Figures

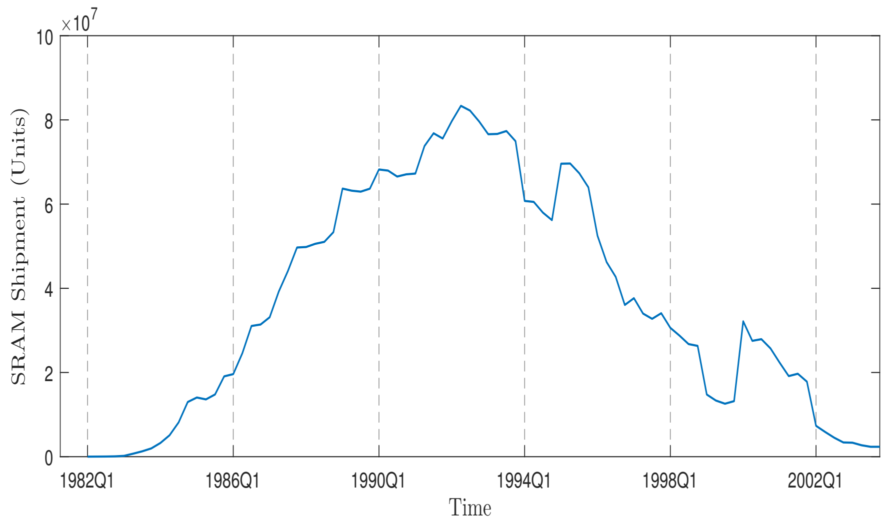

Figure 1: Industry units shipped for the 64Kb generation, 1982-2003.
Source: Gartner Inc.

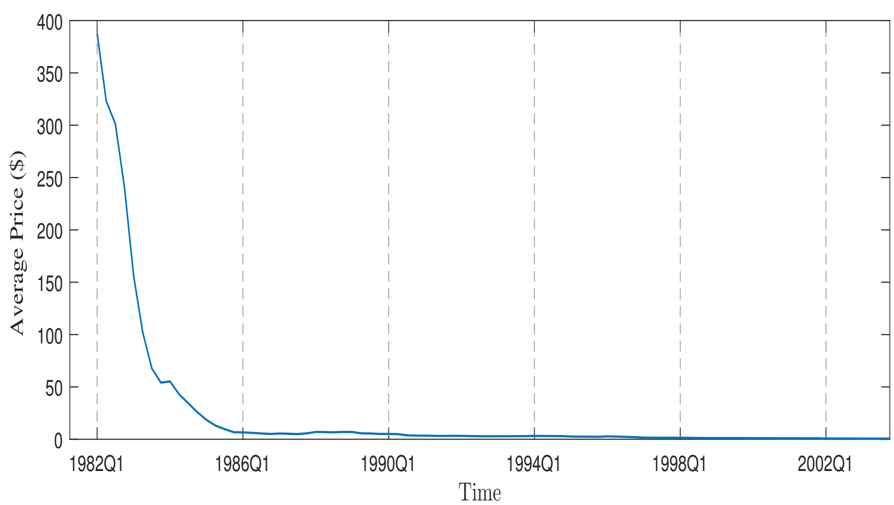

Figure 2: SRAM prices for the 64Kb generation, 1982-2003.
Source: Gartner Inc.

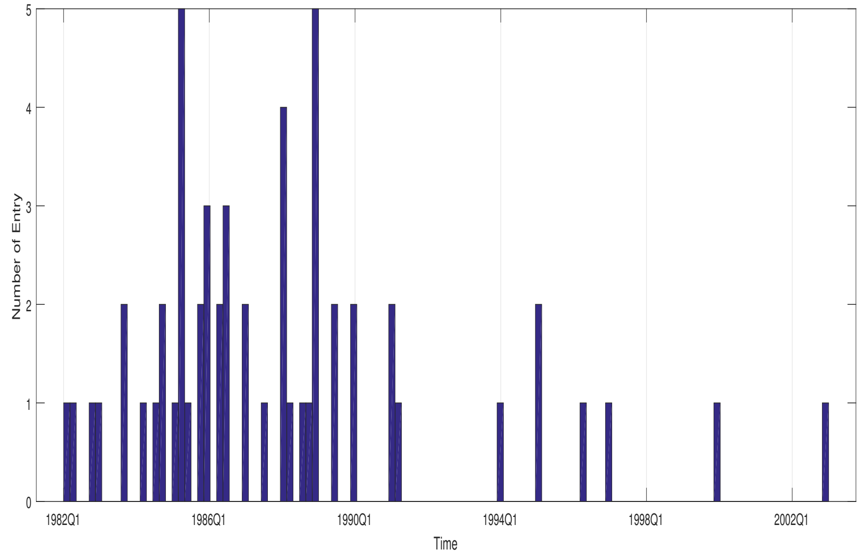

Figure 3: Distribution of Entry in the 64Kb Generation
Source: Gartner Inc.

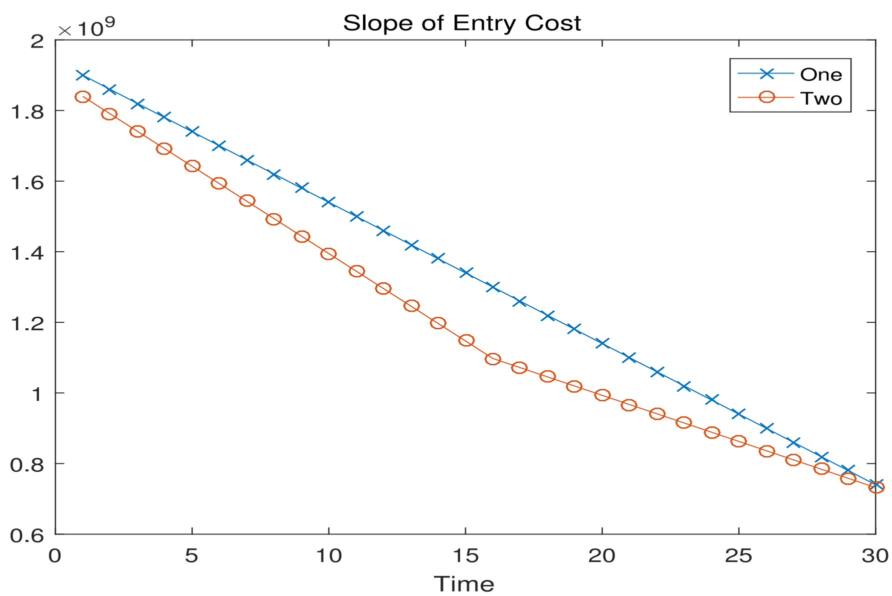

Figure 4: Entry Costs

All values are the discounted values at the timing of the first entry in U.S. dollars. We estimate the decreasing rates of entry costs for the first 30 quarters in which most of the entries occur, that is, from 1982Q1 to 1989Q2.

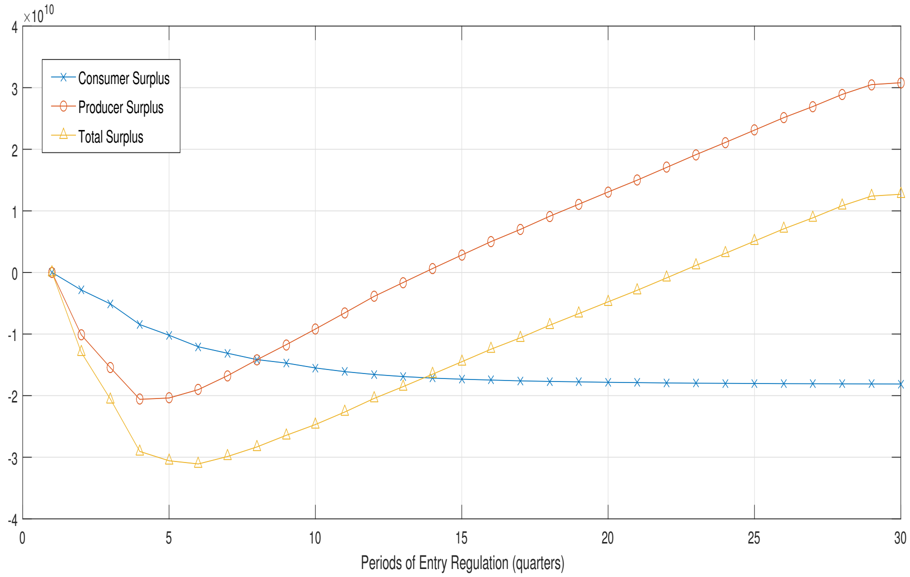

Figure 5: Change in Welfare

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

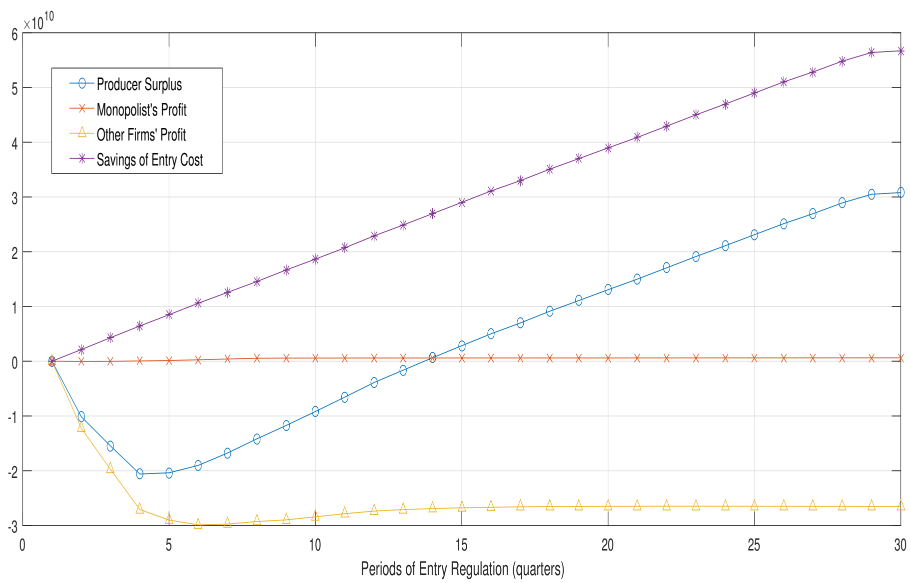

Figure 6: Change in Producer Surplus

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

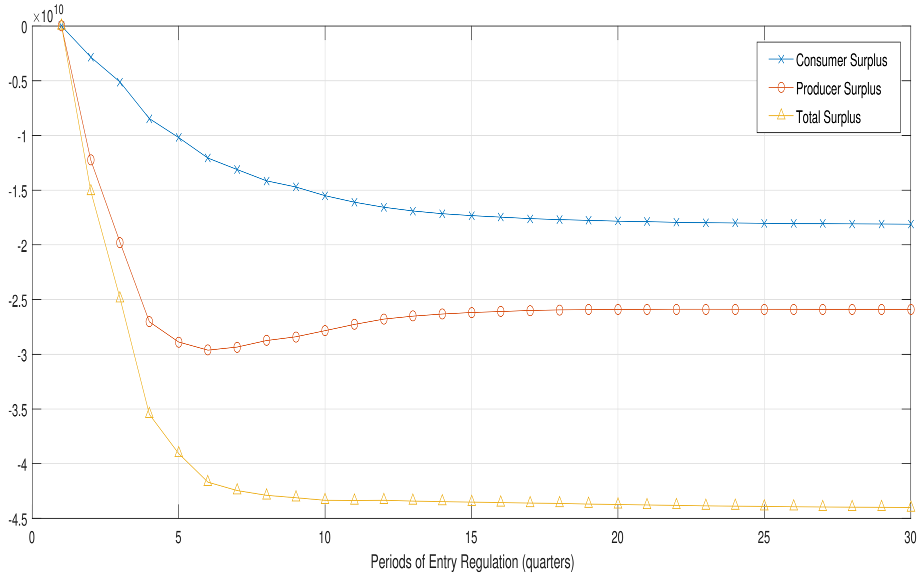

Figure 7: Change in Welfare

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

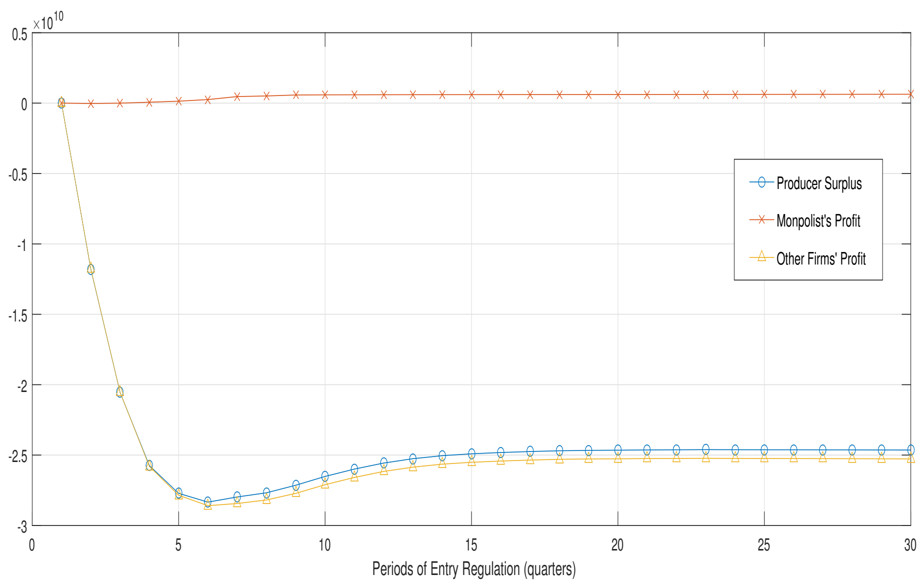

Figure 8: Change in Producer Surplus

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

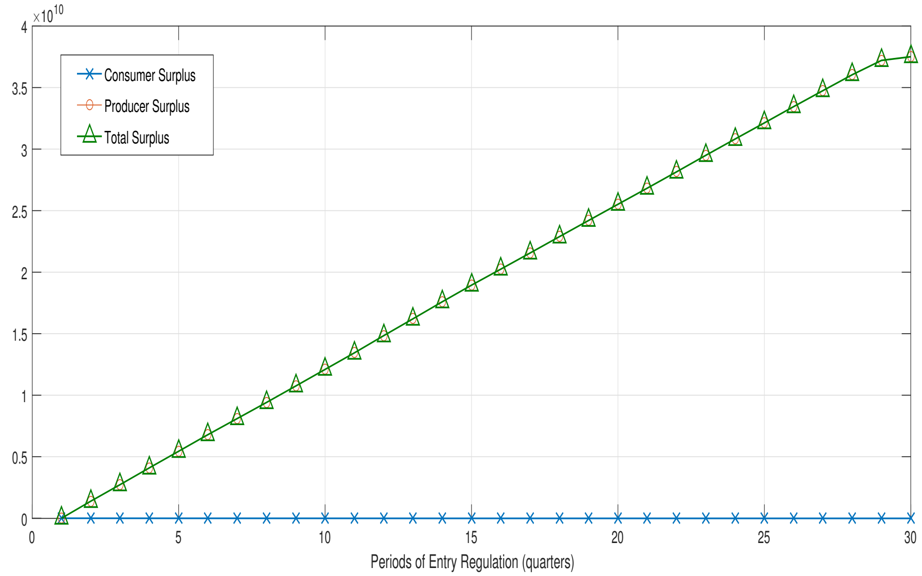

Figure 9: Change in Welfare

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

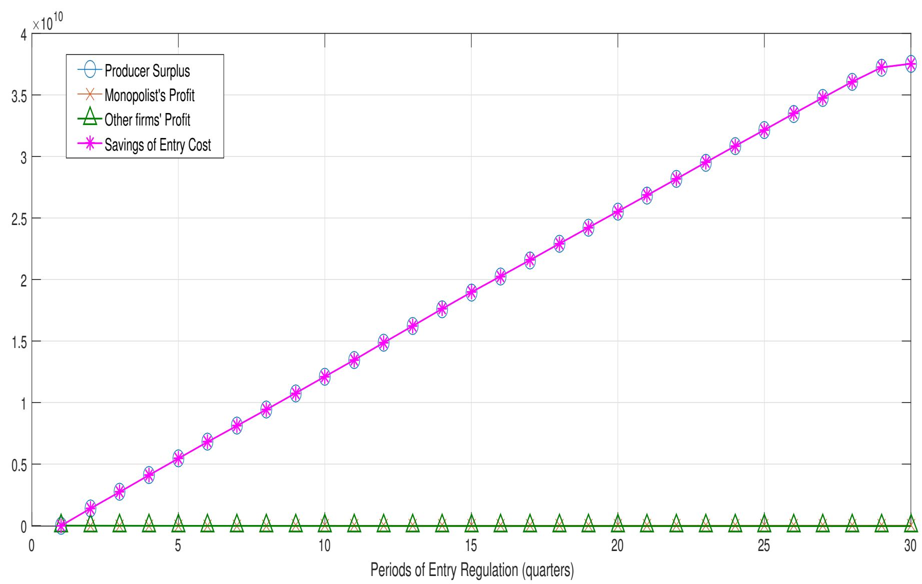

Figure 10: Change in Producer Surplus

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

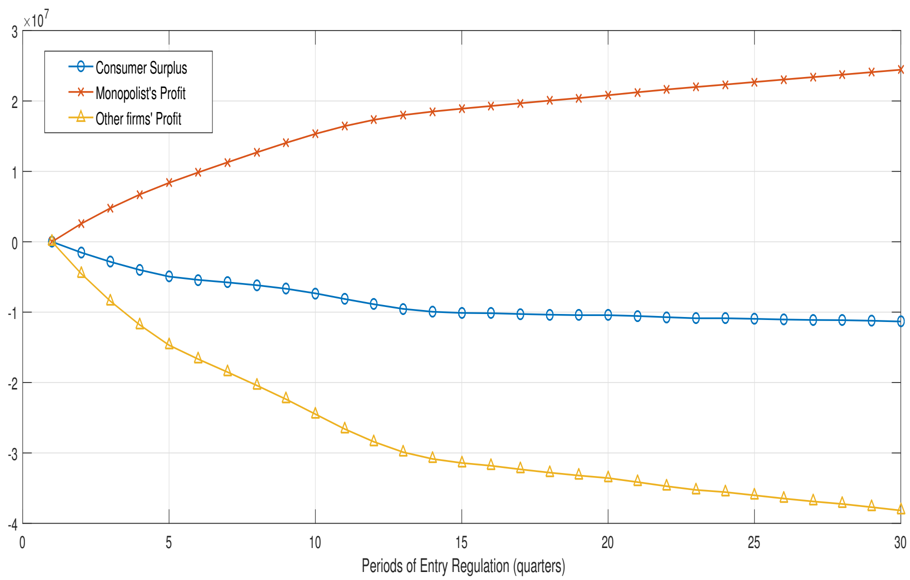

Figure 11: Change in Welfare

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

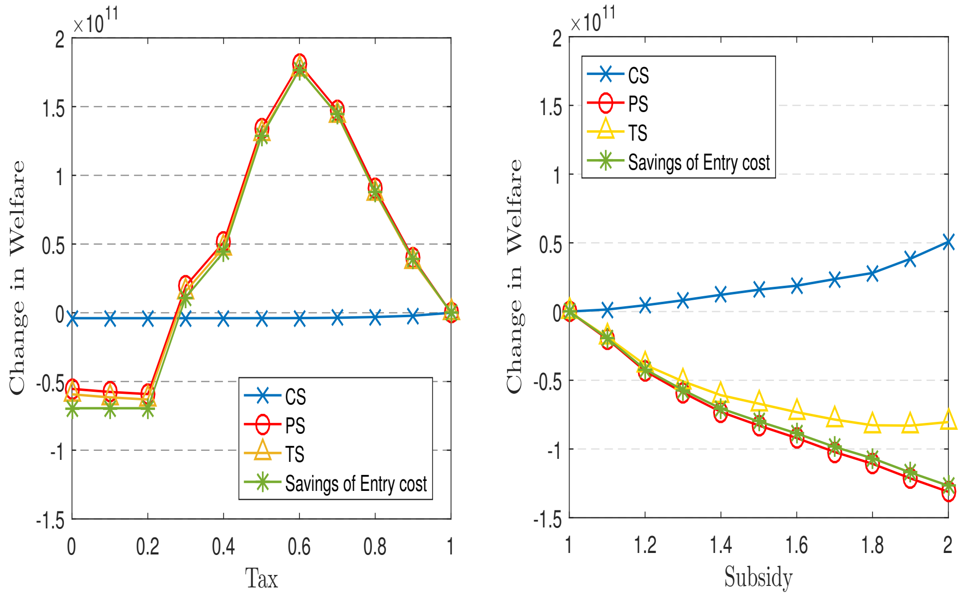

Figure 12: Change in Welfare

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

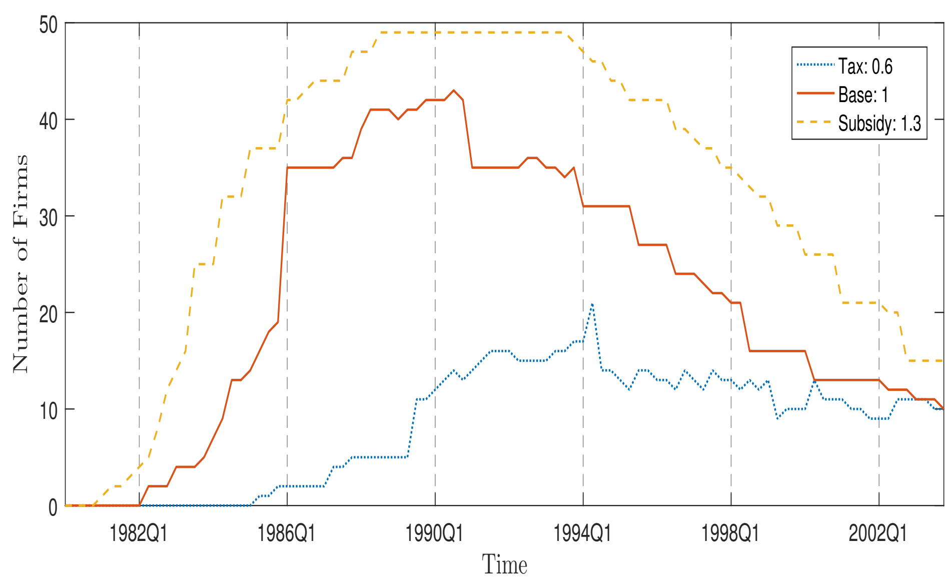

Figure 13: Number of Firms with a Tax and a Subsidy