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Heterogeneous Merger Impacts on Competitive Outcomes

Abstract

Mergers realize heterogeneous competitive effects on profits, production, and prices. To date, it is unclear whether differential merger outcomes are caused mostly by firms' technology or product market attributes. Furthermore, empirical merger studies conventionally assume that, conditional on regressors, the impact of mergers on outcomes is the same for every firm. We allow the merger responses to vary across firms, even after controlling for regressors, and apply a random-coefficient or heterogeneous treatment effect model (in the context of Angrist and Krueger (1999), Heckman, Urzua, and Vytlacil (2006), and Cerulli (2012)). Based on a comprehensive dataset on the static random access memory industry, we find that firms' postmerger output further increases (and postmerger price further declines) if merging firms are more efficient, operate in more elastic product markets, are more innovative, and acquire knowledge in technological areas that are relatively unexplored to themselves. A further interesting insight is that product market characteristics cause stronger postmerger outcome heterogeneities than do technology market characteristics. We also find that the postmerger effects accounting for heterogeneities differ greatly from those that consider homogeneous postmerger outcome effects. Our estimation results provide evidence that ignoring heterogeneous outcome effects can result in heterogeneity bias, just as ignoring premerger heterogeneities can lead to selectivity bias.

JEL-Codes: L110, L130, L520, O310, O320, O380.

Keywords: heterogeneous treatment effects, horizontal mergers, market power effects, merger evaluation, premerger heterogeneity, postmerger heterogeneity.

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1 Introduction

The evaluation of competitive merger effects is an important topic for firm managers and antitrust authorities. An established fact is that mergers realize different competitive outcomes on profits, production, and prices. Empirical merger studies explain heterogeneous merger effects as being caused by differential firm-level characteristics that are related to technology and product markets. To date, however, it is unclear whether differential merger outcomes are caused mostly by firms' technology or product market attributes. This study provides insights into the comparable impact that firm-level technology market and product market characteristics have on explaining heterogeneous merger outcomes. Moreover, empirical merger studies conventionally assume that –conditional on regressors such as technology and product market characteristics– the impact of mergers on outcomes is the same for every firm. In this case the marginal impact of mergers (or the parameter measuring merger responses) is assumed to be homogeneous across firms. In the merger context, assuming homogeneous merger responses is not innocuous, since firms differ in observed as well as unobserved attributes which determine their expected postmerger gains and competitive outcomes. For example, firms characterized by superior unobserved characteristics (e.g., managerial ability) that are more efficient before merger are also likely to achieve higher efficiency gains and beneficial competitive outcomes after merger compared to those merging firms that are characterized by inferior unobserved characteristics. Hence, mergers can exert differential postmerger effects on prices and quantities, even after controlling for regressors. In this case, the merger impact is heterogeneous across merging firms and the response parameter of interest is correlated with the merger variable, such that the merger parameter becomes firm-dependent. The case where the merger response varies across firms, even after accounting for regressors, is called the random-coefficient or heterogeneous treatment effect model. To the best of our knowledge, empirical merger studies usually assume homogeneous postmerger effects, i.e., merging firms achieves the same impact, conditional on covariates, while the random-coefficient or heterogeneous treatment effect model has received very little attention in measuring merger responses. This is surprising since recent empirical contributions in the treatment literature consider this type of heterogeneous treatment effect models and emphasize that ignoring the heterogeneous impact can result in a heterogeneity bias (see, e.g., Angrist and Krueger (1999), Heckman, Urzua, and Vytlacil (2006), and Cerulli

(2012)). More empirical insight is needed on the question whether mergers exert heterogeneous effects on competitive outcomes such as production and prices and whether the heterogeneous postmerger effects are driven mostly by firms' technology or product market characteristics.

A well-established fact in the empirical merger literature is that the impact of mergers is compromised by the fact that mergers are not randomly assigned. Firms make their decisions whether to merger or not in anticipation of the expected gains from merging (sorting on the gain) which are determined by firms' observed and unobserved characteristics such as technology market and product market attributes.[1] Firm heterogeneities cause systematic differences in firms' endogenous merger choices, which is also referred to as *premerger heterogeneity* (or pretreatment heterogeneity in the treatment literature) and estimated using selection models and instrumental variable models.[2] In case the selection mechanism is explained by unobserved characteristics, the selection models account for a potential correlation between the merger dummy and the error term in the outcome equation. As much as firm attributes determine expected gains from merging (sorting on the gain) and cause systematic differences in firms' merger choices, they also cause systematic differences in merger outcomes (also referred to as *postmerger heterogeneity*, *essential heterogeneity*, or *heterogeneous treatment effect* in the treatment literature), and this is what our study concentrates on.

Prominent merger studies emphasize the relevance of firms' technology and product market attributes when evaluating competitive postmerger effects. With regard to product market characteristics, several oligopoly studies on mergers highlight the importance of internalizing competitive external effects by merging firms and the output responses by its rivals (see Stigler (1950), Salant et al. (1983), and Farrell and Shapiro (1990)). Merging firms limit competitive negative externalities through output contraction, which (absent of efficiency gains) results in an industry output reduction and a post-merger price increase, also referred to as the market power effect. The extent to which merging firms internalize competitive external effects depends on price elasticities. Farrell and Shapiro (1990, page 114) and Froeb and Werden (1998) predict that mergers in more inelastic product markets, or mergers between firms offering less closely related

[1] For further information, see also Dafny (2009), Duso et al. (2007 and 2013), Gugler and Szuecs (2016), Hastings (2010), Houde (2012), Ashenfelter and Hosken (2010), Weinberg (2008), Miller and Weinberg (2014), and many others cited therein.

[2] Ignoring premerger heterogeneities can create selection bias and result in biased parameter estimates. In order to eliminate the pretreatment heterogeneity bias, studies adopt selection models (see, e.g., Heckman (1974, 1976a,b, and 1979) and instrumental variable models (see Imbens and Angrist (1994), Angrist and Imbens (1995), Manski and Pepper (2000), and Heckman and Vytlacil (1999), among many others).

products and characterized by lower cross-price elasticities, lead to further postmerger output contractions, lower postmerger output, as well as higher postmerger prices, markups and profits (see also Davidson and Deneckere (1984), Deneckere and Davidson (1985), Werden and Froeb (1994), Farrell and Shapiro (2001 and 2010), Katz and Ordover (1990), and Werden (1996)). Hence, the price elasticity of demand is an important characteristic that determines expected merger gains, merger choices and merger outcomes. The merger literature also emphasized other product market characteristics having an impact on the competitive effects of mergers such as differences in marginal costs across firms (see, e.g., Farrell and Shapiro (1990) and Froeb and Werden (1998)). If marginal costs differ, firms produce different volumes in Cournot equilibrium which explains different firm sizes. Merger studies highlight the fact that firms of different sizes cause different output responses by non-merging firms and require different amounts of efficiency gains to become profitable and restore premerger prices. Standard merger models show that mergers among large efficient firms are more profitable, further reduce postmerger output, and increase postmerger prices. This is explained by the fact that a merger between large efficient firms leaves smaller firms outside the merger and only a negligible output increase by outsiders is expected, which causes smaller output responses by competitors and eventually leads to an increase in postmerger prices and profits of the merging firms. Hence, larger efficiency gains are required to restore premerger prices.[3] Prominent studies such as Stigler (1950), Williamson (1968), Perry and Porter (1985), Farrell and Shapiro (1990), McAfee and Williams (1992), Froeb and Werden (1998), and Nocke and Whinston (2013) have shown that the merged entity must enjoy substantial efficiency gains to overcompensate market power effects such that postmerger prices are restored or will even fall.[4] Farrell and Shapiro (1990, Proposition 1) mention a necessary and sufficient condition for mergers to reduce prices, i.e., if the markup of the merging firm is higher than the sum of the markups of the separate firms (all evaluated at premerger equilibrium quantities), then postmerger prices will fall. Their condition can be rewritten such that necessary cost reductions to restore prices are dependent on the sum of the merging firms' marginal costs, i.e, more efficient merging firms require larger cost reductions. A further merger

[3]Under the U.S. Hart-Scott-Rodino Act, large firms must report any proposed substantial merger to the Department of Justice and the Federal Trade Commission.

[4]The 1984 U.S. Horizontal Merger Guidelines (and the revision from 1992) emphasize the consideration of postmerger efficiency gains in evaluating merger impacts and allow for an efficiency defense. Efficiency arguments were incorporated into the U.S. Merger Guidelines Amendments (Section 4) from 1997 and the European Merger Guidelines in 2004 (Article 77) (see also Motta (2004), Brouwer (2008), and Jovanovic and Wey (2012)).

argument is given by mergers among asymmetric firms offer an opportunity to gain efficiencies by rationalizing production and reallocating output to the facility with lower marginal costs, also referred to as short run economies of scale. The reallocation allows production at a lower unit cost and reduces postmerger prices.

Turning to technology market characteristics, mergers among firms that are more closely related in the technology market provide opportunities to gain synergy effects and learn from each others' technologies which describe positive externalities having an impact on merger choices and merger outcomes. In contrast, a merger between firms less closely related in the technology market can be beneficial to the merging parties since new knowledge is quickly acquired. To what extent these effects generate heterogeneous competitive outcomes is an empirical question.

To summarize, firms differ in unobserved and observed attributes in product markets and technology markets such as managerial ability, price elasticities, relative efficiencies, and synergy effects. Those firm attributes can cause heterogeneous gains from merging which affect firms' merger choices and competitive merger outcomes such as firms' postmerger production or pricing outcomes. Heterogeneous effects of mergers on competitive outcomes can be caused by internalization of competitive externalities by merging firms, output responses by competitors, exploitation of short run economies of scale and synergy effects, and these effects are presumably different across merging firms. The heterogeneity of postmerger outcomes can be ambiguous and is an empirical question.

Several empirical merger studies account for premerger heterogeneities and evaluate the (homogeneous) competitive impact of mergers by focusing on merging firms themselves (see Banerjee and Eckard (1998), Gugler et al. (2003), and Mueller (1997) for an overview). A different approach is to evaluate the reaction of non-merging firms (Dafny (2009) and Duso et al. (2007 and 2013)). For example, Gugler and Szuecs (2016) investigate whether mergers exert profit externalities on competitors. Based on accounting data and information on firms' profitability as a proxy to control for competitive effects, they find that mergers lead to positive profit externalities on rivals. While studies such as Gugler and Siebert (2007) and Dafny (2009) apply instrumental variable methods, other studies use difference-in-difference estimation and employ propensity score matching to establish causality in the evaluation of mergers (see Egger and Hahn (2010) and Ornaghi (2009), among many others). The list of prominent empirical merger contributions is long and includes studies such as Dockner and Gaunersdorfer (2001), Mueller (1980 and 1985), Goldberg (1973), Baldwin and Gorecki (1990), Ravenscraft and Scherer (1987), Gugler et al. (2003), Sweeting (2010), Nevo (2001), and Ciliberto, Williams, and Zhang (2016), among many others.

Our study builds on a comprehensive database that contains detailed firm-level information on mergers, shipments, and patents in the static random access memory market. To consider nonuniformity in response to merger choices, we build on a random coefficient or heterogeneous treatment effects model as suggested by Heckman et al. (2006) and Cerulli (2012). It should be noted that matching estimators (which build on the pairwise stability equilibrium concept) are valid alternatives in estimating the selection equation, but they would not enable us to evaluate the heterogeneous postmerger competitive effects. In a similar context, it should also be noted that a fully structural dynamic oligopoly model faces the problem of endogenizing mergers while accounting for strategic dynamic aspects in merger formation. We therefore chose a model framework related to the heterogeneous treatment effects models. We find substantial postmerger heterogeneities affecting the impact of mergers on competitive outcomes. Our results provide evidence that firms' postmerger output further increases (and postmerger price further declines) if merging firms are more efficient, operate in more elastic product markets, are more innovative, and acquire knowledge in technological areas that are relatively unexplored to themselves. We find that product market characteristics have a much stronger impact on heterogeneous postmerger outcome effects than do technological characteristics. Our estimation results also confirm that postmerger effects accounting for heterogeneities differ greatly from those that consider homogeneous postmerger outcome effects. Our estimation results provide evidence that ignoring heterogeneous outcome effects can result in heterogeneity bias, just as ignoring premerger heterogeneities can lead to selectivity bias. Our results also show that premerger firm heterogeneities are important for describing firms' merger incentives. More specifically, firm-pairs that are located in the same region, operate in product markets characterized by more inelastic demands, have more similar marginal costs, are more efficient, are more innovative, and operate in less related technological areas have higher incentives to merge.

The remainder of the paper is organized as follows: Section 2 introduces the industry and the data sources and provides summary statistics. In Section 3, the empirical model is introduced, and Section 4 presents the empirical results. We conclude in Section 5.

2 Industry and data descriptives

Memory chips define the largest market within the family of semiconductors.[5] Memory chips are designed to store data in binary form and include static random access memory (SRAM), dynamic random access memory (DRAM), mask read-only memory (mask ROM), erasable programmable read-only memory (EPROM), electrically erasable programmable read-only memory (EEPROM), and flash memory chips. SRAMs are a key input for electronic goods, such as computers, workstations, communication systems, and graphic subsystems. Bits in an SRAM chip are stored on four transistors that form two cross-coupled inverters. Memory cells flip-flop between zero and one without the use of capacitors. Information is stored using a static method in which the data remain constant as long as electric power is supplied to the memory chip. Access to information takes place only when it is required, without the need to constantly access all information. Since SRAMs store data statically, no refreshing process is needed. This is different from DRAM chips, which store data dynamically and constantly need to refresh the data stored in the memory. This is one reason why SRAM chips are preferred in electronic devices where energy efficiency is a concern. SRAMs are commonly used in smaller applications, such as CPU cache memory and hard drive buffers. SRAMs are also used in other consumer electronics, such as automotive electronics, household appliances, and synthesizers, as well as handheld electronic devices like digital cameras and cell phones.

SRAM chips are classified into generations according to their information storage capacities, i.e., the number of bits per chip. The evolution of information storage capacity is determined by an underlying technological progress described by Moore's Law. According to this law, the number of transistors per chip doubles every two years. A consequence of Moore's Law is that the number of transistors results in a fourfold increase in memory capacity per chip. The increase in memory capacity per chip across generations is, therefore, determined by a constant technological relationship.

Memory chips are produced on wafers that have silicon as the main material. The manufacturing process of SRAM chips is characterized by advanced photolithographic and chemical

[5]For more details regarding the description of semiconductor products, see Gruber (2000).

processes used to etch electrical circuits onto the wafer surface. The process is highly complex, and manufacturing processes are continuously improved for every product generation with the purpose of reducing material waste and production costs. The production yield rate for a new product generation (defined as the percentage of wafers that successfully pass all production stages) starts at around 20 percent and drastically increases throughout the life cycle. Hence, the manufacturing process for each generation is characterized by significant learning-by-doing (or dynamic economies of scale) effects (see also Fudenberg and Tirole (1983) and Siebert (2010)). The cost of producing an SRAM chip is determined in large part by the price of silicon and the learning-by-doing effects.

The SRAM market constitutes a perfect base and provides a natural setting for studying pre- and postmerger heterogeneities for several reasons. First, mergers are an important strategic instrument and are performed widely in this market. Second, the SRAM product market is defined at a highly disaggregate level and is characterized by well-categorized memory chip generations that differ according to their memory storage capacity. Previous studies assumed that SRAMs within a product generation are homogeneous, while they are differentiated across product generations. At one point in time, only a limited number of generations are offered in the market such that the estimation of cross-price elasticity is constrained to a small number of generations. This keeps the demand estimation relatively simple and facilitates the evaluation of postmerger outcome effects without further complications arising from the demand side. Third, for every generation, our dataset encompasses detailed firm-level production and price information. This allows us to evaluate pre- and postmerger heterogeneities at the level of product generations which define the unit of observation in our study. Moreover, the highly detailed firm-level information across different SRAM generations enables us to consider firms' costs for every generation. Fourth, the concentration level of the SRAM market is not critically high from an antitrust perspective. This serves as an advantage in our study, since merging firms would not expect to be subject to antitrust investigations. Merging firms are, therefore, not only encouraged to form mergers with the purpose of achieving efficiency gains, but also to form mergers that result in postmerger price increases from dominant market power effects. Hence, heterogeneous merger incentives and heterogeneous merger outcomes are not restricted to comparing merging firms with non-merging firms, but they also become relevant for evaluating heterogeneities across merging firms themselves. Finally, the innovative activity of firms is well documented through patents classified into different classes. Highly detailed and classified patent information allows us to develop a proxy for technological spillovers and to measure firms' relatedness in the technology market. To summarize, the detailed firm-level information enables us to properly control for firms' technology and product market attributes.

We gathered data on the worldwide SRAM market from 1974 to 2003. The data were collected from a variety of sources and include firm-level information on production, mergers, and patents. Highly disaggregate production and price information at the firm-level is provided on a quarterly basis by Gartner, Inc.[6] This information is available for several product generations, namely the 4K, 16K, 64K, 256K, 1MB, 4MB, 16MB, and 64MB generations. Table 1 shows the shipments, revenues, patents, and GDP in electronics across all generations.[7] In general, we observe increasing trends until 2000, which is mostly explained by high demand for computers and handheld devices. Table 2 shows the means and standard deviations of variables of interest across generations. Figure 1a shows the evolution of shipments for every generation over time. Generations are typically considered to be homogeneous within a generation and heterogeneous across generations (see also Irwin and Klenow (1994), Siebert (2010), and Zulehner (2003)). Figure 1b shows that the prices of every generation decline (relatively monotonically and continuously) over time. The prices start to decline soon after a new generation has been introduced into the market. This smooth price decline over time supports the fact that learning effects are prevalent. Table 3 shows the market shares of the top-performing firms aggregates across all SRAM generations over the last five years. Figure 2 shows the number of firms across different generations. On average, less than 20 firms are present in one generation. The low number of firms provides evidence that SRAM is a strategic industry that is well characterized by an oligopolistic market structure.

We collected information on horizontal mergers from the Thomson Reuters SDC Platinum database, and we include mergers with a deal value of $1 million and greater.[8] Remember, firms are active in multiple generations, which provides us with a large number of competitive

[6]The production units are measured in thousands.

[7]Due to space constraints, we report only the latest 14 years. The information on the GDP in electronics is taken from the Bureau of Economic Analysis. Monetary values are deflated using the consumer price index, defining 1990 as the base year.

[8]A horizontal merger is characterized by acquirers and targets being active in the static random access memory market. We excluded vertical mergers, as this allows us to relate closely to existing theoretical and empirical studies.

merger outcomes. Given the fact that most merging firms operate in multiple generations (four generations on average), we are able to investigate the competitive impact of a merger for each generation, which results in 56 merger observations. Table 4 shows descriptive statistics for merging firms at the time they formed a merger and non-merging firms at the same time a merger was formed. It is interesting to note that the merging firms' production in generation k and period t (q_{ikt}) is on average about 50 percent higher than the non-merging firms' production.[9] Figure 3a shows a scatter plot of the merging firms' market shares at the time they formed a merger. The figure shows that firms of various market shares engage in merging. Figure 3b displays the corresponding scatter plot of the nonmerging firms' market shares measured at the same time periods. The figure supports the fact that the market shares of merging and nonmerging firms do not show a distinct pattern. This observation gives rise to the fact that merger selection on unobservables should be considered in our study. Figure 4a shows a scatter plot of the changes in the merging firms' market shares at the time of merging and one period later. While some merging firms' market shares increase, pointing toward resulting postmerger efficiency gains and price declines, other merging firms' market shares decrease, hinting toward dominant market power effects and postmerger price increases. The figure provides insights that mergers in the SRAM industry achieve heterogeneous postmerger effects on market shares and suggests the relevance of going beyond summary statistics and applying econometric regression analyses. To gain further insight on postmerger effects on production, we conducted a simple difference-in-difference estimator, i.e., the change in production (at the time of merging and one period after merging) of the merging firms minus the change in production of the non-merged firms measured at the same time periods returned an estimate of -156 with a t-value of -2.42.[10] This means that merged firms reduced their postmerger production compared to non-merging firms. We should keep in mind that this method ignores pre- and post-treatment heterogeneity, which we consider later.

We use SRAM patent information at the firm level from 1974 to 2003. The patent information was procured from the U.S. Patent and Trademark Office (USPTO), and we retrieved patents that have been applied for and subsequently granted.[11] The USPTO has developed a highly

[9]The production is accumulated across all SRAM generations.

[10]Remember that production units are measured in thousands.

[11]The patent information is contained in the National Bureau of Economic Research patent database. A large name-matching effort was undertaken to match the names of patenting organizations and the names of

elaborate classification system for the technologies to categorize the patented inventions. It consists of about 400 main (three-digit) patent classes. To identify the SRAM patents, we linked the technological classifications to the SRAM industry using the correspondences by the USPTO. Table 4 shows that the merging firms have twice as many annual SRAM patents ($Patents$) as non-merging firms.

We proceed establishing variables that capture firm heterogeneities in the technology market, which is important since a merger between more closely related firms in the technology market is an opportunity to benefit from synergy effects and technological spillovers, which determine merger choices and merger outcomes.[12] In order to measure potential synergy effects and technological spillovers between firms, we follow other innovation studies (Jaffe (1986), Bloom et al. (2013), Kaiser (2002), Duso et al (2014), Siebert (2015), and Correa and Ornaghi (2014)) and measure the proximity between two firms in the technology market. A closer technological proximity between merging firms proxies for higher potential synergy effects and technological spillovers between these firms. In contrast, a merger can provide an opportunity for firms to acquire new knowledge in technological areas that are less related to their own. In this case, firms that are active in rather different technological areas. We use the uncentered correlation coefficient to measure potential synergy effects in the technology market and identify the technology classes (c) associated with the SRAM market. Considering firm-pairs (denoted by j) for every period t, the potential synergy effects ($SynEff$) between two firms $i, l = 1, \ldots, n$ and $i < l$ is defined by:

$$SynEff_{jt} = \frac{\sum_c Patents^c_{it} * Patents^c_{lt}}{\sqrt{\sum_c Patents^c_{it} * Patents^c_{it}}\sqrt{\sum_c Patents^c_{lt} * Patents^c_{lt}}}, \tag{1}$$

where $Patents^c_{it}$ and $Patents^c_{lt}$ refer to firm i's and firm l's number of patents in technology class c in period t. The variable takes on values between 0 and 1. If merging firms have an incentive to acquire new knowledge in different technology areas, the synergy effect variable $SynEff$ is approaching zero. A higher value corresponds to firm-pairs having more patents

manufacturing firms, including 30,000 of their subsidiaries (obtained from the *Who owns Whom* directory). The U.S. is the world's largest technology market, and non-U.S.-based firms also frequently file for patents in the U.S. (see Albert et al., 1991). We excluded individually owned patents.

[12]Spillover is involuntary information or knowledge transfer between firms. The information transfers are due to reverse engineering, industrial espionage, or employee turnover. High technological spillovers are prevalent when the R&D investments by one firm exert a positive externality on other firms and they experience benefits such as unit cost reductions.

in the same technological classes and represents a closer technological proximity and proxies higher technological spillover and synergy effects.[13] Table 4 shows the descriptive statistics for the synergy effect variable $SynEff$. The mean of the $SynEff$ variable for firm-pairs that merged in period t is higher than the mean of the non-merging firm-pairs evaluated at the same time periods. Interestingly, the standard deviation of the variable for the merging firms is higher (0.41) than the one for the non-merging firms (0.36). Hence, some firms prefer to merge with firms in closely related technological areas, which enables them to benefit from synergy effects. Other firms rather merge with firms that are active in different technological areas, with the intention of acquiring access to new knowledge in different technological areas.

In the context of synergy effects , we control for the fact that firms with more innovation experience and larger patent stocks have a higher ability to absorb knowledge via technological spillovers, see also Cohen and Levinthal (1989) and Veugelers and Cassiman (1999). Table 4 shows that the merging firms' SRAM patent stock ($SAbsCap_{jt}$) is twice as large compared to non-merging firms.

3 Empirical model

The purpose of our study is to emphasize the relevance of accounting for firm heterogeneities on merger choices and merger outcomes. In the following, we introduce and explain the origins and implications of the pre- and post-treatment heterogeneities. The aim is to allow for nonuniform merger responses across firms (i.e., the postmerger heterogeneities that can be caused by heterogeneities in marginal costs, price elasticities, innovative activity, and technological proximity), even after controlling for regressors. We consider $i = 1, ..., n$ firms. We follow the model descriptions by Heckman et al. (2006), Wooldridge (2010), and Cerulli (2012) and introduce a random coefficient or heterogeneous treatment model. We use q_{1i} to denote the outcome (such as quantity or price) of firm i when it merges, and q_{0i} is the outcome when it does not merge. We are interested in estimating the treatment effect of a merger on the outcome $TE_i = q_{1i} - q_{0i}$. The problem is that the identification of TE_i is not possible since the analyst can observe just one of the two outcomes, but not both events by the same firm at the same time. The observed

[13] We also used various alternative measures of $SynEff$, including the use of each firm-pair's patent shares instead of the number of patents *per se*.

outcome is:

$$q_i = q_{0i} + M_i(q_{1i} - q_{0i}),$$

where M_i is a dummy variable that equals 1 if the firm merges and 0, otherwise. The outcomes are written as:

(a) $q_0 = \mu_0 + v_0$, where $E(v_0) = 0$ and μ_0 is a parameter

(b) $q_1 = \mu_1 + v_1$, where $E(v_1) = 0$ and μ_1 is a parameter

(c) $q = q_0 + M(q_1 - q_0)$.

By substituting (a) and (b) into (c), we get the switching model:

$$q = \mu_0 + M(\mu_1 - \mu_0 + v_1 - v_0) + v_0. \tag{2}$$

Using a regression model:

$$q = \alpha + \beta M + e, \tag{3}$$

where $\alpha = \mu_0$, $\beta = (q_1 - q_0) = \mu_1 - \mu_0 + v_1 - v_0$. The estimation of equation (3) with OLS can cause two potential biases that are caused by firm heterogeneity. First, the selection bias refers to merging firms being atypical in their unobservables $e = v_0$. Hence, firms with better unobservables are the ones that merge ($Cov(M, e) \neq 0$). Second, the β parameter is usually assumed to be the same across (merging and non-merging) firms, and our study concentrates on this heterogeneity in merger outcomes, which is not well explored yet. This is important in the merger context, since firms make their merger decisions with knowledge about their expected gain (sorting on the unobserved gain). Firms' distinct unobservable attributes likely have an impact on the outcome, which leads to a potential correlation between β and the merger dummy M. The coefficient $\beta = (q_1 - q_0) = \mu_1 - \mu_0 + v_1 - v_0$ varies even after controlling for regressors, also referred to as *essential heterogeneity* or the *heterogeneous treatment effect*. We want to allow the merger coefficient β to be heterogeneous. Referring to equation (2), denoting a set of regressors by x and assuming that $v_1 \neq v_0$ and v_1 and v_0 are independent of the instrumental variable z:

$$E(v_0|x, z) = E(v_0|x) = g_0(x) \text{ and}$$

$$E(v_1|x, z) = E(v_1|x) = g_1(x).$$

It is equivalent to write:

$$v_0 = x\beta_0 + e_0 \text{ with } E(e_0|x, z) = 0 \text{ and}$$

$$v_1 = x\beta_1 + e_1 \text{ with } E(e_1|x, z) = 0.$$

Substituting v_0 and v_1 and $u = e_0 + M(e_1 - e_0)$ into the previous switching regression equation for q, we get the outcome equation:[14]

$$q = \mu_0 + \alpha M + x\beta_0 + M(x - \bar{x})\beta + u,$$

where $\beta = \beta_1 - \beta_0$, $\bar{x}$ is the sample mean of x, and the heterogeneous treatment effect (or postmerger heterogeneity effect) is $\hat{\alpha} + (x - \bar{x})\hat{\beta}$. Since M is a potential endogenous variable, we use a switching regression framework, where z is an instrumental variable that does not directly affect the outcome (but does indirectly via its effect on M). Hence, the selection into mergers is described by a threshold measurement model where M_i^* represents the likelihood that firm i forms a merger, where $M_i = 1$ if $M_i^* \geq 0$, and 0 otherwise,

$$M^* = \theta_0 + \theta_1 x + \theta_2 z + a \geq 0. \tag{4}$$

Using $E(a|x, z) = 0$, $a \sim N(0, 1) \implies \sigma_a = 1$, and $p = (x, z)$ we can write:

$$E(q|x, z, M) = \mu_0 + \alpha M + x\beta_0 + M(x - \bar{x})\beta + \rho_1 M \frac{\phi(p\theta)}{\Phi(p\theta)} + \rho_0(1 - M)\frac{\phi(p\theta)}{1 - \Phi(p\theta)}, \tag{5}$$

where $\rho_1 = \sigma_{e_1}\sigma_{a,e_1}$ and $\rho_0 = \sigma_{e_0}\sigma_{a,e_0}$. To get consistent and efficient estimates, we apply a multistep estimation procedure opposed to a simple IV estimation, and that involves the estimation of the selection equation (4) and the outcome equation (5). It should be noted that matching estimators (which build on the pairwise stability equilibrium concept) are valid alternatives in estimating the selection equation, but they would not enable us to evaluate the heterogeneous postmerger competitive effects. In a similar context, it should also be noted that a fully structural dynamic oligopoly model faces the problem of endogenizing mergers while accounting for strategic dynamic aspects in merger formation. We therefore chose a model framework related to the heterogeneous treatment effects models. We now turn to describing our empirical model specification.

3.1 Empirical model specification

We closely connect to the empirical model earlier and account for pre- and postmerger heterogeneity using the proposed method by Heckman et al. (2006) and Cerulli (2012). Premerger heterogeneity relates to the fact that firm attributes are correlated with the merger dummy. We

[14] See also Cerulli (2012) for further details.

control for this and estimate a selection equation as shown in equation (4). Postmerger heterogeneity refers to the fact that (merging) firms achieve different outcomes, a potential correlation between the β coefficient and the merger dummy, as mentioned earlier. To estimate heterogeneous postmerger competitive effects, we estimate an outcome equation as shown in equation (5).

Heterogeneous (post)merger effects

One challenge with estimating the competitive effect of mergers on prices is that price information is rarely available at the product level, frequently suffers from aggregation biases, and does not incorporate price discounts that have been offered to buyers. It is a rather common problem that price information is less reliable than production information. Following Farrell and Shapiro (1990, page 111), we examine the effect of a merger on aggregate output, which is the central question if merger analysis is concerned with consumer welfare.[15] Note that merger studies have shown that the postmerger change in industry output goes toward the same direction as the change in merging firms' postmerger output. Hence, the relationship between merging firms' change in output can be used to make inferences about the change in price. If merging firms reduce postmerger output, we can infer that postmerger price increases and vice versa. Hence, the main equation of interest evaluates how firm heterogeneities affect postmerger output, which is sufficient for drawing conclusions on postmerger prices.

We consider $i = 1, \ldots, n$ firms which are allowed to be heterogeneous in attributes such as marginal costs, price elasticities, innovative activity, and technological proximity. We form firm-pairs, denoted by a subscript j, between firms $i, l = 1, \ldots, n$ and $i < l$ in market k and quarter t. We establish a merger dummy that takes a value of 1 ($M_{jkt} = 1$) if two firms decide to form a merger; otherwise the dummy is 0. The outcome equation, which reflects firms' suply relation, follows the specification by Mueller (1985) and Gugler and Siebert (2007). We consider the sum of firms' production in a firm-pair j (Sq_{jkt}) for generation k in quarter t. Hence, Sq_{jkt} is the joint production if a firm-pair merged in period t, and it is the sum of the firm-pair output if the firms did not merge in period t. We then evaluate the change in production of two merging firms' production (before and after merging) and two nonmerging firms and eventually compare those

[15] See also Mueller (1985) and Duso et al. (2014) for empirical applications.

production changes between merging and non-merging firms.[16] In closely following equation (5), we account for postmerger heterogeneities and specify the outcome equation based on firms' supply relations as follows:

$$Sq_{jkt} = \delta_0 + \delta_1 SMC^*_{jkt} + \delta_2 SElast_{jkt} + \delta_3 SNOF_{kt-1} + \delta_4 SynEff_{jt} + \delta_5 SAbsCap_{jt} + \delta_6 M_{jkt}$$

$$+\delta_7 M_{jkt} * (SMC_{jkt} - \overline{SMC_k}) + \delta_8 M_{jkt} * (SElast_{jkt} - \overline{SElast_k}) + \delta_9 M_{jkt} * (SynEff_{jt} - \overline{SynEff})$$

$$+\delta_{10} M_{jkt} * (SAbsCap_{jt} - \overline{SAbsCap}) + \delta_{11} w_{0,jkt} + \delta_{12} w_{1,jkt} + \delta_{13} \overline{SAbsCap_j}$$

$$+\delta_{14,k} * Generation_k + \epsilon_{jkt}, \tag{6}$$

In closely relating the firm's supply relation to a dynamic Cournot model (we provide more details and a derivation of firms' dynamic supply later) the quantity in a firm-pair is explained by the sum of firms' dynamic marginal costs (SMC^*_{jkt}). Using the dynamic marginal costs accounts for firms' intertemporal production decisions with regard to learning-by-doing. Since firms' production decisions depend on the price elasticities and the associated competitive externalities that firms impose on each other in the product market, we include their price elasticities ($SElast_{jkt}$) for generation k. We control for the degree of competition in the product market and include the number of firms in the product market ($SNOF_{jkt-1}$). We lag this variable to avoid a potential simultaneity bias caused by contemporaneous correlation between the variable and the error term.[17] These variables are defined as a sum in a firm-pair. Furthermore, we control for pairwise synergy effects which are originated by technological proximity between two firms and characterize technological spillovers which exert a positive externality on firms' production decisions. The synergy effects are measured using firms' proximity in the technology market ($SynEff_{jt}$) as described earlier. In the same context, we control for synergy effects caused by absorptive capacity in a firm-pair and measured by firms' patent stocks ($SAbsCap_{jt}$), as described earlier.

Turning to the merger effects, we insert a merger dummy (M_{jkt}) that measures the average treatment effect of mergers on production. Based on the finding by Gugler and Szuecs (2016),

[16]Remember, if merging firms contract output postmerger, postmerger price increases and vice versa.

[17]It should be noted that the other variables are either underlying a long-term decision process (and those decisions have been made by a firm in the past) or are assumed to be exogenous to a firm.

that most postmerger effects materialize within a year, we evaluate the impact of a merger in period t.[18] Importantly, we consider several heterogeneous postmerger effects on production. First, we allow the efficiency levels to have a heterogeneous postmerger impact on production and include the interaction between the merger dummy and the sum of the firm-pair's (static) marginal costs relative to the industry ($M_{jkt} * (SMC_{jkt} - \overline{SMC_k})$).[19]

Second, we control for heterogeneous postmerger effects on production with regard to price elasticities and include the interaction between the merger dummy and the price elasticities in a firm-pair in market k compared to the average price elasticities ($M_{jkt} * (SElast_{jkt} - \overline{SElast_k})$). Third, we consider heterogeneous postmerger effects on production with regard to potential synergy effects between firms and consider the interaction between the merger dummy and firms' proximity in the technology market relative to the average proximity between firms ($M_{jkt} * (SynEff_{jt} - \overline{SynEff})$). Fourth, we control for firms' heterogeneous postmerger impact with regard to firms' absorptive capacity of innovations and include the interaction between the merger dummy and firms' absorptive capacity compared to the overall absorptive capacity ($M_{jkt} * (SAbsCap_{jt} - \overline{SAbsCap})$). Note that the first two effects ($M_{jkt} * (SMC_{jkt} - \overline{SMC_k})$ and $M_{jkt} * (SElast_{jkt} - \overline{SElast_k})$) relate to the postmerger heterogeneities caused by firms' product market characteristics, while the latter two effects ($M_{jkt} * (SynEff_{jt} - \overline{SynEff})$ and $M_{jkt} * (SAbsCap_{jt} - \overline{SAbsCap})$) refer to postmerger heterogeneities originated by firms' technology market characteristics. We are interested in identifying which type of characteristics cause most merger heterogeneities. The variables $w_{0,jkt}$ and $w_{1,jkt}$ refer to the selection terms as shown in equation (5) and will be explained later. We control for firm-level heterogeneities as proposed by Wooldridge (2002) and include firms' average absorptive capacities over time ($\overline{SAbsCap_j}$). This serves as a firm fixed effect and controls for time-invariant unobservable factors. Finally, we include generation dummies ($Generation_k$) to control for generation-specific fixed effects, and ϵ_{jkt} denotes the error term.

In estimating equation (6), we face two problems. The first issue relates to the fact that marginal costs are unobserved. In contrast to other empirical studies that frequently retrieve marginal costs from the static Lerner Index, we have to apply a different approach since our mar-

[18]We also run a robustness check in which we further delay the measurement of postmerger effects (see discussion below for further information).

[19]Note, since the average sum of marginal costs enter equation (6), we had to separate the estimation of this equation from the supply equation as shown in (10) below.

ket is characterized by learning-by-doing. Against the background of learning-by-doing, firms are forward looking and apply intertemporal production strategies. They set their quantities according to their dynamic marginal costs, which lie below static marginal costs. As a consequence, they invest in production experience and overproduce (in a static sense) in early periods to achieve future cost reductions (see Fudenberg and Tirole (1983) and Spence (1981)), as will be explained in more detail in the following paragraphs. Accounting for learning-by-doing and spillovers, we estimate static and dynamic marginal costs based on firms' supply relations. The second problem relates to the endogeneity and heterogeneity of firms' merger choices, which we overcome using an endogenous switching model, as will be explained later. We will also apply robustness checks and use a difference-in-difference estimation method.

Firms' supply relations

Firms' supply relations are derived from an oligopoly model in which firms account for learning-by-doing. We follow Irwin and Klenow (1994) and Siebert (2010) and assume that each firm $i = 1, \ldots, n$ chooses quantities of a homogeneous good q_{ikt} at time $t = 0, \ldots, \infty$ to maximize its discounted present value:

$$\max_{q_{ikt}} \ \Pi_{ik} = E_{k0} \left[\sum_{t=0}^{\infty} \delta^t (P_{kt} - MC_{ikt}) q_{ikt} \right], \tag{7}$$

where E_{k0} is the expectation operator for generation k conditional on information at time 0, δ is the discount factor, P_{kt} is the price for generation k in period t, and MC_{ikt} is the static marginal cost. Competition in quantities implies the following first-order condition relating price and marginal cost:

$$P_{k0} \left(1 + \frac{MS_{ik0}}{\alpha_{1k}} \right) = MC_{ik0} + E_{k0} \left[\sum_{t=1}^{\infty} \delta^t q_{ikt} \frac{\partial MC_{ikt}}{\partial q_{ik0}} \right], \tag{8}$$

where α_{1k} is the price elasticity of demand for generation k and MS_{ikt} denotes firm i's market share in generation k. Against the background of learning-by-doing, firms adopt intertemporal production strategies and increase current production, which serves as an investment into experience and generates future cost reductions (see Wright (1936)). Hence, firms set output in relation to dynamic marginal costs which equal the (current) static marginal cost minus future cost reductions that firms achieve via learning by doing (see also Irwin and Klenow (1994)). Therefore, the static marginal cost (MC_{ikt}) plus an adjustment term that accounts for the discounted value of future cost reductions ($\sum_{t=1}^{\infty} \delta^t q_{ikt} \frac{\partial MC_{ikt}}{\partial q_{ikt}}$) achieved from own-learning characterize dynamic marginal cost (MC^*_{ikt}). Using a recursive formulation, equation (8) becomes:

$$P_{kt}\left(1+\frac{MS_{ikt}}{\alpha_{1k}}\right) - MC_{ikt} - \delta\left[q_{ikt+1}\frac{\partial MC_{ikt+1}}{\partial q_{ikt}} + P_{kt+1}\left(1+\frac{MS_{ikt+1}}{\alpha_1 k}\right) - MC_{ikt+1}\right] = 0 \tag{9}$$

where $\frac{\partial MC_{ikt+1}}{\partial q_{ikt}}$ accounts for production in generation k at time t having an impact on marginal costs in period $t+1$ via learning. Rearranging equation (9), we obtain the following equation:

$$P_{kt}\left(1+\frac{MS_{ikt}}{\alpha_{1k}}\right) = MC_{ikt} + \delta\left[q_{ikt+1}\frac{\partial MC_{ikt+1}}{\partial q_{ikt}} + P_{kt+1}\left(1+\frac{MS_{ikt+1}}{\alpha_1 k}\right) - MC_{ikt+1}\right] + \nu_{ikt}, \tag{10}$$

which includes a normally distributed error term, ν_{ikt}. Following previous studies, we specify the (dynamic) marginal cost function (which will be inserted into equation (10)) as follows:

$$MC^*_{ikt} = \beta_{0i}Firm_i + \sum_k \beta_{1k}Generation_k + \beta_2 ECS_{ikt} + \beta_3 ECS^2_{ikt} + \beta_4 LBD_{ikt} + \beta_5 LBD^2_{ikt}$$

$$+\beta_6 Spill_{ikt} + \beta_7 Spill^2_{ikt} + \beta_8 Silicon_t + \beta_9 Patents_{it} + \beta_{10} DynTerm_{ikt}, \tag{11}$$

where we estimate firm-level (β_{0i}) and generation-specific fixed effects (β_{1k}) to account for heterogeneities across firms and product generations. We include economies of scale (ECS_{ikt}) using the firm's contemporaneous production; own learning-by-doing (LBD_{ikt}) is incorporated using past cumulative generation-specific output for every firm to proxy for a firm's experience. We consider learning from others via spillover effects ($Spill_{ikt}$) using the accumulated production experience of other firms. We include squared ECS, LBD, and $Spillover$ variables to control for nonlinear effects. Potential endogeneity issues and the use of instrumental variables will be addressed in the results section. We also include the material price ($Silicon_t$) and annual SRAM patents ($Patents_{it}$) to control for shifts in marginal costs.[20] Finally, we include a dynamic term ($DynTerm_{ikt}$) that characterizes future marginal cost savings via learning and separates static

[20]For the material price, we use the world market price of silicon compiled by *Metal Bulletin*.

from dynamic marginal costs. Since equation (10) includes the price elasticity of demand (α_{1k}), we will have to estimate a demand equation, which is introduced next.

Demand equation

In our main demand specification, the demand elasticities are estimated at the product-generation level. Following previous studies, we assume that every generation is homogeneous in itself and different generations represent differentiated goods. We specify the following log-linear demand for generations k = 4Kb, 16Kb, 64Kb, 256Kb, 1Mb, 4Mb, 16Mb, and 64Mb. One advantage with the SRAM market is that there are few generations offered on the market at the same time. Consequently, we do not face a dimensionality problem, and we can estimate the demand in linear form. To ensure that we have a sufficiently large sample and to increase the efficiency of the demand estimation, we pool the data and use dummy variables to account for generation-specific elasticities and market size effects:

$$ln(Q_{kt}) = \alpha_0 + \alpha_{0k}Generation_k + \alpha_{1k}\ln(P_{kt}) + \alpha_2\ln(P_{kt}^S) + \alpha_3 Time_{kt} + \alpha_4\ln(DGDP_t) + u_{kt}, \tag{12}$$

where Q_{kt} denotes the market output for generation k in quarter t and P_{kt} is the generation-specific selling price of a memory chip.[21] We also construct a price index (P_{kt}^S) for the closest substitute S of product generation k at time t.[22] $Time_{kt}$ is a generation-specific time trend and captures the effect of the time length that a particular generation has been in the market. $DGDP_t$ is the difference (over time) of the GDP in electronics. It is used as an exogenous demand shifter, since semiconductors are used as an input in many electronic products.[23] The α denotes the vector of coefficients and u is the error term with a mean of zero and a constant variance σ_u. To account for differences in demand over product generations, we include generation-specific dummy variables (α_{0k}). Note that the parameter α_{1k} refers to generation-specific price elasticities of demand, and α_2 refers to the cross-price elasticity. The parameters to be estimated reflect the market dummies, the own-price elasticities of demand, the cross-price elasticity, the

[21] The use of instrumental variables to eliminate potential endogeneity issues will be addressed later.

[22] For each SRAM generation, we identify corresponding substitute generations offered on the market at the same time and use the average weighted prices of these generations as the price of the closest substitute.

[23] We use the GDP of the OECD at constant prices.

effect of a general demand shifter, and a time trend.

Selection into mergers (premerger heterogeneity)

Observed and/or unobserved firm-level attributes determine firms' merger decisions and their production decisions. Firms' self-selection into mergers raises concerns about a potential selection bias, which will be addressed now. A firm's decision to merge or not is based on a comparison between its value from merging (V_{jkt}^{M}) and its value from not merging (V_{jt}), where the superscript M refers to a merger. Firms form a merger if $M_{jkt}^{*} = V_{jkt}^{M} - V_{jkt} \geq 0$, where M_{jkt}^{*} is the latent variable measuring the likelihood to merge and M_{jkt} refers to a merger dummy variable. The selection equation is specified as follows:

$$M_{jkt}^{*} = \sum_{k} \gamma_{0k} * Generation_k + \gamma_1 SameRegion_j + \gamma_2 DMC_{jkt} + \gamma_3 SMC_{jkt} + \gamma_4 SElast_{jkt}$$

$$+\gamma_5 SNOF_{kt-1} + \gamma_6 SynEff_{jt} + \gamma_7 SAbsCap_{jt} + \gamma_8 \overline{SAbsCap_j} + \mu_{jkt}. \qquad (13)$$

All variables have been introduced earlier, with two exceptions, $SameRegion$ and DMC, which will be explained below. The error term (μ) is assumed to follow a normal distribution.

In order to get unbiased estimates of the causal effect of mergers on market outcomes, exclusion restrictions should be used. Note that even without using exclusion restrictions, the outcome equation could still be identified based on the nonlinearity of the Mill's ratio (see, e.g., Cameron and Trivedi (2005)). The selection on unobservables would rule out alternative estimation methods, such as the difference-in-difference and the propensity score method, since the conditional independence assumption would be violated.[24] The selection equation (13) should contain an instrument that is correlated with merger formation but does not directly impact the production in a firm-pair in our case. For further information on endogenizing mergers, see also Dafny (2009), Gugler and Siebert (2007), and Duso et al. (2014). We follow Dafny (2009), Harris and Siebert (2017), and Ahern, Daminelli, and Fracassi (2015) and use as an instrument an indicator whether firms are located in the same country or region ($SameRegion_j$). $SameRegion_j$ refers to a dummy variable that is set to 1 if the firm-pair is headquartered in the same region (USA, Europe, Japan, Taiwan, or Korea). Otherwise, the dummy variable takes on a value of

[24]Nevertheless, later, we will perform robustness checks in which we apply a propensity score method to have a reference case.

0. Dafny (2009) has shown that this variable serves as an appropriate indicator for mergers. In our context, there are four reasons why location is an especially appropriate instrument. First, firms located in the same country face the same financial and institutional conditions, which facilitates a capital-intensive transaction such as a merger. Second, the management and business literature emphasizes sociological and psychological aspects that determine stability and success of mergers and alliances and argue that the unstable character of alliances results from both the structure of industry competition and the relationship between partners (see Contractor and Lorange (1988), Kogut (1989), Teece (1986 and 1992), and Kogut (1988), among others). Those studies find that an advantage of alliances and mergers between firms from the same country is the common language and the correspondence of culture and mentality of the parties. It is of great importance that the partners harmonize in cultural terms. Third, firms' headquarters and locations are exogenously determined, at least given the market and time span in our data. Finally, regional similarities in a firm-pair do not have an impact on a firm's production decision since the SRAM market is characterized by international competition, such that firms' output decisions are independent of a country. The identification argument is also statistically tested (more details later).

The second instrument is based on theoretical studies and accounts for variations across time and firm-pairs. Bergstrom and Varian (1985) and Salant and Shaffer (1999) have shown that in Cournot models, equilibrium quantities and prices in the industry (or in a firm-pair) depend on the average costs in the industry or firm-pair rather than the distribution of costs between firms. Hence, production is dependent on the sum or the average of the marginal costs in a firm-pair rather than the difference in marginal costs in a firm-pair. A mean-preserving spread in marginal costs will leave the industry quantities and prices unchanged (see also Roeller, Siebert, and Tombak (2007) for a similar argument). Hence, the difference in marginal costs between merging firms does not have an effect on combined market shares. Bergstrom and Varian (1985) and Salant and Shaffer (1999) have also shown that an increase in firms' differences in marginal costs increases firms' and industry profits since more efficient firms produce more output at a lower cost, which increases firms' profits in a merger and eventually determines firms' decisions to merge. Since asymmetry between firms will change profits and merger incentives but leave production unaffected, it serves as an appropriate exclusion restriction (see also Harris and

Siebert (2017)). Therefore, we include the absolute difference in marginal costs in a firm-pair ($DMC_{jkt} = |MC_{ikt} - MC_{lkt}|$) in the selection equation, which controls for merger formation. Again, we control for firm-level heterogeneity and include firms' average absorptive capacities over time ($\overline{SAbsCap_j}$). This controls for time-invariant unobservable firm-specific effects that may affect the propensity to merge. As further controls, we include product generation fixed effects ($Generation_k$). From the estimation of equation (13), we construct a selection term ($w_1 = M * \frac{\phi(X\gamma)}{\Phi(X\gamma)}$) that explains firms' selection into mergers, where X and γ represent the regressors and the parameters from the selection equation (13), ϕ is the standard normal density function, and Φ is the standard normal cumulative distribution function. A second correction term ($w_0 = (1 - M) * \frac{\phi(X\gamma)}{1-\Phi(X\gamma)}$) is constructed for the nonmerging firms. Both terms are used in the estimation of equation (6). We assume that the error terms ϵ and μ are jointly normally distributed.

Estimation algorithm

Our estimation process incorporates the following steps:

1. Estimation of generation-specific price elasticities of demand

We get an estimate of the generation-specific price elasticities of demand (α_{1k}) based on equation (12).

2. Retrieval of static and dynamic marginal costs

From the estimation of equation (10), we use the parameter estimates to predict dynamic marginal costs and static marginal costs (i.e., dynamic marginal costs net of the dynamic effects).

3. Heterogeneous impact of mergers

Using the estimated marginal costs, we establish the sum and differences of marginal costs in firm-pairs and apply the heterogeneous treatment effects estimator suggested by Heckman, Urzua, and Vytlacil (2006), while estimating our selection equation (13) and our outcome equation (6).

4 Estimation results

In accordance with the estimation algorithm, we first present the estimation results of the demand equation (12) and the supply equation (10) and then present the results of the heterogeneous selection model (equations (13) and (6), respectively).

4.1 Demand estimation results

We estimate the industry demand (12) and firms' supply using an instrumental variable estimator. In the demand equation, we account for the potential endogeneity of prices and use supply shifters as instruments to identify the slope of the demand function. Since silicon is the main material input for semiconductor production, we use the material price of silicon ($Silicon$) as a supply shifter. A further instrument relates to learning-by-doing, which is an important characteristic in the SRAM industry and, therefore, shifts the supply curves downward as more experience is accumulated. To control for learning-by-doing effects (LBD), we use the accumulated quantity across firms within a generation. Our final instrument relates to traditional Cournot models that show competition has an impact on firms' supply and firms' output choices. We use the lagged number of firms (NOF) as a control for competition and firms' changes in equilibrium output. The lag is used to avoid a potential simultaneity bias.

Table 5 shows the demand estimation results. Regarding the first-stage estimation, as shown in column 1, a test for the joint significance of the instruments indicates that the price of silicon, the cumulative industry output, and the number of firms are highly correlated with the price. With a value of 319.84 for the F-statistic, we reject the null hypothesis that the estimated coefficients of these variables are equal to zero. We also apply a Durbin-Wu-Hausman χ^2 test, which returns a value of $\chi^2 = 2.78$. The test confirms to reject the exogeneity of prices. The first-stage R-square is 0.96. The coefficient for silicon is estimated to be positive and significant, indicating that a 1 percent increase in the silicon price elevates the SRAM price by 3 percent. The estimated coefficient for the learning-by-doing effects turns out to be negatively significant at the 1 percent level. The negative estimate confirms that higher experience shifts the marginal cost curve downward, which leads to an increase in output and a lower price. A learning elasticity of 15 percent represents a reasonable estimate and is consistent with earlier studies.

For the second stage of the demand estimation, we report two specifications. In the first specification (column 2), we estimate a price elasticity that is constant across all product generations. We receive an R-square of 0.52, which confirms a good fit of our model. The estimated own-price elasticity of -4.72 confirms an elastic market demand, i.e., a 1 percent increase in the average SRAM price decreases the quantity demanded by 4.9 percent. The estimate confirms that firms set prices in the elastic portion of the demand function, which is supported by oligopoly theory. The magnitude of the price elasticity is also similar to the results from previous studies (see, e.g., Brist and Wilson (1997), Siebert (2010), and Zulehner (2003)), which further confirms the reliability of our estimation results.

The second specification (column 3) is our main specification, in which we estimate generation-specific price elasticities. An R-square of 0.71 confirms a good fit. The price elasticities range from -3.19 to -4.96 and are comparable to the previously reported own-price elasticity. One exception is the last generation, which shows a much higher elasticity that is explained by using a shorter time series. In this case, the high elasticity is identified and explained by the steeply decreasing prices at the beginning of the life cycle, as shown in Figure 1b. A Chow test is conducted to test whether the price elasticities are significantly different. The F-statistic of 96.22 rejects the null hypothesis of equal coefficients. The test also confirms the relevance of estimating product-specific price elasticities. The estimate for the cross-price elasticity is 2.39, providing evidence that adjacent SRAM generations are substitutes. Note that, as expected by theory, the own-price elasticity is larger in magnitude than the cross-price elasticity. The time trend is negative, confirming that buyers substitute away from one generation to the next as time elapses.

4.2 Firms' supply estimation results

We now turn to the estimation results of firms' supply relations, as shown in equation (10). We account for a potential simultaneity bias, since current and squared output are potentially correlated with the error term. As instruments, we use the lagged variables and further variables that determine firms' marginal costs and their current output choices, such as the lagged cumulative firm-level output in a generation to capture learning-by-doing, the lagged number of firms in the market to control for competition, and the lagged silicon material price. The first-stage results show significant parameter estimates for the instrumental variables, and a Durbin-Wu-Hausman test confirms the necessity of using instruments. Table 6 shows that all coefficients are significantly different from zero, and most estimates are significant at the 99 percent significance level. The coefficients also carry the expected signs. For example, the results confirm that economies of scale are present. We calculated an overall impact of $-6.57e-04$, which is significant with a standard deviation of $1.99e-04$. Hence, an increase in current output by 1 million units reduces unit marginal costs, on average, by \$0.66. Interestingly, the increasing economies of scale are diminishing in output, as shown by the positive coefficient estimate for ECS^2_{ikt}. Our results also confirm significant own learning-by-doing effects. The calculated overall learning effects are significant and amount to $-2.55e-05$ with a standard deviation of $2.40e-06$. In comparing the magnitude of the learning effect with the economies of scale effect, it is interesting to note that the latter has a 26 times higher impact on static marginal costs. The positive parameter estimate for LBD^2_{ikt} shows that learning effects are diminishing. The overall impact of learning-by-doing via spillovers on marginal costs is $-2.79e-07$ and significant with a standard deviation of $5.75e-08$. Similar to the scale economies and own-learning effects, the spillover effects diminish with experience. Dividing the estimated spillover coefficient by the estimated learning-by-doing coefficient, we find that the spillover effect is $3.88e-02$, i.e., 4 percent of the output produced by rival firms contributes to learning. Our results also show that higher silicon prices significantly increase marginal costs, which results in higher prices. We also find that patents significantly reduce marginal costs and price. The significantly positive parameter estimate of the dynamic term confirms that firms set prices according to dynamic marginal costs, and it confirms that the gap between static and dynamic marginal costs is larger at the beginning of the life cycle and becomes smaller as time passes. The estimation also returns significant coefficients on the dummy variables that control for heterogeneities across product generations.

We calculate firms' marginal costs to establish the marginal cost variables that enter the heterogeneous treatment effects model as per equations (13) and (6). The average predicted static firm-level marginal cost (MC) amounts to \$4.34, and the average price-cost markup is \$3.32. These are reasonable numbers that match outcomes of previous studies and are consistent with the reported price evolution in Figure 1b. The absolute difference in marginal costs (DMC) takes on a mean value of \$3.21. Figure 4b shows the distributions of the DMC variable.

4.3 Heterogeneous merger effects results

We present the estimation results of the heterogeneous merger effects model. We control for selection into mergers (premerger heterogeneity) by estimating the selection equation (13) and heterogenous merger effects (postmerger heterogeneity) by estimating equation (6). Both equations are estimated using random effects panel estimation methods.

Selection estimation results

The selection equation (13) is estimated using a random effects probit method, and the results are shown in Table 7, column 1. The probit estimation returns a Wald statistic of $\chi^2 = 2,598.77$, which confirms a good fit.[25] The parameter estimate for the $SameRegion$ variable, one of our exclusion restrictions, is highly significant, providing evidence that firms from the same region are more likely to form mergers. Two firms from the same region have a 37 percent higher likelihood to merge. Our second instrument (DMC) returns a significantly negative parameter estimate, supporting the fact that firms with similar marginal costs are more likely to form mergers. The calculated marginal effect is -3.18, which indicates that a reduction in the marginal cost difference by one dollar increases the likelihood of forming a merger by 3.18 percent. A standard deviation decrease from the average of the DMC variable increases the probability to form a merger by 8.17 percent. The significantly negative parameter estimate on the sum of the static marginal costs (SMC) confirms that more efficient firms have a higher incentive to form mergers. A one dollar reduction in firms' marginal costs increases the probability of forming a merger by 7.56 percent. This result provides evidence that more efficient firms recognize the advantage of internalizing negative competitive externalities in order to soften product market competition, which emphasizes the relevance of the market power argument for merging firms. This result also illustrates the fact that an efficient merging firm recognizes the advantage of keeping inefficient firms outside the merger since the postmerger output expansion of an inefficient outsider firm is lower than the postmerger output expansion of an efficient firm. This is consistent with the findings in the existing merger literature that larger nonmerging firms trigger larger output responses, which reduces prices and makes mergers less attractive (see Salant et al. (1983) and Farrell and Shapiro (1990), among others). The significantly positive estimate for the

[25] Since the Wald statistic can be interpreted as a measure of overall fit of the model specification, it supports the fact that the variables $SameRegion$ and DMC are useful instruments for determining merger incentives.

price elasticities in the product market ($SElast$) shows that firms facing more inelastic price elasticities are more inclined to merge. The negative parameter estimate on the number of firms ($SNOF$) shows that firms have higher incentives to merge in markets with fewer firms or in markets that are more concentrated. It is interesting to note that the synergy effects ($SynEff$) is negatively significant. Firms are more inclined to merge with firms that gathered expertise in different technological areas. That finding supports the notion that a firm prefers to merge to quickly acquire knowledge in technological areas that are relatively unexplored by the firm than to merge with a technologically closely related firm and gain synergy effects. Our results also show that more innovative firms, as measured by the $SAbsCap$ variable, have higher incentives to merge. Finally, the firm-level fixed effect ($\overline{SAbsCap}$) is significant. The estimation results of the selection equation confirm that firms' attributes in technology markets and product markets such as regions, marginal costs, price elasticities, number of firms, synergy effects, and innovation significantly explain firms' merger incentives.

Outcome estimation results

We now turn to discuss the estimation results of the outcome equation (6). The outcome equation is estimated using a random effects generalized least square estimation method, and the results are shown in the second column of Table 7. The Wald statistic of $\chi^2 = 2,764.24$ shows that the model has high explanatory power. The parameter estimates for w_0 and w_1 are significant, which provides evidence for firms' self-selection into mergers based on unobservables. Unobserved attributes positively affect firms' merger decisions and their output choices. The negative estimate on firms' dynamic marginal costs (SMC^*) provides evidence that more efficient firms produce more output. A one dollar reduction in marginal costs increases output by 136 (thousand) units. The results also show that firms operating in more elastic markets produce more output; a result that is consistent with standard Cournot models. More closely related firms in the technology market ($SynEff$) produce more, which indicates that technological spillovers exert a positive externality on firms' output. The results also show that more innovative firms ($SAbsCap$) produce more output.

Turning to merger-related impacts, our estimation results return a negative average treatment effect of mergers (M) on production of -78.93, providing evidence that mergers reduce post-merger production, and we can infer from theoretical studies that the reduction in postmerger production relates to higher postmerger prices. It should be recalled that the average treatment effect assumes homogeneous merger responses and ignores that merger effects can be heterogeneous across merging firms. Most interestingly, our estimation results return a significant amount of heterogeneity across merging firms (postmerger heterogeneity). The heterogeneous impact of mergers with respect to firms' premerger marginal costs ($M_{jkt} * (SMC_{jkt} - \overline{SMC_k})$) turns out to be negative. This result emphasizes that more efficient merging firms will further increase postmerger output relative to less efficient merging firms. In following Cerulli (2012), we evaluate the treatment effects on the treated (merging) firms, also referred to as ATET, while accounting for postmerger heterogeneity in marginal costs. Based on the estimated regression coefficients from equation (6), the $ATET(SMC)$ is calculated as:

$$ATET(SMC) = \left[\delta_6 + (SMC - \overline{SMC_k}) * \delta_7 + (\delta_{11} + \delta_{12}) * \frac{\phi(X\gamma)}{\Phi(X\gamma)}\right]_{(M_{jkt}=1)}, \tag{14}$$

where δ_6 is the coefficient on the merger variable, $SMC - \overline{SMC_k}$ is the deviation of the sum of marginal costs from the mean, δ_7 is the coefficient on the interaction between the merger and the marginal cost variables, and δ_{11} and δ_{12} are the coefficients on the selection terms. The results are shown in Table 8, upper panel. The $ATET(SMC)$ takes on a mean of -45.98, providing evidence that more efficient merging firms further increase postmerger output, which results in decreasing prices. More efficient merging firms leave less efficient firms (whose postmerger output response is smaller) outside the merger, such that mergers among more efficient firms will result in relatively higher postmerger equilibrium outputs and relatively lower postmerger prices. The mean of the $ATET(SMC)$ differs greatly from the mean of the average treatment effect (-78.93), which provides evidence that merging firms achieve relatively more efficiency gains than predicted by the overall effect if we account for postmerger heterogeneity in efficiencies. These gains are, however, not large enough to fully overcompensate the market power effects. Noteworthy is the large standard deviation of the $ATET(SMC)$ ($3,195.68$), which provides evidence that firms achieve different amounts of postmerger efficiency gains that can even result in positive ATET effects. Our results show that mergers greatly vary in their impact on postmerger production and prices depending on the merging firms' efficiency levels.

We also calculate the average treatment effect on the non-treated ($ATENT(SMC)$) (i.e., if non-merging firms did merge) according to:

$$ATENT(SMC) = \left[\delta_6 + (SMC - \overline{SMC_k}) * \delta_7 + (\delta_{11} + \delta_{12}) * \frac{\phi(X\gamma)}{1 - \Phi(X\gamma)}\right]_{(M_{jkt}=0)}. \qquad (15)$$

The results are shown in Table 8, lower panel. Our results return an average treatment effect on the non-treated ($ATENT(SMC)$) of -79, which is almost 50 percent more negative than the ATET, providing evidence that a hypothetical merger between non-merging firms would have lowered the postmerger output even further. This confirms that the observed merging firms achieve higher efficiency gains than nonmerging firms could have achieved if they had merged. The non-merging firms would not have been able to generate as many efficiency gains as the merging firms. This result suggests that mergers between non-merging firms would have resulted in smaller postmerger efficiency gains, lower output, and higher prices. Consequently, the merging firms' efficiency levels play a major role in evaluating merger effects and cause heterogeneous postmerger effects. More efficient firms prior to merging achieve higher efficiency gains post merger.

Next, we evaluate the heterogeneous postmerger impact with respect to the product market elasticities ($M_{jkt} * (SElast_{jkt} - \overline{SElast_k})$). Table 7 shows a significantly negative parameter estimate. This result provides evidence that merging firms operating in more inelastic product markets further reduce postmerger output, leading to higher postmerger prices (or merging firms operating in more elastic product markets further increase postmerger output, leading to lower postmerger prices). This result confirms standard merger studies based on Cournot, as mentioned earlier. Mergers in more inelastic product markets provide opportunities for the merging firms to further reduce postmerger output while aiming toward internalizing negative competitive externalities. We also calculated the heterogeneous treatment effects on the treated with respect to the product market elasticities applying the same principle as shown in equation (14). Table 8, upper panel, shows an $ATET(SElast)$ of -48.74, which is about 50 percent smaller than the ATE. The standard deviation of the $ATET(SElast)$ is 728.39, which is high, but relatively smaller than for the ATET with regard to efficiencies ($ATET(SMC)$). Our results provide evidence that price elasticities cause large heterogeneities in evaluating postmerger effects.

Turning to the heterogeneous postmerger effect with respect to firms' synergy effects in the technology market ($M_{jkt} * (SynEff_{jt} - \overline{SynEff})$) is significant and negative. This result emphasizes that merging firms that are less closely related in the technology market further increase postmerger output, which results in lower postmerger prices. This result is interesting, since we would expect firms more closely related in technologies to further benefit from synergy effects. One explanation is provided by the results of the selection equation, which suggests that merging firms focus on acquiring new knowledge in technological areas that are unrelated to their current expertise (and these give higher returns) instead of focusing on further acquiring technology in their established areas. A further explanation could be that mergers have not been materialized synergy effects in the short run. We report robustness checks on the latter argument below.

Finally, the heterogeneous impact of mergers with respect to firms' absorptive capacity in the technology market ($M_{jkt} * (SAbsCap_{jt} - \overline{SAbsCap})$), Table 7 shows a significantly positive estimate, indicating that more innovative merging firms will further increase postmerger output. Table 8, upper panel, shows an $ATET(SAbsCap)$ of -50.99, which supports the fact that more innovative merging firms achieve relatively more efficiency gains and fewer postmerger output reductions. It is interesting to note that the standard deviation of the $ATET(SAbsCap)$ effect is much smaller (13.00), providing evidence that postmerger heterogeneities are less pronounced with regard to firms' innovative premerger activities.

Taking all heterogeneity effects together and calculating the ATET returns a value of -43.63, which is larger than the average treatment effect (-78.93). The standard deviation of the overall ATET is large ($2,812$), which confirms the large heterogeneity in evaluating postmerger outcomes. The large standard deviation also confirms the fact that some mergers achieve dominant efficiency gains, resulting in higher postmerger output and lower postmerger prices; but on average, postmerger output declines and price increases, supporting the notion that postmerger efficiency effects are smaller than market power effects.

To summarize, our estimation results provide evidence for substantial postmerger heterogeneities affecting the impact of mergers on competitive outcomes. While the averages of the ATET with regard to the technology market and product market attributes are relatively similar, the dispersions (standard deviations) of the ATET varies greatly. Our results show that merger heterogeneities are mostly caused by product market attributes (SMC and $SElast$) rather than by technology market variables ($SynEff$ and $SAbsCap$). Merging firms increase postmerger production relatively more than a hypothetical merger among the set of (originally) nonmerging firms. This finding provides evidence that merging firms achieve relatively higher efficiency gains compared to the counterfactual event when nonmerging firms would have merged.

4.4 Robustness checks

Gugler and Szuecs (2016) have shown that most mergers have a rather instant impact and efficiency gains materialize rather quickly. Nevertheless, we apply a robustness check in which we lag the postmerger outcome variable by four more periods. Table 7, column 3, shows that all estimates (but one) carry the same sign (and significance levels) as in our main specification. We also calculated the average treatment effects on the treated for our postmerger heterogeneity variables (see Table 9). The resulting means are slightly more negative than in our main specification, indicating that internalization of competitive externalities took some time to become fully effective. The standard deviations of the ATET effects are, again, larger for product market variables than for technology market variables.

We also apply a homogeneous merger effect model that does not account for heterogeneous postmerger effects.[26] The results are shown in Table 7, column 4. In the absence of heterogeneous postmerger effects, all parameter estimates are highly significant, and most of them carry the same sign as earlier. One notable difference is that the average merger effect is -149, which is almost twice as negative as the average merger effect from our main specification, as shown in column 2. In comparing the estimation results between the homogeneous and heterogeneous merger effects models, our results provide evidence that ignoring heterogeneous merger effects results in an overestimate of the postmerger impact.

One widely applied criticism in endogenous switching models is the choice of instruments in the selection equation. Even though exclusion restrictions are not strictly required and the parameters could be identified by the nonlinearity of the Mill's ratio given that the dataset encompasses a large variation in covariates (Cameron and Triviedi (2005)), we still used instruments in our selection equation based on findings from empirical and theoretical studies and tested for the validity and significance of instruments. We apply further robustness checks

[26] Remember that ignoring postmerger heterogeneous effects is a problem of essential heterogeneity that can lead to biased parameter estimates.

and test whether our estimation results are robust to using: (i) no exclusion restrictions or instruments as shown in Table 10, columns 1 and 2; (ii) only the $SameRegion$ variable as an instrument as shown in Table 10, columns 3 and 4; and (iii) only the DMC variable as an instrument as shown in Table 9, columns 5 and 6. Table 10 shows that signs and efficiency levels of the parameters remain largely unchanged.

An alternative popular estimation approach in the treatment effects literature is the propensity score method (see Rosenbaum and Rubin (1983)). It estimates treatment effects while imputing the missing potential outcome for each subject by using an average of the outcomes of similar firms declared by estimating event probabilities, also known as propensity scores. For identification, this method relies on independence and assumes that a merger is a random event.[27] This assumption is not plausible in our study and would even contradict our main idea, i.e., the consideration of postmerger heterogeneities and firms selecting themselves into mergers depending on their expected gains. Keeping in mind that the propensity score method does not allow for endogenous selection on observables and selection on unobservables, the average treatment effect on the treated is -66 which is smaller than the overall average treatment effect on the treated (-43.63) we obtained earlier.[28]

5 Conclusion

Estimating the impact of mergers is compromised by the fact that mergers are not randomly assigned but firms select themselves into mergers, also referred to as premerger heterogeneity. To date, most mergers studies account for premerger heterogeneity but ignore postmerger heterogeneity. Merger studies conventionally assume that, conditional on regressors, the impact of mergers on outcomes is the same for all firms. However, it is reasonable to assume that mergers exert differential postmerger effects on prices and quantities, even after controlling for regressors, which is also called the random-coefficient or heterogeneous treatment effect model. Recent empirical contributions in the treatment literature consider this type of heterogeneous treatment (or postmerger) effect models and emphasize that ignoring the heterogeneous im-

[27] Also referred to as the unconfoundedness, the conditional independence, or the ignorable treatment assignment assumption.

[28] We used the Stata modules "psmatch2" "teffects" and "psmatch" for estimating the effects. Note also, the fact that the ATET from the propensity score is in the neighborhood of the ATET we obtained earlier provides further confidence in our treatment effect results.

pact can result in a heterogeneity bias (see, e.g., Angrist and Krueger (1999), Heckman, Urzua, and Vytlacil (2006), and Cerulli (2012)). our study emphasizes the relevance of considering postmerger heterogeneities when evaluating competitive merger outcomes. Our study provides insights into heterogeneous merger effects on competitive outcomes and whether differential merger outcomes are caused mostly by firms' technology or product market attributes.

Based on a comprehensive dataset that includes detailed information on mergers, firm-level production, and innovation, we estimate and evaluate the competitive impact of mergers on outputs and prices. Our estimation results provide evidence for substantial heterogeneous pre- and postmerger effects on competitive outcomes. Most importantly, we find that firms' postmerger output further increases (and postmerger price further declines) if merging firms are more efficient, operate in more elastic product markets, are more innovative, and acquire knowledge in technological areas that are relatively unexplored to themselves. Interestingly, we find that heterogeneous postmerger outcome effects are caused mostly by product market characteristics rather than by technological characteristics. We find evidence that estimates based on a model accounting for postmerger heterogeneities differ greatly from those that do not account for postmerger heterogeneities and treat postmerger effects equal among merging firms. Our estimation results provide evidence that ignoring heterogeneous outcome effects can result in heterogeneity bias, just as ignoring premerger heterogeneities can lead to selectivity bias. We performed several robustness checks and can confirm that our results are robust to selecting different sets of instruments. More work is required in evaluating postmerger heterogeneities in different industries. It would be interesting to know if our result –postmerger heterogeneities are more determined by product market characteristics than by technological characteristics– also applies to other industries.

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Tables

Table 1: Industry-wide trends in SRAMs

Years	Shipments	Revenue	Patents	GDP
1990	620,472	2,584,000	1,436	19,995
1991	703,646	2,576,000	1,824	20,248
1992	842,046	3,038,000	1,868	20,658
1993	906,242	3,908,000	1,912	20,918
1994	875,252	4,514,000	2,852	21,544
1995	1,190,787	6,162,174	3,540	22,027
1996	1,044,523	4,907,913	3,764	22,654
1997	1,107,774	3,827,445	4,560	23,451
1998	1,151,219	2,981,353	4,252	24,111
1999	933,395	2,852,147	4,628	24,869
2000	1,370,305	5,370,999	5,812	25,833
2001	1,002,449	2,839,213	5,132	26,100
2002	746,661	1,578,082	3,648	26,472
2003	706,190	1,748,940	933	26,967

Table 1 shows the annual averages for the SRAM industry. Due to space limitations, we report the last 14 years only. The sum of shipments across all generations is measured in thousands. The sum of revenues across all generations and GDP in electronics is measured in mio. constant US-dollars. Sources: Gartner, Inc. and the U.S. Patent and Trademark Office.

Table 2: Summary statistics across generations

Variables	16Kb	64Kb	256Kb	1Mb	4Mb	16Mb	64Mb
P_k	3.77	9.44	6.15	11.50	22.02	16.95	6.20
	(7.39)	(24.29)	(9.37)	(12.03)	(19.77)	(14.53)	(0.55)
Q_k	19,190	37,036	73,258	52,862	30,680	13,459	1,012
	(18,204)	(26,958)	(46,530)	(43,003)	(33,131)	(10,629)	(1,021)
MS_k	0.39	0.41	0.42	0.40	0.38	0.35	0.47
	(0.26)	(0.25)	(0.25)	(0.26)	(0.22)	(0.22)	(0.31)
NOF_k	16.45	20.03	21.77	18.27	12.15	9.50	2.83
	(9.61)	(9.60)	(6.93)	(7.11)	(6.56)	(4.31)	(1.35)
HHI_k	2,683	1,864	1,233	2,136	2,834	3,008	7,437
	(1,508)	(1,469)	(713)	(1,838)	(1,950)	(1,711)	(1,811)

Table 2 shows the means and the standard deviations in brackets for variables of main interest across generations and time periods. Source: Gartner, Inc. and the U.S. Patent and Trademark Office.

Table 3: Annual SRAM market shares of top 5 firms

Firms	MS 2003	Firms	MS 2002	Firms	MS 2001	Firms	MS 2000	Firms	MS 1999
Cypress	9.5%	Cypress	10.0%	IBM	10.9%	IBM	9.6%	IBM	13.2%
NEC	8.1%	NEC	7.6%	Toshiba	8.8%	Cypress	8.5%	NEC	9.3%
Renesas	7.7%	IBM	7.3%	Hitachi	8.2%	NEC	8.2%	Freescale	7.2%
Toshiba	7.2%	Mitsubishi	6.6%	Cypress	7.9%	Toshiba	7.4%	Toshiba	6.4%
Sharp	6.4%	Sharp	5.8%	NEC	5.0%	Hitachi	5.8%	Cypress	5.9%

Table 3 shows the annual market shares of the top 5 SRAM firms. Source: Gartner, Inc.

Table 4: Production and patents

Merging firms			
q_{ikt}	$Patents_{it}$	$SAbsCap_{it}$	$SynEff_{jt}$
3,807	35	371	0.286

Non-merging firms			
q_{ikt}	$Patents_{it}$	$SAbsCap_{it}$	$SynEff_{jt}$
2,390	19	150	0.264

Table 4 shows the Production, (SRAM) Patents and (SRAM) Patentstocks of merging and nonmerging firms (both, related to the time period when mergers have been formed). Sources: Thomson Financial, Gartner, Inc. and the U.S. Patent and Trademark Office.

Table 5: Demand estimation results

Variable	First stage (1)	Demand (2)	Demand (3)
Constant	2.24	35.88^{***}	46.35^{***}
	(0.53)	(1.99)	(8.41)
$\ln(P_{kt})$		-4.72^{***}	
		(0.31)	
$\ln(P_{16Kbt})$			-4.54^{***}
			(0.30)
$\ln(P_{64Kbt})$			-3.19^{***}
			(0.20)
$\ln(P_{256Kbt})$			-3.55^{***}
			(0.24)
$\ln(P_{1Mbt})$			-3.94^{***}
			(0.28)
$\ln(P_{4Mbt})$			-4.96^{***}
			(0.36)
$\ln(P_{16Mbt})$			-4.27^{***}
			(0.50)
$\ln(P_{64Mbt})$			-20.64^{***}
			(4.69)
$\ln(P^S_{kt})$	0.58^{***}	1.83^{***}	2.39^{***}
	(0.04)	(0.31)	(0.35)
$\ln(Silicon_t)$	0.03^{**}		
	(0.02)		
$\ln(LBD_{kt})$	-0.14^{***}		
	(0.01)		
NOF_{kt-1}	-0.02e-02***		
	(0.01e-02)		
$Time_{kt}$	-0.01^{***}	-0.15^{***}	-0.08^{***}
	(0.001)	(0.01)	(0.01)
$DGDP_t$	-0.05	0.23	-2.88
	(3.94)	(20.17)	(16.23)
$Generation_k$	Yes***	Yes***	Yes***
Number of observations	327	327	327
Adjusted R-squared	0.96	0.52	0.71

Table 5 presents instrumental variable estimation results for the demand equation (12). Instruments for the (generation-specific) log prices are cumulative industry output the number of firms in the market (all generation-specific and in logs), and the price of silicon. The first stage results are shown in column 1. We estimate two specifications. The first specification (column 2) assumes that the demand elasticity is the same across product generations. The second specification (column 3) assumes product-specific demand elasticities as shown in equation (12). Explanatory variables (generation-specific) are the price, the substitute SRAM generation price, a time trend, and product-specific dummy variables. We also use the change of GDP as a demand shifter. Robust standard errors are shown in parentheses below the parameter estimates. **, **, and $(^{*})$ denote the 99%, 95%, and 90% levels of significance, respectively. Sources: Gartner, Inc. and the U.S. Patent and Trademark Office.

Table 6: Firms' supply estimation results

Variable	
Scale economies (ECS_{ikt})	-7.69e-04***
	(0.62e-04)
Scale economies squared (ECS^2_{ikt})	2.81e-08***
	(3.12e-09)
Learning-by-doing (LBD_{ikt})	-2.56e-05***
	(3.32e-06)
Learning-by-doing squared (LBD^2_{ikt})	3.17e-11***
	(6.73e-12)
Spillovers ($Spill_{ikt}$)	-3.09e-07
	(2.27e-07)
Spillovers squared ($Spill^2_{ikt}$)	4.85e-14**
	(2.55e-14)
Silicon	3.16e-03***
	(2.76e-04)
Patents	-1.29e-02***
	(3.48e-03)
DynTerm	25.24***
	(1.01)
16Kb dummy	-7.661***
	(1.10)
64Kb dummy	-5.63***
	(1.11)
256Kb dummy	-3.25***
	(1.12)
1Mb dummy	-0.82
	(1.08)
4Mb dummy	2.40**
	(1.07)
16Mb dummy	-3.96***
	(1.24)
64Mb dummy	-14.43***
	(2.07)
Firm dummies	Yes***
Number of observations	6,519
Adjusted R-squared	0.93

Table 6 presents the estimation results for firms' supply relations as shown in equation (10) based on an instrumental variable estimation method. The dependent variable is the (generation-specific) elasticity- and market share-adjusted average selling price. Explanatory variables are the (generation-specific) firm-specific outputs, learning-by-doing measured by cumulative past firm-specific outputs, spillovers measured by the cumulative outputs of all other firms, and time trends. We also use the price of silicon, firms' SRAM patents, as well as firm-specific and product-specific dummy variables. Robust standard errors are shown in parentheses below the parameter estimates. **, **, and (*) denote the 99%, 95%, and 90% levels of significance, respectively. Sources: Gartner, Inc. and the U.S. Patent and Trademark Office.

Table 7: Results for merger incentives and merger impact

Variables	M_{jkt}	Sq_{jkt}	Sq_{jkt+4}	Sq_{jkt}
	(1)	(2)	(3)	(4)
$Constant$		135.83	172.00	-3,105.35***
		(116.27)	(116.53)	(112.46)
$SameRegion_j$	0.37***			
	(0.15)			
DMC_{jkt}	-0.13***			
	(0.03)			
$SMC_{jkt}^{(*)}$	-0.05***	-136.13***	-135.69***	-139.25***
	(0.01)	(2.53)	(2.54)	(2.54)
$SElast_{jkt}$	0.18***	113.54***	107.48***	-316.44***
	(0.03)	(8.01)	(8.03)	(10.66)
$SNOF_{kt-1}$	-0.04***	89.89***	89.28***	99.82***
	(0.004)	(1.57)	(1.57)	(1.93)
$SynEff_{jt}$	-0.43**	510.76***	657.33***	283.29***
	(0.22)	(63.39)	(63.39)	(65.87)
$SAbsCap_{jt}$	0.65e-03**	3.13***	2.67***	2.19***
	(0.18e-03)	(0.06)	(0.06)	(0.08)
M_{jkt}		-78.93***	-123.81***	-149.81***
		(35.05)	(40.95)	(8.41)
$M_{jkt} * (SMC_{jkt} - \overline{SMC_k})$		-371.61***	-373.65***	
		(166.41)	(161.45)	
$M_{jkt} * (SElast_{jkt} - \overline{SElast_k})$		-499.78***	-431.22**	
		(99.22)	(111.09)	
$M_{jkt} * (SynEff_{jt} - \overline{SynEff})$		-21.95***	46.13***	
		(6.64)	(16.68)	
$M_{jkt} * (SAbsCap_{jt} - \overline{SAbsCap})$		0.016***	-0.005***	
		(0.005)	(0.002)	
$w_{0,jkt}$		-2.85***	96.4*	
		(0.12)	(5.82)	
$w_{1,jkt}$		27.24**	14.75*	
		(11.62)	(8.67)	
$\overline{SAbsCap_j}$	-0.53e-04*	-0.01	-0.01	3.23***
	(0.50e-03)	(0.13)	(0.13)	(0.14)
$Generation_k$	Yes	Yes***	Yes***	Yes***
ρ		0.19	0.18	
Number of observations	71,900	71,900	71,900	71,900

Table 7 reports the estimation results for the selection equation (13), as well as the impact of mergers on production as shown in equation (6). The selection equation is estimated using a random effects probit and the outcome equation is estimated random effects GLS. Exclusion restrictions are the same region variable and the difference in marginal costs between firms. Robust standard errors are reported in parentheses. ***, ** and * refers to a 1%, 5%, and 10% significance level, respectively. Sources: Thomson Financial, Gartner, Inc. and the U.S. Patent and Trademark Office.

Table 8: Average treatment effects on the treated (merging) and nontreated (nonmerging) firms, period t

Variables	Mean	Std	Min	Max
$ATET(SMC)$	-45.98	3,195.68	-8,979.23	3,616.14
$ATET(SElast)$	-48.74	728.39	-723.44	1,384.40
$ATET(SynEff)$	-50.93	8.54	-65.09	-44.91
$ATET(SAbsCap)$	-50.99	13.00	-62.86	-29.91
$ATENT(SMC)$	-78.93	3,185.09	-17,046.51	8,827.91
$ATENT(SElast)$	-76.28	1,161.25	-4,030.08	1,566.98
$ATENT(SynEff)$	-78.09	7.49	-93.54	-72.54
$ATENT(SAbsCap)$	-77.99	6.57	-82.78	-33.73

Table 8, upper panel, reports the average treatment on the treated ($ATET$) effects in period t accounting for different types of heterogeneities. The $ATET$ is calculated as shown in equation (14). The lower panel reports the average treatment on the nontreated ($ATENT$) in period t. The $ATENT$ is calculated as shown in equation (15).

Table 9: Average treatment effects on the treated (merging) and nontreated (nonmerging) firms, period $t+4$

Variables	Mean	Std	Min	Max
$ATET(SMC)$	-103.96	3,212.86	-9,085.24	3,577.85
$ATET(SElast)$	-107.04	629.13	-689.80	1,130.79
$ATET(SynEff)$	-63.16	18.72	-76.34	-32.13
$ATET(SAbsCap)$	-108.99	4.06	-112.71	-102.41
$ATENT(SMC)$	-124.94	3,202.22	-17,183.74	8,829.79
$ATENT(SElast)$	-122.51	1,002.99	-3,537.52	1,296.82
$ATENT(SynEff)$	-123.81	16.42	-135.96	-89.96
$ATENT(SAbsCap)$	-123.99	2.05	-125.49	-110.17

Table 9, upper panel, reports the average treatment on the treated ($ATET$) effects in period $t+4$ accounting for different types of heterogeneities. The $ATET$ is calculated as shown in equation (14). The lower panel reports the average treatment on the nontreated ($ATENT$) in period $t+4$. The $ATENT$ is calculated as shown in equation (15).

Table 10: Robustness results for merger incentives and merger impact

Variables	M_{jkt}	Sq_{jkt}	M_{jkt}	Sq_{jkt}	M_{jkt}	Sq_{jkt}
	(1)	(2)	(3)	(4)	(5)	(6)
Instruments	Instrument: none		Instrument: $SameRegion_j$		Instrument: DMC_{jkt}	
$Constant$				186.29*		210.38*
				(115.87)		(116.42)
$SameRegion_j$			-0.39***			
			(0.15)			
DMC_{jkt}					-0.13***	
SMC_{jkt}	-0.06***	-136.27***	-0.05***	-138.46***	-0.05***	-137.81***
	(0.007)	(2.52)	(0.01)***	(2.52)	(0.01)	(2.53)
$SElast_{jkt}$	0.21***	115.40***	0.21***	119.50***	0.18***	116.03***
	(0.03)	(7.99)	(0.03)	(7.98)	(0.03)	(8.01)
$SNOF_{kt-1}$	-0.04***	89.56***	-0.037	90.31***	-0.04***	89.12***
	(0.004)	(1.56)	(0.004)	(1.56)	(0.004)	(1.57)
$SynEff_{jt}$	-0.40**	431.96***	-0.38*	346.16***	-0.45**	506.25***
	(0.21)	(63.64)	(0.21)	(63.63)	(0.21)	(63.41)
$SAbsCap_{jt}$	0.85e-03***	3.29***	0.85e-03***	3.49***	0.65e-03***	3.08***
	(0.17e-03)	(0.06)	(0.17e-03)	(0.06)		(0.06)
M_{jkt}		-187.05***		-64.46**		-199.99***
		(51.65)		(27.76)		
$M_{jkt} * (SMC_{jkt} - \overline{SMC_k})$		-497.61***		-407.72**		-435.59**
		(195.97)		(195.31)		(195.39)
$M_{jkt} * (SElast_{jkt} - \overline{SElast_k})$		-206.62***		-706.81**		122.09***
		(58.41)		(357.10)		(45.74)
$M_{jkt} * (SynEff_{jt} - \overline{SynEff})$		-39.80***		-17.91***		-43.84***
		(8.93)		(5.58)		(9.24)
$M_{jkt} * (SAbsCap_{jt} - \overline{SAbsCap})$		0.03***		0.01***		0.03***
		(0.007)		(0.004)		(0.007)
$w_{0,jkt}$		-6.48***		-6.61***		-109***
		(0.24)		(0.19)		(35.7)
$w_{1,jkt}$		32.65***		12.63**		30.09***
		(9.19)		(5.73)		(7.45)
$\overline{SAbsCap_j}$	-0.93e-03**	-0.001**		0.14e-03		
	(0.48e-03)	(0.0005)		(0.51e-03)		
$Generation_k$	Yes*	Yes*	Yes*	Yes*	Yes*	Yes*
ρ		0.19		0.18		0.19
Number of observations	71,900	71,900	71,900	71,900	71,900	71,900

Table 10 reports the robustness estimation results for the selection equation (13), as well as the impact of mergers on production as shown in equation (6) based on different sets of exclusion restrictions. The selection equation is estimated using a random effects probit and the outcome equation is estimated random effects GLS. Exclusion restrictions are the same region variable and the difference in marginal costs between firms. Robust standard errors are reported in parentheses. ***, ** and * refers to a 1%, 5%, and 10% significance level, respectively. Sources: Thomson Financial, Gartner, Inc. and the U.S. Patent and Trademark Office.

Figures

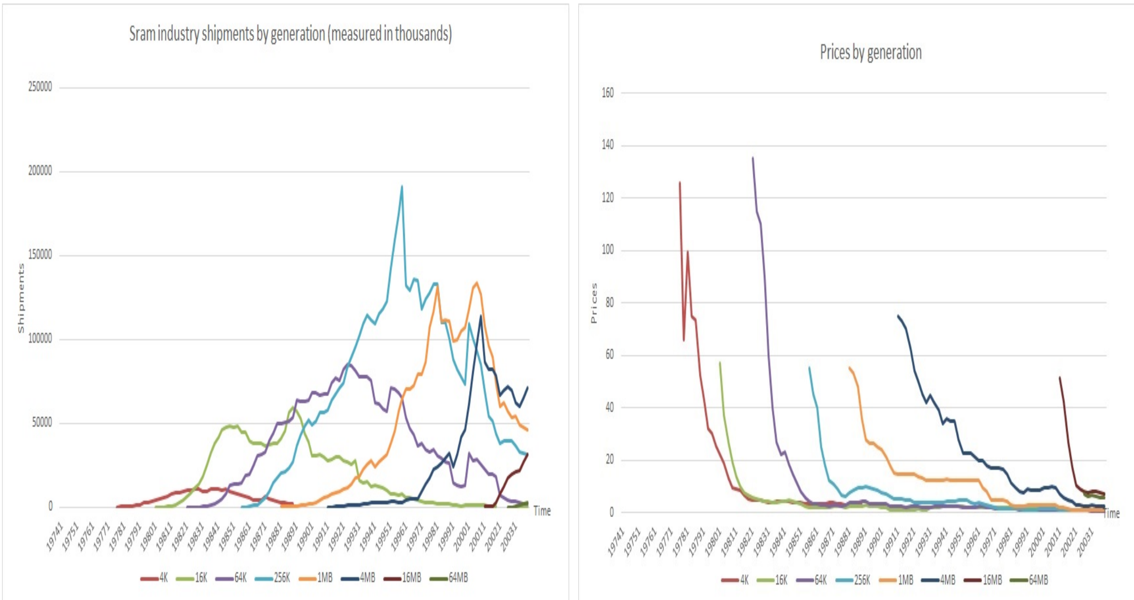

Figure 1: Evolution of shipments (Figure 1a, left) and prices (Figure 1b, right) by generations. Shipments are measured in thousands. Sources: Gartner, Inc. and Thomson Financial.

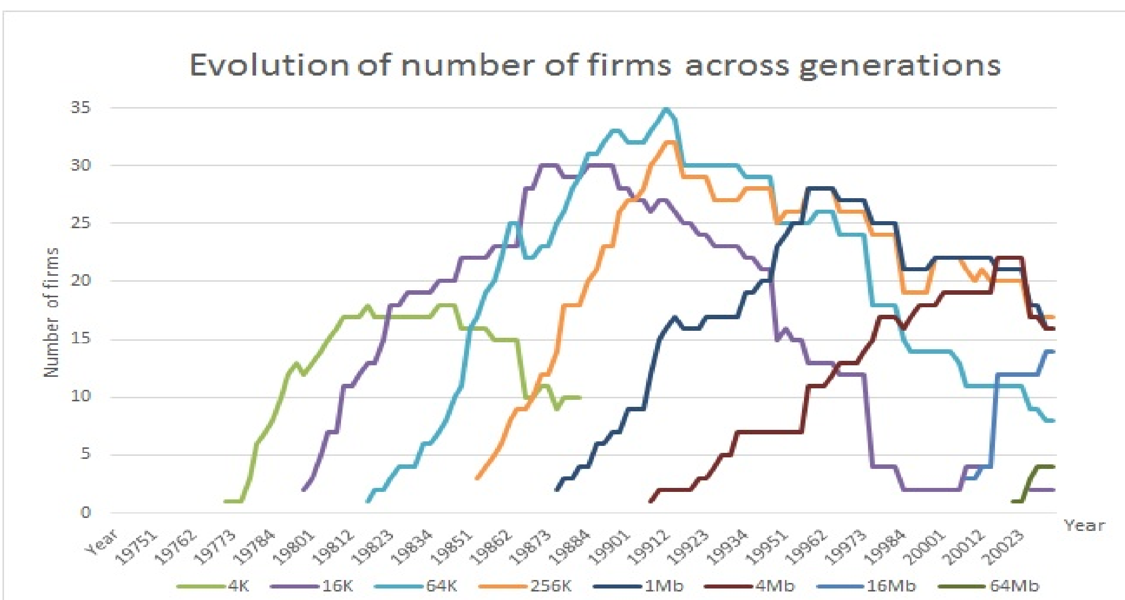

Figure 2: Evolution of number of firms across generations. Sources: Gartner, Inc. and Thomson Financial.

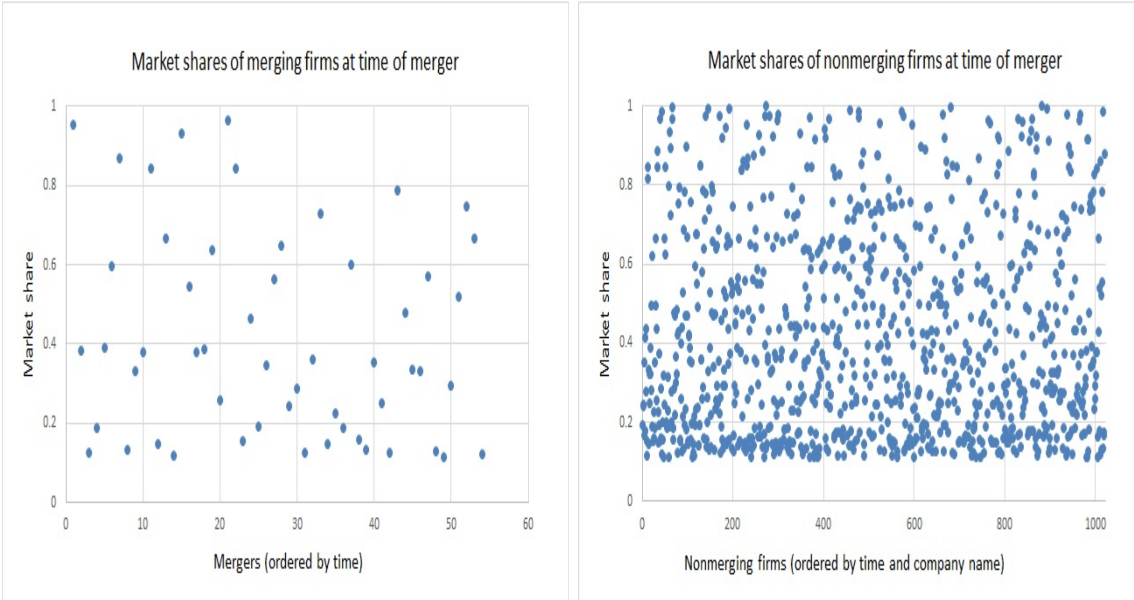

Figure 3: Market shares of merging firms (Figure 3a, left) and nonmerging firms (Figure 3b, right) at the time periods when mergers occurred. Sources: Gartner, Inc. and Thomson Financial.

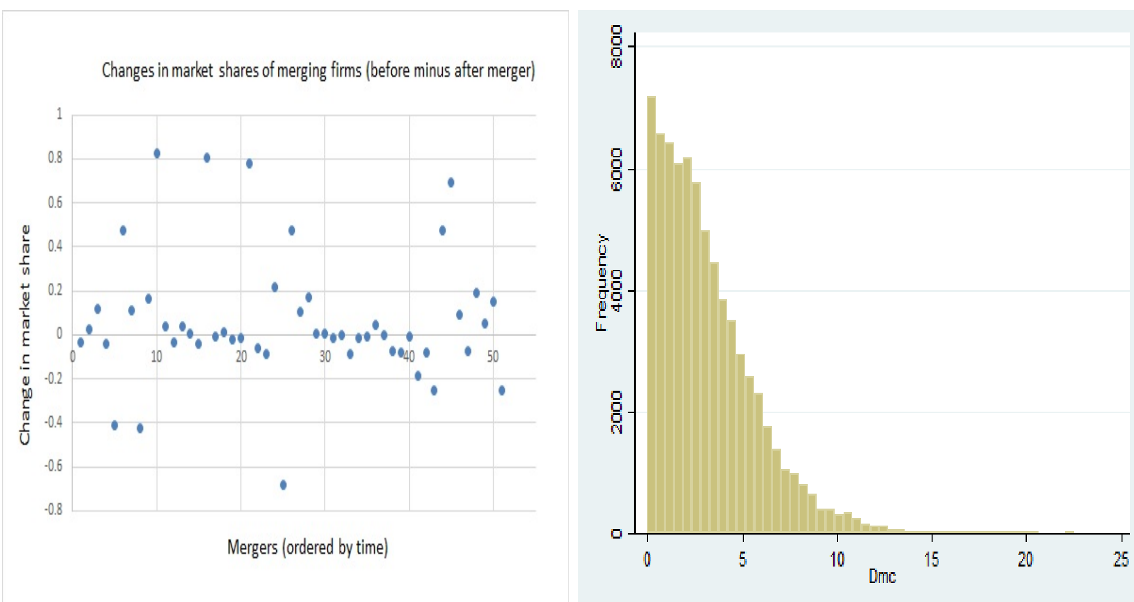

Figure 4: Changes in market shares of merging firms (Figure 4a, left) and absolute differences of marginal costs in a firm-pair(Figure 4b, right). Marginal costs are measured in USD.