WHAT DETERMINES HETEROGENEOUS MERGER EFFECTS ON COMPETITIVE OUTCOMES?*

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We examine whether heterogeneous mergers effects predominantly stem from technological or product market heterogeneities. Using detailed firm- and product-specific information, we employ a heterogeneous merger effects model. Our results show that merging firms realize substantial heterogeneous post-merger effects on competitive outcomes such as production or prices. Merger effects vary substantially across merging firms, depending on the firms' pre-merger efficiency levels, price elasticities, and innovative activities. Firms' efficiency level and price elasticities prior to merging determine large post-merger heterogeneities. The results show that product market attributes (differences in inefficiencies and price elasticities) cause larger post-merger heterogeneities compared with technology market attributes.

I. INTRODUCTION

MERGERS ARE AN IMPORTANT TOOL FOR FIRMS to achieve competitive advantages. Theoretical studies put much effort into predicting the effects of mergers on competition and prices and they provide practical guidance for managers and competition authorities on evaluating potential mergers. Studies have shown that merger effects can vary significantly depending on firm and market attributes such as firms' efficiency and innovative activity and the price elasticities of demand.[1] Several empirical studies found supportive evidence that merger effects on outcomes can be quite different.[2] However, more empirical evidence would be insightful as to whether heterogeneous mergers effects predominantly stem from technological or product

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[1]Competition authorities pay special attention to evaluating merger effects among large and efficient firms operating in concentrated markets. For further information, see Farrell and Shapiro [2010].

[2]Examples are Ashenfelter, Hosken, and Weinberg [2015], Gugler and Szuecs [2016], Craig, Grennan, and Swanson [2018], Siebert [2019], Cunningham, Ederer, and Ma [2020], and Wollmann [2020]. More details are discussed later.

market heterogeneities. In fact, Carlton [2009] remarked that more empirical work is needed on evaluating systematic heterogeneous merger effects. Further exploration of systematic heterogeneous merger effects on competitive outcomes can be useful for merger scrutiny and can provide further critical measures when identifying potential anticompetitive mergers.

The aim of our empirical study is to investigate the extent to which firms achieve different gains from merging. We estimate heterogeneous merger effects on competitive outcomes and evaluate whether these firm-specific merger responses are caused mainly by technology or product market attributes. We account for the fact that merging firms sort into mergers depending on their gains, which can result in heterogeneous merger effects (post-merger heterogeneity) even after controlling for regressors. More specifically, the merger dummy variable is correlated with the marginal impact of mergers (or the coefficient estimate measuring merger responses), so the marginal merger effect becomes firm specific. Hence, the coefficient measuring the marginal effect of a merger on outcome should carry a firm-specific subscript; this is the model of *post-merger heterogeneity* or *heterogeneous treatment effects* (see also Heckman, Urzua, and Vytlacil [2006]). We examine whether heterogeneous merger effects systematically differ, and we pay special attention to differences in firm efficiencies, price elasticities, and innovation activity.

The heterogeneous treatment effects model (conditional on regressors) is well known in the causal inference literature, and it is a popular method in areas such as labor economics (see, e.g., Angrist and Krueger [1999] and Heckman, Urzua, and Vytlacil [2006]). Our study builds on the heterogeneous treatment effects approach and puts special emphasis on the origin of heterogeneous merger effects, that is, whether they are caused primarily by product or technology market attributes. Our study builds on a comprehensive database that contains detailed firm- and product-level production, patent, and merger information in the static random access memory (SRAM) market. SRAM chips are important components designed to store data in electronic devices. The memory chip market is distinct from other well-known electronic products, such as hard disk drives, and it is characterized by very different institutional features, as will be explained in the industry section. When estimating the heterogeneous merger (treatment) effects model, we use a regression adjustment approach that accounts for merger selection on observables.[3]

[3]It should be noted that a matching estimator (which builds on the pairwise stability equilibrium concept) could be considered an alternative method, but it would not enable us to evaluate the heterogeneous post-merger competitive effects (for a survey on selection bias correction, when selection is specified as a multinomial logit

Our estimations return reasonable results on price elasticities, marginal costs, economies of scale, and learning by doing effects. We find that mergers in the SRAM market reduced post-merger production and increased prices, supporting the notion that post-merger market power effects dominate the efficiency effects. Most importantly, our estimation results show that merging firms realize substantial heterogeneous post-merger effects on competitive outcomes such as production or prices. We find that merger effects vary substantially across merging firms, depending on the firms' pre-merger efficiency levels, price elasticities, and innovative activities. For example, firms' efficiency level prior to merging determine large post-merger heterogeneities. Moreover, firms operating in markets with more elastic demands further increase post-merger output, such that post-merger prices further decline. Among all post-merger heterogeneity determinants, firm efficiencies generate the largest heterogeneous post-merger effects.

The price elasticities cause the second largest heterogeneous post-merger effects. Our estimation results show that firms' post-merger output decreases further (and post-merger price increases further) if firms face a more inelastic demand where little possibility for substitution exits for consumers. We also find that product market attributes (differences in inefficiencies and price elasticities) cause larger post-merger heterogeneities compared with technology market attributes. We also show that estimation results stemming from a heterogeneous merger effects model differ greatly from those that consider homogeneous merger effects models. Our estimation results on heterogeneous merger effects can provide additional valuable insights for policy makers and firm managers when evaluating merger cases.

Prominent theoretical studies–such as Deneckere and Davidson [1985] and Perry and Porter [1985]—explored the effect of mergers on profits and competition. One key argument for determining post-merger outcomes is the internalization of competitive external effects by merging and non-merging firms (see Stigler [1950], Salant, Switzer, and Reynolds [1983], and Farrell and Shapiro [1990]). Merging firms have the opportunity to limit competitive negative externalities, 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.[4] The extent to which merging firms

model, see Bourguignon, Fournier, and Gurgand [2007]). 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 (or future potential) merger formation. Therefore, we choose a heterogeneous treatment effects model framework in our study. We apply various robustness checks that build on propensity score methods and selection on unobservables (as discussed in Heckman, Urzua, and Vytlacil [2006]).

[4]Studies have shown that the merged entity must enjoy substantial efficiency gains to compensate for market

are able to internalize competitive negative externalities depends on firm and product market attributes. For example, absent efficiency gains, mergers among larger efficient firms result in larger output contractions and larger post-merger price increases.[5]

Traditional merger studies show that mergers in markets with more inelastic demand result in lower post-merger output and higher post-merger prices and profits (see Farrell and Shapiro [1990] and Froeb and Werden [1998]). Conducting mergers in markets with more inelastic market demands enables merging firms to further increase post-merger price and further contract output since fewer switching alternatives exist for consumers. Other studies show that mergers provide opportunities to gain synergy effects, which exert positive externalities on merger outcomes depending on the merging firms' attributes. In general, the list of empirical merger contributions is long and includes studies such as Dockner and Gaunersdorfer [2001], Mueller [1980, 1985], Goldberg [1973], Baldwin and Gorecki [1990], Ravenscraft and Scherer [1987], Gugler, Mueller, Yurtoglu, and Zulehner [2003], Dafny [2009], Duso, Neven, and Roeller [2007], and Ashenfelter and Hosken [2010], among many others. Merger evaluations have employed different empirical approaches, such as case studies, single merger simulations, and difference-in-difference methods (see Ornaghi [2009], Gugler and Szuecs [2016], Egger and Hahn [2010], Ashenfelter, Hosken, and Weinberg [2013], Aguzzoni, Argentesi, Ciari, Duso, and Tognoni [2016], and Allain, Chambolle, Turolla, and Villas-Boas [2017]). Most empirical merger studies find that mergers result in price increases (see also the surveys in Kwoka [2013] and Ashenfelter, Hosken, and Weinberg [2014]).

Several merger studies focus on the semiconductor market. For example, Gugler and Siebert [2007] use annual firm-level information on the semiconductor market and find that research joint ventures can be viewed as viable alternatives to mergers since they may achieve comparable efficiencies, possibly without the anti-competitive (market power) effects of mergers. Harris and Siebert [2017] use data on dynamic random access memory chips, which belong to a memory market, not the static random access memory chips upon which we focus. They find that firm-specific discount factors have a sizable effect on merger outcomes. For example, acquiring firms with low discount factors merge with highly efficient and innovative firms to achieve instant efficiency gains. It should be noted that their study has a rather different research focus than

power effects such that post-merger prices are restored or will even fall (see Williamson [1968], Perry and Porter [1985], Farrell and Shapiro [1990], McAfee and Williams [1992], Werden [1996], Froeb and Werden [1998], and Nocke and Whinston [2013]).

[5] Under the U.S. Hart-Scott-Rodino Act, large firms must report any substantial merger plans to the Department of Justice and the Federal Trade Commission (see also Wollmann [2019] for further information).

ours, as it explains how firm-specific discount factors and time preferences determine merger incentives and merger outcomes. In contrast, our study concentrates on heterogeneous post-merger effects with regard to technology and product market attributes. We also employ a different method since we directly estimate firms' marginal costs based on firms' supply relations, which are then incorporated into the merger outcome equation.

There are several studies that find differential post-merger effects of which the following studies relate closely to our study. Craig, Grennan, and Swanson [2018] evaluate whether hospital mergers have an effect on marginal costs and input prices for medical supplies. They estimate difference-in-difference models while accounting for heterogeneous merger effects with regard to a variety of firm and market characteristics. Their results show that targets realize higher post-merger input price savings than acquirers. Their results also return differential merger effects that depend on the acquirer's firm size, market characteristics, and the type of medical supply items.

The study by Cunningham, Ederer, and Ma [2020] focuses on evaluating the effects of acquisitions in the pharmaceutical industry. They find that an acquisition between an acquirer and a target firm can drastically reduce drug development success if the acquirer's marketed drug is closely related to the target's drug in development. This finding is even more pronounced depending on the acquirer's pre-merger characteristics such as market power and patent duration. The authors argue that acquisitions can serve an acquirer's purpose—shutting down the target's innovation projects and preempting future competition, also referred to as killer acquisitions.

Wollmann [2019] evaluates the effects of a program that exempts merging firms from notifying competition authorities about their merger intentions. The amendment to the 1976 Hart-Scott-Rodino Act exempts merging firms from notification if they are below specifically determined size and value thresholds. The study finds that the amendment leads to an increase in mergers between competitors. A related study (Wollmann [2020]) focuses on the U.S. dialysis industry. The study finds that those notified mergers that would result in monopolies are blocked more than 80 percent of the time compared with just 2 percent of the time for mergers that were exempt from notifications.

The study by Gugler and Szuecs [2016] is closest to our work. These authors examine whether mergers lead to positive profit externalities that are imposed on rival firms. Using accounting data and information on firms' profitability as a proxy to control for competitive effects, they find that the return on assets of non-merging rival firms increases significantly after a merger. Two other related studies (Ashenfelter, Hosken, and Weinberg [2015] and Hosken, Olson, and Smith [2018]) show an association of post-merger prices with firm size and concentration.

The remainder of the paper is organized as follows: Section II introduces the industry and the data sources and provides summary statistics. In Section III, we introduce the empirical model, and in Section Iv, we present the empirical results. We conclude in Section V.

II. INDUSTRY AND DATA DESCRIPTIVES

Memory chips define the largest market within the semiconductor family.[6] Memory chips are designed to store data in binary form and include SRAM, dynamic random access memory, mask read-only memory, erasable programmable read-only memory, electrically erasable programmable read-only memory, and flash memory chips. In our study, we concentrate on SRAM chips, as they are a key input for electronic goods, such as computers, workstations, communication systems, and graphic subsystems. SRAMs are incorporated into other consumer electronics, such as automotive electronics, household appliances, and synthesizers, as well as in hand-held electronic devices like digital cameras and cell phones. Finally, SRAMs are also commonly used in smaller applications, such as CPU cache memory and hard drive buffers.

The SRAM market constitutes a perfect base and provides a natural setting for studying post-merger 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 capacities. Previous studies assumed that SRAMs within a product generation are homogeneous, while they are differentiated across product generations. At one point in time, a limited number of generations are offered on the market such that the estimation of cross-price elasticities is constrained to a small number of generations. This keeps the demand estimation relatively tractable and facilitates the evaluation of post-merger outcome effects without further complications arising from the demand side. Third, beyond generation-specific price information, our dataset encompasses generation-specific and firm-level

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

production information. This allows us to evaluate production changes due to mergers, which are more reliable and accurate than price changes. Defining quantity as the firms' strategic choice variable is common practice in the economics and management literature due to the relevance of determining product generation-specific plant sizes. Moreover, the availability of highly disaggregate firm-level production information across SRAM generations allows us to evaluate firms' costs and heterogeneous merger effects at the individual firm and generation specific levels over time, which defines the unit of observation in our study. 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. Therefore, merging firms' incentives to form mergers are not constrained to achieving efficiency gains, but also motivated by realizing post-merger price increases stemming from dominant market power effects. Consequently, heterogeneous merger outcomes are likely to be present in the data. 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 ability to absorb external technological knowledge. To summarize, the detailed firm-level information enables us to properly control for firms' technology and product market attributes.

SRAM chips are classified into generations according to their information storage capacities, that is, the number of bits per chip. 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 dynamic random access memory chips, which store data dynamically and constantly need to refresh the data stored in the memory. This is one reason SRAM chips are preferred in electronic devices where energy efficiency is a strong requirement. 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 processes used to etch electrical circuits onto the wafer surface. It is important to recognize that the manufacturing process of SRAM chips is highly complex and specific to every generation, as every generation requires specific machinery and production processes (see also Liu and Siebert [2020]). Manufacturing processes are continuously improved in every product generation, in hopes 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.

We gathered quarterly data on the worldwide SRAM market from 1974 to 2003. We collected data from a variety of sources and include firm-level information on production, mergers, and patents. Firm-level production information is available at a highly disaggregate generation-specific level—namely the 4K, 16K, 64K, 256K, 1Mb, 4Mb, 16Mb, and 64Mb generations.[7] Note that the highly detailed firm-specific production information for every generation at a quarterly basis is far more disaggregate than the usual overall firm-level production information.

Table I shows the shipments, revenue, patents, and GDP in electronics across all generations.[8] In general, we observe increasing trends until 2000.

'Place Table I about here.'

Figure 1 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], Zulehner [2003], and Siebert [2010]). It is interesting to note that shipments of a generation increase and start declining once a new successive generation is introduced into the market, which is one indication that a preceding generation should matter

[7] The data is provided by Gartner, Inc.

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

as a substitute generation when estimating demand for a specific generation.

'Place Figure 1 about here.'

Figure 2 shows that the prices of every generation decline (relatively monotonically) over time. This smooth price decline over time supports the fact that learning effects are prevalent.

'Place Figure 2 about here.'

Figure 3 displays the number of firms across different generations. On average, less than 20 firms are present in one product generation. The low number of firms provides evidence that the SRAM market is a strategic industry that is characterized by an oligopolistic market structure.

'Place Figure 3 about here.'

Table II shows the market shares (MS) of the top-performing firms aggregated across all SRAM generations over the last five years.

'Place Table II about here.'

We collected information on horizontal mergers from the Thomson Reuters SDC Platinum database, and we include mergers with deal values of $1 million and greater.[9] Remember, firms are active in multiple generations, which provides us with a large number of competitive 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 in each generation, which results in 56 merger observations across generations. Table III shows the means and standard deviations of variables of main interest across product generations. The last line of Table III shows the number of merger-observations for every generation across the entire time period. Hence, we observe 7, 16, 14, 9, 8, and 2 mergers in the 16K, 64K, 256K, 1Mb, 4Mb, and 16Mb generations, respectively. The existence of merger observations across product generations and the associated variation in firm and market attributes enable us to identify heterogeneous merger effects (that can differ across product generations) on merger outcomes. We do not observe multiple merger events formed in the same generation at the same quarter.

'Place Table III about here.'

We use SRAM patent information at the firm level from 1974 to 2003. We procured patent information from the U.S. Patent and Trademark Office (USPTO), retrieving patents that had been applied for and subsequently granted.[10] The USPTO has developed a highly elaborate

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

[10] The patent information is contained in the National Bureau of Economic Research patent database. A

classification system 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 corresponding classification by the USPTO.

We proceeded by establishing a variable to capture firm heterogeneities in the technology market. The objective is that more innovative merging firms have better opportunities to absorb external intellectual knowledge and further benefit from synergy effects and technological spillovers, which can determine heterogeneous merger outcomes.[11] Therefore, we control for firms' ability to absorb knowledge via technological spillovers. We follow previous studies (see, for example, Cohen and Levinthal [1989] and Veugelers and Cassiman [1999]) and construct an absorptive capacity variable ($SAbsCap_{it}$) by using a firm i's accumulated SRAM patent stock in period t. The variable captures the fact that firms with more innovation experience and larger patent stocks have a higher ability to absorb new knowledge.

After introducing the data sources, variables, and basic summary statistics, we now turn to a comparison between merging and non-merging firms. Table IV shows descriptive statistics for individual merging and non-merging firm entities. The table shows that the individual merging firms produce more than 50 percent more SRAM chips than non-merging firms. Interestingly, non-merging firms are characterized by an increasing trend in production since the change in production from one period to the next is positive. In contrast, merging firms show a slightly declining trend in production over time. Merging firms operate in markets with more elastic demands, and they are more efficient than non-merging firms. Their marginal cost is about 10 percent below those of the non-merging firms. Merging firms are also more innovative, as their patent flow and absorptive capacity are about 50 percent larger.

'Place Table IV about here.'

Figure 4 shows a scatterplot of the changes in the separate merging firms' market shares at the time of merging and one period later. While some merging firms' market shares increase, pointing toward post-merger efficiency gains and price declines, other merging firms' market

large name-matching effort was undertaken to match the names of patenting organizations and the names of 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, Avery, Narin, and McAllister [1991]). We excluded individually owned patents.

[11] Spillovers relate to involuntary information or knowledge transfers 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.

shares decrease, hinting toward dominant market power effects and post-merger price increases.

'Place Figure 4 about here.'

The figure provides insights that mergers in the SRAM industry may have realize heterogeneous post-merger effects on market shares and suggests the relevance of going beyond summary statistics and applying econometric regression analyses.

III. EMPIRICAL MODEL

The main objective is to evaluate post-merger heterogeneous effects and whether those are caused mainly by product market or technology market characteristics. A simple difference-in-mean estimator would not return consistent estimates since the outcome variable is dependent on merger engagement and a selection bias can arise. We employ an empirical model that uses a regression adjustment approach that builds on firms' selection into mergers based on observables; hence, it treats the sample of merging and non-merging firms as nonrandomly drawn. In the case of selection on observables, the knowledge of firm characteristics may be sufficient to identify causal parameters (see Rosenbaum and Rubin [1983]).[12] This approach provides a good foundation for the inspection of post-merger heterogeneous effects (see also Cameron and Trivedi [2005], Wooldridge [2010], and Cerulli [2014]). We consider a set of variables that can cause heterogeneous merger effects. We specifically consider product market variables, such as firm efficiencies and price elasticities, as well as technology market variables such as firms' innovative activity. In the following, we introduce the heterogeneous treatment model that will be employed to evaluate post-merger heterogeneities.

EXPLANATION AND ILLUSTRATION OF HETEROGENEOUS MERGER EFFECTS

We consider firm i's decision variable q_i, which can stand for a firm's production or price choice. For each firm (q_{1i}, q_{0i}) denotes the two potential outcomes (such as quantity or price) from merging and not merging, respectively. The treatment effect of a merger on the outcome is defined as $TE_i = q_{1i} - q_{0i}$. 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

[12] Note that we conduct robustness checks that also consider firms' selection on unobservables (see further below).

the same time. Denoting M as a dummy variable that equals 1 if the individual firm engages in a merger and 0 otherwise, we can write for the observed outcome in vector form:

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

Using conventional regression notation,

$$q = \delta + \alpha M + \epsilon,$$

where the coefficient $\alpha = q_1 - q_0$ measures the treatment effect. Note that the treatment effect of mergers is expressed by the coefficient α; it is homogeneous (not firm-specific), as it is independent of firm characteristics and does not carry any firm subscript. If the merger effect (α) varied across firms even after controlling for exogenous variables, the α coefficient reflected heterogeneity. This can arise because firms differ in their characteristics. Heterogeneous effects are especially important in the merger context, since firms make their merger decisions with knowledge about their expected gain. If α varies even after controlling for firm characteristics, there may be sorting on the gain that is originated by a potential correlation between the α coefficient and the merger dummy, ($Cov(\alpha, M) \neq 0$). This implies that firms' distinct attributes likely have an impact on the merger outcome, and this leads to a potential correlation between the α and the merger dummy M. In this case, the coefficient α varies even after controlling for regressors (the merger effect (α) is different across firms—which is referred to as the *heterogeneous treatment effect*. This ignorance of essential firm heterogeneity can cause a potential bias. In the following, we will allow for heterogeneous merger effects.

HETEROGENEOUS MERGER EFFECTS

We now introduce the heterogeneous merger effects model that will be employed to evaluate post-merger heterogeneities. We write the merger outcomes as:

(a) $q_0 = \mu_0 + x\beta_0 + e_0$,

(b) $q_1 = \mu_1 + x\beta_1 + e_1$, and

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

where $E(e_0|x) = 0$ and $E(e_1|x) = 0$, μ_0 and μ_1 are parameters, x is a vector that contains firms' observed characteristics, $\beta_{0,1}$ refer to coefficients of main interest, and equation (c) is also referred to as the potential outcome model since q is the observed outcome. We substitute (a) and (b) into (c) and derive the following switching model:

$$q = \mu_0 + (\mu_1 - \mu_0)M + x\beta_0 + M(x\beta_1 - x\beta_0) + e_0 + M(e_1 - e_0). \tag{1}$$

If observable heterogeneity exists, such that $\beta_1 \neq \beta_0$ with unobservable homogeneity ($e_1 = e_0$), and we add an i.i.d. error term, we get the following outcome regression equation that can be estimated for every single merging and non-merging entity:

$$q = \mu_0 + M\alpha + x\beta_0 + M(x - \mu_x)\beta + u, \tag{2}$$

where $\beta = \beta_1 - \beta_0$, and an estimator for μ_x is the sample mean of x, that is, $\bar{x}$. It is important to note that the term $M(x - \mu_x)\beta$ is dependent on firm characteristics that determine heterogeneous merger effects.

Concentrating on the group of merged firms, the average treatment (merger) effect on the treated (merged) firms over x ($ATET(x)$) is defined as:[13]

$$ATET(x) = [\alpha + (x - \bar{x})\beta]_{M=1},$$

where parameters estimates of α and β come from estimation of equation (2). The $ATET(x)$ measures the contribution of a covariate x on merger effects. Note also that the firm characteristic x enters the formula, such that the estimation of equation (2) allows merging firms to achieve different merger outcomes (as described by the dependence of the $ATET$ on firm characteristics (x)).

Similarly, the average treatment (merger) effect on the non-treated (non-merged) firms over x ($ATENT(x)$) is:[14]

$$ATENT(x) = [\alpha + (x - \bar{x})\beta]_{M=0}.$$

[13] The $ATET$ refers to the difference between the outcome of the merged firms and the outcome of the merged firms if they had not merged.

[14] The average treatment effect on the non-treated ($ATENT$) refers to the effect if non-merging firms did merge.

Note when firms select on observables and/or unobservables, treatment effects are heterogeneous such that $ATET \neq ATENT$, since they can be different depending on firm characteristics. In contrast, if we have observed and unobserved homogeneity, then $ATET = ATENT$. Therefore, the $ATET$ and $ATENT$ provide insights into the existence of homogeneous versus heterogeneous merger effects.

EMPIRICAL MODEL SPECIFICATION

Our empirical specification connects closely to the empirical model described in the previous section, accounting for heterogeneous merger effects.

IDENTIFICATION OF HETEROGENEOUS MERGER EFFECTS

As discussed in the previous section, we employ a regression adjustment approach to estimate heterogeneous merger effects on market outcomes. The estimation of heterogeneous merger effects requires a thorough discussion on adopting the proper identification strategy. Several aspects need to be considered.

First, from a social welfare point of view, the primary interest of merger evaluations is to explore their competitive effect on prices. A common problem with using prices, however, is that price information is rarely available at the firm or even product level. Instead, price information is frequently aggregated across firms and products and represents an average market price index. This is a fundamental problem in our case, since we need firm-specific variation to identify the heterogeneous effects of mergers across firms. In order to avoid this aggregation problem, we use production information that is available at the highly disaggregate firm and SRAM product levels.[15] We take advantage of the detailed production data and (instead of evaluating the merger impact on price), we follow Farrell and Shapiro [1990] and examine the effect of a merger on output. The merger effects on production will then allow us to draw inferences on the impact of mergers on prices, which provides insights into the impact on consumer welfare.[16] The theoretical contribution by Farrell and Shapiro [1990] has shown that market shares will

[15] The fact that price information is less reliable than production information is a rather common problem in economics and management studies.

[16] See also Mueller [1985] and Duso, Roeller, and Seldeslachts [2014] for empirical applications.

increase (decrease) if the efficiency effect dominates (is dominated by) the market power effect, and this will be equivalent to a price reduction (increase) (see also Mueller [1985], Gugler and Siebert [2007], and Duso, Roeller, and Seldeslachts [2014]). Hence, the relationship between merging firms' change in output can be used to make inferences about the change in price. If merging firms reduce (increase) post-merger output, we can infer that post-merger price would increase (decrease). Therefore, merger effects on production are conclusive for drawing inferences on prices. To conclude this point, our study concentrates on evaluating heterogeneous merger effects on post-merger production.

Second, our main empirical model builds on a regression adjustment method to estimate heterogeneous merger effects outcomes. The objective is to obtain two values on the quantities for each firm, representing the predictions on quantities assuming that the firm merged or did not merge. We estimate two specifications. We begin with predicting the quantities as measured in levels (see equation (2)) between merging and non-merging firms. This approach may return biased estimates if there are time trends. Therefore, our main empirical specification builds on a difference-in-difference approach that eliminates this bias. The difference-in-difference model is appropriate in our context since we are interested in estimating the causal effects of price or quantity changes due to mergers. Rather than predicting the quantities in levels between both types of firms, we examine the causal merger effect on production changes (after and before merger) between merging and non-merging firms.

Third, it is important to note that our research objective is different from those in most previous merger studies, which has implications on the identification strategy. Most merger studies focus on identifying homogeneous merger effects, i.e, the measurement of price changes that are explained by the merger formation while abstracting from any competitive externalities originated by competitors. Their identification argument builds on comparing the difference between the realized post-merger price and the unobserved counterfactual price that would have been realized in the absence of the merger. Establishing this counterfactual price is challenging since a merger affects non-merging firms' production and price decisions via externalities if non-merging firms operate in the same market as merging firms, also referred to as firms being contaminated by merger effects (see also Gugler and Szuecs [2016]). This fact could raise concerns when including non-merging firms into the control group in studies that compare realized post-merger price with unobserved non-merging prices. These studies occasionally use a control group that consists of non-merging firms from different but somewhat comparable markets to ensure that non-merging firms are unaffected by the merger externalities. In contrast to these studies, our study explores a different research question and requires a different identification approach. We are particularly interested in estimating heterogeneous merger effects on outcomes, and those are determined by firms' characteristics related to the average characteristics in the market, as mentioned earlier in equation (2). So, the inclusion of merging and non-merging firms is fundamentally important in our study that aims to evaluate heterogeneous merger responses (see also McCabe [2002] and Harris and Siebert [2017]). However, we should keep in mind that the inclusion of contamination effects could lead to exaggerated merger effects. On a final note, it should be recognized that we are primarily interested in evaluating the merger effects with regard to product market and technology market heterogeneity. Therefore, any potential exaggerated merger effects due to contamination concerns, may still maintain the relative magnitude of heterogeneous merger effects across product and technology market attributes.

SPECIFICATION OF HETEROGENEOUS MERGER EFFECTS EQUATION

The aim is to evaluate the heterogeneous post-merger effects with regard to firms' product and technology attributes. The specification of the heterogeneous merger outcome equation builds on equation (2). Remember that the equation considers the production of every constituent merging and non-merging individual entity. Our empirical specification is consistent with other empirical approaches (see Goldberg [1973] Mueller [1985], and Gugler and Siebert [2007 , page 651]) that use production or markets share information of every individual merging firm entity before and after the merger. We adopt a Difference-in-Difference approach that evaluates the differences in market shares before and after mergers across every constituent merging and non-merging firm entity.

The heterogeneous effects on output are based on a firm's dynamic supply relation. We consider a dynamic supply due to learning-by-doing effects entering firms' production choices; more details on the firms' dynamic supply are provided later. A firm i's production q in period t and generation k is formulated as a function of heterogeneous firm attributes such as marginal costs, price elasticities, and innovative activity, as well as a merger indicator:[17]

$$q_{ikt} = \beta_0+\beta_1 MC^*_{ikt}+\beta_2 Elast_{ikt}+\beta_3 AbsCap_{it}+\beta_4 M_{ikt}+\beta_5 M_{ikt}*HetMC_{ikt}+\beta_6 M_{ikt}*HetElast_{ikt}$$

$$+\beta_7 M_{ikt}*HetAbsCap_{it}+\beta_8 Time_{ikt}+\sum_l \beta_{9,l} Firm_l+\sum_k \beta_{10,k}*Generation_k+\epsilon_{ikt}. \quad (3)$$

The production is described by the firm's dynamic marginal costs (MC^*_{ikt}).[18] Moreover, we control for the fact that firms' production decisions (q_{ikt}) depend on price elasticities, as they determine potential competitive externalities that firms impose on each other in the product market. Hence, we include their price elasticities ($Elast_{ikt}$) for generation k as a regressor. We also control for the absorptive innovation capacity of a firm, measured by the patent stock ($AbsCap_{it}$), as described earlier.[19]

We now turn to the merger effects.[20] We insert a merger dummy (M_{ikt}) that measures the post-merger impact on production. Based on the finding by Gugler and Szuecs [2016] that most post-merger effects materialize within a year, we evaluate the impact of a merger in period t.[21] Importantly, we consider several heterogeneous post-merger effects on production. First, we allow firm efficiencies to have a heterogeneous post-merger impact on production and include the interaction between the merger dummy and the firm's (static) marginal costs relative to the industry ($HetMC_{ikt} = MC_{ikt} - \overline{MC_k}$).[22] Second, we control for heterogeneous post-merger effects on production with regard to price elasticities and include the interaction between the merger dummy and the heterogeneity in price elasticities ($HetElast_{ikt} = Elast_{ikt} - \overline{Elast_k}$). Third, we control for firms' heterogeneous post-merger impact with regard to firms' absorptive capacity of innovations and include the interaction between the merger dummy and firms' absorptive capacity compared to the average absorptive capacity ($HetAbsCap_{it} = AbsCap_{it} - \overline{AbsCap}$). Remember that we are especially interested in evaluating the extent to which post-merger het-

[17]In accordance with a difference-in-differences approach, our main empirical specification will later replace firm i's production in period t with the change in production (that is, $dq_{ikt} = q_{ikt} - q_{ikt-1}$).

[18]Note that we use the dynamic marginal costs, rather than static marginal costs, to account for firms' intertemporal production decisions with regard to learning-by-doing, as will be explained in more detail later.

[19]It should be noted that firms made technology decisions in the distant past such that a potential correlation between the patent stock and the error term seems unreasonable.

[20]Remember that the heterogeneous treatment effects on output will allow us to derive inferences on price. If production of the merging firms contracts after merger, post-merger price increases, and vice versa.

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

[22]Note, since the average sum of marginal costs enter equation (3), we had to separate the estimation of this equation from the estimation of the supply equation, as shown below.

erogeneities are driven by product market and technology market attributes. In this regard, the first two measurements ($M_{ikt} * HetMC_{ikt}$ and $M_{ikt} * HetElast_{ikt}$) relate to the post-merger heterogeneities caused by firms' product market characteristics, while the latter measurement ($M_{ikt} * HetAbsCap_{it}$) refers to post-merger heterogeneities originated by firms' technology market characteristics. The associated coefficients $\beta_4 - \beta_7$ will be used to calculate the $ATET$ and $ATENT$ effects, as described earlier.

One might suspect that the elasticity is a potential endogenous regressor since the elasticity could potentially be correlated with any unobserved quality, innovation, or distributional effects that may vary across generations, firms, and also possibly follow firm-specific trends. To eliminate this concern we introduce additional regressors, i.e., a firm-specific trend that captures any firm-specific unobserved evolutions, as well as firm-level and generation-level fixed effects. Therefore, we include firm specific time trends ($Time_{ikt}$), firm fixed effects ($Firm_l$), and generation fixed effects ($Generation_k$).[23] These trends and fixed effects also control for any remaining demand variation. The error term is denoted by ϵ_{ikt}.

In estimating equation (3), we face the challenge 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 market is characterized by learning-by-doing. The intertemporal output strategies that firms adopt will make the use of the static Lerner Index inapplicable, as firms do not price according to static marginal costs.[24] Consequently, while accounting for learning-by-doing and spillovers, we will have to estimate firms' dynamic marginal costs (MC^*) based on firms' supply relations.

FIRMS' DYNAMIC MARGINAL COSTS FROM SUPPLY RELATIONS

The goal is to estimate firms' dynamic marginal costs (MC^*) from their 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 assume that each firm i chooses quantities of a

[23] I would like to thank an anonymous referee for pointing this out.

[24] 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 (MC^*), which lie below static marginal costs (MC). 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]).

homogeneous good q_{ikt} at time $t = 0, \ldots, \infty$ to maximize its discounted present value:[25]

$$\max_{q_{ikt}} \ \Pi_{ik} = E_{k0}\left[\sum_{t=0}^{\infty} \delta^t (P_{kt} - MC_{ikt}) q_{ikt}\right], \tag{4}$$

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—which is a reasonable assumption for the SRAM industry (see industry description)—implies the following first-order condition relating price and marginal cost:

$$P_{k0}\left(1 + \frac{MS_{ik0}}{\alpha_{1k}}\right) = MC_{ik0} + E_{k0}\left[\sum_{t=1}^{\infty} \delta^t q_{ikt} \frac{\partial MC_{ikt}}{\partial q_{ik0}}\right], \tag{5}$$

where α_{1k} is the price elasticity of demand for generation k, and MS_{ik0} denotes firm i's market share in generation k at period 0.

Against the background of learning-by-doing, firms adopt intertemporal production strategies and increase current production, which serves as an investment in 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. Therefore, the static marginal cost (MC_{ik0}) plus an adjustment term that accounts for the discounted value of future cost reductions ($\sum_{t=1}^{\infty} \delta^t q_{ikt} \frac{\partial MC_{ikt}}{\partial q_{ik0}}$) achieved from own-learning characterize dynamic marginal cost (MC^*_{ikt}).

Using a recursive formulation, equation (5) becomes:

$$P_{kt}\left(1 + \frac{MS_{ikt}}{\alpha_{1k}}\right) - MC_{ikt} - \delta\left[q_{ikt+1}\frac{\partial MC_{ikt+1}}{\partial q_{ikt}} + P_{kt+1}\left(1 + \frac{MS_{ikt+1}}{\alpha_{1k}}\right) - MC_{ikt+1}\right] = 0, \tag{6}$$

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. The dynamic term in equation (6) accounts for learning effects—$\delta\left[q_{ikt+1}\frac{\partial MC_{ikt+1}}{\partial q_{ikt}} + P_{kt+1}\left(1 + \frac{MS_{ikt+1}}{\alpha_1 k}\right) - MC_{ikt+1}\right]$); that is, firm i's current production decision has an effect on firm i's future marginal costs via learning ($\frac{\partial MC_{ikt+1}}{\partial q_{ikt}}$), which affects

[25] See also Zulehner [2003] and Siebert [2010].

future marginal profits. Hence, this dynamic term separates static from dynamic marginal costs. Rearranging equation (6), we obtain the following equation:

$$P_{kt}\left(1+\frac{MS_{ikt}}{\alpha_{1k}}\right) = MC_{ikt} + \delta\left[q_{ikt+1}\frac{\partial MC_{ikt+1}}{\partial q_{ikt}} + P_{kt+1}\left(1+\frac{MS_{ikt+1}}{\alpha_{1k}}\right) - MC_{ikt+1}\right] + \nu_{ikt}, \tag{7}$$

which includes a statistical error term, ν_{ikt}, that is normally distributed.

Following previous studies (see Zulehner [2003] and Siebert [2010]), we specify the (dynamic) marginal cost function (which will be inserted into equation (7)) as follows:

$$MC^*_{ikt} = \sum_i \delta_{0i} Firm_i + \sum_k \delta_{1k} Generation_k + \delta_2 ECS_{ikt} + \delta_3 ECS^2_{ikt} + \delta_4 LBD_{ikt} + \delta_5 LBD^2_{ikt}$$

$$+\delta_6 Spill_{ikt} + \delta_7 Spill^2_{ikt} + \delta_8 Silicon_t + \delta_9 Patents_{it} + \delta_{10} DynTerm_{ikt}, \tag{8}$$

where we estimate firm-level fixed effects (δ_{0i}) and generation-specific fixed effects (δ_{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 $Spill$ variables to control for nonlinear effects. (Note, potential endogeneity issues and the use of instrumental variables will be addressed in the results section.) We also consider material price ($Silicon_t$) and annual SRAM patents ($Patents_{it}$) to control for shifts in marginal costs.[26] Finally, we insert a dynamic term ($DynTerm_{ikt}$) that characterizes future marginal cost savings via learning—that is, firms price according to dynamic marginal costs, which lie below the static marginal costs. Therefore, the dynamic term captures the differences between dynamic and static marginal costs, and it is proxied by the inverse of the number of periods that a chip generation is on the market. Since equation (7) includes the price elasticity of demand (α_{1k}), we will have to estimate a demand equation, which is introduced next.

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

DEMAND EQUATION

For the demand estimation we consider the SRAM generations k = 4K, 16K, 64K, 256K, 1Mb, 4Mb, 16Mb, and 64Mb. Following previous studies, we assume that every generation is homogeneous in itself and that different generations represent differentiated goods. 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. In our main demand specification, the demand elasticities are estimated at the product generation level. We pool the data and use dummy variables to account for generation-specific elasticities and market size effects. We specify the following log-linear demand for generations:

$$ln(Q_{kt}) = \alpha_0 + \sum_k \alpha_{0k} Generation_k + \sum_k \alpha_{1k} ln(P_{kt}) + \alpha_2 ln(P^S_{kt}) + \alpha_3 Time_{kt} + \mu_{kt}, \qquad (9)$$

where Q_{kt} denotes the market output for generation k in quarter t. The coefficient α_0 is an overall intercept. To account for differences in demand over product generations, we include generation-specific dummy variables ($Generation_k$). P_{kt} are the generation-specific selling prices of SRAM chips. The coefficients α_{1k} refer to generation-specific own-price elasticities of demand. We also include the price of a close substitute (P^S_{kt}), where S refers to the substitute generation of product generation k at time t, and α_2 refers to the cross-price elasticity.[27] It is important to note that the prices of the generation under consideration(P_{kt}) and the prices of the substitute generations (P^S_{kt}) are potentially endogenous regressors. The reason is that, unobserved firm-level effects and trends (such as trends in quality, innovation or distribution) can have an impact on pricing, especially at the early stages of a generations when only one or a very small number of firms entered the market. Hence, the prices might be correlated with the error term. This argument is different than the one in the merger outcome equation since the demand is characterized by a more aggregate data structure as would not allow us to introduce firm-specific trends that absorb those effects and prevent those from entering the error term. Therefore, prices need to be instrumented for, which will be addressed later. $Time_{kt}$ is a generation-specific time trend. The error term μ has a mean of zero and a constant variance σ_μ.

[27]For all SRAM generations, we identify the corresponding substitute generations offered on the market at the same time.

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 (9).

2. Retrieval of static and dynamic marginal costs: From the estimation of equation (7), we use the parameter estimates to predict firm-specific dynamic and static marginal costs.

3. Heterogeneous impact of mergers: Using the estimated marginal costs and price elasticities, we estimate equation (3).

4. We recover the treatment effects using the estimated parameters.

IV. ESTIMATION RESULTS

In accordance with the estimation algorithm, we first present the estimation results of the demand equation (9) and the supply equation (7) and then present the results of the heterogeneous merger effects model (equation (3)).

DEMAND ESTIMATION RESULTS

We estimate the industry demand equation (9) and firms' supply equation (7) using an instrumental variable estimator. Table V shows the demand estimation results.

'Place Table V about here.'

We estimate two main specifications. The first specification (Table V, column 3) returns an estimated price elasticity that is constant across all product generations. The second specification (Table V, column 5) is our main specification, which returns generation-specific price elasticities. In both specifications, we account for the potential endogeneity of prices for the current generations (P_k) and substitute generations (P_k^S).[28] As instruments, we use supply shifters to identify the slope of the demand function. One appropriate instrument relates to learning-by-doing, which is an important characteristic in the SRAM industry. Learning-by-doing shifts

[28] As the substitute generation for generation k, we consider the preceding generation $k-1$ since it is simultaneously offered on the market throughout most of generation k's life cycle (see Figure 1). Alternatively, using the successive generation $k+1$ would result in a large loss of observations.

the supply curve downward as more experience is accumulated. As mentioned earlier, learning-by-doing is measured at the industry level using the accumulated quantity across firms for a specific a generation. Since we instrument for the prices of the current and substitute generations, we use the past accumulated output for the current generation (LBD) and the substitute generation (LBD^S). A further instrument that shifts supply is the material price of silicon ($Silicon$), as silicon is the main material input in the semiconductor production process. Our final instrument relates to traditional Cournot models that show that competition or the number of firms shifts supply. Using the number of firms of the same generation as an instrument could cause a potential concern; that is, any serially correlated unobserved demand shocks of a specific generation k could potentially be correlated with the number of firms in that generation. In order to avoid this concern, we use the number of firms from the substitute generation as an instrument (NOF^S). This is an appropriate instrument in our case, due to the nature of the memory chip production process, where every generation requires specific machineries and plants (as mentioned earlier). Therefore, this variable should be rather unaffected by any persistent demand shocks having an effect on the current generation's number of firms.[29]

Focusing on the results of the first demand specification in which we estimate an overall price elasticity, the F-test returns a value of 51.43, which confirms that the instruments are jointly significant. The first-stage results, in which the price of the current generation ($ln(P_k)$) is instrumented for, are displayed in column 1 of Table V. The estimated coefficient for the learning-by-doing effects (LBD) 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 18 percent represents a reasonable estimate and is consistent with earlier studies. The coefficient estimate for intergenerational learning-by-doing (LBD^S) confirms that firms learn from their production experience accumulated in previous generations. The learning elasticity is less than half the size of the learning elasticity of current generations. 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 0.47 percent. A higher number of firms (NOF^S) shifts firms' supply outward and puts downward pressure on the prices. The first-stage results, in which the price of the

[29]Note that we also run a robustness check and estimate the demand function without this instrument, as will be reported later.

substitute generation (P_k^S) is instrumented for, are shown in column 2 of Table V. The coefficient estimates are highly significant and support the same economic rationale as the previously reported estimates.

Turning to the second stage of our first demand estimation specification (Table V, column 3), the estimation returns an adjusted R-squared of 0.57, which confirms a good fit of our model. The estimated own-price elasticity of -3.76 confirms an elastic market demand—that is, a 1 percent increase in the average SRAM price decreases the quantity demanded by 3.76 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 appears a little high but it should be noted that is comparable to those estimated in previous studies (see, e.g., Brist and Wilson [1997], Zulehner [2003], and Siebert [2010]), which further confirms the reliability of our estimation results.[30]

The estimate for the cross-price elasticity is 0.37, providing evidence that other SRAM generations are, in fact, substitutes. Note also that the cross-price elasticity is smaller in magnitude than the own-price elasticity, as expected by theory. The time trend is negative, confirming that buyers substitute away from one generation to the next as time elapses.

We conducted two robustness checks. The first robustness check addresses the potential endogeneity of the number of firms in the generation that was replaced with the number of firms in the previous generation (NOF^S). One might still suspect that even the number of firms in the substitute generation could be susceptible to persistent demand shocks in the current generation k. Therefore, we estimated the same demand equation, but we removed the number of firms from the set of instruments. Table V, column 4 shows that the estimated coefficients are very similar in signs, magnitudes, and efficiencies to the estimates shown in column 3.

The second robustness check relates to using an additional demand shifter. We use the GDP in electronics as an additional exogenous demand shifter, since semiconductors are used as an input in many electronic products and the GDP in electronics could proxy a demand pull effect, which affects quantities demanded.[31] While the own-price elasticities increase slightly, our main estimation results remain quantitatively and qualitatively unchanged.

[30] The demand elasticity is also comparable to a further SRAM study that estimates an elasticity of -3.35 for the SRAM industry (see Liu and Siebert [2020]). Moreover, Harris and Siebert [2017] estimate a price elasticity of -2.24 for the more broadly defined semiconductor industry.

[31] We use the GDP of the Organisation for Economic Co-operation and Development (OECD).

We now turn to our main demand specification (see Table V, column 5), in which we estimate generation-specific price elasticities. The estimation of generation-specific price elasticities is reasonable since the data span a period of 30 years, which is rather long for a high-tech industry. The concern arises that an overall price elasticity would not capture any changes in price elasticities across generations or time. Those elasticity changes, especially across generations, are reasonable considering the fact that the demand for memory chip generations is application specific, as specific memory chips serve as an input to specific devices such as personal computers, cameras, automotive devices, etc. The estimation of generation-specific price elasticities appeases this concern. Note that we also include a time trend that is generation specific and captures a potential depreciation of consumer utility over time.

We instrument for the generation-specific prices using the same set of instruments (but this time specific to every generation) as in the first demand specification. The F-test returns a value of 43.51, and the second-stage estimation returns an adjusted R-squared of 0.69, which confirms a good fit. The own-price elasticities range from -3.27 to -2.45. 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 explained by the steeply decreasing prices at the beginning of the life cycle, as shown in Figure 1. The coefficient on the cross-price elasticity is again positive, which confirms that other generations are substitutes.[32] The negative coefficient on the time trend reflects consumers' declining generation-specific utility over time and the fact that they substitute to other generations over time.

To put the demand estimation results in relation to the quantity evolution (see Figure 1) a few aspects are noteworthy to mention: First, the generation-specific fixed effects show a positive trend across SRAM generations. The positive trend across vintages reflects an increase in demand across generations that can be explained by new more complex applications entering the (downstream) market that require more memory storage. The trend could explain part of the increasing demand trend shown in Figure 1. Second, the negative time trend captures the fact that consumer substitute away from existing generations, which reflects the downward

[32]While the price elasticities still appear somewhat high they are now closer or even below the ones estimate in previous studies as mentioned above. Once concern with estimating large elasticities is that they have strong implications on the definitions of product markets as often determined by the Small but Significant and Non-transitory Increase in Price (SSNIP) test, see also Werden [2003] for further information. In our case, the estimation of the significant cross-price elasticities provide confidence for different generations belonging to the same product market.

trend within each product generation. Finally, as will be shown later, the production process of SRAM chips is characterized by generation-specific learning effects that are especially large at the beginning of each life cycle. Those can cause the drastic marginal cost and price reductions within each generation over time which could explain the strong increase in demand at the early stages of the life cycle.

FIRMS' SUPPLY ESTIMATION RESULTS

We now turn to the estimation results of firms' supply relations, as shown in equation (7). We account for a potential simultaneity bias since contemporaneously chosen output (that is used to measure ECS and ECS^2) are potentially correlated with the error term. As instruments, we use their lagged variables and further variables that characterize firms' marginal costs and firms' current output choices, including the lagged cumulative firm-level output in a generation to capture learning-by-doing and the lagged silicon material price.[33]

One concern with estimating the supply equation is that some regressors are generated due to endogeneity correction and the inclusion of the elasticity. Since these generated regressors do not represent the actual variables but are rather estimated from the data they contain additional sampling variance that needs to be accounted for when calculating the variance of the parameter estimates. The usual standard error calculations ignore this additional variation and would underestimate the actual sampling variation. A common procedure how to deal with the generated regressors problem is to bootstrap the standard errors. Our bootstrap procedure accounts for the data structure in which observations vary across generations and firms. Hence, the generated regressors may contain systematic additional variance stemming from various firm and generation specific features including variation in efficiencies, application specific demand factors, etc. We accordingly group the observations in the data and cluster the bootstrap procedure at the firm level and the generation level. We bootstrapped standard errors based on 250 replications with replacements. Note that we also use firm-level and generation-specific fixed effects to control for remaining heterogeneities across firms and generations.

Note that we also use firm-level and generation-specific fixed effects to control for remaining

[33]We also ran a robustness check and inserted the lagged number of firms in the previous generation to control for competition effects and supply shifts (see also the demand estimation). Since the coefficient estimates were similar (which somewhat replicates our test for the demand estimation), we decided to report the results without the number of firms to avoid any remaining potential endogeneity concerns.

heterogeneities across firms and generations. The F-test returns a value of 142.58, and the Sargan test (as an overidentification test of all instruments) returns a value of 31.64, which supports the explanatory power of our instruments. The Wu-Hausman test of 3.94 leads us to reject the null hypothesis and confirms the necessity of using instruments.

Table VI shows that all coefficients (with only one exception) are highly significant, that is, almost all coefficient estimates are significant at the 1 percent level. The coefficients also carry the expected signs. For example, the results confirm the presence of economies of scale. We calculated an overall impact of $-5.86e-04$, which is significant with a standard deviation of $1.85e-04$. Hence, an increase in current output by 1 million units reduces unit marginal costs, on average, by \$0.59. Interestingly, the increasing economies of scale are diminishing in output, as shown by the positive coefficient estimate for ECS_{ikt}^2.

'Place Table VI about here.'

Our results also confirm significant learning-by-doing effects. The calculated overall learning effects are significant and amount to $-3.40e-05$. An increase in current output by 1 million units reduces unit marginal costs by \$0.03 in every future period. The positive parameter estimate for LBD_{ikt}^2 shows that learning effects are diminishing. The overall impact of learning-by-doing via spillovers on marginal costs is $1.98e-08$ and significant with a standard deviation of $8.80e-09$. Similar to the scale economies and own-learning effects, the spillover effects diminish with experience. Comparing the magnitude of the spillover effect with the own learning-by-doing effect shows that firms learn significantly more from their own production experience. Moreover, our results 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 becomes smaller as the life cycle proceeds. The estimation procedure also returns significant coefficients on the dummy variables that control for heterogeneities across product generations and firms.

We calculate firms' marginal costs since they enter the heterogeneous treatment effects model as per equation (3). The average predicted static firm-level marginal cost (MC) amounts to

$4.28, and the average price-cost markup is $3.38. These are reasonable numbers that match outcomes of previous studies and are consistent with the reported price evolution in Figure 2.

HETEROGENEOUS MERGER EFFECTS RESULTS

We present the estimation results of the heterogeneous merger effects model that incorporates an outcome equation.[34]

MERGER FORMATION

Before we report the results of the outcome equation, we provide further insights into firms' incentives to engage in mergers by estimating a probit equation. The probit estimation results are shown in Table VII, column 1.

'Place Table VII about here.'

The coefficient estimate for marginal costs (MC) is significantly negative, providing evidence that more efficient firms are more likely to form mergers. A reduction in the marginal cost by $1 increases the likelihood of forming a merger by 9.48 percentage points. This result suggests that more efficient and larger 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 finding confirms arguments related to theoretical studies, as shown in Bergstrom and Varian [1985], Salant and Shaffer [1999], and Roeller, Siebert, and Tombak [2007]. This result could also be interpreted as efficient merging firms recognizing the advantage of keeping inefficient firms outside the merger. In the absence of dominant efficiency gains, the post-merger output expansion of an inefficient non-merging firm (as a reaction to the merger) is lower than the post-merger output expansion of an efficient non-merging firm. This is consistent with the findings in the existing merger literature that output responses of larger non-merging firms are more pronounced, which reduces prices and makes mergers less attractive (see Salant, Switzer, and Reynolds [1983] and Farrell and Shapiro [1990], among others).

[34] The explicit inclusion of an outcome equation is especially useful in our case since it provides additional information. The alternative estimations of matching and re-weighting approaches would not include an outcome equation. Later, we also apply robustness checks that are based on different matching procedures such as propensity score, nearest neighbor, and kernel matching methods.

The significantly negative estimate for the price elasticities in the product market ($Elast$) shows that firms facing more inelastic price elasticities are more inclined to merge. This result is consistent with oligopoly theory predicting that merging firms operating in more inelastic product markets earn higher post-merger profits, as inelastic demands enable merging firms to further contract post-merger output and elevate post-merger prices, which increases profits. Moreover, post-merger output responses by non-merging firms will impose smaller negative competitive externalities on the merging firms themselves, which increases the merging firms' profitability.

Firms' absorptive capacity, as measured by $AbsCap$, provides no significant incentives to merge. This result could be explained by process innovation having a cost-reducing effect that enters the marginal cost measurement, which then absorbs any variation related to firms' absorptive capacities. Finally, the firm-level and generation-specific fixed effects are significant.

MERGER OUTCOME ESTIMATION RESULTS

We now turn to the estimation results of the merger outcome equation (3) while concentrating on heterogeneous merger effects (post-merger heterogeneity). We estimate two specifications: The first specification estimates the effect of mergers on quantities as measured in levels (q_{ikt}) (see equation (3)). This estimation compares the merger effects of merging and non-merging firms. The second specification is the one in which we are ultimately interested. It builds on a difference-in-differences model such that it measures the causal effect of mergers on production as measured by the production difference after and before merger formation ($dq_{ikt^*} = q_{ikt^*} - q_{ikt^*-1}$ where t^* stands for the period when the merger was formed).

Due to the fact that marginal cost and elasticity regressors are generated, we follow the same rationale as for the supply relation and bootstrap the standard errors clustered at the firm and generation level. We use 250 replications with replacements. Note, that firm-level and generation-specific fixed effects enter every regression to further control for remaining firm heterogeneities across firms and chip generations.

Turning to the results of our first specification (as shown in column 2 of Table VII), the adjusted R-squared of 0.49 shows that the model has high explanatory power. The negative coefficient estimate on firms' dynamic marginal costs (MC^*) supports the fact that more efficient firms produce more output. A \$1 reduction in marginal costs (which is equivalent to a 23 percent reduction) increases output by 602,000 units and this corresponds to a 17 percent change in production.[35] Furthermore, the results also show that firms operating in more inelastic markets produce more output. This result is consistent with standard Cournot models. That is, firms operating in less elastic markets usually operate in less competitive markets, which reduces business-stealing effects and results in higher firm-level output. Moreover, firms with higher absorptive capacities ($AbsCap$) produce more output.

Turning to merger-related impacts, our estimation returns a negative coefficient of $-1,116$ on the merger dummy variable (M).[36] Most interestingly, our estimation results return a significant amount of heterogeneity across merging firms, indicating that production scales differ across merging firms. We discuss the details of post-merger heterogeneity and report various treatment effects when we turn to our main specification.

Next, we estimate the causal heterogeneous merger effects on production changes as measured by $dq_{ikt} = q_{ikt} - q_{ikt-1}$, see column 3 of Table VII.[37] Most importantly, the estimation results return significant coefficient estimates on the merger dummy and all the coefficients measuring post-merger heterogeneities. The heterogeneous impact of mergers with respect to firms' pre-merger marginal costs ($M * HetMC$) is highly significant, which supports the notion that firms' efficiency levels cause heterogeneous merger effects on post-merger production.

In the following, we evaluate the treatment effects on the treated (merging) firms, $ATET(HetMC)$, while accounting for post-merger heterogeneity in marginal costs.[38] Based on the estimated regression coefficients of the outcome equation (3), the $ATET(HetMC)$ is calculated as:

$$ATET(HetMC) = [\beta_4 + (HetMC) * \beta_5]_{M=1}\,, \tag{10}$$

where β_4 is the coefficient on the merger variable, $HetMC$ is the heterogeneous merger effect

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

[36] Many studies find a post-merger output reduction. For further information see, for example, Gugler and Szuecs [2016, page 235]. Note that even though the market shares of the merging firms fall, mergers can still be profitable, see Mueller [1985, p. 259]. Note also that several studies, such as Perry and Porter [1985] etc., show that post-merger output can increase. The cost structures and the generated efficiencies are usually the key features of these models that cause an increase in post-merger output. Finally, Perry and Porter [1985] show that mergers can still be profitable even when market shares of the merging firms fall.

[37] Note that signs and magnitudes can change in comparison to the results in column 2 since we now consider production changes as opposed to production measured in levels.

[38] Remember, the $ATET$ refers to the difference between the quantities of the merged firms and the quantities of the merged firms if they had not merged.

over marginal costs (as defined earlier), and β_5 is the coefficient on the interaction between the merger and the heterogeneous marginal cost variable.

The results are shown in the upper panel of Table VIII, column 1. The $ATET(HetMC)$ returns a value of -56.89, which shows that, on average, the post-merger effect on production evaluated over marginal costs is negative and results in a post-merger reduction in output. On average, merging firms decrease post-merger production by 56,890 units (which corresponds to an output reduction of approximately 1.6 percent). This negative number shows that mergers reduce post-merger production, which results in higher post-merger prices. Hence, the efficiency gains alone are not large enough to fully compensate for the market power effects.

'Place Table VIII about here.'

Next, we further elaborate on quantifying the heterogeneity of merger effects. We evaluate the merger effects at the 40'th and 60'th percentiles of the marginal cost distributions (see columns 2 and 3 of Table VIII, respectively). The marginal cost changes return a range of merger effects from -68.07 to -45.70, which provides evidence for a large amount of post-merger heterogeneity—that is, 22.37. The merger effect at the 60'th percentile is larger (less negative) than the effect evaluate at the 40'th percentile, which shows that less efficient merging firms reduce post-merger production by less. This result could be explained by the fact that less efficient merging firms are able to absorb higher efficiency gains possibly due to learning.

Our results provide evidence that heterogeneity in efficiency gains is a relevant argument when evaluating post-merger output effects. Mergers vary substantially in their impact on post-merger production and prices, depending on the merging firms' efficiency levels. Merging firms' efficiency levels are a major contributor to heterogeneous post-merger effects. Firms that are more efficient prior to merging achieve higher efficiency gains post merger.

We also calculate the average treatment effect on the non-treated over marginal costs—that is, if non-merging firms did merge ($ATENT(HetMC)$). It is calculated according to:

$$ATENT(HetMC) = [\beta_4 + (HetMC) * \beta_5]_{M=0}\,. \tag{11}$$

The comparison of the $ATENT(HetMC)$ with the $ATET(HetMC)$ also serves as a test for heterogeneous treatment effects with regard to this variable—that is, if no heterogeneous treatment effects over the marginal costs exist, the $ATENT(HetMC)$ and $ATET(HetMC)$ should be the same. The results are shown in the lower panel of Table VIII, column 1. Our results show an average treatment effect on the non-treated over MC of -43.62. The negative value of the $ATENT(HetMC)$ indicates that a hypothetical merger between non-merging firms of the same efficiency levels would have reduced post-merger output by 1.2 percent.

Next, we evaluate the heterogeneous post-merger impact with respect to the price elasticities ($M * HetElast$). Table VII, column 3, shows a significant parameter estimate, providing evidence that price elasticities cause heterogeneous merger effects on output. We calculate the heterogeneous treatment effects on the treated with respect to the product market elasticities, applying the same principle as shown in equation (10). The upper panel of Table VIII, column 1, shows an $ATET(HetElast)$ of -73.45. The negative number confirms that the average merger effects over heterogeneous elasticities in isolation would result in an output reduction.

We provide further insights into the heterogeneous merger effects and evaluate the merger effects at the 40'th and 60'th percentiles of the elasticity distribution. Table VIII, column 3, shows that the merger effect at the 40'th percentile results in an output reduction of -83.26. This result provides evidence that firms operating in more inelastic markets further reduce post-merger output, leading to higher post-merger prices. The result that merging firms further contract post-merger output in markets with more inelastic demands is reasonable since merging firms account for consumers' limited opportunities to substitute to another generation, which adds more opportunities for merging firms to internalize negative competitive externalities, to increase prices, and to reduce output. This result is also consistent with oligopoly theory. Evaluating the merger effects at the 40'th and 60'th elasticity percentiles return values of -83.26 and -63.63 (columns 2 and 3 of Table VIII, respectively). The heterogeneity of the treatment effect over this range is 19.63, which is smaller than the heterogeneity that was returned from evaluating a change in marginal costs (22.37). Hence, the heterogeneous merger effect caused by price elasticity variation is smaller than the corresponding effect caused by marginal cost differences. In comparing the $ATET(HetElast)$ with the $ATENT(HetElast)$, Table VIII shows that a merger between non-merging firms would have caused an output reduction of -44.30—that is, a hypothetical merger between non-merging firms would have resulted in less post-merger output contraction.

Turning to the average treatment effect on the treated with respect to firms' absorptive capacities in the technology market, we find an $ATET(HetAbsCap)$ of -25.24, meaning that more innovative firms further reduce their post-merger output. This result is surprising, since we may have expected that more innovative firms would be able to absorb and exploit more efficiency or synergy effects. One explanation for this result could be that mergers have not yet materialized any synergy effects in the short run. We report robustness checks on this argument later. It should be noted that this effect is smaller than the other merger effects that are related to the product market, providing evidence that post-merger heterogeneities are less pronounced with regard to firms' innovative pre-merger activities. The merger effects evaluated at the 40'th and 60'th percentiles of the absorptive capacity distribution returns the smallest heterogeneity of merger effects (4.49) compared to the other two merger heterogeneities. Also noteworthy is the fact that the average treatment effect on the non-treated is even more negative, indicating that non-merging firms would have reduced post-merger output even further.

Next, we compare our estimation results with a model that does not account for post-merger heterogeneities.[39] The results of the homogeneous merger effect model are shown in Table VII, column 4. In the homogeneous merger effect model the average treatment effect on the treated is -41, which is equivalent to the treatment effect on the non-treated.

In comparing the estimation results between the homogeneous and heterogeneous merger effects models, usually the homogeneous effects model predicts less negative post-merger effects. The discrepancy between both models is mostly pronounced when comparing the treatment effects in the homogeneous merger effect model (-41) with the treatment effects over marginal costs and elasticities in the heterogeneous merger model. Hence, our results show that ignoring heterogeneous merger effects results in largely different estimates for the average treatment effects on the treated and the non-treated. The ignorance of heterogeneous merger effects would have resulted in higher post-merger output and lower post-merger prices. Overall, our estimation of the heterogeneous merger effects model returns large degrees of variety, where product market attributes (differences in inefficiencies and price elasticities) cause larger post-merger heterogeneities compared with differences in technology market attributes.

ROBUSTNESS CHECKS

[39] Remember that ignoring post-merger heterogeneous effects is a problem of essential heterogeneity that can lead to biased parameter estimates.

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 post-merger effect by four more periods, so we redefine the endogenous variable as $dq_{ikt+4} = q_{ikt+4} - q_{ikt-1}$. Table VII, column 5, shows that most estimates carry the same signs and they are of similar magnitudes and significance levels compared with our main specification. It is noteworthy that the heterogeneous post-merger effect over firms' efficiency is still present four periods after merger formation. In contrast, the heterogeneous merger effects with regard to price elasticities and innovation activity are insignificant, suggesting that they were already fully absorbed in the short run.

Table VIII, column 4, shows that the average treatment effects on the treated over firm efficiencies ($ATET(HetMC)$) are more negative than in our main specification. This result suggests that the internalization of competitive externalities became more effective over time. Overall, the $ATET$ effects are again larger for product market variables than for technology market variables.

Another robustness check related to the regression adjustment approach building on the conditional mean independence assumption. The assumption would be violated when firms' selection into mergers is governed by unobservables (selection on unobservables), as outlined in Dafny [2009]. In order to provide greater confidence, we conducted a robustness check that accounts for pre-merger heterogeneities (selection into mergers) when estimating post-merger heterogeneities. We estimate a selection equation that accounts for the fact that firm attributes are potentially correlated with the merger dummy. We employ the heterogeneous treatment model by Heckman, Urzua, and Vytlacil [2006] to control for truncation and selection issues.[40] The main results remain unchanged, as shown in an earlier version of the paper (see Siebert [2017] for further details).

Finally, we apply a robustness check that builds on the propensity score method to compare the outcomes of treated and control observations (see Rosenbaum and Rubin [1983]). The propensity score method allows us to find a close match of non-merging firms to merging firms. For the propensity score (that describes the conditional (predicted) probability of merging) we use a nearest neighbor and a kernel matching method. The estimated merger effects are fairly

[40] For further information, see Gugler and Siebert [2007], Weinberg [2008], Dafny [2009], Ashenfelter and Hosken [2010], Miller and Weinberg [2014], Duso et al. [2014], and Gugler and Szuecs [2016], among many others cited therein.

comparable to our earlier results in terms of magnitudes.

V. CONCLUSION

Recent empirical contributions in the treatment literature consider heterogeneous treatment effect models and emphasize that ignoring the heterogeneous impact can result in a heterogeneity bias (see, for example, Angrist and Krueger [1999] and Heckman, Urzua, and Vytlacil [2006]). This study adopts the heterogeneous treatment effects model to evaluate if differential merger effects on competitive outcomes are mainly caused by firms' technology or product market attributes. Based on a comprehensive dataset that includes detailed firm- and product-level information on mergers, production, and patents, we estimate and evaluate heterogeneous competitive impacts of mergers. Overall, we find substantial post-merger heterogeneities. Our estimation results provide evidence that the average treatment (merger) effects of the merged firms show vast heterogeneities across merging firms. We find strong support that firms' efficiencies, price elasticities, and innovative activities cause substantial heterogeneous causal merger effects on competitive outcomes such as production. Our estimation results show that product market attributes (firm efficiencies and price elasticities) lead to larger heterogeneous post-merger effects on output compared with firms' technology market attributes.

We also find firms that are less efficient prior to merging benefit from relatively higher efficiency gains. Our results also show that estimates based on a model accounting for post-merger heterogeneities differ from those that assumed homogeneous causal merger effects among merging firms. The systematic heterogeneous competitive effects of mergers could be insightful for antitrust scrutiny. For example, firm and market attributes (such as efficiencies, price elasticity and innovative activity) could provide additional insight when identifying potentially harmful mergers.

More work is certainly required in evaluating post-merger heterogeneities in different industries. It would be interesting to know if one of our main results—post-merger heterogeneities are more determined by product market characteristics than by technological characteristics—also applies to other industries especially those where price setting behavior is a more reasonable assumption for firm conduct. On a final note, for future research it would be interesting to consider differential effects between acquiring and target firms. This would also allow to relate to the financial economics area.

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TABLES

Table I: 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 I 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 million constant U.S. dollars. Sources: Gartner, Inc. and the U.S. Patent and Trademark Office.

Table II: 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 II shows the annual market shares of the top 5 SRAM firms. MS refers to firms' market shares. Source: Gartner, Inc.

Table III: Summary statistics across generations

Variables	16K	64K	256K	1Mb	4Mb	16Mb	64Mb
P	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	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	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	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	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)
$Mergers$	7	16	14	9	8	2	/

Table III shows the means and the standard deviations in brackets for variables of main interest across generations and time periods. K and Mb stand for Kilo- and Megabit, respectively. P denotes the price, Q is industry quantity, MS is market share, NOF is the number of firms, and HHI refers to the Herfindahl-Hirschman Index. $Mergers$ shows the number of merger-observations for every generation across the entire time period. Source: Gartner, Inc. and the U.S. Patent and Trademark Office.

Table IV: Summary statistics for non-merging and merging firms per period

	Non-merging firms	Merging firms
Production	2,056	3,598
Change in production	59	-4
Price elasticity	-1.89	-2.46
Marginal cost	4.61	4.14
Patents	19	28
Absorptive capacity	139	258

Table IV shows the summary statistics for non-merging and merging firms per time period. Sources: Thomson Financial, Gartner, Inc. and the U.S. Patent and Trademark Office.

Table V: Demand estimation results

Variable	First stage: $\ln(P_k)$	First stage: $\ln(P_k^S)$	Demand	Demand	Demand
	(1)	(2)	(3)	(4)	(5)
Constant	2.93***	0.24***	30.51***	26.821***	59.47***
	(0.10)	(0.04)	(0.32)	(0.53)	(1.04)
$\ln(P_k)$			-3.76***	-3.39***	
			(0.06)	(0.08)	
$\ln(P_{16K})$					-3.27***
					(0.05)
$\ln(P_{64K})$					-2.45***
					(0.03)
$\ln(P_{256K})$					-2.53***
					(0.04)
$\ln(P_{1Mb})$					-2.66***
					(0.05)
$\ln(P_{4Mb})$					-3.27***
					(0.07)
$\ln(P_{16Mb})$					-3.23***
					(0.05)
$\ln(P_{64Mb})$					-25.32***
					(0.57)
$\ln(P_k^S)$			0.37***	0.55***	1.08***
			(0.16)	(0.19)	(0.19)
$\ln(LBD)$	-0.18***	-0.03e-01***			
	(0.02e-01)	(0.06e-02)			
$\ln(LBD^S)$	-0.08***	-0.13***			
	(0.01)	(0.01)			
$\ln(Silicon)$	0.47***	0.33***			
	(0.01)	(0.04e-01)			
NOF^S	-0.07***	-0.24***			
	(0.02)	(0.01)			
$Time$	-0.03***	-0.01***	-0.16***	-0.13***	-0.09***
	(0.03e-02)	(0.02e-02)	(0.02e-01)	(0.03e-01)	(0.02e-01)
$Generation_k$	Yes***	Yes***	Yes***	Yes***	Yes***
Number of observations	327	327	327	327	327
Adjusted R-squared	0.94	0.84	0.57	0.60	0.69

Table V presents instrumental variable estimation results for the demand equation (9). We estimate two demand specifications. The first specification (column 3) assumes that the demand elasticity is the same across product generations. The second specification (column 5) assumes product-specific demand elasticities as shown in equation (9). We use instruments for the log prices of the current and substitute generations, such as, the logs of cumulative industry output in the specific generations and the previous generations, the log of silicon price, the number of firms in the previous generation, a time trend, and product generation fixed effects. The first stage results of the first demand specification are shown in columns 1 and 2. Column 4 shows the results from the robustness check when we removed the number of firms from the set of instruments. **, **, and (*) denote the 99%, 95%, and 90% levels of significance, respectively.

Table VI: Firms' supply estimation results

Variable	
Scale economies (ECS)	-7.01e-04***
	(0.51e-04)
Scale economies squared (ECS^2)	2.64e-08***
	(3.07e-09)
Learning-by-doing (LBD)	-3.48e-05***
	(5.04e-06)
Learning-by-doing squared (LBD^2)	4.26e-11***
	(7.05e-12)
Spillovers ($Spill$)	-4.40e-08
	(3.29e-07)
Spillovers squared ($Spill^2$)	7.21e-14**
	(3.65e-14)
Silicon ($Silicon$)	3.21e-03***
	(0.35e-03)
Patents ($Patents$)	-0.01***
	(0.03e-01)
DynTerm ($DynTerm$)	25.19***
	(2.82)
16K dummy	-7.78***
	(0.81)
64K dummy	-5.86***
	(0.86)
256K dummy	-3.36***
	(0.85)
1Mb dummy	-0.75***
	(0.83)
4Mb dummy	2.14***
	(0.88)
16Mb dummy	-4.15***
	(1.24)
64Mb dummy	-14.45***
	(2.06)
Firm FE	Yes***
Number of observations	6,605
Adjusted R-squared	0.66

Table VI presents the estimation results for firms' supply relations as shown in equation (7). The dependent variable is the (generation-specific) elasticity- and market share-adjusted average selling price. Explanatory variables are the generation-specific and firm-specific outputs, learning-by-doing, spillovers, and time trends. We also use the price of silicon, firms' SRAM patents, a dynamic term, as well as firm and product generation fixed effects. We instrumented for firms' contemporaneous outputs. **, **, and (*) denote the 99%, 95%, and 90% levels of significance, respectively.

Table VII: Robustness check on elasticities: Results for merger incentives and merger impact

Variables	M_{ikt}	q_{ikt}	dq_{ikt}	dq_{ikt}	dq_{ikt+4}
	(1)	(2)	(3)	(4)	(5)
$Constant$	-5.446	3,239.112***	-218.804	-240.574	-524.786
	(124.999)	(444.249)	(194.899)	(194.765)	(372.769)
$MC^{(*)}$	-0.514***	-602.261***	16.324***	20.237***	57.853***
	(0.026)	(13.260)	(6.068)	(5.888)	(11.071)
$Elast$	-1.927***	-340.984***	-60.113**	-75.756***	-260.491***
	(0.179)	(62.171)	(28.319)	(26.133)	(52.023)
$AbsCap$	0.146e-03	3.118***	0.220**	0.179**	0.827***
	(0.192e-03)	(0.239)	(0.108)	(0.087)	(0.201)
M		-1,116.512***	-39.587***	-40.633***	-212.117***
		(146.971)	(6.550)	(5.854)	(12.179)
$M * HetMC$		7.337***	27.469***		60.150***
		(2.242)	(10.200)		(18.647)
$M * HetElast$		-2,069.881***	13.944***		25.374
		(241.274)	(5.806)		(20.116)
$M * HetAbsCap$		1.187***	0.063***		0.285
		(0.286)	(0.013)		(0.239)
$Time$		101.421**	175.833**	170.454**	80.353
		(48.017)	(79.474)	(78.846)	(149.502)
Firm FE	Yes***	Yes***	Yes***	Yes***	Yes***
Generation FE	Yes***	Yes***	Yes***	Yes***	Yes***
Number of observations	2,814	6,605	6,078	6,078	5,514

Table VII reports the estimation results for the probit equation (column 1). Columns 2 to 5 show the results for the heterogeneous merger effects on production levels and differences. Column 5 shows the results of the homogeneous merger effect estimation. ***, ** and * refers to a 1%, 5%, and 10% significance level, respectively.

Table VIII: Treatment effects on the treated (merging) and non-treated (non-merging) firms

Variables	dq_{ikt}	40'th percentile	60'th percentile	dq_{ikt+4}
	(1)	(2)	(3)	(4)
$ATET(HetMC)$	-56.887	-68.071	-45.703	-233.991
$ATET(HetElast)$	-73.445	-83.262	-63.628	-196.734
$ATET(HetAbsCap)$	-25.241	-27.484	-22.998	-144.456
$ATENT(HetMC)$	-43.618	-56.129	-31.107	-204.315
$ATENT(HetElast)$	-44.302	-73.263	-55.448	-200.822
$ATENT(HetAbsCap)$	-35.584	-36.792	-34.375	-177.029

Table VIII, upper panel, reports the average treatment on the treated effects ($ATET$) effects accounting for different types of heterogeneities. The lower panel reports the average treatment on the non-treated effects ($ATENT$).

FIGURES

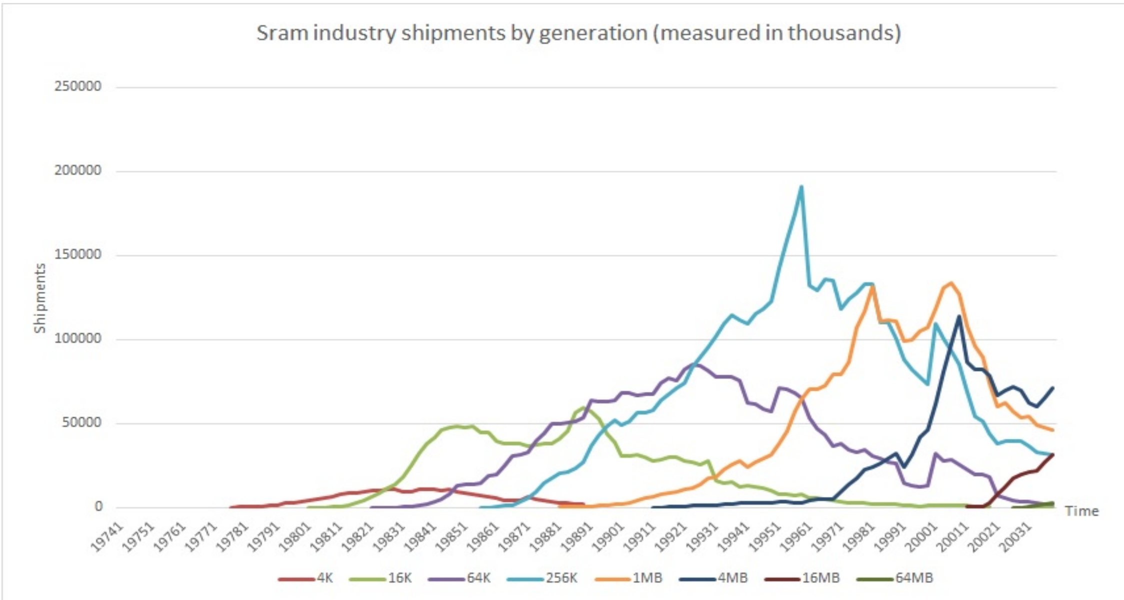

Figure 1: Evolution of shipments by generations. Shipments are measured in thousands. Sources: Gartner, Inc. and Thomson Financial.

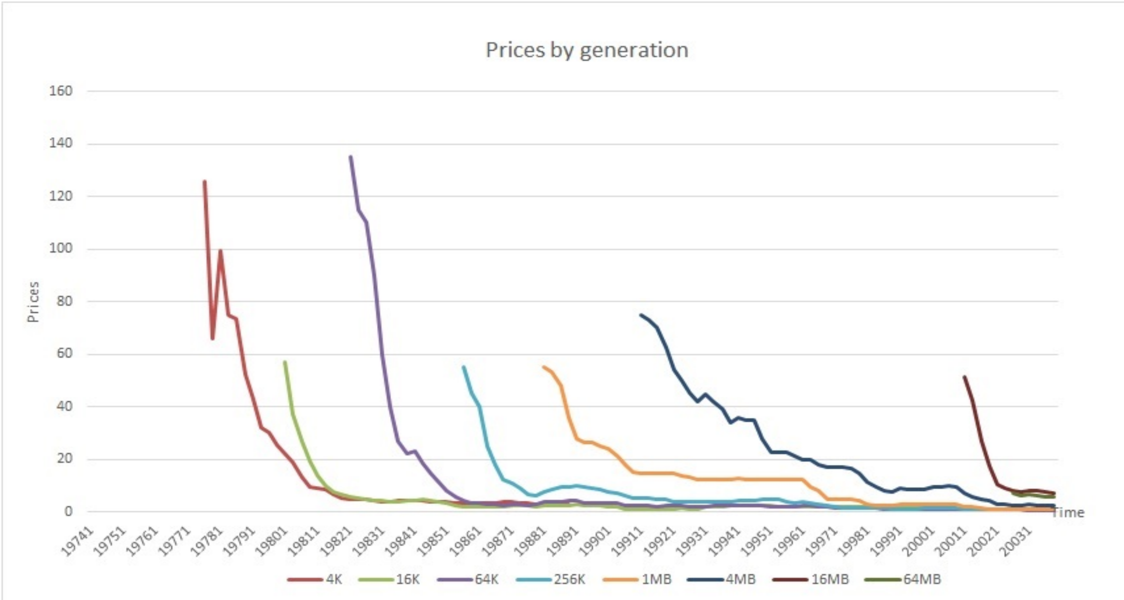

Figure 2: Evolution of prices by generations. Source: Gartner, Inc.

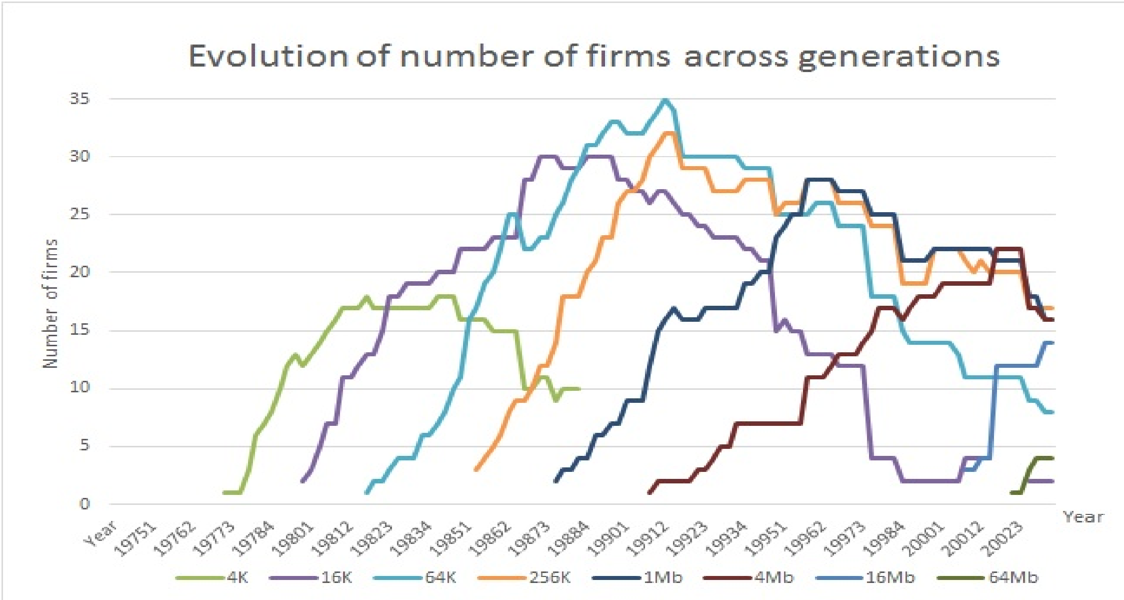

Figure 3: Evolution of number of firms across generations. Source: Gartner, Inc.

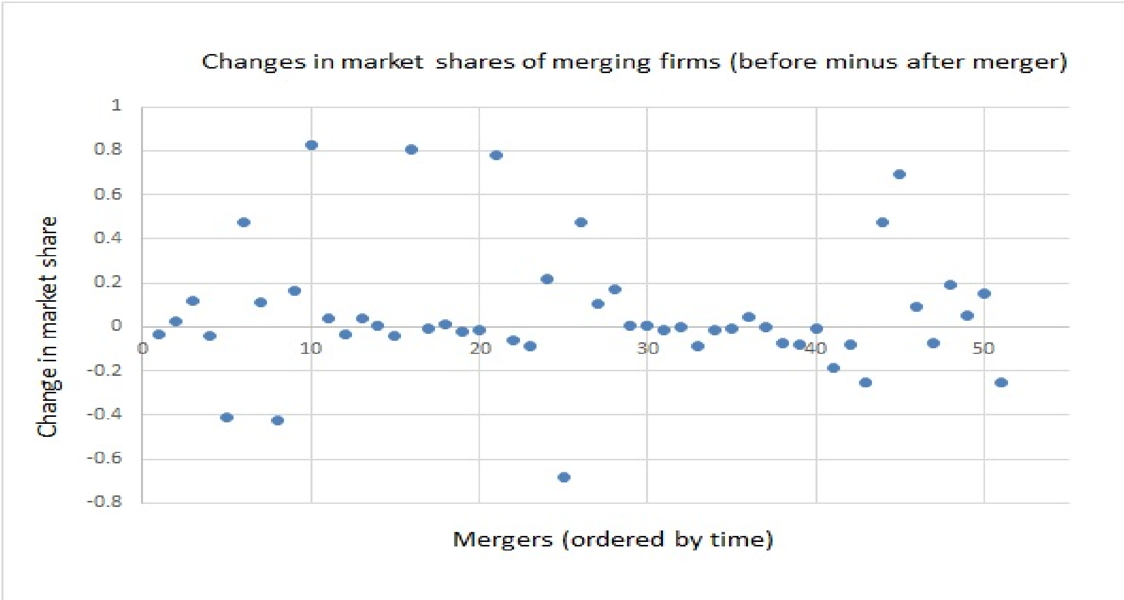

Figure 4: Changes in market shares of merging firms. Source: Gartner, Inc.