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Abstract

This study investigates the impact of firm-specific discount factors on merger formation and market performance. We estimate firm-specific discount factors for 228 publicly traded and privately held firms operating in the semiconductor market and apply a heterogeneous treatment effects model which accounts for firms' endogenous selection into mergers, as well as the heterogeneous impact of mergers on the product market. Our study provides evidence that firms' discount factors explain merger formation and the impact on product market performance. More specifically, we find that acquiring firms characterized by high discount factors (patient firms) merge with efficient and innovative target firms, and achieve high efficiency gains. In contrast, acquiring firms characterized by low discount factors (impatient firms) merge with less innovative target firms, and achieve higher market power effects.

JEL-Code: D240, D430, G340, L130, L220.

Keywords: discount factor, discount rate, dynamic oligopoly model, market performance, mergers and acquisitions, semiconductor industry.

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1 Introduction

It is a well established fact in the economics and finance literature that imperfect capital markets grant firms differing access to capital markets, which may result in different firm-specific costs of capital.[1] One commonly used measure which represents firms' access to capital markets and the associated cost of capital is the discount rate (see e.g. Easley and O'hara (2004) and Diamond and Verrecchia (1991)). For capital budgeting purposes, the discount rate is frequently applied to evaluate optimal investment levels accounting for the riskiness of investment opportunities, which often varies across firms and projects. Hence, a firm-level discount rate is an integral component in the evaluation of firm-specific investment projects and firm values.

Recent studies have also established insight into the link between the discount rate and merger formation.[2] The studies provide evidence that the discount rate has an impact on firms' merger and acquisition decisions. Moreover, it has been shown that acquiring firms are frequently characterized by a lower cost of capital than target firms (Erel, Jang, and Weisbach (2014), Fluck and Lynch (1999), and Khatami, Marchica, and Mura (2014)).[3] The value of investment projects or mergers is frequently assessed in a dynamic context, in which future cash flows are discounted to determine a present value, see e.g., Pesendorfer (2003), Gowrisankaran (1999) and Davis and Huse (2010).[4] The future cash flows are discounted according to a firm-level discount factor, which plays a crucial role in determining the present value of an investment project such as a merger. It reflects the opportunity cost of spending limited resources today in exchange for expected payoffs tomorrow.[5] Discount factors reflect firms' patience levels or willingness to wait for the returns to investments. More specifically, firms characterized by higher discount factors place more weight on future cash flows; they are more patient and more willing to wait for future returns on investments than firms characterized by lower discount factors. Thus, firms

[1] Capital markets may be imperfect due to a variety of reasons, such as asymmetric information and monitoring costs (Akerlof, 1970), limited commitment, and/or costly default (Andrade and Kaplan, 1998).

[2] Over the last two decades, mergers have become a more common investment strategy for firms achieving growth and competitive advantages. From 1990 to 2007, the number of mergers increased over three-fold and the transaction value of mergers increased more than five-fold. The values are based on merger data taken from the Thompson Financial SDC Platinum Global merger database, and calculated in constant 1983 US-dollars.

[3] Mergers are considered as an appropriate instrument for target firms to overcome financial constraints.

[4] This evaluation process is often referred to as the discounted cash flow (DCF) method. Mukherjee, Kiymaz, and Baker (2004) provide a survey on the application of the DCF method.

[5] Note, the firm-level discount factor (δ_i) is inversely related to the firm-level discount rate (r_i), i.e. $\delta_i = \frac{1}{1+r_i}$.

with higher discount factors might see comparatively greater value in investments into a merger project as future profits are valued higher than by impatient acquirers which are characterized by a lower discount factor.[6]

Mergers differ with respect to when they realize added value. While some mergers generate instant added value due to a dominant market power effect, other mergers generate value added due to efficiency gains which are realized in the more distant future (Kim and Singal, 1993).[7] Since firms with higher discount factors attach a greater value to returns realized in the more distant future, they assign a higher net present value to mergers that generate value added in the longer run due to realized efficiency gains. In contrast, firms with lower discount factors might favor mergers that generate a more instant payoff due to market power effects. Therefore, depending on the acquirers' discount factors, we would expect acquirers to sort themselves into different types of mergers, depending on whether mergers are profitable in the short run or rather become profitable in the longer run. Accounting for the fact that firms have different incentives to select themselves into different types of mergers (efficiency versus market power driven mergers), it is reasonable to believe that those mergers will also cause different impacts on market performance, especially on consumer welfare and the prices offered in the product market.

Our study examines if firms with different discount factors select themselves into mergers for different purposes, i.e., mergers to primarily achieve efficiency gains versus mergers aiming to increase market power.[8] Our study also evaluates if firm-specific discount factors contribute to explaining the ultimate impact on consumer welfare through changes in output and prices. This is an important question, as the dominance of those arguments determines market performance and total surplus. Up to date, very little is known about the link between firm-level discount factors and the impact of mergers on consumer welfare.

[6]Firms with higher discount factors are frequently referred to as patient firms in the literature. Likewise, firms with lower discount factors are often referred to as an impatient firm.

[7]For example, the merger between Delta and Northwest Airlines and the merger between United and Continental Airlines realized value added only after one and a half years.

[8]For more information on endogenous merger formation, see Tombak (2002), Compte, Jenny, and Rey (2002), Vasconcelos (2005), and Javonovic and Wey (2012). As an example for endogenous merger formation, Tombak (2002) shows that firm size (and firm efficiency) explains firms' incentives to merge, i.e., the largest firm acquires the next largest firm etc.

In the merger literature, it is common to distinguish whether the value created from merging, which could be a mix of efficiency gains and increased market power, is dominated by efficiency gains or by increased market power.[9] Efficiency benefits gained from merging are beneficial to producer and consumer surplus, as output units are transferred from less efficient to more efficient production facilities (Salant and Shaffer (1998; 1999)). In contrast, market power effects are associated with elevated prices which are beneficial to producers but harmful to consumers.[10]

In addition to the impacts on market performance discussed above, it should be noted that firms' discount factors may also impact merger activity through several alternative channels that are not explicitly modeled in this paper. Because a merger includes firms with differing discount factors, it is possible that financial synergies may occur when the merger enables the new entity to access the capital markets at a lower cost (Erel, Jang, and Weisbach, 2014; Mueller, 1969). Additionally, the discount factor may influence mergers during the negotiating process—either via discussions on the method of payment or how the surplus is divided. Impatient target firms will have lower bargaining power during the negotiations and often prefer cash over equity.

Our study concentrates on semiconductors, which are used as an input for electronic devices.[11] The semiconductor industry provides a natural object for assessing the role of the discount factors in the formation and impact of mergers for the following reasons: First, a large number of horizontal mergers are performed in the industry. Second, the industry is characterized by a large degree of heterogeneity across firms in production and innovation, which allows us to emphasize the impact of mergers on market power and efficiency gains. Third, our dataset contains detailed firm-level production data, which enables us to use future profits to identify firm-specific discount factors. Fourth, learning-by-doing, which is well documented in the semiconductor industry, leads firms to incorporate future discounted earnings into current production. Against the background of learning by doing, firms' intertemporal production decisions enable us to identify

[9] Williamson (1968) highlighted the trade-off between market power and efficiency benefits in determining the impact of mergers on consumer welfare.

[10] Common oligopoly models predict that if the merger results in sufficient cost synergies to outweigh the market power benefits then the price will decline and market share will increase. Likewise, if the market power benefits outweigh the cost synergies, then the price will increase and market share will decline, see also Farrell and Shapiro (1990), Stigler (1964), Perry and Porter (1985), Salant, Switzer, and Reynolds (1983), or Gugler and Siebert (2007).

[11] A detailed industry description is provided in the next section.

firm-specific discount factors. To summarize, the industry provides a natural object for assessing the role of the discount factors in the formation and impact of mergers.

We use detailed firm-level production and innovation data on the semiconductor industry from 1989–2004. Our dataset contains publicly traded and privately held firms. For publicly traded firms, it is common procedure in the finance literature to use stock market price data to calculate the discount factors.[12] This procedure would constrain our study to publicly traded firms. Since the majority of firms in our dataset are privately held, however, it would cause information loss and a potential selection bias. Moreover, using price data to determine discount rates could introduce bias because the market often anticipates mergers and adjusts for the effects on both the merging firms and their competitors (Duso, Neven, and Röller, 2007; Fridolfsson and Stennek, 2005). Thus, one empirical challenge in our study is to obtain the firm-specific discount factors for privately held firms. Building on a framework by Irwin and Klenow (1994), we estimate firm-specific discount factors from firms' supply relations.[13]

Using the estimated firm-level discount factors, we proceed with evaluating firms' incentives to form mergers, as well as their competitive effects against the background of firm-specific efficiency levels and discount factors. Our estimation procedure will explicitly account for firm heterogeneities, as firms achieve different profit gains from merging and realize different impacts on the product market depending on their efficiency levels. Following Heckman, Urzua, and Vytlacil (2006), we apply a heterogeneous treatment effects model to control for two potential biases, i.e., (i) the pre-treatment heterogeneity bias or selection bias, and (ii) the treatment-effect heterogeneity bias.[14]

The pre-treatment heterogeneity relates to the fact that heterogeneous firms select themselves into mergers based on their anticipated gains. For example, firm pairs characterized by more asymmetric costs might be able to gain higher profits from merging via production rationalization and synergy effects. Not accounting for firms' self-selection into mergers might imply that

[12]Common methods to calculate the discount rate include the CAPM (Sharpe, 1964), Fama-French 3-factor model (Fama and French, 1993), or the Fama-French Carhart 4-factor model (Carhart, 1997).

[13]Note, that the estimation from firms' supply relations is similar to the methods proposed by Berry and Pakes (2000) and Aguirregabiria and Magesan (2013).

[14]See also Angrist and Krueger (1999), Heckman, Urzua, and Vytlacil (2006), Morgan and Winship (2007), Dehejia and Wahba (2002), and Brand and Xie (2010), Brand and Thomas (2013), and Pais (2011).

mergers have drastic competitive impacts, simply because some merging firms are more efficient than non-merging firms. Consequently, the ignorance of firms' self-selection into mergers may result in an upward bias if estimated by ordinary least squares. The (post) treatment-effect heterogeneity relates to the fact that firms experience heterogeneous impacts after merging. For example, research and production intensive firms might achieve higher gains in the technology and product markets irrespective of whether they formed a merger or not. Ignoring the treatment-effect heterogeneity might support the finding that mergers appears to increase the competitiveness in the product market, simply because merging firms were already more research and production intensive than non-merging firms, before they selected themselves into mergers.

Our study provides evidence that firms' discount factors largely contribute to explaining merger formation and also explain the impact on product market performance. Our estimated firm-level discount factors confirm a significant degree of heterogeneity between firms. We find that acquiring firms characterized by high discount factors (patient firms) merge with efficient and innovative target firms. Their market shares increase from 1.28% pre merger to 1.73% post merger. This result implies that efficiency benefits dominate market power benefits for mergers among firms with high discount factors. The associated increase in market shares translate into price reductions, as predicted by common oligopoly models, see e.g., Farrell and Shapiro (1990). In contrast, acquiring firms characterized by low discount factors (impatient firms) merge with large and less innovative target firms. They achieve higher market power effects in mergers, and their market share reduces from 3.29% to 3.0%, which indicates an increase in prices.[15] In summary, our results show that the discount factor determines firms' incentives to engage in mergers, and also explains the dominance between market power and efficiency gains in mergers.

Our counterfactuals show that potential mergers between nonmerging firms would have generated mostly market power effects, i.e., the average treatment effect on market share is overwhelmingly negative. This result provides evidence that nonmerging firms would have not achieved the magnitude of efficiency gains that was realized by actual merging firms. Hence,

[15] Although market power may not be large in this situation, the decrease in market share is consistent with an increase in price and a reduction in output.

efficiency gains play a relevant role in mergers.

This study is structured as follows: Section 2 provides a description of the industry and the data. Section 3, introduces the empirical model and explains the estimation procedure. Section 4 discusses the estimation results for discount factors and the marginal costs. Next, we present the estimates from the heterogeneous treatment model and assess the role of discount factors on merger formation and the impact of mergers. Finally, Section 5 concludes.

2 Industry and Data Description

The semiconductor industry is one of the most important high-technology industries because it affects many downstream industries. Semiconductors are widely used in the computer industry, consumer electronics, and in communication equipment. Semiconductors are usually distinguished between microprocessors, memory chips and other related devices.

The firm-level revenue data are provided by the Gartner Group. The dataset contains annual firm-level revenue from 1989 to 2004 for the semiconductor market overall, as well as several submarkets, i.e., static and dynamic random access memories, and flash memories.[16] It includes international firms which actively produce in the semiconductor industry and generate more than one million US-dollar in annual revenue. Using the producer price index (PPI) as a proxy for the price of a semiconductor, we convert semiconductor revenue into quantity.[17]

Our merger data are taken from the Thomson Reuters SDC Platinum database for global mergers for the 1989-2004 time period. Since our focus is on the relation between efficiency and market power effects, we focus on horizontal mergers and select mergers where both, the acquirer and the target firm are active semiconductor chip producers according to the production data provided by the Gartner Group.[18] This results in 133 mergers. We account for changes in ownership by assigning all revenue from the target firm to the acquiring firm beginning the year the merger becomes effective. In the rare cases where the same target is acquired multiple times

[16]For a more thorough description of this data see Gugler and Siebert (2007).

[17]The PPI for "Semiconductor and Other Electronic Component Manufacturing" is provided by the Bureau of Labor Statistics using 1988 as the base year, `http://www.bls.gov/ppi/`.

[18]At a high level, 'Semiconductors and Related Devices" corresponds to the Standard Industry Classification (SIC) of 3674.

by different acquiring firms over time, we assign the target's revenue to the first acquirer until the time of the subsequent merger. At this point, all revenue from the target firm is reassigned to the second (or next) acquiring firm.[19] Table 1 shows the number of firms with revenue data, total industry revenue, as well as the number of mergers per year. The table shows that the number of mergers increased from the mid 1990s until peaking in year 2000. On average, 8 mergers were performed each year. Moreover, the number of producing firms, total revenue, and average production increased until roughly 2000 and then slightly declined afterwards. The production pattern is highly correlated with the number of mergers in the industry. Within the industry, there is much heterogeneity among firms, especially with regard to quantity produced. Figure 1 shows a scatter plot of annual quantity by firm.[20] As shown in the figure, the industry consists of many small producers and a few large producers. Note, the order between firms, i.e., which firm is the largest and second largest producer, remains relatively stable over time. This observation indicates that time-invariant heterogeneity across firms is an important characteristic to control for.

Additionally, we use patent information from the United States Patent and Trademark Office available in the National Bureau of Economic Research database.[21] For descriptors on the data and methodological methods see Hall, Jaffe, and Trajtenberg (2001). The patent database allows us to track the patent applications of firms over time. The dataset provides information for more than 109,000 patent applications submitted between 1975 and 2004 in the semiconductor industry.[22] We establish a patent stock for every firm by accumulating the annual firm-level patents over time, allowing for an annual depreciation rate of 5%. Figure 2 shows the accumulated number of patents for every firm and provides evidence that firms also exhibit heterogeneity in innovation, in addition to heterogeneity in production. Moreover, it is interesting to note that the firms with higher production levels also have larger patent stocks.[23] The large degree of firm-

[19] In the single case where a target firm is acquired by two firms in the same year, we assign all target production to the merger that occurred later in the year.

[20] The following largest producers are illustrated in the figure: Intel, Toshiba, Hitachi, Texas Instruments, NEC Corporation, Fujitsu, and Vitesse.

[21] The patent data is available at `https://sites.google.com/site/patentdataproject/Home`.

[22] Since each patent is categorized into technology classes, we are able to retrieve the patents that belong to semiconductors.

[23] IBM is the one notable exception with the highest accumulated patents but very little production. It is well known in the industry that IBM frequently licenses production to other firms.

level heterogeneity in production and innovation indicates that firms' selection into mergers is an important fact to consider when evaluating the impact of mergers.

We also use several additional controls. First, it is well documented that learning-by-doing from own experience and from other firms' experience via spillovers is an important phenomenon in the semiconductor industry. To account for own learning-by-doing, we use past accumulated firm-level production as a proxy, and to account for spillover learning we use past industry-level production by all other firms. Also, we include several industry-level variables that will serve as supply and demand shifters: semiconductor wage, number of firms, and the GDP in electronics.[24] Table 2, provides the summary statistics for these variables. The average firm has a market share of 0.7%, which corresponds to average annual production of 14.56 million semiconductor chips. The accumulated production at the firm level is, on average, 54.10 million units and the average accumulated production by others in the industry is much larger at 11.188 billion units. A firm applies on average for 36.27 semiconductor patents per year and is described by a patent stock that consists of 227.04 semiconductor patents. The average semiconductor price over the period is $71.98 USD.

3 The Empirical Model

Our ultimate goal is to investigate the role of firm-level discount factors in evaluating the impact of mergers on market performance. We are especially interested in the relationship between the discount factor and efficiency gains. In evaluating the competitive impact of mergers we take advantage of our highly detailed production data and measure the impact of mergers on the post-merger output of merging firms. We follow seminal theoretical contributions on mergers and evaluate the change in market shares before and after the merger which is sufficient for drawing conclusions for post-merger prices. Farrell and Shapiro (1990), among others, have shown that if the market power effects dominate the efficiency effects in a merger, the market shares decline after merger formation and prices will increase. In contrast, if the efficiency gains

[24]Wage information is from the Yearbook of Labour Statistics (1988–2004), ISIC second revision 3832 which includes "semiconductor and related sensitive semiconductor devices" for U.S. manufacturers. The GDP information is from the Bureau of Economic Analysis for "Electrical equipment, appliances, and components".

dominate the market power effects, market shares will increase and prices will decline.[25]

Since a merger is described by two independent firms merging to one entity, we formulate firm-pairs and evaluate the change in market shares (before and after merging) and compare those changes between merging and non-merging firms in firm-pairs. To formally formulate the outcome equation, we consider a set of semiconductor firms $i \in I$ and form firm-pairs by matching each firm with each other for every year t. Firm-pairs are denoted by a subindex j, k, where $j \in I$ is specific to the acquiring firm in a merger, and $k \in I$ refers to the target firm. The main equation of interest evaluates the effect of a merger—indicated by the merger dummy $M_{j,k,t}$, which takes on a value of 1 if firms j and k merged in period t, and 0 otherwise—on the change in market shares MS from year $t-1$ to year t and, for robustness, to year $t+1$. In specifying the outcome equation, we follow Mueller (1985) and Gugler and Siebert (2007) and specify firms' market shares as functions of the mergers, and past market shares. We consider the sum of the market shares between firm j and k ($MS_{j,k,t} = MS_{j,t} + MS_{k,t}$) in every period t. Hence, $MS_{j,k,t}$ is the joint production if a firm-pair merged in period t, and it is the sum of the firm-pair market share if the firm did not merge in period t. The outcome equation is formulated as follows:

$$MS_{j,k,t} \quad = \quad \rho_0 + \rho_1 MS_{j,k,t-1} + \rho_2 M_{j,k,t} + \rho_3 M_{j,k,t}(\delta_j - \overline{\delta}) + \rho_4 \delta_j + \gamma X + \epsilon_{j,k,t}. \tag{1}$$

Note, the interaction between the merger indicator and the acquirer's discount factor allows for heterogeneous effects. Hence, we allow the impact on market shares to vary for acquiring firms with different discount factors ($M_{j,k,t}(\delta_j - \overline{\delta})$). It is important to remember that we assume the heterogeneity of the discount factors mostly stems from imperfections in capital markets, such that the discount factors enter our model exogenously. The matrix X contains additional controls which we introduce further below, γ is a vector of parameters, and $\epsilon_{j,k,t}$ represents the error term.

In estimating the outcome equation, we face two important challenges: first, firm-level discount factors (δ_j) are unobserved and second, mergers ($M_{j,k,t}$) are endogenous events. To over-

[25] See also Mueller (1985) and Gugler and Siebert (2007).

come the first problem, we estimate firm-specific discount factors from firms' supply relationships as we explain in detail in Section 3.1. Next, in order to to control for endogenous selection into mergers, we apply a heterogeneous treatment effects estimator suggested by Heckman, Urzua, and Vytlacil (2006). This endogenous merger selection is explained in Section 3.2.

3.1 Supply Relationship

In following Irwin and Klenow (1994) and Siebert (2010), we consider an oligopolistic market and estimate firm-specific discount factors (δ_i) from firms' supply relations. We consider the set of all semiconductor firms $i \in I$ in this section. Note, that we have firm-specific production information at the semiconductor market level, which is more disaggregate than overall firm-level information.[26] Therefore, applying the same assumptions as Irwin and Klenow (1994), we assume that each semiconductor firm chooses its output ($q_{i,t}$) within a Cournot framework to maximize its discounted firm value. The firm's maximization problem is given by

$$\max_{q_{i,t}} \;\; \Pi_i = E_0 \left[\sum_{t=0}^{\infty} \delta_i^t (P_t - MC_{i,t}^{stat}) q_{i,t} \right], \tag{2}$$

where E_0 is the expectation operator conditional on information at time 0, P_t is the price at period t, $MC_{i,t}^{stat}$ is the static marginal cost, and δ_i is the firm-level discount factor. As mentioned above, the firm-level discount factor relates to the firm-level discount rate (r_i) as follows: $\delta_i = \frac{1}{1+r_i}$. As modeled, the discount factor measures the value a firm places on future profits and is used to calculate present value. A lower discount factor indicates that a firm values future profits less. The first order condition with respect to quantity becomes:

$$P_0 \left(1 + \frac{MS_{i,0}}{\alpha_1} \right) = MC_{i,0}^{stat} + E_0 \left[\sum_{t=1}^{\infty} \delta_i^t q_{i,t} \frac{\partial MC_{i,t}^{stat}}{\partial q_{i,0}} \right], \tag{3}$$

where α_1 is the price elasticity of demand. The first order condition (3) indicates that price, adjusted for a firm-specific markup, is equated to the dynamic marginal cost. The dynamic

[26] Focusing on more disaggregate markets such as the Dynamic Random Access memories or Static Random Access would leave us with very few merger cases. Another advantage with focusing on the semiconductor level is given by the fact that most firms are specialized in semiconductors and we are able to better evaluate an overall firm-level discount factor in the semiconductor industry.

marginal cost is composed of the static marginal cost ($MC_{i,0}^{stat}$) plus an adjustment term that accounts for the discounted value of future cost reductions ($\sum_{t=1}^{\infty} \delta_i^t q_{i,t} \frac{\partial MC_{i,t}^{stat}}{\partial q_{i,0}}$) achieved from learning. This incorporates firms' intertemporal production strategy, as they increase current production to achieve future cost reductions (Wright, 1936). Firms with higher discount factors obtain the most benefit from learning by doing. Hence, firms optimize production according to their dynamic marginal costs which lie below static marginal costs ($MC_{i,t}^{stat}$).

Using a recursive formulation, the equation becomes

$$P_t \left(1 + \frac{MS_{i,t}}{\alpha_1}\right) - MC_{i,t}^{stat} - \delta_i \left[q_{i,t+1} \frac{\partial MC_{i,t+1}^{stat}}{\partial q_{i,t}} + P_{t+1} \left(1 + \frac{MS_{i,t+1}}{\alpha_1}\right) - MC_{i,t+1}^{stat} \right] = 0, \quad (4)$$

where $\frac{\partial MC_{i,t+1}^{stat}}{\partial q_{i,t}}$ accounts for changes in the marginal costs in time $t+1$, which result from production in time t. The discount factor (δ_i) describes the intertemporal link between current quantity and future savings in the next period through learning by doing. Equation (4) forms the center of how we identify the discount factor. Firms characterized by a higher discount factor (more patient firms) value future profits streams higher than firms with lower discount factors (more impatient firms). Firms with lower discount factor impose less weight on profits realized in the future.[27] Our identification argument builds on a well established institutional feature of the semiconductor industry, i.e., the existence of learning by doing. In the presence of learning by doing, firms account for the fact that a higher contemporaneous production accumulates more experience in the future, which generates future cost savings. Forward looking firms price according to dynamic marginal costs and increase production beyond the statically optimal production level. They "overproduce" in a static sense to benefit from further future experience and cost savings. Hence, instead of determining their optimal output according to firms' static marginal cost, they produce along their dynamic marginal costs which lie below the static marginal costs. In contrast, impatient firms place more weight on current profits and value future returns less. They have a lower incentive to overproduce and invest in future cost reductions. In the extreme case, myopic firms value only current profits, adopt a statically

[27]The economics and management literature frequently refers to firms with higher discount factors as being more patient than firms with lower discount factors.

optimal production plan, and produce according to their static marginal costs. To summarize, interdependence between today's optimal production and the incentive to invest in future cost reductions enables us to identify firms' discount factors. Rearranging equation (4), we obtain the following estimation equation:

$$P_t\left(1+\frac{MS_{i,t}}{\alpha_1}\right)=MC^{stat}_{i,t}+\delta_i\left[q_{i,t+1}\frac{\partial MC^{stat}_{i,t+1}}{\partial q_{i,t}}+P_{t+1}\left(1+\frac{MS_{i,t+1}}{\alpha_1}\right)-MC^{stat}_{i,t+1}\right]+\nu_{i,t}, \quad (5)$$

which includes a normally distributed error term, $\nu_{i,t}$.

We follow Irwin and Klenow (1994) and assume a semi-log marginal cost function,[28]

$$MC^{stat}_{i,t}=\lambda_i+\lambda_1 log(Acq_{i,t})+\lambda_2 log(Acq_{-i,t})+\lambda_3 log(Wage_t)+\lambda_4 Pat_{i,t}. \quad (6)$$

Learning by doing is incorporated at the firm-level, using a firm's total past accumulated production ($Acq_{i,t}$) as a proxy for its experience. We also account for learning from others via spillovers from accumulated production of all other firms ($Acq_{-i,t}$). We expect both, own learning and spillover learning, to lower the marginal cost (i.e., $\lambda_2 < 0$ and $\lambda_3 < 0$). Also, the factor price of semiconductor wages is included to account for shifts in the marginal costs due to changes in input prices.[29] Patent applications are included to control for innovations that could affect the cost of production. Finally, we allow for a firm intercept (λ_i) to account for firm heterogeneity. The final estimation equation is obtained by inserting the corresponding marginal cost equation (6) into equation (5).

3.2 Outcome Equation and Endogenous Selection

Our main equation of interest, also referred to as the outcome equation (1), assesses the evolution of firms' market shares over time. To properly estimate the outcome equation, we must account for the endogenous selection into a merger. Our solution to the selection problem is to use the heterogeneous treatment effects estimator which is detailed below.

As detailed above, we regress the joint market shares of firms j and k in period t ($MS_{j,k,t}$) on

[28] Liu, Siebert, and Zulehner (2013) also apply this functional form.

[29] We also added the factor price of silicon, the main material input, however, it was highly correlated with wages and had no significance.

their joint market shares in period $t-1$ ($MS_{j,k,t-1}$). In order to capture longer–term benefits, we also evaluate the effect of mergers on joint market shares one year in the future (i.e., $MS_{j,k,t+1}$).[30] The outcome equation is specified as:

$$\begin{aligned} MS_{j,k,t} &= \rho_0 + \rho_1 MS_{j,k,t-1} + \rho_2 M_{j,k,t} + \rho_3 M_{j,k,t}(\delta_j - \overline{\delta}) + \rho_4 \delta_j + \rho_5 N\_Firms_t \\ &+ \rho_6 GDP_{elec,t} + \rho_7 HEC1_{j,k,t} + \rho_8 HEC0_{j,k,t} + \sum_{y=9}^{23} \rho_y Year_t + \epsilon_{j,k,t} \end{aligned} \tag{7}$$

We apply the heterogeneous treatment effects estimator suggested by Heckman, Urzua, and Vytlacil (2006), which allows us to control for a potential pre-treatment bias (i.e., endogenous merger formation) as well as the post-treatment effect.[31] In closely following the heterogeneous treatment effect literature, we account for heterogeneities in the effect of the merger for acquirers of different discount factors by including the interaction term, $M_{j,k,t}(\delta_j - \overline{\delta})$, where $\overline{\delta}$ is the mean of the discount factors across all firms. The outcome equation also includes the number of firms (N_Firms) to control for the degree of competition in the product market, electronic GDP to control for downstream shifts in demand, and two Heckman correction terms ($HEC1$ and $HEC0$).[32] The first correction term ($HEC1 = P_{j,k,t}\frac{\phi(Z\beta)}{\Phi(Z\beta)}$) explains firms' endogenous selection into mergers, where Z and β represent the regressors and parameter estimates from the selection equation (8) shown below, ϕ is the standard normal density function and Φ is the standard normal cumulative distribution function. The second correction term ($HEC0 = (1 - P_{j,k,t})\frac{\phi(Z\beta)}{1-\Phi(Z\beta)}$) becomes active when firms do not form a merger and is calculated in a similar manner. Finally, we include year fixed effects and $\epsilon_{j,k,t}$ as the error term.

To account for endogenous merger formation and to derive the two Heckman correction terms, we use a selection model that formulates firms' decisions to merge. Firms simultaneously decide if and with whom they want to merge. We have to consider all feasible pairwise merger opportunities, since we allow every individual firm to be a potential merger candidate. We specify the selection equation according to firms' incentives and the value they generate from

[30] These results can be found in column (3) of Table 6

[31] Please note that equation (7) could be separately estimated on the treated and untreated group. For efficiency, we combine the two groups for estimation.

[32] The structure of the outcome equation and the formaiton of the Heckman correction terms are based off of the work of Cerulli (2012) and Heckman et al. (2006).

merging. Hence, the decision for two firms j and k to form a merger in period t is based on a comparison between firms' values when they merge and when they do not merge. Let $V^*_{j,t}$ and $V^*_{j,t}$ be the present value of the firms in period t. The merged pair realizes a post-merger value of $V^M_{j,t} + V^M_{k,t}$, which is the summation of the individual payoffs to the acquirer and target and the superscript M refers to a merger. If the firms do not merge, they earn profits denoted by $V_{j,t} + V_{k,t}$. Hence, firms form a merger if $M^*_{j,k,t} = V^M_{j,t} + V^M_{k,t} - (V_{j,t} + V_{k,t}) > 0$, where $M^*_{j,k,t}$ is the latent variable measuring the underlying propensity to merge. Our selection model is based on a probit model where $M_{j,k}$ represents a dummy variable and takes on a value of 1 if firms j and k merge in period t; otherwise it is 0. Hence, if firms engage in a merger in period t, $M_{j,k,t} = 1$ and $M^*_{j,k,t} > 0$, while if they don't merge $M_{j,k,t} = 0$ and $M^*_{j,k,t} \leq 0$. The specification of the selection equation looks as follows:

$$
\begin{aligned}
M^*_{j,k,t} \;&=\; \beta_0 + \beta_1 \Delta^{MC}_{j,k,t-1} + \beta_2 \Delta^{\delta}_{j,k} + \beta_3 TR_{j,k,t-1} + \beta_4 Same\_Region \\
&+\; \beta_5 \overline{MS}_j + \beta_6 \overline{MS}_k + \beta_7 \overline{AcPat}_j + \beta_8 \overline{AcPat}_k + \sum_{y=9}^{23} \beta_y Year_t + \tau_{j,k,t}.
\end{aligned} \tag{8}
$$

In order to properly estimate the outcome equation (7), the selection equation (8) must contain instruments that impact the formation of mergers but do not impact the combined market share (exclusion restriction). We use four instruments in the selection equation (8): two instruments account for variation across time and firm-pairs, and two further instruments account for variation across firm-pairs.

The first instrument, $\Delta^{MC}_{j,k,t-1}$, represents the relative absolute difference between marginal costs the year before a potential merger occurs, $\Delta^{MC}_{j,k,t-1} = \frac{|MC_{j,t-1} - MC_{k,t-1}|}{\max(MC_{j,t-1}, MC_{k,t-1})}$, and is based on arguments made in other theoretical studies. The studies by Bergstrom and Varian (1985) and Salant and Shaffer (1998; 1999)) have shown that under Cournot assumptions, the equilibrium quantities and prices in the industry (or a firm-pair) depend on the average costs. However, they have also shown that Cournot industry output and prices are independent of the distribution of marginal costs in the industry or between firm-pairs. A mean-preserving spread in marginal costs (i.e., an increase in the differences in marginal costs) will leave the equilibrium quantities unchanged, see also Röeller, Siebert and Tombak (2007). Hence, the production is dependent on the sum or the average of the firms' marginal costs, but independent of the difference in firms' marginal costs. Therefore, the difference in marginal costs between firms will not have an impact on the outcome or production equation. It is important to note that an increase in firms' differences in marginal costs increases firms' and industry profits since more efficient firms produce more output at a lower cost, which increases firms' profits, see Bergstrom and Varian (1985) and Salant and Shaffer (1999). Thus, an increase in firms' differences in marginal costs will increase the merging firms' profits and therefore determine firms' decisions to merge. Therefore, asymmetries between firms directly effect the market share only through the merger channel and the difference in marginal costs is an appropriate instrument for merging.[33] The identification argument is also statistically tested, see further below.

Next, we discuss $\Delta^{\delta}_{j,k}$ which represents the difference between the acquirer's and target's discount factor, $\Delta^{\delta}_{j,k} = \frac{|\delta_j - \delta_k|}{\max(\delta_j, \delta_k)}$. Recent literature has shown that potential merger benefits can exist if the two firms have differing access to capital markets, see (Erel, Jang, and Weisbach, 2014). As firms make the decision to merge, they will consider the potential benefits from acquiring a target that has different access to capital markets. The increased profits from providing a constrained firm with better access to capital markets will directly affect the decision to merge. Note, the difference in discount factors between merging firms satisfies the exclusion restriction because it only impacts combined market shares if the merger occurs. Also, following again from the work by Bergstrom and Varian (1985), the industry output is independent of the distribution of costs (i.e., capital costs).

Third, we establish a measure of technological redundancy ($TR_{j,k,t-1}$) as an instrument in the selection equation. Because many research efforts are substitutable, mergers between more related firms in technology markets will results in avoidance of duplicate R&D efforts which leads to savings in fixed costs. Upon implementation, we expect mergers between closely related firms to increase joint profits. Note, the redundancy in technology does not directly impact firms' market shares, but rather has an indirect impact on firms' market shares via mergers.

[33] For further discussion of this result in a merger context see Siebert and Roy (2014).

We establish the measure of technological redundancy by adopting a measure frequently used in other studies, see e.g., Jaffe (1986), Bloom, Schankerman, and Van Reenen (2005), and Siebert and von Graevenitz (2010), and calculate the relatedness of firms' levels of activities in different technological (sub)markets, which belong to the semiconductor industry. We formulate an uncentered correlation coefficient, which measures technological relatedness between firms each period. Using the USPTO technological classification, we categorize all firms' semiconductor patent applications into 10 different classes.[34] For each firm and technological classification (c), we define $A^c_{j,t}$ and $A^c_{k,t}$ as firm-level variables which count the number of patent applications in each technological class:

$$TR_{j,k,t} = \frac{\sum_{c=1}^{10} A^c_{j,t} A^c_{k,t}}{\sqrt{\sum_{c=1}^{10} A^c_{j,t}}\sqrt{\sum_{c=1}^{10} A^c_{k,t}}}.$$

This measure results in a value between 0 and 1, where a value of 0 refers to firm-pairs with completely unrelated technological research and a value of 1 refers to firm-pairs which are active in the exact same technological areas.

As our last instrument, we follow Dafny (2009) and use an indicator for firms located in the same region ($Same\_Region$) which accounts for important unobserved factors determining mergers, such as cultural differences (Ahern, Daminelli, and Fracassi, 2012), trade barriers, regional conditions, and technological market spillovers (Jaffe, Trajtenberg, and Henderson, 1993). Since the semiconductor industry is characterized by international production, it is unlikely that the region variables have a direct significant impact on market shares. The dummy variable, $Same\_Region$, is set to one if the firm-pair is headquartered in the same region (USA, Europe, Japan, or Other Regions), otherwise the dummy variable takes on a value of zero.

In order to control for firm-level heterogeneity in the selection equation, we follow Wooldridge (2002) and include averages of the acquirers' and targets' market shares ($\overline{MS}$) and accumulated patents ($\overline{AcPat}$) over time.[35] This controls for time-invariant unobservable factors such as managerial talent, capital access, industry trends, macro market conditions, etc., which may

[34] We recover patents belonging to the semiconductor industry using the following technological classes: 257, 326, 360, 365, 369, 438, 505, 711, 712, 714, see also the USPTO webpage for further information.

[35] We follow this method instead of including firm fixed effects because our estimate for the discount factor does not vary with time. Firm fixed effects would encompass the estimated discount factors and make it impossible to determine the effects of the discount factor on merger decisions.

effect the propensity to merge. Moreover, as a further control, we include year fixed effects. Lastly, $\tau_{j,k,t}$ denotes the error term.

3.3 Estimation Algorithm

The complete estimation process incorporates the following steps. The details of each step will be discussed below:

1. **Estimation of price elasticity of demand (α_1):** Following Zulehner (2003), Siebert (2010), and Liu, Siebert, and Zulehner (2013), we estimate the following demand equation:

$$log(Q_t) = \alpha_0 + \alpha_1 log(P_t) + \alpha_1 log(GDP_{elec,t-1}) + e_t. \tag{9}$$

   We instrument for price and apply a 2SLS method using a supply shifter (input price of silicon, which is the main input for semiconductor production) and a proxy for competition (number of firms) as instruments for price. A demand shifter (electronics GDP) is included which controls for demand shifts originated by changes in the electronics (downstream) markets.

2. **Retrieval of marginal cost and discount factors:** Using the estimated elasticity from equation (9), we estimate the firm's supply relation in combination with each firm's marginal cost to obtain firm-specific discount factors and firm/time-specific marginal costs.

3. **Impact on product market:** We estimate the impact of mergers on the product market by applying the heterogeneous treatment effects estimator suggested by Heckman, Urzua and Vytlacil (2006).

   - Using the estimated discount factors ($\widehat{\delta_i}$) and the constructed marginal costs ($\widehat{MC}_{i,t}^{stat}$), we estimate the probit selection equation to investigate firm's incentives to merge.
   - Accounting for endogenous selection, we finally estimate the heterogeneous impact of mergers on market performance (outcome equation (1)).

4 Estimation Results

According to our outlined estimation algorithm, we begin with the estimation of the price elasticity of demand from equation (9).

4.1 Price Elasticity of Demand

We proceed by instrumenting for price using the input price of silicon ($log(Silc_{t-1})$) and the number of firms ($log(N\_Firms_{t-1})$) as supply shifters. Controlling for supply shifters enables us to trace out the slope of demand. The results for the 2SLS estimation are shown in Table 3. The first stage regression returns a F-value of 40.62 with a p-value of < 0.001 and an R-squared of about 0.92 which confirms a good fit for our regression. As well, the weak identification test reports a Cragg-Donald Wald F-statistic of 44.02 which is larger than the Stock-Yogo 10% critical value of 19.23, implying strong instruments. The estimated price elasticity of demand (α_1) takes on a value of -2.236 which is perfectly in line with the elasticity estimates of -1.5 to -2.3 frequently seen in previous studies.[36] The estimate for the GDP in electronics is positive and significant illustrating the fact that higher GDP in electronics shifts demand outwards.

4.2 Marginal Cost and Discount Factor

Using the estimated price elasticity of demand, we continue with the estimation of the marginal costs and discount factors. Ideally, we would like to simultaneously estimate equations (5) and (6). However, a simultaneous estimation procedure would require estimating a firm fixed effect in the marginal cost and another firm fixed effect as the discount factor. Instead, we proceed with two different methods to circumvent this complication.

The first method accounts for firm and time heterogeneity by including average accumulated patent applications at the firm level (Wooldridge, 2002) and by including a year effect in each firm's marginal cost (equation (6)).[37] The firm average accumulated patent applications and

[36] See the following studies for further references on estimates on price elasticities of demand for semiconductors: Irwin and Klenow (1994), Webbink (1977), Wilson, Ashton, and Egan (1980), Finan and Amundsen (1986), Flamm (1993), and Baldwin (1988).

[37] The year effect in the marginal cost counts the number of years until 2004, starting at 16 and counting down to 1.

the year effect are used in the place of a firm fixed effect. This allows us to treat the discount factor as the only firm fixed effect in the estimation of equation (5).

Second, we separately estimate the dynamic marginal cost with firm fixed effects and then include the predicted static marginal cost (dynamic marginal cost excluding a dynamic adjustment) into equation (5). Following Irwin and Klenow (1994), we estimate the dynamic marginal cost as being equal to the price, adjusted for firm specific markup, $P_t\left(1+\frac{MS_{i,t}}{\alpha_1}\right) = MC_{i,t}^{dyn}$. Since the dynamic marginal cost consists of the static marginal cost plus a dynamic component, we combine equation (6) with a dynamic adjustments term and estimate $P_t\left(1+\frac{MS_{i,t}}{\alpha_1}\right) = MC_{i,t}^{stat} + \lambda_5 Dynamic\_Adj_t + u_{i,t}$. We allow the dynamic adjustment term to refer to the time period in the product life cycle $(1, 2, \cdots, 16)$, which proxies the difference between static and dynamic marginal costs. Firms operating at the early stages of the life cycle are able to benefit from higher learning by doing effects and further increase output, such that dynamic marginal costs are further below static marginal costs, see also Zulehner (2003) and Siebert (2010). A negative coefficient on the dynamic term reflects that dynamic marginal costs lie below static marginal costs. The error term is denoted as $u_{i,t}$. To calculate the static marginal costs ($\widehat{MC}_{i,t}^{stat}$) we remove the effect of the dynamic adjustment (set $\lambda_5 = 0$) from the predicted dynamic marginal costs. Finally, we estimate equation (5) while treating the discount factor as a firm fixed effect.

Upon execution, both methods provide estimates for firm-specific discount factors that are highly correlated ($corr(\delta_1, \delta_2) = 77.81\%$). However, the first method yields more estimates for the discount factor, which allows for greater efficiency due to additional mergers in the final sample.[38] Moving forward, we will focus on the results from the first estimation method.[39]

For the first method, the supply equation (5) in combination with the marginal cost equation (6) is estimated via constrained OLS methods. As mentioned above, we use firm average accumulated patents and a year effect to account for potential firm-level heterogeneity. For the term $\frac{\partial MC_{i,t+1}}{\partial q_{i,t}}$, we apply a grid search and specify different values from previous literature between -0.1 and -0.3, settling on $\frac{\partial MC_{i,t+1}}{\partial q_{i,t}} = -0.1$.[40] Finally, in order to ensure reasonable results for the

[38] In both estimation routines, if the estimated discount factor is pushed to the boundary (0.667 or 1) then the firm is dropped and the discount factor and corresponding marginal cost is not included in the summary statistics. This explains the difference in observations between Table 4 Panel B and Table 7 Panel B.

[39] Corresponding estimation results and summary statistics from the second method can be found in Table 7.

[40] The results by Zulehner (2003) suggest a similar effect. We attempted all different values within this range

discount factor, we constrain $\delta_i \in (0.667, 1)$ which corresponds to a discount rate of $r_i \in (0, 0.5)$.

The estimated discount factors (δ_i) from equation (5) are summarized in Table 4, Panel B. The average estimated discount factor is 0.931 (equivalent to a discount rate of $r_i = 0.076$) which is in line with other studies confirming the reliability of our estimates. For instance, Davis and Huse (2010) find an average discount factor of 0.886 using the CAPM for a similar group of 18 technology firms from the server industry. Figures 3a and 3b show the distribution of the estimated discount factors and the discount rates, respectively. The discount factors and discount rates are quasi-normally distributed around the mean with a higher (lower) median than the mean for the discount factor (rate). Overall, the estimation results provide evidence that discount factors differ between firms.

Turning to the estimated static marginal cost equation (6), Table 4, Panel A, shows that the coefficient for own learning (λ_1) is negative and significant and provides a learning elasticity or -0.605 which corresponds to a learning rate of 34.25% (i.e., doubling accumulated production reduces marginal costs by 34.25%). Likewise, the significant coefficient λ_2 is negative indicating that spillover learning lowers the marginal costs of production. For spillover learning, the learning elasticity is -8.908 which, when scaled by the average number of firms, results a learning rate of 3.85%.[41] In comparison with previous literature, the own learning rate is low. However, components of own learning may be picked up in the coefficients on patent applications and mean accumulated patents.[42] Moreover, our estimates show that the wage is significant and positive and captures upward shifts in marginal costs. Finally, the controls for firm heterogeneity (accumulated patents) enter significantly and negatively.

Using the estimated coefficients, we calculate the static marginal costs for each firm based on equation (6), see Table 4 (Panel B) which shows a summary statistic.

(grid search) and the resulting estimates for the discount factors are highly correlated (i.e., $> 99\%$) and the main difference is seen in the magnitude of the discount factor which ranges from an average of 0.930 to 0.934.

[41] The own learning elasticities are evaluated using the following relationship: $\frac{\partial MC_{i,t}}{\partial X_{i,t}} = \hat{\lambda}_2 = \alpha = -0.605$. Spillover learning is adjusted by the average number of firms in the market and we use the following: $\frac{\partial MC_{i,t}/\partial X_{-i,t}}{N\_Firms} = \frac{\hat{\lambda}_3}{N\_Firms} = \alpha = \frac{-8.908}{157.278} = -0.057$. Learning rates are calculated from $1 - 2^{\alpha}$, where α represents the respective learning elasticity. See Siebert (2010) and Zulehner (2003) for a similar procedure.

[42] See also Irwin and Klenow (1994) and Siebert (2010).

4.3 Merger Formation

Using the results from the estimation of the discount factors and the marginal costs, we now discuss firms' incentives to form mergers. We especially emphasize the role of the discount factor in firm's incentives to merge for efficiency or market power benefits. We condition on firms with discount factors, marginal costs, and production the year before and after merging to arrive at 49 mergers for the remaining tests.[43] We begin with discussing the descriptive statistics on the discount factors and marginal costs separated by acquirers and targets the year before the merger occurs, as shown in Table 5, Panel A. The following facts become clear: first, the acquiring firms have significantly different and larger market shares (MS) than the target firms (p-value = 0.074).[44] Likewise, the accumulated production (Acq), patents (Pat), and accumulated patents ($AcPat$) all report that the acquiring firms are on average larger than the targets. Finally, the acquirers are characterized by lower marginal costs, neither one being significantly different between acquirers and targets. The problem in interpreting the results is that the descriptive statistics do not allow for any heterogeneity between firms.

We further allow for firm heterogeneities and separate acquiring firms into two groups: acquirers characterized by low discount factors and acquirers characterized by high discount factors.[45] We use the median discount factor to define a threshold which separates between both groups. Table 5, Panel B, shows that acquirers with low discount factors merge with targets that are characterized by comparatively lower production (p-value = 0.007), higher marginal costs (p-value = 0.006), fewer patents (p-value = 0.337), and fewer accumulated patents (p-value = 0.402). The higher marginal costs and patent activity for these acquirers with low discount factors hints that their targets are less efficient than the acquiring firms and that efficiency is not the objective.

In contrast, Table 5, Panel C, shows that acquirers with high discount factors merge with

[43]The selection equation is estimated on 44 mergers. We removed 5 mergers that took place in the year immediately following another merger by the same acquiring firm.

[44]Unless specified otherwise, the null hypothesis in this, and latter, comparisons is that the two values are not different from one another.

[45]As acquiring firms decide with whom to merge, we concentrate on separating the acquirers into different groups. In fact, tests on heterogeneities show that most of the heterogeneity comes from acquiring firms. The results are reported in Section 4.4.

targets that have more patents (p-value = 0.064), more accumulated patents (p-value = 0.154), and lower marginal costs (p-value = 0.319). This fact suggests that these target firms on average are more efficient than their acquirers, which have high discount factors. This hints that acquiring firms with high discount factors (patient firms) attribute greater value toward more efficient targets, presumably for acquiring intellectual property rights in order to produce more efficiently.

Comparing the mergers characterized by acquirers with low discount factors (Panel B) with mergers with acquiring firms characterized by high discount factors (Panel C) we gain several interesting insights. First, we note that the acquirers' discount factors in Panel B ($\delta = 0.870$) are significantly different from the acquirers' discount factors in Panel C ($\delta = 0.936$) with a p-value of < 0.0001. Moreover, the acquiring firms with lower discount factors produce more (p-value = 0.0002) at a lower marginal cost (p-value < 0.0001) than acquiring firms with higher discount factors. As mentioned before, the comparison shows that acquirers with low discount factors (impatient firms) merge with comparatively smaller and less efficient targets. Note however, the targets in this group (Panel B) are larger than the targets acquired by firms with high discount factors (patient firms). This fact suggests that acquirers with low discount factors (impatient firms) acquire relatively larger targets to gain from immediate market power benefits. In contrast, acquirers with high discount factors (patient firms) acquire more innovative targets, which supports the notion that they aim for efficiency gains.

To provide descriptors relating discount factors to whether market power or efficiency effects dominate in specific mergers, we calculate the change in market shares before and after merging for mergers by firms with high and low discount factors. Remember, common oligopoly models predict that market shares will increase (decrease) if efficiency (market power) benefits outweigh market power (efficiency) benefits. Our results show that acquiring firms with high discount factors increase market shares from 1.28% before merging to 1.73% after merging. In contrast, acquiring firms with low discount factors reduce market shares from 3.29% before merging to 3.0% after merging. This change in market shares reconfirms the notion that more patient firms (acquiring firms with higher discount factors) acquire for efficiency reasons, and more impatient firms (characterized low discount factors) merge for market power reasons.

4.4 Heterogeneous Impact of Mergers

To further elaborate on the impact of mergers and assess the relationship between discount factors, efficiency gains, and market power, we evaluate the change in market shares before and after a merger occurred and compare this effect to the change in market shares of nonmerging firms as outlined in Section 3. Since different types of firms self-select into mergers, we are concerned with potential biases arising from the fact that observed and/or unobserved firm-level attributes highly correlate between firms' decisions to merge and their decisions to produce. We therefore continue estimating a heterogeneous treatment effects estimator by Heckman et al. (2006) which controls for pre- and post-merger heterogeneities. We begin with reporting the results from firms selecting into mergers, i.e., the selection equation (8), and then turn to discussing the impact of mergers on market performance, i.e., the outcome equation (7).

In preparation for the estimation of the selection equation (8), we test for the presence of unobserved heterogeneity by estimating $\rho = \frac{\sigma_c^2}{1+\sigma_c^2}$ where σ_c^2 is the panel-level variance. The estimated ρ is the proportion of total variance contributed by the panel-level variance component. When ρ is zero, the panel-level variance is unimportant and the panel estimator is not different from the pooled estimator. To test if unobserved heterogeneity is related to the target firms, the acquiring firms, or the acquirer-target pairs, we estimate the full specification (equation (8) without $\overline{MS}$ and $\overline{AcPat}$) which results in an estimate of ρ =0.949 for acquirers, $\rho = 0.953$ for targets, and ρ =0.0001 for acquirer-target pairs which correspond to p-values of 0.000, 0.000, and 0.495, respectively. The tests confirm that the main part of heterogeneity is originated by the acquiring and target firms. Thus we control for unobserved firm-specific heterogeneity originating from acquirers ($\overline{MS}_j$ and $\overline{AcPat}_j$) and target ($\overline{MS}_k$ and $\overline{AcPat}_k$).

We next discuss the results from estimating the heterogeneous treatment effects model, equations (7) and (8). Table 6, Column (1), shows the results of estimating the first stage selection equation (8).[46] Most importantly, the results show that the four instruments all enter signif-

[46]One potential problem might arise due to small number of mergers in comparison to the large number of potential mergers. This is commonly referred to as a rare event problem. A potential solution is use the ReLogit

icantly. The probit selection equation returns a Likelihood Ratio (LR) Chi-Square value of 122.04 which corresponds to a p-value of < 0.0001 and a pseudo R-squared of 0.162. Specifically, the results show that the first two instruments, the differences in marginal costs ($\Delta^{MC}_{j,k,t-1}$) and discount factor ($\Delta^{\delta}_{j,k}$) enter significantly implying differences contribute to the formation of mergers.

Turning to the other instrumental variables, we find that the measure of technological redundancy (TR) show a significantly positive impact on merger formation. This result emphasizes that more related firms in the technological markets achieve cost savings from merging as they benefit from removal of redundant expenses. Moreover, the dummy for the same region has a positive impact on merger formation, which indicates that unobserved firm-level factors, such as organizational and cultural differences, play an important role in merger formation.

The controls for firm heterogeneities, i.e., the acquirer and target size (MS_j and MS_k), positively impact merger formation.

From the first stage estimation, we derive the Heckman correction terms ($HEC1$ and $HEC0$) which enter the outcome equation (7). We include the Heckman correction terms in the outcome equation (7) and first estimate the effect of merging on the joint market share for the year of the merger in column (2). The estimates show that almost 86% of the current market share is explained by the lagged market share. This result indicates the time series on market share is highly persistent over time.

It is interesting to note that the Heckman correction term for merging firms turns out to be significant. This result provides evidence that firms self-select into mergers, i.e., unobserved firm attributes drive a firm's decision to merge and positively impact market shares after merging due to efficiency gains.

Our results show that mergers significantly decreases market share on average. The interaction term between mergers and the acquirers' discount factors emphasize that acquirers' discount factors determine the impact of mergers. An increase in the acquiring firm's discount

by King and Zeng (2001). The problem with using this approace is that it would not allow for the use of the Heckman correction in outcome equation. However, we estimated several different specifications and the results appear to be robust. Hence we are confident that the low probability of merger and the associated flat cumulative density function will not cause major problems for the first stage.

factor results in an increase to the combined market share following the merger suggesting greater efficiency benefits.

To quantify the impact of mergers on the product market, accounting for heterogeneity in firms' discount factors, we calculate the average treatment effects from merging on both the treated ($ATET$) and non-treated groups ($ATENT$). Further, we evaluate how the impact of mergers varies across firms with different discount factors. For answering the first question, we calculate the average treatment effect on the treated ($ATET$), i.e., the impact on market shares of merging firms, as a function of acquirers' discount factors (δ_j):

$$ATET(\delta_j) = \left[\rho_2 + (\delta_j - \bar{\delta}) * \rho_3 + (\rho_7 + \rho_8) * \frac{\phi(X\beta)}{\Phi(X\beta)}\right]_{(P_{j,k,t}=1)}. \tag{10}$$

We also calculate the average treatment effect on the nontreated ($ATENT$), i.e., the impact on market shares if nonmerging firms did merge, dependent on the acquirers' discount factor (δ_j):

$$ATENT(\delta_j) = \left[\rho_2 + (\delta_j - \bar{\delta}) * \rho_3 + (\rho_7 + \rho_8) * \frac{\phi(X\beta)}{1 - \Phi(X\beta)}\right]_{(P_{j,k,t}=0)}. \tag{11}$$

Figure 4 shows the plotted kernel density for the $ATET$ represented by the solid line and the $ATENT$ represented by the dashed line. The $ATET$ ranges from -1.46% to 0.90%. On average, the $ATET$ is slightly greater than zero ($\overline{ATET} = 0.016\%$) and indicates that the average merger experiences efficiency benefits.

We next evaluate the impact of mergers on changes in market shares with respect to acquirer's discount factors, see the right panel of Figure 4. The graph illustrates a positive relationship between the acquirer's discount factor and the impact on market shares. If we consider the $ATET$ for the firms with higher discount factors (greater than the median, patient firms), we find that they increased market share by 0.198 percentage points and that more than 69% of the mergers resulted in a positive $ATET$. This results provides further evidence that firms with higher discount factors (patient firms) increase market shares which reflects that efficiency gains dominate market power effects. In contrast, the firms with low discount factors on average had an $ATET$ on market share of -0.184 percentage points and just over 52% of the mergers resulted in an negative $ATET$. Thus firms with lower discount factors (impatient firms) decrease market shares more due to market power effects. The $ATET$'s for the firms with low discount factors and firms with high discount are significantly different (-0.184% versus 0.198%, p-value = 0.001).

Turning to the $ATENT$, we find the remarkable result that a merger between nonmerging firms would have lowered the market shares by 2.7 percentage points on average, see Figure 4. This significant decline is about 16 times higher than for the actual mergers and emphasizes the fact that firms who engage in actual mergers were able to gain significant efficiencies, including those mergers that are dominated by market power effects. It is interesting to note that the entire range of the $ATENT$, as well as the mean, is lower than the $ATET$. This result provides evidence that mergers between nonmerging firms would have resulted in lower market shares and higher market power effects. The set of nonmerging firms would have not been able to generate as much on efficiency gains as the merging firms. This provides strong evidence that merging firms achieved more efficiency gains than nonmerging firms could have gained. Consequently, efficiency gains play a major role in mergers and are valued even more by firms with high discount factors (patient firms). Finally, the estimation results from Table 6 show that our controls for competition (N_Firms) and demand (GDP) describe a significant impact on market shares.

As a robustness check, we estimate the outcome equation on joint market shares the year after merging (column (3) of Table 6). The average treatment effects and the relationship between the average treatment effect and the acquiring firms' discount factors are plotted in Figure 5. It is interesting to note the $ATET$ has shifted to the right implying that the effect of merging one year later leans toward efficiency benefits. Consistent with our previous results, the increase in average treatment effect is greater for firms with higher discount factors.

5 Conclusion

Our study assesses the relationship between firm-level discount factors and their incentives to form mergers as well as their impact on consumer welfare. We estimated firm-specific discount factors from firms' supply relations and estimate a heterogeneous treatment effects model, accounting for pre-treatment and post-treatment heterogeneity between mergers.

Our results show that those acquiring firms, which are characterized by high discount factors (patient firms), merge with targets characterized by lower marginal costs and more patents (both implying more efficient production) than the acquiring firm itself. This type of merger usually generates long run efficiency gains. In contrast, those acquiring firms, which are characterized by low discount factors (impatient firms), merge with targets characterized by comparatively higher marginal costs than the targets of firms with high discount factors. Our estimation results show that these mergers mostly achieve higher market power effects. Our counterfactuals also stress the fact that nonmerging firms would have not been able to generate comparable efficiency gains as realized in actual mergers. Hence, the results emphasize the importance of achieving efficiency gains in mergers.

To conclude, this study provides evidence that the acquirers' discount factors are related to specific types of mergers as well as the channels through which mergers generate value added. From a policy point of view, our study suggests that firm-level discount factors play a critical role in explaining the dominance between market power and efficiency effects. However, policy and antitrust conclusion only go so far without further studies exploring the relationship between firm-level discount factors and the impact of mergers. For example, it would be interesting to examine if a similar pattern is observed in different industries.

References

Aguirregabiria, Victor, and Arvind Magesan, 2013, *Structural Econometric Models (Advances in Econometrics)* . chap. Euler Equations for the Estimation of Dynamic Discrete Choice Structural Models, 3–44 (Emerald Group Publishing Limited).

Ahern, Kenneth R., Daniele Daminelli, and Cesare Fracassi, 2012, Lost in translation? The effect of cultural values on mergers around the world, *Journal of Financial Economics,* forthcoming.

Akerlof, George A., 1970, The market for 'Lemons': Quality uncertainty and the market mechanism, *The Quarterly Journal of Economics* 84, 488–500.

Andrade, Gregor, and Steven N. Kaplan, 1998, How costly is financial (not economic) distress? Evidence from highly leveraged transactions that became distressed, *Journal of Finance* 53, 1443–1493.

Angrist, Joshua D., and Alan B. Krueger, 1999, Empirical strategies in labor economics, vol. 3 of *Handbook of Labor Economics* . chap. 23, 1277–1366 (Elsevier).

Baldwin, Richard E., 1988, *Empirical Methods for International Trade* . chap. Market Access and International Competition: A Simulation Study of 16K Random Access Memories (Combridge Mass: MIT Press).

Bergstrom, Theodore C., and Hal R. Varian, 1985, Two remarks on cournot equilibria, *Economics Letters* 19, 5–8.

Berry, Steve, and Ariel Pakes, 2000, Estimation from the optimality conditions for dynamic controls, *Working Paper.*

Bloom, Nicholas, Mark Schankerman, and John Van Reenen, 2005, Identifying technology spillovers and product market rivalry, CEP Discussion Papers dp0675 Centre for Economic Performance, LSE.

Brand, Jennie E., and Yu Xie, 2010, Who Benefits Most from College? Evidence for Negative Selection in Heterogeneous Economic Returns to Higher Education, *American Sociological Review* 75, 273–302.

Brand, Jennie E., and Juli Simon Thomas, 2013, Causal effect heterogeneity, in Stephen L. Morgan, ed.: *Handbook of Causal Analysis for Social Research* Handbooks of Sociology and Social Research . 189–213 (Springer Netherlands).

Carhart, Mark M, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Cerulli, Giovanni, 2012, Ivtreatreg: a new stata routine for estimating binary treatment models with heterogeneous response to treatment under observable and unobservable selection, CERIS Working Paper 201203 Institute for Economic Research on Firms and Growth - Moncalieri (TO).

Compte, Olivier, Frederic Jenny, and Patrick Rey, 2002, Capacity constraints, mergers and collusion, *European Economic Review* 46, 1–29.

Dafny, Leemore, 2009, Estimation and identification of merger effects: An application to hospital mergers, *Journal of Law & Economics* 52, 523–550.

Davis, Peter J., and Christian Huse, 2010, Estimating the 'coordinated effects' of mergers, *Working Paper*.

Dehejia, Rajeev H., and Sadek Wahba, 2002, Propensity Score-Matching Methods For Nonexperimental Causal Studies, *The Review of Economics and Statistics* 84, 151–161.

Diamond, Douglas W., and Robert E. Verrecchia, 1991, Disclosure, liquidity, and the cost of capital, *The Journal of Finance* 46, 1325–1359.

Duso, Tomaso, Damien J. Neven, and Lars-Hendrik Röller, 2007, The political economy of european merger control: Evidence using stock market data, *Journal of Law and Economics* 50, 455–489.

Easley, David, and Maureen O'hara, 2004, Information and the cost of capital, *The Journal of Finance* 59, 1553–1583.

Erel, Isil, Yeejin Jang, and Michael S. Weisbach, 2014, Do acquisitions relieve target firms financial constraints?, *The Journal of Finance,* forthcoming.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Farrell, Joseph, and Carl Shapiro, 1990, Horizontal mergers: An equilibrium analysis, *American Economic Review* 80, 107–26.

Finan, William F., and Chris B. Amundsen, 1986, Modeling U.S.–Japan competition in semiconductors, *Journal of Policy Modeling* 8, 305–326.

Flamm, Kenneth, 1993, *Forward Pricing versus Fair Value: An Analytical Assessment of 'Dumping' in DRAMS* (Chicago: Chicago University Press).

Fluck, Zsuzsanna, and Anthony W Lynch, 1999, Why do firms merge and then divest? A theory of financial synergy, *The Journal of Business* 72, 319–46.

Fridolfsson, Sven-Olof, and Johan Stennek, 2005, Why mergers reduce profits and raise share prices-a theory of preemptive mergers, *Journal of the European Economic Association* 3, 1083–1104.

Gowrisankaran, Gautam, 1999, A dynamic model of endogenous horizontal mergers, *The RAND Journal of Economics* 30, pp. 56–83.

Gugler, Klaus, and Ralph Siebert, 2007, Market power versus efficiency effects of mergers and research joint ventures: Evidence from the semiconductor industry, *The Review of Economics and Statistics* 89, 645–659.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, Working Paper 8498 National Bureau of Economic Research.

Heckman, James J., Sergio Urzua, and Edward Vytlacil, 2006, Understanding instrumental variables in models with essential heterogeneity, *The Review of Economics and Statistics* 88, 389–432.

Irwin, Douglas A, and Peter J Klenow, 1994, Learning-by-doing spillovers in the semiconductor industry, *Journal of Political Economy* 102, 1200–1227.

Jaffe, Adam B, 1986, Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value, *American Economic Review* 76, 984–1001.

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson, 1993, Geographic localization of knowledge spillovers as evidenced by patent citations, *The Quarterly Journal of Economics* 108, 577–598.

Jovanovic, Dragan, and Christian Wey, 2012, An equilibrium analysis of efficiency gains from mergers, DICE Discussion Papers 64 Heinrich-Heine-Universität Düsseldorf, Düsseldorf Institute for Competition Economics (DICE).

Khatami, Hossein, Maria-Teresa Marchica, and Roberto Mura, 2014, Corporate acquisitions and financial constraints, *Working Paper*.

Kim, E Han, and Vijay Singal, 1993, Mergers and Market Power: Evidence from the Airline Industry, *American Economic Review* 83, 549–69.

King, Gary, and Langche Zeng, 2001, Logistic regression in rare events data, *Political Analysis* 9, 137–163.

Liu, An-Hsiang, Ralph Siebert, and Christine Zulehner, 2013, Excessive entry and social inefficiencies: A policy experiment on dunamic efficiency gains, *Working Paper*.

Morgan, Stephen L., and Christopher Winship, 2007, *Counterfactuals and Causal Inference Methods and Principles for Social Research* (Cambridge University Press) 1st edn.

Mueller, Dennis C, 1969, A theory of conglomerate mergers, *The Quarterly Journal of Economics* 83, 643–59.

——— , 1985, Mergers and Market Share, *The Review of Economics and Statistics* 67, 259–67.

Mukherjee, Tarun K., Halil Kiymaz, and H. Kent Baker, 2004, Merger motives and target valuation: A survey of evidence from CFOs, *Journal of Applied Finance* 14, 7–24.

Pais, Jeremy, 2011, Socioeconomic background and racial earnings inequality: A propensity score analysis, *Social Science Research* 40, 37 – 49.

Perry, Martin K, and Robert H Porter, 1985, Oligopoly and the incentive for horizontal merger, *American Economic Review* 75, 219–27.

Pesendorfer, Martin, 2003, Horizontal mergers in the paper industry, *RAND Journal of Economics* 34, 495–515.

Röller, Lars-Hendrik, Ralph Bernd Siebert, and Mihkel M. Tombak, 2007, Why Firms Form (or do not Form) RJVS, *Economic Journal* 117, 1122–1144.

Salant, Stephen W., and Greg Shaffer, 1998, Optimal asymmetric strategies in research joint ventures, *International Journal of Industrial Organization* 16, 195–208.

——— , 1999, Unequal treatment of identical agents in cournot equilibrium, *American Economic Review* 89, 585–604.

Salant, Stephen W, Sheldon Switzer, and Robert J Reynolds, 1983, Losses from horizontal merger: The effects of an exogenous change in industry structure on Cournot-Nash equilibrium, *The Quarterly Journal of Economics* 98, 185–99.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

Siebert, Ralph, and Moumita Roy, 2014, The competititve effects of horizontal mergers in markets characterized by differentiated goods, firm asymmetries and technological spillovers, *Working Paper*.

Siebert, Ralph, and Georg von Graevenitz, 2010, Jostling for advantage or not: Choosing between patent portfolio races and ex ante licensing, *Journal of Economic Behavior & Organization* 73, 225–245.

Siebert, Ralph B., 2010, Learning-by-doing and cannibalization effects at multi-vintage firms: Evidence from the semiconductor industry, *The B.E. Journal of Economic Analysis & Policy* 10, 1–32.

Stigler, George J., 1964, A theory of oligopoly, *Journal of Political Economy* 72, 44–61.

Tombak, Mihkel M., 2002, Mergers to monopoly, *Journal of Economics & Management Strategy* 11, 513–546.

Vasconcelos, Helder, 2005, Tacit collusion, cost asymmetries, and mergers, *RAND Journal of Economics* 36, 39–62.

Webbink, Douglas A., 1977, *The Semiconductor Industry: A Survey of Structure, Conduct, and Performance* (Washington: Federal Trade Commission).

Williamson, O.E, 1968, Economies as an antitrust defense: The welfare tradeoffs, *American Economic Review* 58.

Wilson, Robert W., Peter K. Ashton, and Thomas P. Egan, 1980, *Innovation, Competition, and Government Policy in the Semiconductor Industry* (Lexington, Mass: Lexington Books).

Wooldridge, J.M., 2002, *Econometric Analysis Cross Section Panel Data* (Massachusetts Institute of Technology 2002 .).

Wright, Theodore P., 1936, Factors affeting the cost of airplanes, *Journal of Aeronautical Sciences* 3, 122–128.

Zulehner, Christine, 2003, Testing dynamic oligopolistic interaction: evidence from the semiconductor industry, *International Journal of Industrial Organization* 21, 1527–1556.

A Appendix: Tables

Table 1: Industry Description

Year	Mergers	N Firms	Industry Revenue	Firm Revenue
1989	2	130	52,720	405.538
1990	3	138	54,571	395.442
1991	3	130	59,310	456.231
1992	5	155	64,705	417.452
1993	4	151	85,184	564.132
1994	5	152	109,181	718.296
1995	6	195	171,281	878.364
1996	7	182	160,685	882.885
1997	7	187	159,799	854.54
1998	11	205	149,120	727.415
1999	18	193	184,866	957.855
2000	21	155	226,766	1,463.01
2001	11	166	151,954	915.386
2002	11	169	155,629	920.882
2003	13	200	178,242	891.21
2004	6	201	219,880	1,093.93
Average	8.31	169.31	136,493.31	783.91

Table 1: Summary of the number of mergers, number of firms, industry revenue (mil USD), and revenue per firm (mil USD). The data is provided by SDC Platinum and the Gartner Group.

Table 2: Variable Summary Statistics

Variables	Label	N	MEAN	STD	MIN	MAX
P_t	Semiconductor price	1,829	71.983	16.765	45.903	96.927
$MS_{i,t}$	Market share per firm	1,829	0.007	0.014	0.000	0.113
$q_{i,t}$	Quantity produced	1,829	14.560	34.644	0.014	540.580
$Acq_{i,t}$	Accumulated quantity produced	1,829	54.096	157.281	0.000	2,386.690
$Acq_{-i,t}$	Accumulated quantity produced by others	1,829	11,188.070	9,018.520	485.732	29,443.310
$Pat_{i,t}$	Annual patent applications	1,829	36.266	98.529	0.000	1,020.000
$AcPat_{i,t}$	Accumulated patent applications, with 5% depreciation	1,829	227.044	640.828	0.000	4,973.760
$Wage_t$	Semiconductor wage, PPI adjusted	1,829	13.162	0.975	11.476	14.521
N_Firms_t	Number of semiconductor firms	1,829	157.278	19.400	124.000	189.000
$GDP_{elec,t}$	U.S. Electronics GDP	1,829	41.696	2.357	38.100	45.600

Table 2: Summary statistics of variables used for model estimation. Sources and methodologies are described in Section 2.

Table 3: Elasticity Estimation

Variables	(1) Dep. Var: $log(Q_t)$
Constant	7.935
	(5.935)
$log(P_t)$	-2.236***
	(0.321)
$log(GDP_{elec,t-1})$	2.440*
	(1.370)
Observations	15
Adjusted R-Squared	0.860

Table 3: Price elasticity of demand estimation of equation (9) using 2SLS. Dependent variable is $log(Q_t)$. The following instruments for price are used: number of firms and material price of silicon. Standards errors in parentheses, *** (**,*) denotes 1% (5%, 10%) level of significance.

Table 4: Static Marginal Cost/Discount Factor Estimation

Panel A: Static Marginal Cost Coefficients

Variables	(1) Dep. Var: Price adj. for markup
Constant	204.194***
	(13.198)
Own Learning	-0.605***
	(0.168)
Spillover Learning	-8.908***
	(0.696)
Wages	55.299***
	(2.178)
Patent Applications	-0.008***
	(0.002)
Mean Accumulated Patents	-8.295***
	(1.450)
Observations	1,592
Adjusted R-Squared	0.982
Discount Factor FE	Yes
Year Effect	Yes***

Panel B: Summary Statistics for Estimated Factors

Variables	N	MEAN	STD	MIN	MAX	5th %	MED	95th
δ_i	228	0.931	0.034	0.709	0.963	0.846	0.942	0.959
r_i	228	0.076	0.044	0.038	0.410	0.043	0.061	0.182
$\overline{MC}$	1,829	187.679	23.277	124.757	236.573	145.281	190.227	223.700

Table 4, Panel A: : Estimation of marginal cost ($MC_{i,t}$) and discount factor (δ_i) from equation (5) and equation (6) substituting mean accumulated patents for the firm fixed effect. The price adjusted for firm markup is the dependent variable. The results are obtained using constrained nonlinear OLS methods. The estimation includes a firm-specific discount factor and year effect. The summary statistics for the discount factor (δ_i) are shown in Panel B and in Figure 3. Standards errors in parentheses, *** (**,*) denotes 1% (5%, 10%) level of significance.
Panel B: Descriptive statistics for estimated δ_i, r_i, and marginal costs. The δ_i is estimated as a firm fixed effect according to equation (5). The estimation routine constrained δ_i such that $\delta_i \in (.66, 1)$. All boundary estimates for δ_i were dropped (two firms). The interest rate, r_i is calculated as $r_i = \frac{1}{\delta_i} - 1$. The marginal cost is calculated based on equation (6).

Table 5: Merger Summary Statistics

	Panel A: All Mergers				Panel B: Mergers with Low δ Acquirers				Panel C: Mergers with High δ Acquirers			
	Acquirers		Targets		Acquirers		Targets		Acquirers		Targets	
Variable	MEAN	STD	MEAN	STD	MEAN	STD	MEAN	STD	MEAN	STD	MEAN	STD
δ_i	0.902	0.049	0.917	0.038	0.870	0.050	0.909	0.044	0.936	0.009	0.926	0.028
r_i	0.112	0.067	0.093	0.048	0.154	0.073	0.103	0.056	0.068	0.011	0.082	0.034
MS_{i,t_i-1}	0.014	0.016	0.009	0.011	0.023	0.018	0.010	0.013	0.005	0.006	0.008	0.009
q_{i,t_i-1}	34.617	41.425	22.544	28.051	55.721	47.590	23.280	30.411	12.634	15.152	21.777	25.998
MC_{i,t_i-1}	180.528	22.389	186.739	22.235	164.127	16.895	180.268	24.123	197.612	12.299	193.479	18.211
Acq_{i,t_i-1}	129.275	217.115	103.763	150.133	223.674	270.359	116.356	166.325	30.943	48.264	90.645	133.495
Pat_{i,t_i-1}	96.429	168.048	82.469	174.651	181.800	202.242	131.080	229.451	7.500	9.027	31.833	58.968
$AcPat_{i,t_i-1}$	547.515	920.076	444.756	1,033.340	1,038.580	1,085.110	794.307	1,363.100	35.990	53.690	80.640	135.817

Table 5: Summary statistics for both the acquiring firm and the target firm for completed mergers. Results shown for all mergers and then mergers by acquirers with low and high discount factors, as determined by median acquirer discount factor. All time variant measures are shown for the year before the merger.

Table 6: Change in Market Share Following Merger

Variables	(1) Dep. Var: $M_{j,k,t}$	(2) Dep. Var: $MS_{j,k,t}$	(3) Dep. Var: $MS_{j,k,t+1}$
$\Delta^{MC}_{j,k,t-1}$	1.540*		
	(0.861)		
$\Delta^{\delta}_{j,k}$	-9.191***		
	(2.334)		
$Same\_Region$	0.570***		
	(0.117)		
$TR_{I,j,t-1}$	0.360**		
	(0.151)		
$\overline{MS}_j$	35.656***		
	(6.232)		
$\overline{MS}_k$	29.616***		
	(5.974)		
$\overline{AcPat}_j$	-0.000		
	(0.000)		
$\overline{AcPat}_k$	-0.000		
	(0.000)		
Constant	-4.161***	0.026***	0.026***
	(0.250)	(0.001)	(0.002)
MS_{j,k,t_i-1}		0.857***	0.708***
		(0.002)	(0.003)
M_{j,k,t_i}		-0.027***	-0.060***
		(0.007)	(0.010)
$M_{j,k,t_i} * (\delta_j - \overline{\delta})$		0.010	-0.098***
		(0.019)	(0.027)
δ_j		-0.018***	-0.033***
		(0.001)	(0.001)
N_Firms_t		-0.000***	-0.000***
		(0.000)	(0.000)
$GDP_{elec,t}$		-0.000***	0.000***
		(0.000)	(0.000)
$HEC1$		0.009***	0.017***
		(0.002)	(0.003)
$HEC0$		-0.001	0.004
		(0.003)	(0.004)
Observations	82,977	87,284	79,091
Year FE	Yes	Yes	Yes

Table 6: Estimation of a Heckman selection model as discussed in Section 4.4 for the change in market share from the year before the merge to the year of the merger (column (2)) and the year after the merger (column (3)). Column (1) provides results from estimating the probit selection equation (8), column (2) provides results from estimating the outcome equation (7) using OLS for the year of the merger, and column (3) provides similar results for the effect of merging on the market share the year after the merger. Standards errors in parentheses, *** (**,*) denotes 1% (5%, 10%) level of significance.

Table 7: Robustness: Fixed Effect Marginal Cost Estimation

Panel A: MC Estimation

Variables	(1) Dep. Var: Price adj. for markup
Constant	-100.936***
	(3.584)
Own Learning	-0.158**
	(0.066)
Spillover Learning	-4.019***
	(0.183)
Wages	85.807***
	(1.461)
Patent Applications	-0.002***
	(0.001)
Dynamic Adjustment	-1.417***
	(0.071)
Observations	1,853
Adjusted R-Squared	0.993
Firm FE	Yes

Panel B: Summary Statistics for Estimated Factors

Variable	N	MEAN	STD	MIN	MAX
$\overline{MC}^{dyn}$	1,601	71.770	16.673	41.300	98.064
$\overline{MC}^{stat}$	1,601	84.664	10.850	63.982	100.899
δ_i	196	0.860	0.080	0.671	0.996
r_i	196	0.173	0.116	0.004	0.491

Table 7: Estimation of the marginal cost from equation (6) with price adjusted for firm markup as the dependent variable. To incorporate the difference between the dynamic and static marginal cost, a dynamic adjustment term is included that counts from 1 to 16 for each year. The predicted dynamic marginal cost is obtained and the static marginal cost is calculated by removing the dynamic adjustment component. The predicted static marginal cost is included in equation (5) and then the equation is estimated to obtain the discount factors at the firm level. Standards errors in parentheses, *** (**,*) denotes 1% (5%, 10%) level of significance. The summary statistics for the estimated marginal costs and discount factors are shown in Panel B.

B Appendix: Figures

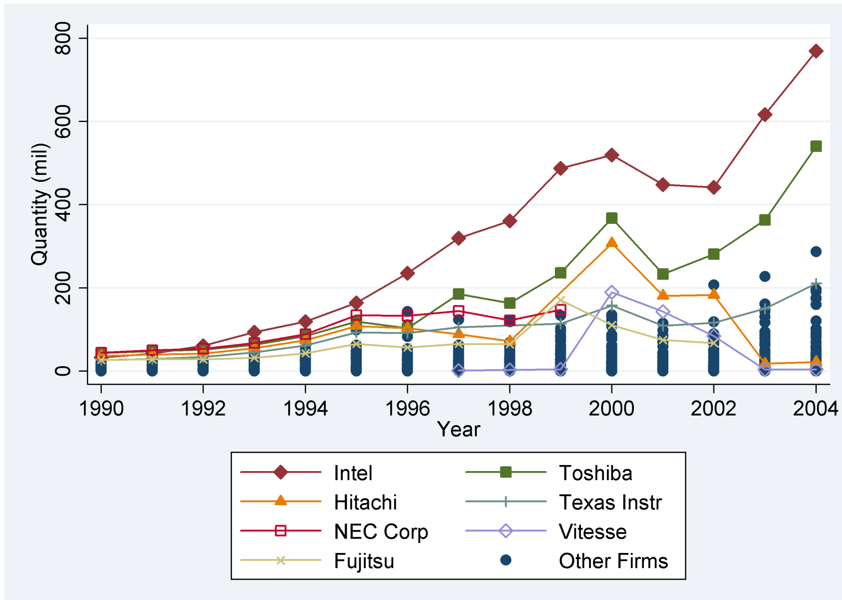


Figure 1: Firm Quantity by Year from 1990-2004
Source: Gartner Group

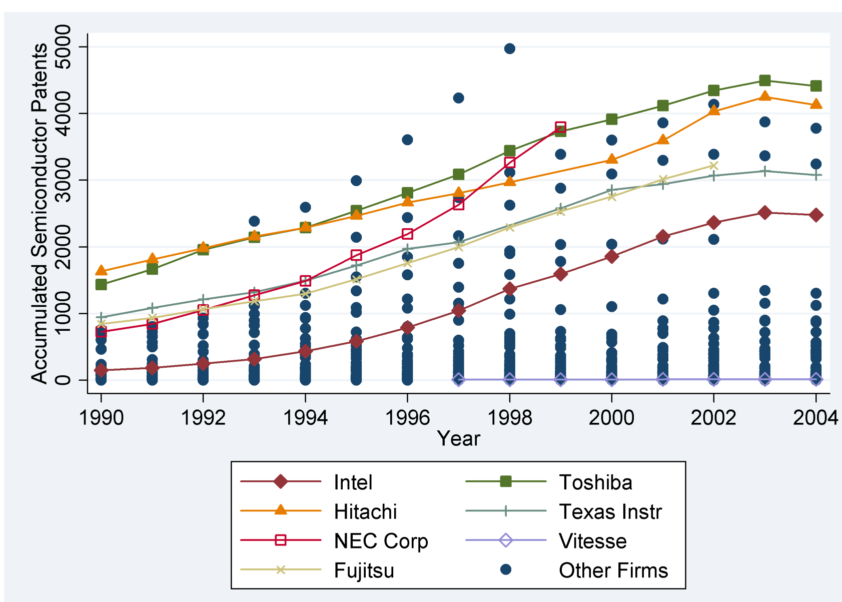
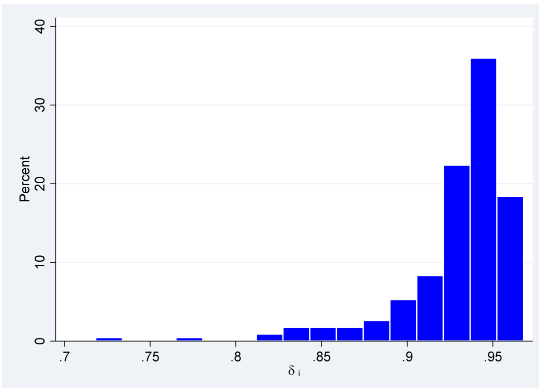
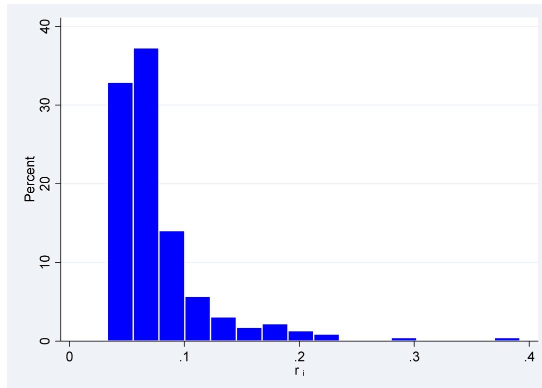


Figure 2: Accumulated Patents by Year from 1990-2004 using a 5% depreciation rate
Source: NBER Patent Database (Hall, Jaffe, and Trajtenberg, 2001)



(a) δ_i Histogram



(b) r_i Histogram

Figure 3: Histogram: firm-level discount factor and discount rate estimates for 228 firms

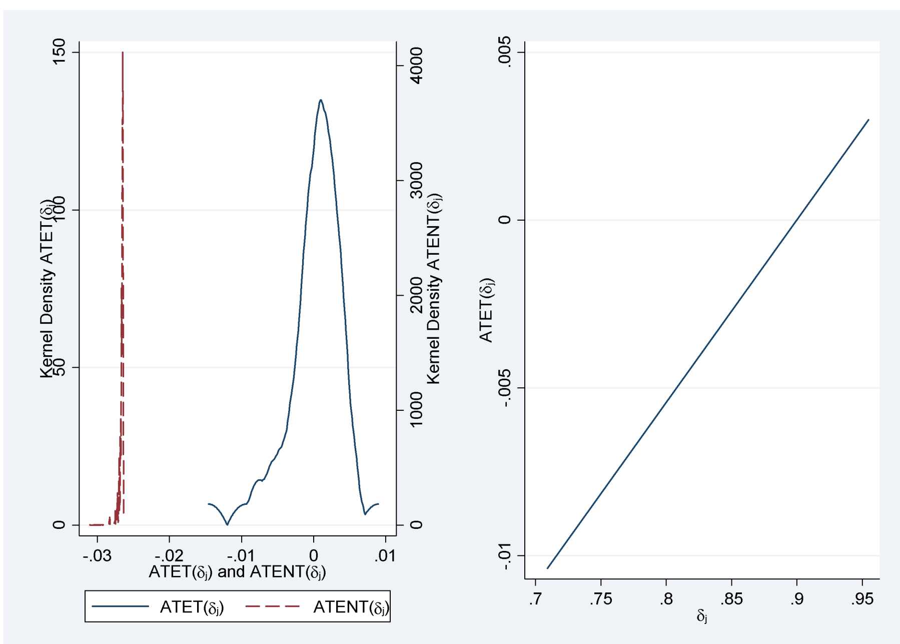


Figure 4: Heterogeneous Treatment Effect Estimates, Merger Year
Figure provides kernel density and relationship between $ATET(\delta_j)$ and the acquirer discount factor. Second stage estimated via OLS.

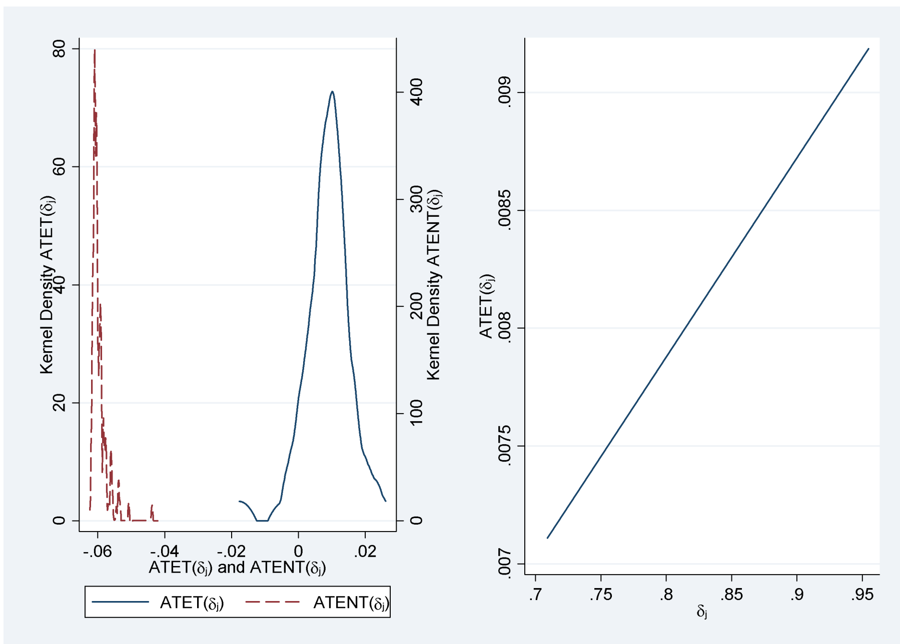


Figure 5: Heterogeneous Treatment Effect Estimates, Year After Merging
Figure provides kernel density and relationship between $ATET(\delta_j)$ and the acquirer discount factor. Second stage estimated via OLS.