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Abstract

Merger value is frequently evaluated in single market contexts without considering possible gains stemming from firms' multimarket presence. This study concentrates on the question through which channels, and of which magnitude, mergers among multimarket firms create incremental value. We establish a simple theoretical model that determines merger value in a multimarket firm environment. The model enables us to derive merger values as being independent of post-merger market shares, but rather dependent on pre-merger market shares. We test our hypotheses using a comprehensive dataset that encompasses information on mergers and firm-level multimarket production and innovation within the semiconductor industry. Using the pairwise stable equilibrium concept, we estimate firms' structural value functions. Our results show that multimarket effects contribute, on average, 20% of the total merger value added. Moreover, we find that multimarket efficiency gains dominate multimarket power effects by contributing majority of the value added. We also find that our estimated merger values are well aligned with the merging firms' post-merger stock market performance.

JEL-Codes: L100, L130, L200.

Keywords: efficiency gains, market power, matching, merger formation, merger value, multimarket competition.

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1 Introduction

Mergers have long been a popular strategy among firms, and they have become increasingly important over time involving trillions of dollars spent on merger transactions every year. A well-established fact in the merger literature is that a consolidation between firms can create value, see, e.g., Stigler (1950), Williamson (1968), Perry and Porter (1985), and Farrell and Shapiro (1990), Hitt et al. (2001), and King et al. (2004) among many others. While most studies concentrate on merger value creation in single markets, mergers usually take place between firms operating in multiple product markets. The multimarket firm character can be attributed to product and geographic market diversification (Gimeno and Woo 1999). For example, a vast majority of firms in the semiconductor dynamic random access (DRAM) industry are also present in other markets such as static random access memories, Flash memories etc.[1] Recent studies emphasize that mergers among multimarket firms can soften competition via coordinated effects (Miller and Weinberg (2015), Kim and Singal (1993), and Singal (1996)). Despite the prevalence of mergers among multimarket firms, mergers are frequently evaluated in single market contexts without considering possible gains stemming from firms' multimarket presence. The multimarket merger aspect has received little attention in the merger literature and more insight is desired. This study concentrates on the question through which channels mergers among firms competing in multiple markets create additional value.

A well established argument that increases merger value is the market power effect. Merging firms can internalize the competitive externalities they imposed on each other pre-merger, which allows them to raise their price above the pre-merger equilibrium price (see Stigler (1950), Williamson (1968), Salant et al. (1983), Perry and Porter (1985), Farrell and Shapiro (1990), and McAfee and Williamson (1992)). The extent to which competitive externalities can be internalized and market power can be achieved through mergers will likely be augmented in the number of markets that merging firms operate in.

A further argument that can add value to a merger is the achievement of merger-specific efficiency gains. The efficiency gains can be originated by economies of scale and scope, production rationalization, and innovation.[2] It is reasonable to believe that firms' multimarket presence

[1] Most pharmaceutical firms operating in the therapeutic market cancer are also active in other markets such as cardiovascular etc. Many more examples can be provided for other industries.

[2] See also Ravenscraft and Scherer (1987), Farrell and Shapiro (1990), Focarelli and Panetta (2003), Harrison et

determine efficiency gains and merger value.

A third merger value-increasing argument is related to the fact that multimarket activity across firms can have several strategic implications on firms' behavior.[3] First, firms competing against each other in multiple markets can refrain from engaging in aggressive pricing behavior in one market to avoid aggressive responses in other mutual markets, also referred to as tacit collusion or mutual forbearance. Hence, multimarket contact can help support tacit collusion among firms and result in softer competition (see Edwards (1955), Bernheim and Whinston (1990), Hughes and Oughton (1993), and Evans and Kessides (1994)).[4] If a merger is formed among multimarket firms, these firms will give away the possibility to engage in tacit collusion or mutual forbearance practices with the merging partner, which might reduce the value of the merger. A second strategic aspect that could have an effect on merger value among multiproduct firms is that mergers leave fewer firms competing in the market, which facilitates collusion in product markets. Therefore, multimarket activity further expands collusion possibilities, which may add merger value. A third strategic aspect of mergers between multimarket firms is that these firms may be better informed about one another given their close interdependence across multiple markets. Better information may translate into less uncertainty which, in turn, may benefit the merger value.

To what extent the above-mentioned multimarket firm arguments create incremental merger value is an empirical question which forms the center of our study. Ideally, we would like to compare pre- and post-merger values of firms with differing degrees of multimarket contacts. This approach, however, is empirically challenging for several reasons. First, the post-merger value depends on post-merger market shares and closed form solutions are difficult to derive and highly complex even in the simplest settings. A closed form solution for post-merger shares will depend on costs and realized efficiency gains which data are frequently not available. To overcome this problem, we establish a simple theoretical model that determines merger value in

al. (1991), Hitt et al. (1998), Larsson and Finkelstein (1999), Datta, Pinches, and Narayanan (1992), Ramaswamy (1997), Shelton (1988), and Singh and Montgomery (1987).

[3]For more information on multimarket competition, see Karnani and Wernerfelt (1985: 87).

[4]The majority of empirical studies find that multimarket contact weakens product market competition and enables firms to sustain higher levels of profits and prices (see, e.g., Busse (2000) and Parker and Roeller (1997) on the telecommunications industry, Evans and Kessides (1994), Singal (1993), Miller (2010), and Ciliberto and Williams (2014) on the airline industry, and Heggestad and Rhoades (1978) and Rhoades and Heggestad (1985) on the banking industry). Further empirical studies are Azar et al. (2015), Schmitt (2015), Parker and Roller (1997), Jans and Rosenbaum (1994), Hughes and Oughton (1993), and Scott (1991), among others.

a multimarket firm environment. We apply a conventional approach in the merger literature, and evaluate merger values based on infinitesimal output changes, see e.g., Farrell and Shapiro (1990). This approach enables us to derive merger values as being independent of post-merger market shares, but rather dependent on pre-merger market shares. Our model provides us with a set of results that illustrate how mergers among multimarket firms can generate incremental value, i.e., multimarket activity interacted with efficiency gains and market power effects as well as multimarket strategic effects in isolation. The results are hypothesized and tested in our empirical model. The basic theoretical model also serves as a basis for the specification of our empirical model.

The empirical evaluation of merger value is afflicted with several challenges for econometricians. While merger value is the driving force in firms' merger decisions, it is frequently unobserved, and quantifying the value that mergers create is difficult. Another challenge is that strategic interactions between firms that compete within the merger market and which affect the resulting merger assignments are also difficult to account for. Strategic interactions result from the fact that in forming mergers, firms take into consideration not only the characteristics of their merger partner, but also the characteristics–and merger decisions–of all other firms within the merger market. To overcome these challenges, we estimate a structural matching model in which mergers are the result of a mutual agreement where each merging firm searches for the best match of a merging partner that maximizes profits. The observed sorting of firms into merger pairs, that is based on merger value, enables us to recover the unobserved merger value.[5] The choice of the structural matching model also takes care of strategic interactions between forward looking firms, i.e., merger decisions do not only depend on the characteristics of the merging firms under consideration, but also on the characteristics of other firms and on the consequences on other mergers formed among other firms (see, e.g., Hall (1988), Park (2013), Akkus et al. (2015), and Baccara et al. (2012)). We assume that the mergers between firms in the data represent an equilibrium outcome that is pairwise stable. Using the pairwise stable equilibrium concept, we estimate a one-to-one, one-sided matching game with transferable utility.[6]

[5]For additional background on the relevant matching literature, see Appendix B. For an overview of this literature, see Fox (2009) and Graham (2011).

[6]One-to-one means that each merging firm merges with another one firm. One-sided relates to the fact that every firm is allowed to be a potential acquirer. Transferable utility indicates that each acquiring firm gives money to its target firm, and both merging firms express their utilities in terms of money.

Our empirical model concentrates on estimating the merger value-enhancing impact of multimarket firm arguments using a comprehensive dataset on the semiconductor industry. Our dataset comprises 115 mergers for the years 1991-2004, as well as detailed firm-level production data across different product markets and innovation data across different technology markets. Based on firms' matching and sorting patterns into mergers and the specification derived from our basic theoretical model, our study explores the estimation of structural value functions, which represent the preferences of merging firms over the characteristics of potential merging partners. Our empirical model evaluates to what extent multimarket efficiency gains, multimarket power effects, and multimarket strategic arguments will create value in mergers among multimarket firms. Most interestingly, we find multimarket effects contribute, on average, 20% of the total merger specific value added. We also find that multimarket efficiency gains contribute more value added than do multimarket power effects, and that our estimated merger values are positively correlated with the acquiring firm's post-merger stock market performance, which provides support for our estimation procedure and for mergers being motivated by merger value creation.

The remainder of this paper is organized as follows: Section 2 presents our basic theoretical model. Section 3 describes the industry and data sources, outlines our variable definitions, and presents data descriptives. Section 4 outlines the matching model and describes the estimation procedure. We report our results in Section 5 and conclude in Section 6.

2 Basic Model

In the following, we introduce our basic theoretical model, which purpose is threefold: First, it introduces the arguments through which multimarket firms can add value to mergers. Second, the model allows us to use pre-merger market shares and avoids endogenizing the changes of post-merger equilibrium market shares. Third, it serves as a basis for specifying our empirical framework.

Our model is related to the study by Farrell and Shapiro (1990) which uses infinitesimal changes in firms' pre-merger outputs for their merger analysis. We consider a setting where firms operate in multiple markets $m \in M$. N_m is the set of firms that are active producers within-market m, and we also define $M_i \subseteq M$ as the subset of markets that firm i is present in. Goods within each market are homogeneous. Let the inverse demand in each market be given by $P_m(Q_m)$, where P_m is price in market m, Q_m is market output in market m, and the inverse demand is downward sloping $P'_m(Q_m) < 0$. Let q_{im} denote firm $i's$ output and Q_{-im} denote the output in market m of all firms except firm i. Total cost, $TC_m(q_{im})$, of firm i, in market m, is an increasing function of firm $i's$ output q_{im} ($\frac{\partial TC_m}{\partial q_{im}} > 0$). It should be noted that total costs are market specific. As such, we do not allow for scope economies across markets. Firms choose quantities in order to maximize profits. The single market profit of firm i that operates in market m is:

$$\pi_{im} = P_m(q_{im} + Q_{-im})q_{im} - TC_m(q_{im}).$$

To summarize, we assume an oligopolistic model in which quantity-setting firms are allowed to operate across different product markets that can differ in their demand and cost structures.

Merger Value

Merger value is defined as the difference between post- and pre-merger profits. To be able to formally describe these profits, we first need to define a few relevant sets and terms. Let $K_{ij} = \{m \mid m \in M_i \wedge m \in M_j\}$ be the set of markets that firms i and j have in common and let $K_i = \{m \mid m \in M_i \wedge m \notin M_j\}$ be the set of markets that firm i is active in, but not firm j. Similarly, we define $K_j = \{m \mid m \notin M_i \wedge m \in M_j\}$ the set of markets that only firm j operates in. Moreover, $|.|$ denotes the absolute value for scalars and the cardinality for the sets. For example, $|K_{ij}|$ denotes the number of common markets for firms i and j (i.e., the number of elements of K_{ij}). The pre-merger profit of firm i that operates in markets M_i is given by:

$$\Pi_i = \sum_{m \in M_i} \pi_{im}. \tag{1}$$

We model a merger as a complete combination of the merging firms' assets and of the control of the merging firms. Hence, the post-merger (PM) profit of firms i and j is:[7]

$$\Pi_{ij}^{PM} = \sum_{m \in K_{ij}} \pi_{ijm}^{PM} + \left(\sum_{m \in K_i} \pi_{im}^{PM} + \sum_{m \in K_j} \pi_{jm}^{PM} \right), \tag{2}$$

[7] Note, a superscript PM refers to post-merger variables, while no superscript refers to pre-merger variables.

where post-merger profit is composed of the profits across both common markets (first summand) and non-common markets (summands in brackets).

A merger between firms i and j is profitable, if:

$$V(i,j) = \Pi_{ij}^{PM} - (\Pi_i + \Pi_j) > 0, \tag{3}$$

where $V(i,j)$ is the merger-specific value added.

Substituting equations (1) and (2) into equation (3), we can write the additional value generated by a merger as:

$$V(i,j) = \sum_{m \in K_{ij}} \pi_{ijm}^{PM} + \left(\sum_{m \in K_i} \pi_{im}^{PM} + \sum_{m \in K_j} \pi_{jm}^{PM} \right)$$

$$- \left(\left(\sum_{m \in K_{ij}} \pi_{im} + \sum_{m \in K_i} \pi_{im} \right) + \left(\sum_{m \in K_{ij}} \pi_{jm} + \sum_{m \in K_j} \pi_{jm} \right) \right) > 0.$$

Collecting terms, we get:

$$V(i,j) = \sum_{m \in K_{ij}} \pi_{ijm}^{PM} + \left(\sum_{m \in K_i} \pi_{im}^{PM} + \sum_{m \in K_j} \pi_{jm}^{PM} \right)$$

$$- \left(\sum_{m \in K_{ij}} (\pi_{im} + \pi_{jm}) + \left(\sum_{m \in K_i} \pi_{im} + \sum_{m \in K_j} \pi_{jm} \right) \right) > 0. \tag{4}$$

It is important to recognize, since there is no change in N_m or TC_m for the non-common markets $m \in K_i \cup K_j$, it follows that $\pi_{im}^{PM} = \pi_{im}$ and $\pi_{jm}^{PM} = \pi_{jm}$. Therefore, the merger has no effect on profits in the non-common markets and the non-common markets of equation (4) cancel out. The value added from merging is written as:

$$V(i,j) = \sum_{m \in K_{ij}} \pi_{ijm}^{PM} - \sum_{m \in K_{ij}} (\pi_{im} + \pi_{jm}) > 0. \tag{5}$$

Equation (5) informs us that only the common markets between firms i and j affect the merger-specific value added.

For further developing equation (5), we illustrate the channels through which merging multi-market firms can add value. We consider an infinitesimal effect of a merger on pre-merger market shares, which allows us to ignore challenges related to the formulation of post-merger market shares, such as solving for post-merger market shares in closed form or to endogenize post-merger market shares with regard to market power and efficiency arguments.[8] Since pre-merger market shares can be smaller or larger than post-merger market shares, we will have to consider the two cases of output-reducing and output-increasing mergers. For each case, we explore the conditions that need to apply for equation (5) to hold. The first case, output-reducing merger, is summarized by Proposition 1 as follows:

Proposition 1:

Suppose that multiproduct firms i and j are involved in an output-reducing merger, i.e., $q_{ijm}^{PM} < q_{im}+q_{jm}$, where m refers to the common markets between firms i and j. A merger will add value, if:

$$V(i,j) = \sum_{m \in K_{ij}} \left(|1+\lambda_m| \left(\frac{s_{im}+s_{jm}}{\left|\eta_{Q_{pm}}\right|} \right) - \left(\frac{\Delta TC_m + mr_m}{mr_m} \right) \right) > 0, \tag{6}$$

where λ_m is the conjectural variation, s_{im} and s_{jm} denote firm $i's$ and firm $j's$ pre-merger market shares, $\left|\eta_{Q_{pm}}\right|$ is the absolute price elasticity of demand, mr_m is the change in revenues, and ΔTC_m is the difference between post-merger and pre-merger total costs evaluated at the corresponding pre- and post-merger equilibrium outputs. It is important to recognize, since we consider an output-reducing merger $q_{ijm}^{PM} < q_{im}+q_{jm}$, and given that $\partial TC_m/\partial q_{i,jm} > 0$, it follows that $\Delta TC_m = TC_m(q_i+q_j-\epsilon)-TC_m(q_i)-TC_m(q_j) < 0$ must apply, even in the absence of any merger-specific efficiency gains. The consideration of merger-specific efficiencies would provide further support for equation (5) to be satisfied since it further reduces ΔTC_m which increases π_{ijm}^{PM}.

Proof: See Appendix A1.

In the following, we discuss four arguments that determine merger surplus in the output-reducing merger case as shown in Proposition 1.

First, as shown in equation (6), merging firms characterized by larger pre-merger market shares in their common markets m ($s_{im}+s_{jm}$) add more value to mergers. In economic terms, larger firms impose higher negative competitive externalities on each other which can be internalized

[8] The endogeneity of post-merger market shares is conflicted by the challenge to separately identify market power and efficiency gains.

through merging, further reduces post-merger output and raises post-merger price and profits, also known as the market power effect. Moreover, larger merging firms leave smaller firms outside the merger, causing smaller post-merger output responses which are less harmful to the merging firms' profits.[9] The market power effect becomes more powerful and further increases merger value if firms merge in markets with less elastic demands. With less elastic demands, markups are larger and more profits to gain. The fraction of market shares weighed by the elasticity of demand is also commonly referred to as the Lerner index in the economics literature and used as a proxy for firms' market power. The market power incentive, as shown in equation (6), scales in the number of markets that the merging firms have in common (K_{ij}). This is plausible since a merger between multimarket firms removes, by definition, a competitor from multiple markets, which increases market power across multiple markets and adds incremental value to a merger. Hence, the merger value increases in the market power argument interacted with the number of common markets, which we refer to as *multimarket power effects*. It should be noted that equation (6) expresses the increase in merger value, as originated by the market power effect and the internalization of competitive externalities, using pre-merger market shares, price elasticities of demand and the set of common markets. No post-merger market shares enter the equation and no closed form solution of post-merger market shares or further information on how post-merger market shares were generated are needed.

Second, equation (6) shows that the merger value is increasing in the potential merger-specific cost savings (ΔTC_m) within common markets. The efficiency gains shift the merging firms' reaction functions outwards and increase output and profits. This efficiency effect is also known from previous merger studies that concentrated on single markets. Merger-specific cost savings could be caused by the merging firms' rationalization of production, economies of scale, the unification of knowledge, or other technological complementarities.

Third, equation (6) shows that merger value increases in merger-specific cost savings (ΔTC_m) achieved across common product markets K_{ij}. The efficiency effect of merging multimarket firms scales in the number of jointly operated product markets, which we refer to as *multimarket efficiency gain effects*.

Fourth, equation (6) indicates that merger value is determined by strategic aspects related

[9] Salant et al. (1983) show that the output response of non-merging firms matters for the profitability of a merger, i.e., smaller output responses are more valuable to merging firms.

to firms' degree of competitiveness in product markets. These effects are captured by the multimarket component (K_{ij}), and we refer to this as *multimarket strategic effects*. The combination of both aspects relates to an argument stemming from the multimarket contact literature, i.e., multimarket contact can serve as a strategic device by firms to soften competition (also known as tacit collusion or mutual forbearance). In the context of a merger between multimarket firms, which lowers the degree of post-merger multimarket contact, this argument implies that merging firms give away the possibility to engage in tacit collusion or mutual forbearance practices with the merging partner. As a result, the post-merger market may become more competitive, which will be reflected by a change in the conjectural variation (λ_m), and reduces the incentives of multimarket firms to merge. A further strategic aspect having a potential impact on the post-merger conjectural variation (λ_m) and merger value is explained as follows. A merger leaves fewer firms in the product market, which facilitates collusion in product markets making mergers more valuable. Finally, an increase in the firms' common markets K_{ij} can increase knowledge of each merging firm's operations, reduce merger-specific uncertainty and may increase the value of mergers.

The second case concentrates on an output-reducing merger, which is summarized by Proposition 2.

Proposition 2:

Suppose that multiproduct firms i and j are involved in an output-increasing merger $q_{ijm}^{PM} > q_{im} + q_{jm}$ where m refers to the common markets between firms i and j. A merger will add value, if:

$$V(i,j) = \sum_{m \in K_{ij}} \left((1+\lambda_m) \left(\frac{s_{im} + s_{jm}}{|\eta_{Q_{pm}}|} \right) - \left(\frac{\Delta TC_m - mr_m}{mr_m} \right) \right) > 0, \tag{7}$$

where all the terms are defined as in equation (6).

Proof: See Appendix A2.

Equation 7 is similar to equation 6, and confirms that merger value depends on market power, potential efficiency gain, and multimarket contact arguments. Moreover, the earlier argument is confirmed that market power and the associated potential internalization of competitive externalities matter impact merger value, which can be solely expressed by using pre-merger market shares and elasticities. Hence, equations 6 and 7 require no information on how post-merger market shares are realized. The model provides guidance for our empirical specification and provides us with the following four hypotheses.

Hypothesis 1: *(Multimarket Power Effects) Merger value increases in the merging firms' market power which scales with the number of markets that the merging firms have in common.*

Hypothesis 1 is based on the fact that merging multimarket firms gain from internalizing their negative competitive externalities which scale with the number of markets that the merging firms are active in together.

Hypothesis 2: *(Efficiency Gains) The value of mergers increases in efficiency gains achieved within markets.*

Hypothesis 2 states that merger-specific efficiency gains increase merger value, which is a common argument in standard merger literature.

Hypothesis 3: *(Multimarket Efficiency Gains) The merger value increases in efficiency gains which scale with the number of markets that the merging firms have in common.*

Hypothesis 3 states that mergers generate value via merger-specific efficiency gains which scale with the number of jointly operated markets.

Hypothesis 4: *(Multimarket Strategic Effect) The merger value is determined by strategic effects between firms across markets.*

Hypothesis 4 reflects the fact that the value of mergers is determined via strategic aspects between multimarket firms.

The goal of our empirical model is to test these hypotheses. Next, we present details on the industry, our data sources, variable definitions, and descriptive statistics.

3 Industry and Data Descriptives

The semiconductor industry presents an appropriate setting for empirically exploring the determinants of the merger value for several reasons. First, and importantly for our purposes, it is an industry that has experienced a substantial number of mergers. For the period 1991-2004, we observe 115 mergers in our sample. Second, firms within the semiconductor industry commonly compete across multiple product markets and technological areas. This competition can be within memory markets such as the static random access memory (SRAM) market, the dynamic random access memory (DRAM) market, flash memory (FLASH) market, and the market for other integrated circuits (SEMI). Finally, it is one of the most important high-tech industries, with $33 billion spent on R&D in 2013 (the highest share of revenues of any industry).[10] Much in accordance with the predictions of Moore's law (1965, 1997), the number of transistors that can be fit onto a chip has been roughly doubling every two years.[11] This rapid pace of innovation has also put pressure on the accumulation of intellectual property rights, with semiconductor firms often requiring access to a large stock of patents in order to advance their technology or to legally produce and sell their products (see Hall and Ziedonis (2001)).

The merger data is taken from the Thomson Reuters SDC Platinum database for global mergers, which includes mergers with a deal value of at least $1 million. We study 115 mergers across the time period of 1991-2004. Figure 1 shows the number of mergers for each of these years. The majority of mergers in our sample occurred in the years 1995-2004. We focus on mergers between firms that were active in technology and product markets. The product market activity data is compiled by Gartner Inc. and includes yearly production data for all four markets, SRAM, DRAM, FLASH, and SEMI. In our sample, all 230 firms are active within the product market, with 78 of these being active across multiple product markets. Part 1 (of Table 1) provides further details on the product market presence of our sample, and shows that 24 of the multimarket firms are active within two markets, 44 are active within three markets and 10 are active within all four markets. Part 2 (of Table 1) provides additional details on the product markets presence of firms. Here we see that 60 firms are active within the SRAM market, 54 are active within the DRAM market, 30 are active within the FLASH market, and 228 are active within the SEMI market. Our patent data is retrieved from the United States Patent and Trademark Office and

[10]Source: http://www.semiconductors.org/.

[11]For additional industry details, see Jorgenson (2001), who presents a nice account of the important role that the semiconductor industry has played, and continues to play, within the modern world of information technology. Starting with the invention of the first transistor at Bell Labs in 1947 and the milestone coinvention of the integrated circuit by Jack Kilby (Texas instruments) in 1958 and Robert Noyce (Fairchild Semiconductor) in 1959, these technological advancements laid the foundation for the modern microprocessors with functions that can be programmed by software.

was obtained from the National Bureau of Economic Research (NBER) Patent Database (for details on this database, see Hall, Jaffe, and Trajtenberg (2001)).[12] All firms within our sample are active technology firms with positive patent stocks. Finally, our firm-level financial data is from Compustat at WRDS, DataStream, and Wolfram Research.

Using our data on intellectual property rights and product market activity, we define five merger-specific measures in order to empirically test the hypotheses of Section 2.

To test our first hypothesis, we control for multimarket power effects (MMP) as follows: First, let s_{im} denote firm $i's$ market share in product market $m \in \{SRAM, DRAM, FLASH, SEMI\}$. Given the market presence of firms i and j, we define our multimarket power effect (MMP) measure as the summed interaction of firm $i's$ and firm $j's$ market shares:

$$MMP_{ij} = \sum_{m \in K_{ij}} \frac{s_{im} * s_{jm}}{\left|\eta_{Q_{pm}}\right|},$$

where the sum is taken over all the markets $m \in K_{ij}$ that firms i and j have in common, and $\eta_{Q_{pm}}$ refers to the price elasticity of demand within market m.[13,14]

The second hypothesis states that firms sort into merger pairs on the basis of efficiency gains. To empirically approximate this notion of efficiency, we draw upon Cohen and Levinthal's (1990) idea of absorptive capacity, which states that more similar firms are better able to extract value from one another's activities. As such, firms that are more "similar" in terms of their technologies (or knowledge) may be better able to extract value from one another when merging. We refer to this notion of knowledge relatedness as technological proximity (TP). To capture the technological proximity of firms, we use the uncentered correlation between firm $i's$ and firm $j's$ patent portfolios. We let $\Gamma_i = (\Gamma_{i1}, \Gamma_{i2}, ...)$ be firm $i's$ patent portfolio, where Γ_{ik} denotes the number of patents that firm i holds in patent class k.[15] Our technological proximity measure

[12] A crosswalk was devised to match firms within the production dataset to firms within the patent data. This matching was done using the firm names.

[13] In choosing our $\eta_{Q_{pm}}$ measures we draw upon the literature and use the following values: -3.3 for SRAM, -2.4 for DRAM, -3.5 for FLASH and -2 for SEMI.

[14] It should be noted that this specification of our MMP measure uses the product between the market shares rather than the sum of these market shares (which was suggested by our theoretical model). The reason for this is due to an empirical limitation of the matching approach that we employ within our empirical analysis–in particular, these models are unable to identify a parameter on a firm characteristic that is not interacted with the characteristic of any other firm (see Fox (2010a: 15)).

[15] We used data on the following 10 patent classes: 257 (active solid state drives), 326 (electronic digital logit circuitry), 438 (semi-devices manufacturing process), 505 (super conductor technology apparatus, material, and processes), 360 (dynamic magnetic information storage and retrieval), 365 (SRAM), 369 (DRAM), 711 (FLASH), 712 (computer processors etc.), and 714 (error detection and correction).

is:[16]

$$TP_{ij} = \frac{(\Gamma_i \Gamma_j^{'})}{(\Gamma_i \Gamma_i^{'})^{\frac{1}{2}} (\Gamma_j \Gamma_j^{'})^{\frac{1}{2}}},$$

where $TP_{ij} \in [0,1]$ is increasing in the degree of patent portfolio overlap of firms i and j.[17] In addition to technological proximity, we also want to control for the scale of firms' patent stocks. The reason for this is that larger patent stocks may provide more opportunities for meaningfully recombining firms' patents in order to derive additional merger value. Our patent stock measure is simply defined as the product of the two firms' individual log patent stocks:

$$PS_{ij} = log\,(PatStock_i) * log\,(PatStock_j)\,,$$

where $PatStock_i$ denotes the discounted patent stock of firm i.[18]

The third hypothesis refers to the multimarket efficiency gains (MME) caused by the interaction of multimarket competition and the aforementioned efficiency gain benefits. As such, we define our MME measure as the interaction between the number of common markets and our technological proximity measure (TP):

$$MME_{ij} = \sum_{m \in K_{ij}} \mathbb{1}[m \in K_{ij}] * TP_{ij},$$

where $\mathbb{1}[.]$ is an indicator function taking the value of 1 if the market m is common to both firms and 0 otherwise.

The fourth hypothesis states that the merger-specific value will also depend on the merging firms' multimarket strategic effect. As such, we need another measure that will simply capture the degree of multimarket contact (MMS) between the merging firms i and j. This is defined as:

$$MMS_{ij} = \sum_{m \in K_{ij}} \mathbb{1}[m \in K_{ij}],$$

[16] To ensure that TP_{ij} is defined for all possible match pairs within our dataset, we consider only firms with non-zero patent portfolios, i.e., we focus on technology firms. Also, to avoid endogeneity concerns related to our technology and market share measures, we use lagged values of these measures (i.e., for the market share at year t, we use that in period $t-1$).

[17] For uses of this proximity measure within the industrial organization literature, see, for example, the original application in Jaffe (1969), and, more recently, Bloom, Schankerman, and Van Reenen (2010) and Siebert and Roy (2015).

[18] The patent stock measures have been discounted using a discount factor of 0.85 (see Hall, Jaffe, and Trajtenberg (2001)).

which is a commonly applied measure of multimarket contact (see also Evans and Kessides (1994) and Gimeno and Woo (1996)).

Next, Table 2 provides summary statistics for our variables across two samples. The first sample consists of our 109 realized mergers. The second sample considers hypothesized mergers of randomly merged firms.

Comparing Columns (1) and (2) in Table 2, we note that merged firms tend to match on the size of their (log) patent stocks (means: $24.50 > 23.42$), their technological proximity ($0.57 > 0.49$), multimarket efficiency gains ($0.81 > 0.57$), multimarket power effects ($0.003 > 0.001$), and multimarket strategic effects ($1.30 > 1.11$).[19] These findings are well aligned with our hypotheses.

4 Empirical Matching Model

This section presents the matching model, introduces the match value function, and outlines how we estimate the parameters using a maximum score estimation method. We also discuss the consistency of the estimates and the applied numerical optimization method.[20]

4.1 Matching Model

We consider a finite set of firms F and an observable merger assignment $\mu : F \mapsto F$ that assigns firms into merger pairs. A merged pair (i, j) receives merger value of $V(i, j)$. If the observed matches are based on a pairwise stable equilibrium concept, then it must be the case that firm i seeks to maximize $V(i, j)$ across all potential partner firms $j \in F \backslash \{i\}$ and, likewise, that firm j seeks to maximize $V(i, j)$ across its possible partner firms $i \in F \backslash \{j\}$.[21] Building on this concept, it follows that for any two observed merger pairs $\mu_{ij} = (i, j)$ and $\mu_{kl} = (k, l)$, there cannot exist a transfer t from μ_{ij} to μ_{kl} such that the bilateral exchange of partners specified by μ improves the outcomes of the firm-pairs. Therefore, for any transfer t the following conditions apply:

$$V(i, j) \geq V(i, k) - t \quad \wedge \quad V(k, l) \geq V(j, l) + t, \tag{8}$$

[19]Note that the relevant sample means are reported within the parentheses.

[20]See Appendix B for a brief review of the closely related matching literature.

[21]We focus on the notion of a merger as a bilateral agreement between two firms, as such, $V(i, j) = V(j, i)$ applies.

and

$$V(i,j) \geq V(i,l) - t \quad \wedge \quad V(k,l) \geq V(k,j) + t. \tag{9}$$

Adding the inequalities in equation (8),

$$V(i,j) + V(k,l) \geq V(i,k) + V(j,l), \tag{10}$$

must hold. Adding the inequalities in equation (9),

$$V(i,j) + V(k,l) \geq V(i,l) + V(j,k), \tag{11}$$

must apply. An assignment that satisfies both inequalities as shown in equations (10) and (11) is pairwise stable.[22]

4.2 Match Value Function Specification

Firms are matched according to the following match value function $V(i,j)$. In choosing a functional form, we follow our model and previous work on mergers and specify a linear form for our match value function:[23]

$$V(i,j) = \theta_1 PS_{ij} + \theta_2 TP_{ij} + \theta_3 MMS_{ij} + \theta_4 MMP_{ij} + \theta_5 MME_{ij}. \tag{12}$$

This functional form is specified in accordance with the set of hypotheses derived in Section 2. Our main focus relates to the effects due to firms' technological proximity (TP), multimarket efficiency gains (MME), multimarket power effects (MMP), and the merging firms' multimarket strategic effects (MMS). We also control for firms' technological stocks using the interaction of the merging firms' patent stocks (PS).

4.3 Maximum Score Estimation

Given our parametric form for $V(i,j)$ in equation (12), we take the inequalities implied by equations (10) and (11) and estimate the parameters using a semiparametric maximum score

[22] Pairwise stability was first used by Gale and Shapley (1962) as a stability notion within matching. Our notion of stability is similar to that of Baccara et al. (2012). See Appendix B for additional details on the relevant matching literature.

[23] See, for example, Baccara et al. (2012) and Akkus et al. (2015).

estimation technique.[24] Our objective function is given by:

$$Q(\theta) = \sum_{t \in T} \left(\sum_{\mu_{ij} \in M_t} \sum_{\mu_{kl} \in M_t} \mathbb{1}\left[V(i,j) + V(k,l) \geq V(i,k) + V(j,l)\right] + \mathbb{1}\left[V(i,j) + V(k,l) \geq V(i,l) + V(j,k)\right] \right), \tag{13}$$

where $\theta' = \{\theta_1, \theta_2, \theta_3, \theta_4, \theta_5\}$ denotes the parameter vector of interest, and the inner two sums are taken over all possible match pair combinations within the match market (set) M_t.[25] The index t of M_t refers to the year $t \in T = \{1991, 1992, ..., 2004\}$. The outer sum is then taken over all of these separate matching markets (or years). The estimates $\widehat{\theta}$ maximize the number of times that the inequalities in equation (13) apply; that is, we choose $\widehat{\theta}$ to maximize the score $Q(\widehat{\theta})$ in equation (13).

This methodology was proposed by Fox (2010a and 2010b), who provides consistency results for two cases: (i) when the matching market is defined as one large market and (ii) when there are many individual markets. The choice of model framework affects whether the asymptotics of the consistency results relate to the number of firms (within the one market) or across the number of markets (within the many small markets case). Within our setup, we choose to treat each year as a separate merger market, and as such, the consistency in our cases depends on the number of individual markets. We choose this approach for two reasons. First, comparing possible merger swaps across years does not seem desirable within a market where technological progress is drastic such that comparison across time would be problematic. Second, by considering within-market (year) swaps, our setup effectively controls for time fixed effects. If we instead pooled all mergers into one market we would not be able to control for time effects, something that could bias our estimates.

In terms of identification, this estimation approach allows us to identify the relative impact of different covariates on the merger value $V(i,j)$ and the relative scale of these values across different mergers. Another benefit of this approach is that any omitted variable that affects firms' merger value from merging with a particular firm equally is differenced out of the previous inequalities in equations (10) and (11) and, therefore, does not bias the parameter estimates from equation (13). This is a particularly appealing feature of this estimator since it essentially means

[24] This estimation procedure was introduced by Manski (1975, 1985).

[25] Within our application the match market set M_t includes all theoretically feasible inequalities due to pairwise swaps, however, since some years contain firms that are part of multiple mergers we do not include pairwise swaps across matches that contain a common firm since these are not theoretically feasible.

that the omission of firm-specific fixed effects does not bias the estimates.[26]

Lastly, it should be noted that our objective function in equation (13) is not smooth. Consequently, numerical techniques are required to find parameter values that maximize the objective function. We follow the recommendation by Fox (2010a) and employ a method known as differential evolution to find our parameter estimates.[27]

5 Results

Table 3 presents our estimation results for two different specifications of the merger value function. Adopting Fox's methodology, we fix one of the estimates to unity (± 1). This is done for the patent stock parameter, and it implies that the scale of all other point estimates are estimated relative to the patent stock.[28] We report 90% confidence regions below each of the point estimates. The confidence regions are obtained by bootstrapping 100 subsamples, where the subsample size consists of 12 (out of 14) merger markets (years). The subsampling is done without replacement.[29]

The first column of Table 3 controls for the variables PS, TP, and MMS. This specification is able to predict 64 percent of the 1,188 inequalities. It shows us that technological complementarities, knowledge relatedness, and the degree of multimarket contact all contribute positively, and significantly toward merger value creation. In the second column, we add our additional multimarket controls for the multimarket efficiency gains (MME) and multimarket power effects (MMP). This is our main specification since it addresses all the hypotheses from Section 2 and because it is able to explain the largest share of inequalities (66 percent of the 1,188 inequalities). In comparing columns (1) and (2), we note that TP is significant across both, and that MME is also significant within our main specification. This suggests that while efficiency arguments matter, their importance depends on the multimarket interdependence of the merging firms. We also note that our individual measure for multimarket strategic effects (MMS) is positive and significant within the first specification, and while it remains positive within the main specificaiton, it is no longer significant when we add the additional multimarket controls MME and

[26]For more of a discussion on the identification and bias correction, see Levine (2009).

[27]This method is also used by Akkus et al. (2015), Fox and Bajari (2013), and Levine (2009). For details on the estimation procedure and implementation, see Fox and Santiago (2014).

[28]Note that for each specification in Table 2, we ran the estimation for $\theta_1 = +1$ and $\theta_1 = -1$. We report those results that returned the highest score (largest percentage of inequalities satisfied).

[29]For more details on the subsampling, see Fox and Santiago (2014).

MMP. We now relate these results to our hypotheses of Section 2 to derive further economic content.

The first hypothesis holds that firms will seek to merge due to multimarket power effects that can help create value from increased post-merger market power. Our main specification in column (2) controls for these effects using MMP, which we find to be a strong, and significant, positive influencer of merger matching behavior within the semiconductor industry.

Our second hypothesis describes that firms will match so to benefit from merger-specific cost savings and efficiencies. Such cost efficiencies may derive from rationalization of production, economies of scale, and the degree of technological relatedness between the two firms, and this is what we seek to capture with our TP and PS measures–both of which are found to have positive, and significant, point estimates across both specificaitons. As such, we conjecture that these efficiency gains may importantly depend upon the multimarket interaction of merging firms. This is what we seek to address with our third hypothesis.

The third hypothesis states that merger value derives from multimarket efficiency gain arguments, i.e., within a multimarket setting, these effects will scale with the degree of multimarket competition between the merging firms. Our main specification in column (2) (of Table 3) provides support for this hypothesis by showing a positive and statistically significant multimarket efficiency gain (MME) effect. Thus, we find that both multimarket efficiency gains and multimarket power effects importantly contribute towards the merger-specific value.

The fourth hypothesis implies that merger value will depend on firms' level of multimarket strategic effects. However, we argued that the anticipated effect on the resulting merger value may be ambiguous due to the fact that it may capture negative effects (due to the reduction of multimarket contact post-merger) and positive effects (due to a reduction of competitors across multiple markets; better informational certainty from merging with a multimarket competitor). Looking at our two specifications, we see that we obtain a positive point estimate for our MMS variable in both column (1) and column (2) of Table 3, however, the effect is not statistically significant when we include our other multimarket controls (MME and MMP) within the main specification of column (2). This finding suggests that the positive and negative merger effects that are proxied by the MMS variable tend to cancel out.

The estimation results in Table 3 are further used to obtain estimates of the unobserved merger values. These are showcased in Figure 2. Note that since only the relative difference of these values matters, we have scaled them by the median merger value. As such, the median firm has a value of 1, while half of the merger values are located to the left (and right) of the median merger. Figure 2 shows that the values range from 0.03 to 3.0, which indicates a substantial amount of heterogeneity between the merger values. The long right tail within this distribution further indicates that there are some mergers that result in exceptionally high merger values. This finding is interesting because it suggests that firms face scarcity in the number of good matches, something that may induce them to compete for attractive partner firms. As we have previously argued, these strategic interactions have implications for the resulting merger assignment and, therefore, need to be controlled for within the empirical approach–something we have done by virtue of using a matching model.

Lastly, we want to investigate the relative contribution of each of our controls towards the total additional merger specific value added. This is done by dividing the mean contribution of each control by the mean merger value, $V_{i,j}$.[30] This analysis informs us that multimarket effects (MME, MMP and MMS) contribute close to 20% of the total additional merger value, while the remaining value is contributed by merger-specific cost savings and efficiencies (given by the PS and TP controls). These findings suggest that within multimarket settings firms merger decisions will be influenced by the firms multimarket characteristics. Of particular interest is the finding that the multimarket efficiency effects (MME) dominate both multimarket power (MMP) and multimarket strategic arguments (MMS).

5.1 Merger Value and Merger Performance

We are interested in exploring whether our fitted merger values hold any information regarding the eventual performance of the post-merger firm. We view this as a specification test in that a positive correlation between our estimated merger value and the post-merger performance of the acquiring firm provides support for our value function being appropriately specified.

To explore this relationship, we take our fitted merger values and use them to predict merger performance. We define merger performance as the difference between the acquiring firm's stock market price relative to the performance of the general market, which we proxy using the perfor-

[30] For example, to assess the relative contribution of PS we compute $\left(\hat{\theta}_1 * \overline{PS}\right) / \overline{V(i,j)} = (1 * 24.5)/60.3 = 0.4$, where $\overline{PS}$ is the average PS across all realized mergers, and $\overline{V(i,j)}$ is similarly defined.

mance of the S&P 500. In particular, we do this by comparing the cumulative fractional changes (CFC) of the firms in relation to that of the cumulative fractional change of the S&P 500 as a whole. We concentrate on two periods: (i) one month before the merger announcement until one month after the merger effective date ($1b1a$) and (ii) one month before the merger announcement until six months after the merger effective date ($1b6a$). As an example, Figure 3 presents a visualization of the stock market performance of Fujitsu Ltd., who merged with Hitachi Ltd in April of 1999. Fujitsu's stock market price is depicted by the blue (top) solid line, while the performance of the S&P 500 is illustrated by the orange (lower) solid line. These lines show each party's cumulative fractional change over this two-month period. The relative performance of Sony to the S&P 500 index is given by the difference between these cumulative fractional changes at the end of the time period, i.e., the gap between the two lines at the far right of Figure 3.

These measures of acquirer performance are regressed on the fitted merger values that we obtained using specification (2) in Table 2 and on controls for the merging firm's market value or their Tobin's-Q values.[31] These regression results are reported within Table 4. Across all the regressions using the using the $1b6a$ measure for the cumulative fractional change, we note that our merger value measure ($V(i,j)$) appears to be significant at the 5% level (Specifications 2, 3, and 4). The positive sign of the measure implies that a higher merger value is positively correlated with our estimates of merger performance.

To summarize, while our sample size is modest, we find a significant positive correlation between our estimated merger value measure and the post-merger performance of the acquiring firm's stock price relative to the performance of the S&P 500 for the same time period. This finding lends support to our model being appropriately specified, in that conditional upon merger, firms seem to be sorting into merger pairs so as to maximize post-merger value.[32]

6 Conclusion

The multimarket merger aspect has received little attention in the merger literature. The goal of this paper has been to identify and quantify through which channels mergers among firms

[31] These regressions are performed using standard ordinary least squares (OLS) with robust standard errors. The fitted merger values used are those reported within Figure 2.

[32] It should be noted that this does not imply that mergers are, in general, value generating; rather, it means that conditional upon deciding to enter the merger market, firms will sort into merger pairs so to maximize their resulting merger value.

competing in multiple markets can create additional value. Our theoretical model provided us with several arguments on how mergers among multimarket firms can increase value. We derived four hypotheses that we set out to test using an empirical matching framework. We use a matching model to characterize the merger market because it allows us to account for strategic interactions between firms and the notion that mergers, within our setting, are best thought of as being the outcome of mutual agreements.

The estimation results of firms' structural value functions show that firms match into merger pairs based on cost saving and efficiency considerations, as well as on multimarket driven effects. In particular, we find that the multimarket effects (on average) contribute close to 20% toward the merger value added—a considerable amount. Out of the multimarket effects, we find that multimarket efficiency gains dominate both multimarket power, and multimarket strategic, arguments so to contribute the most value. Finally, our structural matching model provides estimates of the unobserved merger values. These were found to be positively correlated with the acquiring firm's post-merger stock market performance. While this does not imply that mergers are in general value creating, it does suggest that firms within the merger market tend to sort into merger pairs in order to maximize post-merger performance.

Further work in this direction seems warranted as it may provide more insight into the determinants of merger value creation within other industries and settings. Work focusing on further untangling the possible effects of the multimarket strategic effect would also be interesting. This paper has shown that drawing upon economically motivated variables and recent developments of matching models for structural empirical work may be well suited for future research.

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Figures

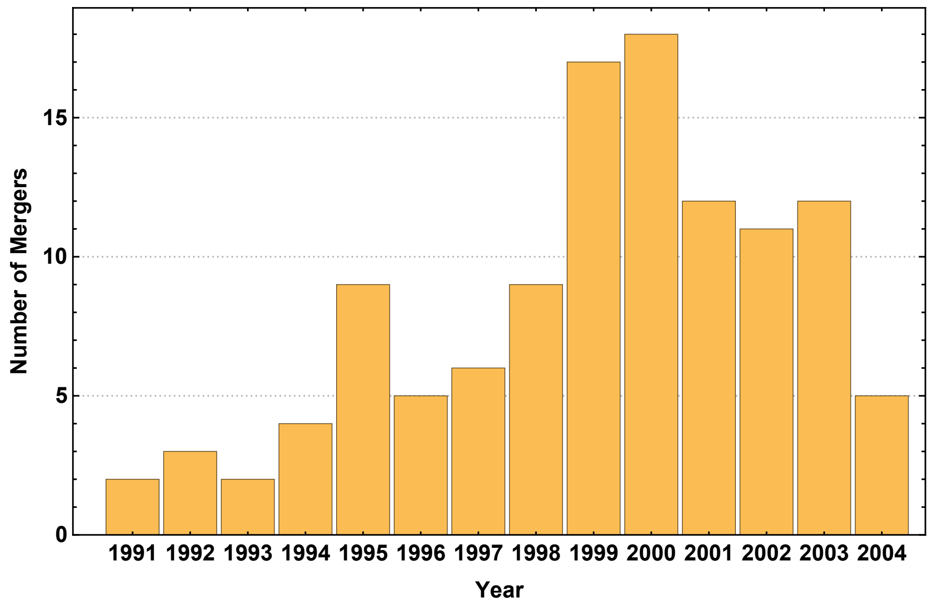

Figure 1: Merger Distribution Over Time (1990-2004).

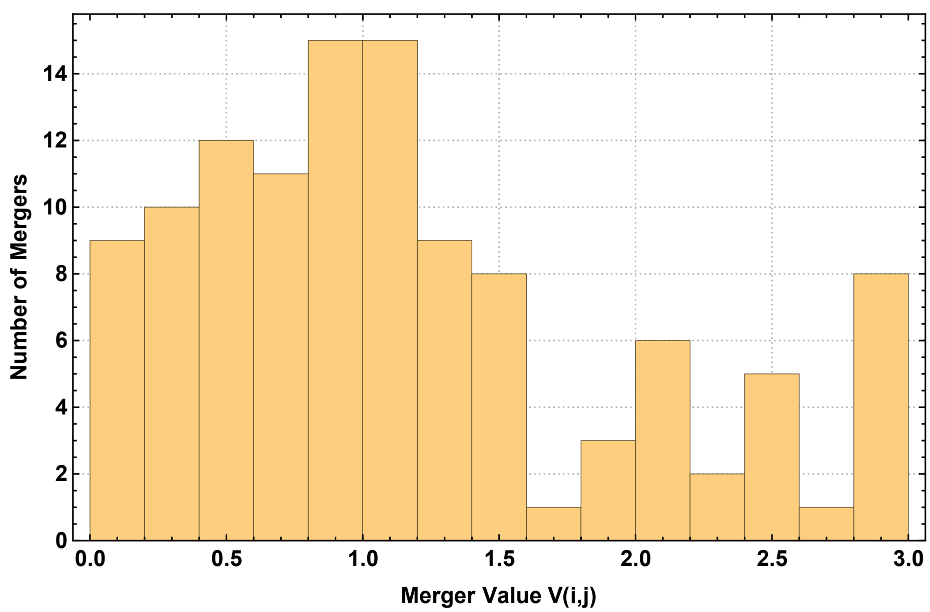

Figure 2: Realized Merger Value Distribution.

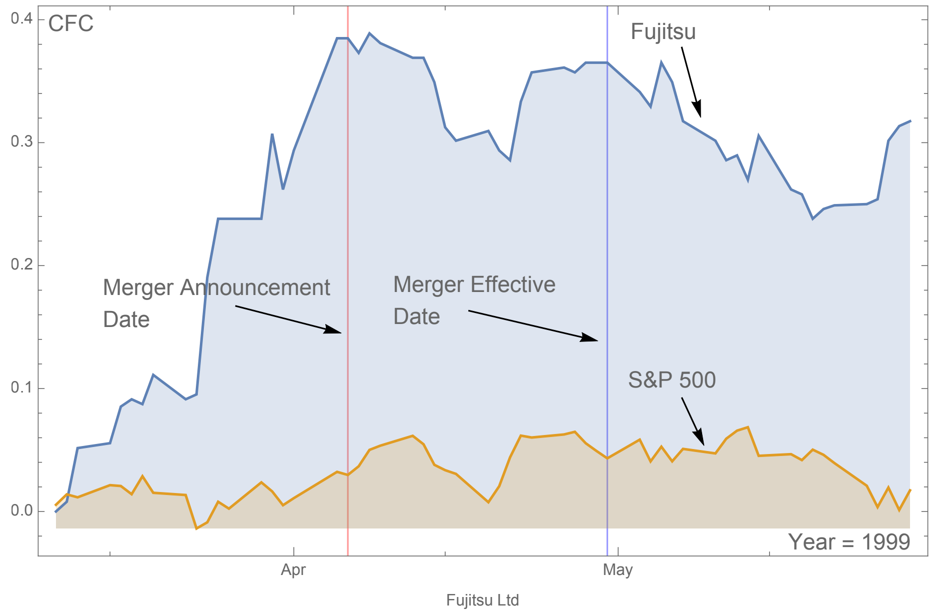

Figure 3: Measure of Merger Performance. Shows the cumulative fractional change (CFC) of Fujitsu's stock market price (blue solid line) for the period of one month before the merger announcement and one month after the merger was confirmed (effective date). The merger announcement and confirmation date are here the same and are visually represented by the vertical line that divides the figure into two parts. Merger success is taken to be the amount by which the firm outperforms the S&P 500 (orange solid line) for the full extent of this period of time.

Tables

Part 1: Product Market Presence				
Numb. of Markets:	1	2	3	4
Numb. of Firms:	152	24	44	10

Part 2: Product Market				
Market:	SRAM	DRAM	FLASH	SEMI
Numb. of Firms:	60	54	30	228

Table 1: Descriptives of Sample. Part 1 describes the product market presence of the 230 firm observations (115 mergers) within our sample. Part 2 describes the firms' market presence by each specific product market.

	(1) Realized Mergers		(2) Random Mergers	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
$PS^{\dagger}$	24.502	24.160	23.358	21.190
TP	0.570	0.319	0.485	0.286
MME	0.813	0.796	0.575	0.520
MMP	0.003	0.011	0.001	0.004
MMS	1.300	0.713	1.114	0.468
N	115		2,333	

† – denotes variables defined with logs.

Table 2: Summary Statistics of Variables. These are provided for two cases: (i) realized mergers and (ii) random matching within the merger population.

Variables	(1) V(i,j)	(2) V(i,j)
PS	+1	+1
	[1 , 1]	[1 , 1]
TP	13.7*	42.8*
	[9.6 , 25.0]	[43.3 , 78.9]
MME	-	12.6*
	[- , -]	[2.9 , 22.5]
MMP	-	88.3***
	[- , -]	[64.1 , 204.4]
MMS	8.8***	0.7
	[8.0 , 14.4]	[-1.3 , 2.1]
Numb. Mergers:	115	115
Numb. Ineq.:	1,188	1,188
% Ineq. Satisfied:	64%	66%

Table 3: Maximum Score Estimates. We report the 90% and 99% confidence regions within the brackets below the point estimates. * – indicates significance at the 10% level, i.e., the 90% confidence region does not include 0. *** – indicates significance at the 1% level, i.e., the 99% confidence region does not include 0. The confidence regions were computed using bootstrapping: subsamples = 100, subsample size = 12 (out of 14) nests. Subsampling is done without replacement.

Variables	(1) 1b1a	(2) 1b6a	(3) 1b6a	(4) 1b6a
V(i,j)	0.10	0.16**	0.18**	0.29**
	(0.06)	(0.06)	(0.08)	(0.11)
$MktVal_i$			-2.23e-07	
			(1.23e-06)	
$MktVal_j$			1.44e-06	
			(2.38e-06)	
TQ_i				-0.001
				(0.02)
t_tobins_q				-0.07
				(0.05)
Observations	60	62	49	49
R-squared	0.05	0.09	0.12	0.14

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Merger Success Regressions (ordinary least squares with robust standard errors). Variable definitions: 1b1a = cumulative fractional change (measured 1 one month before the merger announcement date until one month (or six months) after the merger is confirmed) difference between the firm stock price performance and the general market (S&P 500) performance; $MktVal_i$ = Market value for firm i at time of merger; TQ_i = firm $i's$ Tobin's-Q value at time of merger.

Appendix

Appendix A: Proofs and Computational Details

A1. Proof for Proposition 1.

In the following, we concentrate on one market and drop the market subscript m. Now, let the post-merger output be denoted by $q_{ij}^{PM} = (q_i + q_j - \epsilon) < q_i + q_j$, where $\epsilon = dq_{ij}^{PM} > 0$, and let the post-merger price be $P(\widetilde{Q})$ where $\widetilde{Q} = Q_{-ij} + q_{ij} + dQ$, with $dQ = \delta = \frac{dQ}{dq_{ij}^{PM}} dq_{ij}^{PM}$. For a merger to add value, the following equation has to apply:

$$\pi_{ij}^{PM} > \pi_i + \pi_j \iff P(\widetilde{Q})q_{ij}^{PM} - P(Q)(q_i + q_j) > TC(q_{ij}^{PM}) - (TC(q_i) + TC(q_j)) = \Delta TC.$$

Remember that $\Delta TC < 0$, and since $q_{ij}^{PM} < q_i + q_j$, this will also hold if there are post-merger synergies. Next, we can simplify the above expression to:

$$P(Q-\delta)(q_i + q_j - \epsilon) - P(Q)(q_i + q_j) > \Delta TC \iff (P(Q-\delta) - P(Q))(q_i + q_j) - P(Q-\delta)\epsilon > \Delta TC.$$

This can further be rewritten as:[33]

$$dP * (q_i + q_j) - P(Q-\delta)\epsilon = dP * (q_i + q_j) - P(Q-\delta)\left|dq_{ij}^{PM}\right| > \Delta TC.$$

Next, we recognize that $dQ < 0$ and that $\frac{dQ}{dQ} = 1$, so we can rewrite the equation above as:[34]

$$dQ\frac{dP}{dQ}(q_i + q_j) - P(Q-\delta)\left|dq_{ij}^{PM}\right| > \Delta TC,$$

multiplying both sides by $\frac{Q}{P(Q-\delta)Q}$:

$$dQ\left(\frac{dP}{dQ}\frac{Q}{P}\right)\frac{(q_i + q_j)}{Q} - \left|dq_{ij}^{PM}\right| > \frac{\Delta TC}{P},$$

where $(\frac{dP}{dQ}\frac{Q}{P})$ is the absolute inverse price elasticity of demand $\frac{1}{|\eta_{Q_P}|}$. The above equation can further be rewritten as:[35]

[33] Note that we take ϵ to represent an infinitesimal small change in the production of the merged firm and as such, $-\epsilon = -\left|dq_{ij}^{PM}\right|$ applies. We write this in terms of the absolute value to make it clearer what the sign of the terms are.
Also, since δ is taken to represent an infinitesimal small change in the market output, we take that $dP \approx \Delta P = P(Q-\delta) - P(Q) > 0$. Note that the equality holds strictly in the limit as $\delta \to 0$.

[34] Note, if all firms adjust to reestablish a Cournot equilibrium, then $\epsilon < \delta < 0$ will hold here. This follows from the Lemma provided in Farrell and Shapiro (1990: 111). However, if the outsiders are assumed to not respond to the change, then $\epsilon = \delta$.

[35] Note the negative sign within the parentheses results from: $\frac{dP}{dQ} = P'(Q) = \lim_{\epsilon\to 0} \frac{P(Q-\epsilon)-P(Q)}{(Q-\epsilon)-Q} = \lim_{\epsilon\to 0} \frac{P(Q-\epsilon)-P(Q)}{-\epsilon} =$

$$dQ\left(-\frac{(s_i+s_j)}{|\eta_{Q_p}|}\right)-\left|dq_{ij}^{PM}\right|=|dQ|\left(\frac{(s_i+s_j)}{|\eta_{Q_p}|}\right)-\left|dq_{ij}^{PM}\right|>\frac{\Delta TC}{P}.$$

Dividing by $\left|dq_{ij}^{PM}\right|$:

$$\frac{|dQ|}{\left|dq_{ij}^{PM}\right|}\left(\frac{(s_i+s_j)}{|\eta_{Q_p}|}\right)-1>\frac{\Delta TC}{P\left|dq_{ij}^{PM}\right|}.$$

Noting that $\frac{|dQ|}{\left|dq_{ij}^{PM}\right|}=\left|\frac{dQ}{dq_{ij}^{PM}}\right|=\left|\frac{dq_{ij}^{PM}}{dq_{ij}^{PM}}+\frac{dQ_{-ij}}{dq_{ij}^{PM}}\right|=|1+\lambda_{ij}|$, where $\lambda_{ij}\leq 0$, and that $mr=P*\left|dq_{ij}^{PM}\right|$ we have:

$$|1+\lambda_{ij}|\left(\frac{(s_i+s_j)}{|\eta_{Q_p}|}\right)>\frac{\Delta TC+mr}{mr}.$$

Scaling this result over the m common markets of firms i and j we get the result of Proposition 1. **QED.**

A2. Proof of Proposition 2:

While this proof is similar to that in Proposition 1, there are some important departures we illustrate here.

For notational simplicity, we again consider one market and omit the subscript m. Now, suppose that post-merger output is given by $q_{ij}^{PM}=(q_i+q_j+\epsilon)>q_i+q_j$, where $\epsilon=dq_{ij}^{PM}>0$ and that the post-merger price is $P(\widetilde{Q})$, where $\widetilde{Q}=Q_{-ij}+q_{ij}+dQ$, with $dQ=\delta=\frac{dQ}{dq_{ij}^{PM}}dq_{ij}^{PM}$. A merger is profitable if:

$$\pi_{ij}^{PM}>\pi_i+\pi_j\iff P(\widetilde{Q})q_{ij}^{PM}-P(Q)(q_i+q_j)>TC(q_{ij}^{PM})-(TC(q_i)+TC(q_j))=\Delta TC.$$

Note that $\Delta TC>0$ since $q_{ij}^{PM}>q_i+q_j$, and we have assumed no synergies.[36] Next, we can simplify this expression to:

[37]

$$P(Q+\delta)(q_i+q_j+\epsilon)-P(Q)(q_i+q_j)>\beta\iff(P(Q+\delta)-P(Q))\,(q_i+q_j)+P(Q+\delta)\epsilon>\Delta TC,$$

$$\iff -dP*(q_i+q_j)+P(Q+\delta)\epsilon=-dP*(q_i+q_j)+P(Q+\delta)dq_{ij}^{PM}>\Delta TC,$$

multiplying both sides by $\frac{1}{dQ*Q}$ we get:

$(-1)*\lim_{\epsilon\to 0}\underbrace{\left(\frac{P(Q-\epsilon)-P(Q)}{\epsilon}\right)}_{positive}$. Hence, even though we are dealing with a decreasing change in output, the sign of the elasticity of demand is as previously expected; however, we note that $dQ<0$ here.

[36] Allowing for synergies may reverse this sign. That is, the presence of additional synergies may yield $\Delta TC<0$ even when $q_{ij}^{PM}>q_i+q_j$.

[37] As previously noted, if all firms adjust to reestablish a Cournot equilibrium, then $\epsilon>\delta>0$ due to the Lemma provided in Farrell and Shapiro (1990: 111).

$$-\frac{dP}{dQ}\frac{(q_i+q_j)}{Q}+\frac{P(Q+\delta)}{Q}\frac{dq_{ij}^{PM}}{dQ}>\frac{\Delta TC}{dQ*Q},$$

multiplying by $\frac{Q}{P(Q+\delta)}$:

$$-\left(\frac{dP}{dQ}\frac{Q}{P}\right)\frac{(q_i+q_j)}{Q}+\frac{dq_{ij}^{PM}}{dQ}>\frac{\Delta TC}{P*dQ},$$

recognizing that $\frac{q_i}{Q}=s_i$ and that we have the price elasticity of demand:[38]

$$\left(\frac{s_i+s_j}{|\eta_{Q_p}|}\right)+\frac{dq_{ij}^{PM}}{dQ}>\frac{\Delta TC}{P*dQ},$$

multiplying through by $P*dQ$:

$$\left(\frac{s_i+s_j}{|\eta_{Q_p}|}\right)(dQ*P)+dq_{ij}^{PM}*P>\Delta TC,$$

and dividing through by $\frac{1}{dq_{ij}^{PM}}$:

$$\left(\frac{s_i+s_j}{|\eta_{Q_p}|}\right)\left(\frac{dQ}{dq_{ij}^{PM}}*P\right)+P>\frac{\Delta TC}{dq_{ij}^{PM}}.$$

Note that $\frac{dQ}{dq_{ij}^{PM}}=1+\frac{dQ_{-i}}{dq_{ij}^{PM}}=1+\lambda$ where $\lambda\leq 0$. Hence,

$$P*\left(1+(1+\lambda)\frac{s_i+s_j}{|\eta_{Q_p}|}\right)>\frac{\Delta TC}{dq_{ij}^{PM}},$$

and noting that $mr=P*dq_{ij}^{PM}$, we have:

$$(1+\lambda)\frac{s_i+s_j}{|\eta_{Q_p}|}>\left(\frac{\Delta TC}{P*dq_{ij}^{PM}}-1\right)=\left(\frac{\Delta TC-mr}{mr}\right).$$

Scaling this result over the m common markets of firms i and j, we get the result of Proposition 2. **QED.**

Appendix B: Relevant Literature on Matching

The study of mergers is, at its core, a study of assignments and matching. General matching games were first studied by Gale and Shapley (1962), who introduced the concept of pairwise stability within a matching market and proved existence of pairwise stable equilibria for markets characterized by a

[38] Note: $\left(\frac{dP}{dQ}\frac{Q}{P}\right)=1/\left(\frac{dQ}{dP}\frac{P}{q}\right)=\frac{1}{\eta_{Qp}}=-\frac{1}{|\eta_{Qp}|}$

bipartite structure (e.g., where men can match only with women within a marriage) and where players have non-transferable utilities.[39]

Shapley and Shubik (1972) later showed that many of the results of Gale and Shapley's marriage market can be extended to a setting where people instead have transferable utilities (e.g., an environment where buyers are matched to sellers of a particular good). Within a transferable utility (two-sided and one-to-one matching) setting, the pairwise stable assignment coincides with the solution of a linear programming problem where the objective function is the sum of all individual match payoffs. As such, the existence of pairwise stable assignments within this type of game is assured by the existence of a solution to the linear programming problem: a result that was proved by Dantzig (1963).[40]

While Gale and Shapley (1962) and Shapley and Shubik (1972) focus on deriving existence results for the case of general preferences, Becker (1973) sets out to use a matching model with far more structured preferences in order to tease out testable predictions regarding the sorting behavior within the marriage market. In so doing, Becker also provides a bridge between the previously theoretical work on matching and its use as a foundation for empirical work. While Becker's focus was on the marriage market, his framework is general enough to be applied across any setting where the matching market is characterized by heterogeneous players, two-sided matching and where there may be strategic interactions between the players.

The use of a matching model to describe merger activity originates with Hall (1988), who also described the limitations of utilizing a standard discrete choice model when characterizing mergers.[41] In particular, Hall's (1988) matching model is an adaptation of Becker's (1973) marriage market model to the problem of mergers. It depicts the market for corporate assets as two sided (acquirers and targets) and assumes the presence of transfers (which the acquirer pays to the target). While transfer prices are endogenous, a benefit of the matching framework is that these prices are not needed for the analysis. This is because the transfers can be substituted out of the final inequalities necessary for empirical estimation. Another

[39] Gale and Shapley (1962) provided a deferred acceptance algorithm for the marriage market, which yields a pairwise stable assignment. This assignment is either man or woman optimal, depending on which side is assumed to be the proposing side of the game. In addition to the marriage problem, the authors also studied the college admission problem (two-sided, one-to-many matching) and the roommate problem (one-sided matching).

[40] For more details on the literature regarding assignment problems of this type see Chapter 8 in Roth and Sotomayor (1990) and Roth and Sotomayor (1992).

[41] It is worth reiterating some of the limitations of traditional discrete models that have been noted within the literature. As pointed out by Hall (1988), traditional discrete choice models are unable to accommodate the key features of merger markets, such that firms are unique, mergers are two sided, and that competing firms are subject to strategic interactions. These features are important for the purposes of applied work because they present econometric challenges that need to be considered and addressed. They also suggest that mergers are better thought of within a matching framework than as a one-sided discrete choice problem. In fact, Hall (1988) shows that it is not possible to derive the standard Logit models rigorously when the market consists of a finite number of differentiated firms. When estimating the demand for any given firm using a discrete choice model, the identification of the demand curve is achieved by assuming an infinite supply of the particular good at the market price in question. This is clearly an unacceptable assumption when considering mergers and acquisitions. Another (often unstated) assumption in discrete choice models is that there can be no strategic interactions between firms. Furthermore, these models also fail to accommodate the two-sided nature of matches.

benefit of the matching approach is that it fully accounts for the features of the merger market. That is, it is able to accommodate strategic interactions between competing firms because firms are unique (there is scarcity in terms of good matches) and merger decisions are two-sided. As previously mentioned, these are features that cannot be accommodated by alternative tools such as traditional discrete choice models.[42]

While Hall (1988) presented the first matching model representation of mergers, she did not estimate her model. Fox (2009) notes that Hall (1988) likely did not estimate her model due to computational concerns, since, a key difficulty in matching games is that the number of firms or agents within a market can be very large, and this can make standard maximum likelihood and method of moments estimators computationally infeasible. Fox (2010a) introduces a maximum score estimator that maximizes the number of inequalities (implied by pairwise stability).[43] This approach gets rid off the computational curse of dimensionality because not all inequalities need to be included for the estimator to be consistent (see Fox (2009, 2010a, 2010b)).[44]

In terms of identification within these models, Fox (2009, 2010b) presents two important results for matching games with transfers. The first is that the only the relative contribution of complementarities in payoffs is identified. Within our merger setting this means that we can recover whether, for example, the merger value is primarily driven by efficiency or market power incentives. The second is that the ranking of match payoffs is identified. This means that we can use our fitted match value function to rank order the merger value of all matches. We can also compare the realized merger value with the value from hypothetical mergers for counterfactual comparisons.[45]

Following Fox's contributions, several authors have applied structured matching models to examine transferable utility scenarios in a variety of settings (Akkus et al. 2015, Baccara et al. 2013, and Levin 2009). Baccara et al. (2013) apply Fox's estimator to the study of professors' office choices. The authors

[42] Parker (2012) further elaborated on restrictions of using a discrete choice model by illustrating how the set of available mergers changes with each matching. Suppose firms i and j merge. Then firm j will no longer be in the consideration set of firms that might otherwise have had firm j within their choice set. That is, the action of one pair has direct implications on the possible actions of other firms within the merger market. While this feature is explicitly accounted for within a matching framework by the consideration of pairwise stable matchings, it is not accounted for when using traditional discrete choice models.

[43] The maximum score estimator was first introduced by Manski (1975).

[44] It should also be noted that in developing his identification results, Fox (2010a, 2010b) provides a generalization of Becker's (1973) model to a setting where agents may match over a vector of characteristics, rather than just one feature.

[45] A few more things are worth noting about the scope and limitation of matching models for empirical work (see Fox (2010a) for additional details). First, the type of objects that can be recovered differs across many-to-many and other types of matching settings, such as one-to-one matching. In many-to-many matching, it is possible to recover attributes of each individual's objective function separately. However, for other cases, such as one-to-one matching, one can identify only the sum of these functions (the match production function). Since our interest is in the estimation of the joint merger value and not with the payoff of each individual firm, this does not impose any restrictions for our estimation. Second, there is an identification issue for this class of models, which is common across all specifications, that is, the inability to identify a parameter on a firm characteristic that is not interacted with the characteristic of any other firm (see Fox (2010a: 15)). While this, again, does not put any restrictions on our choice of model specification, it will generally put restrictions on the set of feasible functional forms that one can use when using a matching model for empirical work.

find that it is not only office characteristics, but also friendship/professional networks that impose an externality upon the choice behavior of the professors.

To our knowledge, only one study to date specifically utilizes Fox's methodology and estimator within a merger framework. Akkus et al. (2015) study merger value creation within the banking industry and perform their estimation using data on observed merger transfers. The authors find that merger value within this industry arises from cost efficiencies due to economies of scale and scope, additional market power, and the degree of market overlap between the merging firms. Another interesting finding is that their matching value function greatly outperforms a traditional logit model in predicting merger formations. This result, again, highlights the benefit of utilizing a matching framework instead of traditional discrete choice models for the study of mergers and acquisitions.