Technology Spillover, Product Market Synergies and Value Creation in Mergers*

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Abstract

Existing researches focus on the effects of technology spillover and product market competition on merger decision and outcomes, but the influences of technology spillover across patent classes and product market synergies have been overlooked. Using a sample of 224 mergers between public firms in U.S. manufacturing industries over the period 1996-2006, we estimate a structural model of two-sided matching between acquirer and target with transferable utility to examine value creation in mergers. Our model not only includes the choice of whom to merge with but also the decision of being acquirer or target. We find that a merger between firms with similar technologies and products creates value, which suggests mutual benefits for both merging firms from assortative matching in similar technologies and products. The similarities in technology and product contribute a substantial portion of value creation from mergers and improve the predictive power of our model. Turning to economic impacts, we find an increase in Tobin’s Q from a merger between firms with similar technologies and products. In particular, mergers between firms with similar technologies create value by increasing innovation quantity, quality, originality, and risk. Finally, our results are robust to the inclusion of a set of control variables in the merger value function, the use of an alternative market definition and the relaxation of model assumptions to allow firms staying independent.

Keywords: Merger, Two-Sided Matching, Similarity

JEL Codes: D830, G340, L130, L200, L600

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1 Introduction

Mergers have become a major strategy for firm growth in research-intensive industries. Nonetheless, the value creation in mergers depends on whether there is any synergy between the merging firms. While Apple’s $278 million purchase of microchip designer P.A. Semi in 2008 is an example of a successful synergistic merger, Daimler’s $36 billion-valued acquisition of Chrysler in 1998 is an example of merger failure due to a misunderstanding of synergy\textsuperscript{1} (Christensen, Alton, Rising, & Waldeck, 2011). Technology and product similarities have received much attention as key merger synergies (Bena & Li, 2014; Chondrakis, 2016; Hoberg & Phillips, 2010; Linde & Siebert, 2016; Ornaghi, 2009; Ozcan, 2015; Rao, Yu, & Umashankar, 2016). Mergers motivated by technology and product similarities potentially benefit from a larger knowledge base and a less competitive market, respectively.

The existing merger literature has focused on the technology and product similarities without allowing technology spillovers across patent classes and product market synergies between complementary products. As Bloom, Schankerman, and Reenen (2013) point out, however, this measure of the narrow similarity has a caveat in the sense that it cannot reflect knowledge transfer across complementary technologies or product markets. Moreover, a broad range of mergers gains synergy based on knowledge spillovers between merger partners’ different technologies or products. For example, the merger between Wellfleet and Synoptics in 1994 was based on technology spillover across patent classes. While Synoptics specialized in information transfer within a single network, Wellfleet had a comparative advantage in controlling information flow between networks. The merged firm could process a variety of information including voice and video, indicating significant post-merger synergies through combining their broadly similar technologies. Further, the merger between Amazon and Whole Foods in 2017 is an example of the merger based on

\textsuperscript{1}By purchasing P.A. Semi in 2008, Apple could produce microprocessors optimized for its products on its own. This allowed Apple to maintain its price premium which could make it more competitive relative to other mobile-device manufacturers. Daimler acquired Chrysler in 1998 because of the latter’s efficient production system. That is, Chrysler could reduce its design cycle from 5 years to 2 years by outsourcing its car parts assembly to tier-one suppliers. However, Daimler failed to benefit from Chrysler’s production system because the acquirer integrated the target’s resources into its own resources.
broadly similar product markets. The former excels in its online shopping and delivery system, whereas the latter is well-known for selling high-quality groceries. Through the merger, Amazon can gain extra profits from food retailing and Whole Foods can benefit from Amazon’s distribution channels.

Our paper thus examines the roles of the technology spillover and product market synergies between merging firms as potential sources of value creation in mergers. A firm that merges with another company that has similar technologies can increase its technology spillover across different R&D areas, which can serve as the basis for absorbing additional stimuli and information from the external environment. The absorptive capacity hypothesis suggests that the acquired similar knowledge can provide a cross-fertilization effect wherein old problems can be addressed through new approaches, while maintaining the elements of commonality that facilitate interaction between the acquired and acquiring knowledge bases (Cohen & Levinthal, 1990). Further, mergers between firms with similar products allow the merged firms to sell products with complementary demand and cost structures. First, in the context of two firms that each sell a product complementary to that sold by the other, neither internalizes the effect that its own price has on the demand for the others product. If the two firms merge, the merged firm will increase its profits by accounting for this pricing externality when it sets prices (Cournot, 1838). The merged firms can also increase profits when the sales of one product generate information spillover on the demand of the other product (Gal-Or, 1988). Second, the merged firms can increase profits by sharing costs across products, that is, exploit scope economies.

However, consideration must be made to the challenges that occur in mergers, specifically the roles of similar technologies and products in merger value creation. First, the merger value driving the decision to merge is unobserved. Quantifying merger value creation is an empirical challenge due to similar technologies and products between the acquirer and the target. Second, mergers not only affect the merging firms but also influence the rest of firms in the same merger market. Once a firm is acquired, then it is excluded from the choice set of other acquirers. Accordingly, every merger in a merger
market is interdependent with each other. Therefore, the empirical method estimating merger value needs to account for such strategic interaction among firms competing within a merger market.

To overcome those challenges, we consider mergers as a two-sided matching problem (Roth & Sotomayor, 1992): where firms are heterogeneous in their technological and production capacities, and where the merger value depends on the synergy between the acquirer and target. Since our paper focuses on technology spillover and product market synergies as sources of merger value creation, we postulate that the merger value function depends on the similarity between merging firms’ technologies and products. Specifically, we measure the similarity in technologies by using the Mahalanobis distance between firms’ vectors of patent share over patent classes (Bloom et al., 2013). Merging firms with more similar technologies are expected to gain from technology spillover. We also measure the similarity in products by using the Mahalanobis distance between firms’ vectors of sales share over business segments. Merging firms with more similar products are expected to gain from reducing competition in their product market, coordinating pricing between complementary products and exploiting scale and scope economies. Additionally, the merger value function contains a set of control variables, including geographical proximity, Tobin’s Q, and R&D intensity.

We estimate a structural model of two-sided matching to analyze the determinants of the merger value function. In this model, the same acquirer matched with different targets generates different merger values, and the merger market is in a pairwise stable equilibrium. That is, a matched acquirer-target pair cannot gain by forming a counterfactual merger. Further, we model the observed acquirer cannot gain by acting as target in any counterfactual merger, and vice versa. We then estimate the merger value function using a maximum score estimator approach with the necessary conditions derived from the stable equilibrium (Fox, 2010a). The strength of technology spillover and product market synergies in creating merger value is identified from comparisons of actual versus counterfactual mergers. They are the estimated parameters in the merger value function that make the observed matches best fit the equilibrium matches in terms of merger value.
Specifically, the total value of any two observed mergers exceeds the total value of their counterfactual mergers formed by exchanging merger partners.

Our empirical results show that similar technologies and products between acquirer and target are important determinants in creating value in mergers. Taking advantage of the structural estimation, we conduct counterfactual experiments to examine the importance of the similarity between merging partners’ technologies and products in creating merger value. If the similarity in either the technology or product in the merger value function was ignored, the model prediction rate, a measure of goodness-of-fit, would fall by about 10 and 7 percentage points relative to that of benchmark model, respectively. The merger value would fall by about 68% and 15% compared to the benchmark case if it is assumed to be no impact of the similarity in technologies and products on the merger value function, respectively.

We then extend our benchmark model by employing various model assumptions. First, we use the targets’ market instead of the acquirers’ as an alternative market definition. This model extension examines whether our benchmark estimation results are driven by a specific merger market definition. Second, we restrict the model to allow firms only to choose whom to merge, but the role of being either as acquirer or target is predetermined. This model examines whether fixing the role of each firm to either the acquirer or target makes a difference in the parameter estimates. Third, we extend the model to allow firms not only to choose whom to merge with but also to choose whether to merge. By including stand-alone firms in our sample, we alleviate the endogeneity problem caused by the correlation between unobservables driving the merger value and merger decision. Encouragingly, our results are robust to those modifications.

Firms merge with each other under the expectation of mutual gains, but the sources of gain can vary across different mergers. Mergers with the technology similarity at the top quartile enjoy 14 percentage points higher Tobin’s Q than mergers with the broad technology similarity at the bottom quartile. This difference relates to the more than 1.8 times more patents granted and citations received, more diversified technologies developed and riskier innovation projects undertaken by the merged firms that acquired
more similar technologies. Further, mergers with the product similarity at the top quartile enjoy 10 percentage points higher Tobin’s Q than mergers with the product similarity at the bottom quartile, but there is no evidence to show that this difference is driven by post-merger innovations. We suggest that mergers with broadly similar products may seek synergy in pricing coordination and cost reduction. These results confirm that our model captures the initial merger-specific value reasonably well, and the mergers between firms with similar technologies and products do have economic impacts.

Our paper contributes to the growing literature using a two-sided matching model to examine merger partner choices. Akkus, Cookson, and Hortaconsu (2015), Ozcan (2015), and Linde and Siebert (2016) are three closest papers to ours in that they use the two-sided matching model with transferable utility. Akkus et al. (2015) find positive effects of scale economies on the partner choices in bank mergers. In particular, they show that banks are more likely to merge with each other if they have similar asset size and number of branches. In a closer relationship with our work, Ozcan (2015) and Linde and Siebert (2016) find that the similarities in technology and product between acquirer and target increase merger value.

Our paper also adds to another growing set of empirical literature on two-sided matching with non-transferable utility, which jointly examines the determinants of merger partner choice and post-merger outcomes. M. Park (2013) analyzes mergers in the U.S. mutual fund sector. She finds that firms using similar fund distribution channels are more likely to merge, and they achieve a higher asset growth rate after the merger. After analyzing 1,979 mergers in various industries, Rao et al. (2016) conclude that knowledge similarity has positive impacts on both merger partner choice and post-merger patent application. Ishihara and Rietveld (2017) examine 85 acquisitions and 5,916 products in the U.K. video game industry. They find that the number of past collaborations and geographical closeness between video game publishers and developers positively affect the

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2There are previous studies looking into this problem without using matching model, such as Ornaghi (2009) and Bena and Li (2014). The former work investigates the impact of the narrow technology similarity on post-merger outcomes such as growth rate of either stock market value or the number of patents in the U.S. pharmaceutical industry. The latter work looks into mergers of U.S. public firms and suggests that technological overlap between firms increases the probability of occurring merger between them. Also, more overlapping knowledge between acquirer and target produces more patents afterward.
merger value function by developing high-quality products and improving sales performance after the merger.

Our paper differs from those previous studies in three aspects. First, we examine a larger set of post-merger outcomes than previous studies do. In addition to the post-merger market valuation effect, we examine various sets of innovation activities to identify the channels through which mergers create value. In particular, we show that mergers motivated by technology spillover create value through improving their innovativeness. Second, we extend the two-sided matching model with transferable utility to allow firms to choose to be the acquirer or target in a merger and to choose to be stand-alone firms. Third, we employ the Mahalanobis distance to measure technology and product similarities between merging firms, which allows us to examine the impact of technology spillover across patent classes and product market synergies across complementary products.

Section 2 discusses the model and estimation methodology. Section 3 describes data. Section 4 presents empirical results. Last section concludes.

2 Model and Estimation

We consider merger as a two-sided matching problem (Roth & Sotomayor 1992). First, firms are heterogeneous in their technological and production capacities. Second, the merger value depends on the synergy between acquirer and target.

Merger market is defined by merger transaction year and target firm’s industry type based on standard industrial classification (SIC) code following Ozcan (2015). In other words, a merger transaction performed in some merger market is independent of a merger deal made in another market. For instance, there are two merger deals performed by Cisco systems in our sample. One is a transaction with Summa Four in 1998, a firm that operates in SIC code 3661 (Telephone & Telegraph apparatus). The other one is a deal with Scientific-Atlanta in 2006, a firm that operates in SIC code 3663 (Radio & TV broadcasting & Communications equipment). According to our market definition, the former deal does not affect the latter because they are made in two different merger
markets, even though the acquirer in those two transactions is the same. This assumption implies that a single acquirer is treated as two different firms when it matches with two distinct targets in two different merger markets. Further, we assume the matching is one-to-one because a target disappears after merger, so that it cannot merge with more than one acquirer.

2.1 Model

There are two sets of merger participants in each merger market $m = 1, 2, ..., n$: one is a set of acquirers, $A_m$, and the other one is a set of targets, $T_m$. Thus, a set of potential mergers in a merger market $m$ is $M_m = A_m \times T_m$. A collection of realized mergers in the merger market $m$ is called a matching $\mu_m \subset M_m$. Hence, an acquirer $a$’s merger partner is written as $\mu_m(a)$, and a target $t$’s merger partner is denoted by $\mu_m(t)$. For notational simplicity, we drop the subscript $m$ for a merger market in later sections.

Every potential merger has a merger value, which is an expected net present value (NPV) measured at the time of merger. We denote $V(a, t)$ as the expected value of a merger between acquirer $a$ and target $t$. Let the acquirer $a$’s valuation for merging with target $t$ be $V_a(a, t)$. Then, $V_a(a, t) = V(a, t) - p_{at}$, where $p_{at}$ is the transfer payment from $a$ to $t$. Accordingly, the target $t$’s value from this merger becomes $V_t(a, t) = p_{at}$. Therefore, the merger value between $a$ and $t$ becomes $V_a(a, t) + V_t(a, t) = V(a, t)$.

The concept of equilibrium used is pairwise stability. We define a merger match to be pairwise stable if there is no blocking pair whose firms want to deviate from their current merger and form a new merger by themselves. Formally, $\mu$ is pairwise stable if the following inequalities hold

$$V(a, t) - p_{at} \geq V(a, \tilde{t}) - p_{at},$$  

(1)

$$V(\tilde{a}, \tilde{t}) - p_{\tilde{a}\tilde{t}} \geq V(\tilde{a}, t) - p_{\tilde{a}t}.$$  

(2)

$V(a, t)$ and $V(\tilde{a}, \tilde{t})$ are match values of realized mergers in $\mu$, where $\tilde{a} \in A \setminus a$ and $\tilde{t} \in T \setminus t$. The above inequality requires that acquiring firms $a$ and $\tilde{a}$ cannot gain
from counterfactual mergers formed by swapping targets $t$ and $\tilde{t}$. We assume that every acquirer or target has non-overlapping preference rankings over all the potential partners in the same merger market. This assumption implies that a matching equilibrium is unique.

Merger transaction price is a transfer payment from acquirer to target. For our model with transferable utility, it allows a weaker acquiring firm to induce a stronger target firm to participate in the merger by offering higher proportion of their merger value to the target. The transfer $p_{a,t}$ and $p_{\tilde{a},\tilde{t}}$ are not available from data on observed mergers. For the acquirer $a$ to be able to purchase the target $t$ against its rival firm $\tilde{a}$, the transfer payment $p_{a,t}$ should be weakly higher than $p_{\tilde{a},\tilde{t}}$. Moreover, $p_{a,t}$ should not be strictly greater than $p_{\tilde{a},\tilde{t}}$ because $a$’s payoff from the realized match $V_a(a,t)$ ($= V(a,t) - p_{a,t}$) falls as $p_{a,t}$ increases. Thus, $p_{a,t} = p_{\tilde{a},\tilde{t}}$. We apply this logic to another observed match between acquirer $\tilde{a}$ and $\tilde{t}$, so that $p_{\tilde{a},\tilde{t}} = p_{a,t}$. Accordingly, the inequalities (1) and (2) can be written as

$$V(a,t) - p_{\tilde{a},\tilde{t}} \geq V(a,\tilde{t}) - p_{a,t},$$  

(3)

$$V(\tilde{a},\tilde{t}) - p_{a,t} \geq V(\tilde{a},t) - p_{\tilde{a},\tilde{t}}.$$  

(4)

Then, we add inequality (3) to (4) to derive the following inequality for a stable merger matching equilibrium:

$$V(a,t) + V(\tilde{a},\tilde{t}) \geq V(a,\tilde{t}) + V(\tilde{a},t).$$  

(5)

In other words, the total value of realized mergers is weakly greater than the total value of counterfactual mergers.

The existing literature assumes that the sets of acquirers and targets are separate, i.e. there is no overlapping firm in both sets. However, whether a firm is an acquirer or a target is not pre-determined. Rather, it can be a part of merger decision. Hence, we use broader sets of acquirers and targets in our matching model by incorporating actual acquiring firms into the set of potential target firms, and vice versa.

This extended model need to incorporate additional inequalities. The first set of
inequalities are the same in the inequality condition (5) from the pairwise stable equilibrium between two observed matches \((a, t)\) and \((\tilde{a}, \tilde{t})\). Since the actual acquirer \(a\) might be purchased by another actual acquiring firm \(\tilde{a}\) before the realized merger between \(a\) and \(t\), we additionally include the inequality (10) into the objective function in maximum score estimation. This means that

\[ V(t, a) + V(\tilde{a}, \tilde{t}) \geq V(t, \tilde{t}) + V(\tilde{a}, a). \]  

(6)

2.2 Estimation

In this sub-section, we first discuss the specification of merger value function. Then, we discuss the estimation of our structural model, which is based on the maximum score estimation proposed by Fox (2010a). Several authors apply this methodology to their merger analyses (Akkus et al., 2015; Linde & Siebert, 2016; Ozcan, 2015; Y. Park, 2016).

2.2.1 Specification of Merger Value Function

Our paper explores the impacts of complementary technologies and products on value creation of merger. Thus, we assume that the merger value function depends on ex-ante technology and product complementarity between potential merging partners.

Merging with firms with complementary technologies can increase a firm’s knowledge base and allow knowledge transfer across different R&D area, which can serve as the basis for absorbing additional stimuli and information from the external environment. The absorptive capacity hypothesis suggests that acquired complementary knowledge can provide a cross-fertilization effect as old problems can be addressed through new approaches or by a combination of old and new approaches, while maintaining the elements of commonality that facilitate interaction between the acquired and acquiring knowledge bases (Cohen & Levinthal, 1990). Although complementary technologies do not draw much attention as drivers of merger value function, the existing papers focus on its impacts on post-merger outcomes (Cassiman, Colombo, Garrone, & Veugelers, 2005; Makri, Hitt, & Lane, 2010). They present that complementary technologies between merger partners
improve post-merger innovation performances, such as patent count. These results suggest that firms have incentives to merge with the other firm with more complementary technologies. Thus, we present our first hypothesis as follows:

**Hypothesis 1.** Complementarity technologies between acquirer and target create merger value.

Merging with firms with complementarity products allow the merged firms selling products with complementary demand and cost structure. First, in the context of two firms that each sell a product complementary to that sold by the other, neither internalizes the effect that its own price has on the demand for the others product. This leads to double marginalization. If the two firms merge, the merged firm will increase its profit by accounting for this pricing externality when it sets prices (Cournot, 1838). The merged firms can also increase profit when the sales of one product spillover information on the demand of the other product (Gal-Or, 1988). Second, the merged firms can increase profit by sharing cost across products, i.e. scope economies. Yu, Umashankar, and Rao (2015) examines the role of complementarity between pharmaceutical firms’ products on the acquiring firm’s choice of acquisition partner. One of their conclusions is that a potential acquirer chooses a target firm with products complementary to its own products rather than another firm with similar products. Accordingly, we suggest our second hypothesis as follows:

**Hypothesis 2.** Complementarity products between acquirer and target create merger value.

Based on the aforementioned hypotheses, we specify the following merger value func-
\[ F(a, t|\alpha) = \alpha_1 TS_{at} + \alpha_2 PS_{at} + \alpha_3 SameState_{at} + \alpha_4 (\text{Tobin's } Q_a \times \text{Tobin's } Q_t) + \alpha_5 (\text{R&D intensity}_a \times \text{R&D intensity}_t) + \eta_{at}, \quad (7) \]

where \( \eta_{at} \) represents an unobserved error term for the merger between \( a \) and \( t \). \( TS_{at} \) and \( PS_{at} \) represent measures of the broad similarity in technology and product between acquirer \( a \) and target \( t \), respectively. The parameters of interest are \( \alpha_1 \) and \( \alpha_2 \). A positive and significant \( \alpha_1 \) supports Hypothesis 1, whereas a positive and significant \( \alpha_2 \) supports Hypothesis 2.

In Equation (6), we include two sets of control variables. The first set contains a variable related to geographical proximity. \( SameState_{at} \) is a dummy variable equal to 1 if acquirer and target firm are located in a same state, and zero otherwise. It is a proxy variable for geographical distance between merging firms. Some previous studies suggest that when two firms are located close to each other, they are more likely to merge \( [\text{Erel, Liao, & Weisbach} \ 2012, \text{Ozcan} \ 2015] \). Thus, we include this variable into the merger value function to control for geographical closeness between merging firms.

The second set of control variables includes the interaction term of Tobin’s Q and that of R&D intensity between acquirer and target. \( \text{Rhodes-Kropf and Robinson} \ (2008) \) suggest that two firms with similar Tobin’s Q are more likely to merge. The synergy from this type of merger is supported by the property rights theory introduced by \( \text{Grossman and Hart} \ (1986) \). According to the theory, if two firms’ assets have similar valuations, they should be controlled by a single ownership to realize benefits of complementary assets. Further, existing studies suggest R&D intensity is the main determinant of merger \( \text{Bertrand} \ 2009, \text{Blonigen & Taylor} \ 2000, \text{Desyllas & Hughes} \ 2010 \). Particularly, a firm with lower R&D intensity is more likely to acquire firms with higher R&D intensity for improving its innovation. For example, in 1998, Hewlett-Packard acquired Heartstream, a maker of automated external defibrillators, which has a R&D intensity about 30 times higher than itself[^3].

[^3]: HP with 0.069 of R&D intensity, while Heartstream with 2.039 of R&D intensity.
2.2.2 Maximum Score Estimation

We employ the maximum score estimation to estimate the merger value function. Let the merger value function between acquirer \(a\) and target \(t\) be \(F(a, t) = V(a, t) + \eta_{at}\), where \(V(a, t)\) refers to observable merger values and \(\eta_{at}\) represents an unobserved merger-specific error term. Suppose that there are two realized mergers, \((a, t), (\tilde{a}, \tilde{t}) \in \mu\). Also, define

\[
q(\alpha) = V(a, t|\alpha) + V(\tilde{a}, \tilde{t}|\alpha) - V(a, \tilde{t}|\alpha) - V(\tilde{a}, t|\alpha),
\]

where \(\alpha\) represents a vector of parameters to be estimated in the observable part of the merger value function. Thus, \(q(\alpha)\) indicates a difference between total match values of observed mergers and total match values of counterfactual mergers formed by exchanging merger partners. According to Fox (2010b), the only necessary condition to identify parameters in the merger value function using maximum score estimation is the following rank order property:

\[
q(\alpha) \geq 0 \text{ if and only if } \text{Prob}\{(a, t), (\tilde{a}, \tilde{t}) \in \mu\} \geq \text{Prob}\{(a, \tilde{t}), (\tilde{a}, t) \in \mu\}.
\]

In other words, if the total value of two observed mergers exceeds the total value from counterfactual mergers, then the probability of observing realized mergers is higher than the probability of observing counterfactual mergers. And the reverse is also true. Under this rank order condition, the maximum score estimator \(\alpha\) can maximize

\[
Q(\alpha) = \sum_{m=1}^{n} \left\{ \sum_{(a,t),(\tilde{a},\tilde{t}) \in \mu_{m}} 1[q(\alpha) \geq 0] \right\}, \tag{8}
\]

over the parameter space in a stable matching equilibrium, where \(Q(\alpha)\) is the number of holding inequality (5) in all merger markets. Even though the derivation of the stable matching equilibrium condition requires the transfer payments, the inequality (5) for implementing the equilibrium does not contain them. We thus adopt the estimation method proposed by Fox (2010a), which does not require the information on the merger
transaction price (i.e., transfer data). Nonetheless, we need to normalize the coefficient of interaction term between Tobin’s Q of acquirer and target to +1 and the interpretation of the other variables is relative to Tobin’s Q_a × Tobin’s Q_t. Further, since we assume that the role of firms in the merger as either the acquirer or target is not pre-determined, the parameter estimates from this estimation maximize

\[
Q(\alpha) = \sum_{m=1}^{n} \left\{ \sum_{(a,t), (\tilde{a}, \tilde{t}) \in \mu_m} 1 \left[ \{q_1(\alpha) \geq 0\} \cap \{q_2(\alpha) \geq 0\} \right] \right\},
\]

where

\[
q_1(\alpha) = V(a, t|\alpha) + V(\tilde{a}, \tilde{t}|\alpha) - V(a, \tilde{t}|\alpha) - V(\tilde{a}, t|\alpha),
\]

\[
q_2(\alpha) = V(a, t|\alpha) + V(\tilde{a}, \tilde{t}|\alpha) - V(a, \tilde{a}|\alpha) - V(t, \tilde{t}|\alpha).
\]

In addition, since acquirer- and target-specific attributes cancel out in the inequality, the only relevant terms in merger value function are match-specific features and interactions between each merger partner’s characteristics. For example, merger occurs when acquiring firm’s free cash flow increases because managers tend to use the increased free cash in performing merger instead of paying it to shareholders (Jensen, 1988). Such non-interactive term could contribute to merger value, but are differenced out in equilibrium because both the actual and counterfactual partners value them in the same way. Our matching model is thus robust to, for example, acquirer-specific attributes, target-specific attributes, and firm fixed effects.

The objective function in (7) yields only integer values. The more inequalities satisfied, the better the matching model statistically fits the data. This estimation technique is semiparametric in the sense that it does not impose any restriction on unobservables in the objective function. This estimator is easy to implement because it only requires a set of inequalities necessary to derive a stable matching equilibrium. Thus, it is not computationally burdensome due to multidimensional integration of idiosyncratic error

\[4\text{If data on merger transaction price is available, then the maximum score estimator can achieve a stronger identification. The reason is that it allows the merger value function to respond to changes in merger- as well as target-specific characteristics. See Akkus et al. (2015).}
terms, which avoids the curse of dimensionality (Fox 2010b). Following Akkus et al. (2015) and Ozcan (2015), we apply the differential evolution algorithm for obtaining point estimates of parameters that maximize the objective function. Since the maximum score inequality condition (5) does not uniquely determine estimated values of parameters, we run the estimation repeatedly by using 20 different starting values of point estimates and select the coefficient vector that maximizes the number of equilibrium inequalities satisfied.

2.2.3 Confidence Intervals

To generate confidence intervals for point estimates from the maximum score estimation, we employ subsampling procedures suggested in the literature (Delgado, Rodriguez-Poo, & Wolf 2001; Politis & Romano 1992). First, we set the subsample size to be 75 observations, which is about 1/3 of the entire sample size, i.e. 224 observations. For each subsample, we compute the parameter vector by maximizing the objective function and use 100 replications to construct the confidence intervals. Let the parameter vector based on the subsamples be $\hat{\alpha}_{sub}$, and the parameter vector based on the full sample be $\hat{\alpha}$. The approximate sampling distribution for our parameter vector can be computed by using $\bar{\alpha}_{sub} = (75/224)^{\frac{1}{3}}(\hat{\alpha}_{sub} - \hat{\alpha}) + \hat{\alpha}$ for each subsample. Our maximum score estimates converge to the sampling distribution of $\bar{\alpha}_{sub}$ at the rate of $\sqrt{\frac{75}{224}}$. We compute 95% confidence intervals from the 2.5th percentile and 97.5th percentile of this empirical sampling distribution.

3 Data

3.1 Data Sources and Sample Construction

We study the matching market of acquirers and targets with the merger records from DYNASS file[^5] which is offered in the National Bureau of Economic Research (NBER) Patent Data Project website[^5]. For the period between 1996 and 2006, we observe 224

[^5]: It is the file of firms’ ownership change.
merger deals in the U.S. manufacturing industries (SIC code 2000-3999). Table I shows these merger transactions classified by target firm’s industry type and transaction year. Our sample mergers cover five target firm’s industry types, namely pharmaceutical, semiconductor, electronics, computer & communications, and others. These industries are appropriate to examine the role of complementary technologies and products in determining merger value function for the following reasons. First, they have experienced many merger transactions in recent decades according to Shleifer and Vishny (2003). Second, firms in these sectors are more technology- and product-dependent than firms in other industries such as finance or service sector. Thus, the relationship between merging partners’ technologies and products would play a critical role in merger decision.

Our merger sample only covers firms actually participated in merger deals as in Akkus et al. (2015) and Ozcan (2015). In other words, stand-alone firms are not included in the samples. Our sample provides sufficient data variations to identify the match-specific determinants driving the decision of whom to merger with. We also perform a robustness check in later section by including standalone firms into our samples. In that case, we also model the decision of merging or staying alone.

According to model assumptions, merger transaction occurs between firms within a single merger market. Each merger market is constructed by the combination of merger deal year, from 1996 to 2006, and target firms’ 5 industry types, pharmaceutical, semiconductor, electronics, computer & communications, and other sectors. Estimating the inequality (5) for a pairwise stable matching equilibrium requires at least two observed matches. Accordingly, we merge some of the acquirer-target pair with others in a different merger market but with same industry type when the former is the only match in its original market. After adjusting the number of merger matches in every market, we identify 46 merger markets for empirical analysis.

We obtain the information on financial variables of our sample firms from the Compustat. The Compustat provides the information on stock market capitalization, book value, total assets, sales and R&D expenditure. We use those financial features to construct control variables used in our matching model and to measure post-merger outcomes.
Table 1: Merger Transactions in U.S. Manufacturing Industries

<table>
<thead>
<tr>
<th>Year</th>
<th>Pharmaceutical</th>
<th>Semiconductor</th>
<th>Electronics</th>
<th>Computer &amp; Communications</th>
<th>Other</th>
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<tr>
<td>2006</td>
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<td>2</td>
<td>4</td>
<td>2</td>
<td>4</td>
<td>15</td>
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<tr>
<td>Total</td>
<td>49</td>
<td>19</td>
<td>29</td>
<td>41</td>
<td>86</td>
<td>224</td>
</tr>
</tbody>
</table>

Further, We obtain the data on patents and patent citations from Lai, D’Amour, and Fleming (2014) in the Institute for Quantitative Social Science at Harvard University (IQSS) website. We include the information on all the U.S. patents applied during 1994 and 2008. While the sample period of the merger dataset is from 1996 to 2006, we extend the period of the patent dataset to 1994-2008 to construct the pre-merger patent portfolio for mergers in 1996 and post-merger outcomes for mergers in 2006. Note that the number of patent citations significantly decreases as time approaches 2008 (the last year of the patent dataset) due to sample period truncation. That is, since the entire sample does not contain patent citations received after 2008, the number of patent citations in the data is less than actual citation counts reflecting post-2008 information.

3.2 Variable Definitions

We measure technology similarity by the correlation between firms’ vectors of patent share over patent classes. The United States Patent and Trademark Office (USPTO) categorizes all the granted patents into 642 technology-based classes. A firm $i$’s vector
of patent shares over classes is represented by
\[ F_i = (F_{i,1}, F_{i,2}, ..., F_{i,642}), \]
where \( F_{i,c} \) is a firm \( i \)'s ratio of patent counts in class \( c \) to the total number of patents. Following Jaffe (1986), the technological similarity is measured by the correlation between merger partners’ technologies as follows:

\[
CR(F_A, F_T) = \frac{\text{Cov}(F_A, F_T)}{\sqrt{\text{Var}(F_A) \cdot \text{Var}(F_T)}},
\]

where \( F_A \) (\( F_T \)) represents acquirer A’s (target T’s) vector of patent shares over patent classes. Some previous studies construct a measure of technology similarity by using this patent distribution vector of firms. Ozcan (2015) measures technology similarity for his sample of industrial firms with the Euclidean distance between merging firms’ vectors of patent share over patent classes, whereas Linde and Siebert (2016) measure technology similarity for their firms in the U.S. semiconductor industry by using the correlation between merging firms’ vectors of patent share over patent classes. We use the correlation (CR) between pre-merger patent distribution vectors of two firms to measures technology similarity between firms, which is consistent with Linde and Siebert (2016). Two firms have more similar technologies before their merger when CR is higher.

We measure technological complementarity by Mahalanobis distance (MAHA) between firms following Bloom et al. (2013). First, contruct a matrix of every firm’s vector of patent shares over technology classes. That is, the \( 642 \times N \) matrix, \( F = [F'_1, F'_2, ..., F'_N], \) is the matrix of all the firms’ patent distributional vectors over 642 classes, where \( F_i \) is a firm \( i \)'s \( 1 \times 642 \) vector of patent shares across classes and \( N \) is the total number of firms. Then, normalize each column of the matrix \( F \), so that obtain another matrix \( \tilde{F} = [\frac{F'_1}{(F'_1)^{1/2}}, \frac{F'_2}{(F'_2)^{1/2}}, ..., \frac{F'_N}{(F'_N)^{1/2}}]. \) Third, form the \( N \times N \) matrix \( C = [F'_{(1,1)}, F'_{(2,2)}, ..., F'_{(642,642)}], \) where \( F_{(c)} \) is a class \( c \)'s \( 1 \times N \) vector of patent shares over \( N \) firms. Then, \( \tilde{C} = [\frac{F'_{(1,1)}}{(F_{(1,1)})^{1/2}}, \frac{F'_{(2,2)}}{(F_{(2,2)})^{1/2}}, ..., \frac{F'_{(642,642)}}{(F_{(642,642)})^{1/2}}] \) is the normalized \( N \times N \) matrix of \( C \). Thus, the \( 642 \times 642 \) matrix \( \text{CCORR} = \tilde{C}'\tilde{C} \) indicates the uncentered correlation between vectors of all the classes’ patent shares across firms. Finally, to capture technological relatedness between different patent classes, use the \( N \times N \) matrix \( \text{TECHSPILL} = \tilde{F}' \times \text{CCORR} \times \tilde{F}. \) Hence, each element of the TECHSPILL matrix is
the MAHA distance between two corresponding firms. Therefore, MAHA is the weighted correlation between firms’ patent class distributional vectors, where the weight is defined by the correlation among all the patent classes (CCORR).

Technology similarity assumes that the spillovers occur only within the same patent class, thus ruling out spillovers between different classes. In particular, CR partitions technology space according to 642 patent classes, and it assumes that patent classes are orthogonal to each other. As a result, in the case that two firms have no patent filed in overlapping classes, the spillover effect between the two would be assigned as zero. However, knowledge could flow not only within a class, but also across classes. Therefore, MAHA is better in reflecting knowledge complementary across different patent classes. We illustrate the difference between CR and MAHA with the following example. Suppose that there are only 3 patent classes, and that acquirer A’s and target T’s vectors of patent shares over 3 classes are 
\[ F_A = (0.1, 0.4, 0.5) \] and 
\[ F_T = (0, 0.8, 0.2) \].

The correlation between two merger partners’ technologies A and T (CR\textsubscript{AT}) is 0.5. To compute MAHA, we take the following steps. Consider 
\[ F = [F'\text{A}, F'\text{T}] = \begin{bmatrix} 0.1 & 0 \\ 0.4 & 0.8 \\ 0.5 & 0.2 \end{bmatrix} \],

so that 
\[ \tilde{F} = \frac{F'\text{A}}{(F_A F_A')^{1/2}}, \frac{F'\text{T}}{(F_T F_T')^{1/2}} = \begin{bmatrix} 0.15 & 0 \\ 0.62 & 0.97 \\ 0.77 & 0.24 \end{bmatrix} \].

Moreover, 
\[ C = [F'\text{(1)}, F'\text{(2)}, F'\text{(3)}] = \begin{bmatrix} 0.1 & 0.45 & 0.5 \\ 0 & 0.89 & 0.2 \\ 0.8 & 0.2 & 0 \end{bmatrix} \], and 
\[ \tilde{C} = \frac{F'\text{(1)}}{(F_{(1)} F_{(1)})^{1/2}}, \frac{F'\text{(2)}}{(F_{(2)} F_{(2)})^{1/2}}, \frac{F'\text{(3)}}{(F_{(3)} F_{(3)})^{1/2}} = \begin{bmatrix} 1 & 0.45 & 0.93 \\ 0.45 & 1 & 0.75 \\ 0.93 & 0.75 & 1 \end{bmatrix}. \]

Thus, the matrix CCORR = \[ \tilde{C}'\tilde{C} = \begin{bmatrix} 1 & 0.45 & 0.93 \\ 0.45 & 1 & 0.75 \\ 0.93 & 0.75 & 1 \end{bmatrix} \]. Finally, the matrix TECHSPILL = 
\[ \tilde{F}' \times CCORR \times \tilde{F} = \begin{bmatrix} 2.02 & 1.56 \\ 1.56 & 1.35 \end{bmatrix} \], so that Mahalanobis distance between two merger partners A and T (MAHA\textsubscript{AT}) is 1.56.

We measure product similarity by the correlation between firms’ vectors of sales share.
over business segments. The Compustat provides the information of each firm’s business segments classified by 4 digit SIC. We construct each firm’s pre-merger sales distribution over 216 business segments based on the product market segment data. That is, a firm \( i \)’s vector of sales across business segments is denoted by \( S_i = (S_{i,1}, S_{i,2}, \ldots, S_{i,216}) \), where \( S_{i,b} \) is a firm \( i \)’s ratio of sales in a business segment \( b \) to the total sales before the merger. The PCR is the correlation between the pre-merger sales distribution vectors of two firms, which measures product market similarity between them. Two firms are more likely to compete in similar product markets before their merger when PCR is higher. Further, we measure product complementarity by PMAHA, which is the correlation among firms’ vectors of market share in various business segments weighted by the correlation across those business segments.

Turning to the post-merger outcomes, we use the average of a firm’s Tobin’s Q during 1 year (TOBINQ) and 3 years (AVERQ) after merger as measures of short-run and long-run valuation effects, respectively. There have been several attempts to explore the relationship between R&D or patents and stock market value (Hall, 2000; Hall, B. H., Jaffe, A., & Trajtenberg, 2005; Pakes, 1985). According to those studies, other measures such as profit or total factor productivity (TFP) do not precisely reflect value of R&D inputs (e.g., technologies) or R&D outputs (e.g., patents, citations, or products). On the other hand, Tobin’s Q is a better indicator of expected net present value generated by those factors related to R&D.

We employ total patent counts (PAT) and a total number of citation-weighted patents (CWP) during 3 years after merger as measures of post-merger innovation outcomes. Many researchers use patent counts as a proxy of innovation output (Ahuja & Katila, 2001; Benner & Waldhof, 2008; Fleming, 2001; Hausman, Hall, & Griliches, 1984; Oragni, 2009). However, each patent has different technological influence or economic value. In this case, the number of citation-weighted patents can be an alternative measure to simple patent counts in the sense that the number of citations to a patent represents the patent’s value (Hall, B. H., Jaffe, A., & Trajtenberg, 2005; Trajtenberg, 1990). For instance, a patent cited by other 100 patents is more valuable than another patent without
citations because the former is technologically more influential to other patents than the latter. In order to construct citation-weighted patent counts, we apply the linear weighting scheme to the analysis following Trajtenberg (1990). That is, let a firm $i$’s number of citations received for each patent $k$ be $CIT_{ik}$, then the firm $i$’s citation-weighted patent counts ($CWP_i$) become

$$CWP_i = \sum_{k=1}^{n} (1 + CIT_{ik}),$$

(11)

where $n$ is the number of patents granted to the firm $i$. For our analysis, we use the number of patents to measure the quantity of innovation outputs and the citation-weighted patent counts to measure the quality of innovation outputs. Additionally, we compute the ratio of citation to patent ($CITINT$) to measure the average quality of patent.

In addition to patent count, citation-weighted patents and citation per patent, we consider the following post-merger innovation outcomes: (1) the 90 percentile of originality of patents (ORIG), (2) the 90 percentile of generality of patents (GENERAL), and (3) the standard deviation of CWP during 3 years after merger (STDV). Specifically, we employ originality and generality index provided by National Bureau of Economic Research (NBER) Patent Data Project website. Following Hall, Jaffe, and Trajtenberg (2001), the measure of originality (generality) is constructed by Measure$_i = 1 - \sum_c C_{ic}^2 s_{ic}$, where $s_{ic}$ indicates the ratio of citations made (received) by patent $i$ in patent class $c$ to $C$ patent classes. While ORIG and GENERAL measure technological diversity after merger (Hall et al., 2001), STDV measures the risk of post-merger patenting activity (Amore, Schneider, & Zaldokas, 2013).

### 3.3 Descriptive Statistics

Table 2 reports the descriptive statistics. All financial variables are adjusted to dollar values in 2000 using consumer price index (CPI). Target firms show higher R&D intensity than acquirers, which is consistent with the results in Blonigen and Taylor (2000). Moreover, acquirers have larger stock market values than targets, so that they are more
Table 2: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>N</th>
</tr>
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<tbody>
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<td><strong>Acquirer</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>log ( \frac{R&amp;D \text{ expenditure}}{Sales} )</td>
<td>0.166</td>
<td>0.266</td>
<td>224</td>
</tr>
<tr>
<td>Tobin’s Q</td>
<td>log ( \frac{Stock \text{ market value}}{Total \text{ asset}} )</td>
<td>1.104</td>
<td>0.126</td>
<td>224</td>
</tr>
<tr>
<td>IND1</td>
<td>Pharmaceutical Industry</td>
<td>0.232</td>
<td>0.423</td>
<td>224</td>
</tr>
<tr>
<td>IND2</td>
<td>Semiconductor Industry</td>
<td>0.103</td>
<td>0.304</td>
<td>224</td>
</tr>
<tr>
<td>IND3</td>
<td>Electronics Industry</td>
<td>0.107</td>
<td>0.310</td>
<td>224</td>
</tr>
<tr>
<td>IND4</td>
<td>Computer &amp; Communications Industry</td>
<td>0.161</td>
<td>0.368</td>
<td>224</td>
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<tr>
<td>IND5</td>
<td>Other Industry</td>
<td>0.397</td>
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<td><strong>Target</strong></td>
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<td></td>
</tr>
<tr>
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</tr>
<tr>
<td>IND3</td>
<td>Electronics Industry</td>
<td>0.129</td>
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<td>224</td>
</tr>
<tr>
<td>IND4</td>
<td>Computer &amp; Communications Industry</td>
<td>0.183</td>
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<tr>
<td>IND5</td>
<td>Other Industry</td>
<td>0.384</td>
<td>0.487</td>
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<td><strong>Match-Specific Characteristic</strong></td>
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<td>CR</td>
<td>Correlation distance of technologies</td>
<td>0.382</td>
<td>0.313</td>
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<tr>
<td>MAHA</td>
<td>Mahalanobis distance of technologies</td>
<td>0.941</td>
<td>0.598</td>
<td>224</td>
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<tr>
<td>PCR</td>
<td>Correlation distance of products</td>
<td>0.436</td>
<td>0.467</td>
<td>224</td>
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<tr>
<td>PMAHA</td>
<td>Mahalanobis distance of products</td>
<td>0.352</td>
<td>0.356</td>
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<td><strong>Post-Merger Outcome</strong></td>
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<td>TOBINQ1</td>
<td>Tobin’s Q in merger year</td>
<td>1.032</td>
<td>0.497</td>
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<tr>
<td>TOBINQ3</td>
<td>3-year average of Tobin’s Q after merger</td>
<td>0.966</td>
<td>0.442</td>
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<tr>
<td>PAT</td>
<td>log(Patent counts)</td>
<td>3.727</td>
<td>1.941</td>
<td>224</td>
</tr>
<tr>
<td>CWP</td>
<td>log(Citation-weighted patent counts)</td>
<td>4.778</td>
<td>2.445</td>
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<tr>
<td>CITINT</td>
<td>log ( \frac{Citations}{Patents} )</td>
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<td>0.811</td>
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</tr>
<tr>
<td>ORIG</td>
<td>Originality of patents</td>
<td>0.588</td>
<td>0.342</td>
<td>224</td>
</tr>
<tr>
<td>GENERAL</td>
<td>Generality of patents</td>
<td>0.460</td>
<td>0.390</td>
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<tr>
<td>STDV</td>
<td>3- year standard deviation of CWP after merger</td>
<td>10.435</td>
<td>6.131</td>
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</table>
capable to finance a merger. Before taking a logarithm, the average of acquirers’ stock
market value before merger is about $16 billion, whereas the average of targets’ stock
market value is approximately $2.3 billion. The average Tobin’s Q of acquirers is slightly
higher than that of targets. The composition of targets’ industry is similar to that of
acquirers’ industry because most of the deals are horizontal mergers. Pharmaceutical
firms involve in more merger transactions than firms in the other manufacturing sectors.
In particular, more than 20% of mergers belong to pharmaceutical industry.

Turning to the match-specific characteristics, which play the key role in merger value
function. The averages of CR and MAHA are 0.382 and 0.941, respectively. The averages
of PCR and PMAHA are 0.436 and 0.352, respectively. 40.2% of our mergers with the
acquirer and target locating in the same state. Finally, the descriptive statistics of post-
merger outcomes are presented in the bottom panel of Table 2.

4 Empirical Results

4.1 Matching Model Estimation

This sub-section discusses the results of merger value function reported in Table 3.
First, the coefficients for CR and PCR are positive and significant in Column (1), and the
coefficients for MAHA and PMAHA are positive and significant in Column (2). These
results indicate that the more similar the merger partners’ technologies and products,
the higher their merger value. These results suggest that technology spillover and prod-
uct market synergies between merging firms create merger value. Our results support
Hypotheses 1 and 2.

Turning to the control variables, we find that a firm with high Tobin’s Q derives more
value from another high Q firm, indicating a positive assortative matching in Tobin’s Q.
This is supported by the fact that we obtain more maximum score inequalities satisfied
by setting the coefficient for an interaction term between merging partners’ Tobin’s Q
to +1 instead of -1. It implies that merging partners with higher level of Tobin’s Q can
create larger synergies through the merger (Rhodes-Kropf & Robinson, 2008).
Table 3: Merger Value Estimation

<table>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
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<td><strong>MAHA</strong></td>
<td>95.27**</td>
<td>95.857**</td>
<td>64.116**</td>
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<td>[35.333, 95.302]</td>
<td>[35.323, 94.703]</td>
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<tr>
<td><strong>PMAHA</strong></td>
<td>79.635**</td>
<td>74.076**</td>
<td>77.104**</td>
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<tr>
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<td>[35.333, 95.302]</td>
<td>[35.323, 94.703]</td>
<td>[23.973, 86.925]</td>
<td>[130x203]</td>
<td>(1) (2) (3) (4) (5) (6) (7) (8)</td>
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<tr>
<td><strong>CR</strong></td>
<td>69.251**</td>
<td>65.042**</td>
<td>82.762**</td>
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<td>[25.541, 93.370]</td>
<td>[31.247, 91.619]</td>
<td>[25.889, 91.178]</td>
<td>[130x203]</td>
<td>(1) (2) (3) (4) (5) (6) (7) (8)</td>
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<tr>
<td><strong>PCR</strong></td>
<td>22.259**</td>
<td>22.483**</td>
<td>83.457**</td>
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<td>[14.775, 74.487]</td>
<td>[11.456, 74.244]</td>
<td>[30.233, 91.065]</td>
<td>[130x203]</td>
<td>(1) (2) (3) (4) (5) (6) (7) (8)</td>
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<td><strong>SameState</strong></td>
<td>3.288</td>
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<td>7.583</td>
<td>12.193</td>
<td>10.984</td>
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<td>[-27.897, 15.920]</td>
<td>[-25.619, 39.262]</td>
<td>[-11.296, 52.144]</td>
<td>[-18.976, 60.679]</td>
<td>[130x203]</td>
<td>(1) (2) (3) (4) (5) (6) (7) (8)</td>
<td></td>
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</tr>
<tr>
<td><strong>Tobin's Q</strong></td>
<td>1**</td>
<td>1**</td>
<td>1**</td>
<td>1**</td>
<td>1**</td>
<td>1**</td>
<td>1**</td>
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<tr>
<td></td>
<td>Normalized</td>
<td>Normalized</td>
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<td>Normalized</td>
<td>Normalized</td>
<td>Normalized</td>
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</tr>
<tr>
<td><strong>R&amp;D intensity</strong></td>
<td>7.342</td>
<td>2.167</td>
<td>94.391</td>
<td>42.731</td>
<td>87.434</td>
<td>42.534</td>
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<td><strong>Inequalities</strong></td>
<td>2.684</td>
<td>2.684</td>
<td>3.064</td>
<td>3.064</td>
<td>671</td>
<td>671</td>
<td>13.250</td>
<td>13.250</td>
</tr>
<tr>
<td><strong>% of Ineq. satisfied</strong></td>
<td>71.76%</td>
<td>71.68%</td>
<td>72.58%</td>
<td>72.69%</td>
<td>88.82%</td>
<td>90.31%</td>
<td>%</td>
<td>%</td>
</tr>
<tr>
<td><strong>Merger markets</strong></td>
<td>46</td>
<td>46</td>
<td>41</td>
<td>41</td>
<td>46</td>
<td>46</td>
<td>46</td>
<td>46</td>
</tr>
</tbody>
</table>

**Note:** We use the maximum score estimation in all the columns and run the estimation first setting the coefficient for an interaction term between merging firms’ Tobin’s Q to +1, and then fixing it to -1. We then select the vectors of parameter estimates that maximize the maximum score objective function. The selected coefficient for the interaction term of Tobin’s q (Tobin’s Q at) is +1. R&D intensity at is the interaction term between acquirer’s and target firm’s R&D intensity. 95% confidence interval is shown in brackets. The coefficients are significant at the 5% level when the confidence interval does not contain 0. Merger market is defined by the combination of target firms’ industry type and merger transaction year in Columns (1), (2), (5) to (8). For Columns (3) and (4), merger market is constructed by using acquiring firms’ industry type and merger year.

**p < 0.05**
Furthermore, since the coefficient for the interaction term of Tobin’s Q is normalized to +1, we measure the relative importance of each covariate in generating merger value. In Table 4, we multiply one standard deviation of each covariate to its corresponding point estimate reported in Columns (1) and (2) of Table 3 for comparison. According to the results, MAHA has the largest impact in creating merger value, and then followed by PMAHA. That is, when we increase MAHA by one standard deviation (0.51), the merger value rises by 48.59. The increase in one standard deviation of PMAHA (0.26) raises the merger value by 20.71. On the other hand, an increase in one standard deviation of CR and PCR raises the match value by 17.25 and 7.81, respectively. The impact of MAHA is three times larger than that of CR, which suggests that the technology spillover across and within patent classes are both important to create merger value. The impact of PMAHA is four times larger than that of PCR, which suggests that the product market synergies from reducing competition and from internalizing externality across complementary products are both important to create merger value. Furthermore, when there is an increase in one standard deviation (0.266) of interaction term between merging firms’ Tobin’s Q, the merger value increases by 0.266, only about 0.5% of the rise in the merger value due to the changes in MAHA.
Table 4: Relative Importance of Covariates in Match Value

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>69.29</td>
<td>0.25</td>
<td>17.25</td>
<td>65.04</td>
<td>0.25</td>
<td>16.26</td>
<td>82.76</td>
<td>0.25</td>
<td>20.69</td>
</tr>
<tr>
<td>PCR</td>
<td>22.26</td>
<td>0.35</td>
<td>7.81</td>
<td>22.48</td>
<td>0.35</td>
<td>7.87</td>
<td>83.46</td>
<td>0.35</td>
<td>29.21</td>
</tr>
<tr>
<td>MAHA</td>
<td>95.27</td>
<td>0.51</td>
<td>48.59</td>
<td>95.86</td>
<td>0.51</td>
<td>48.89</td>
<td>64.12</td>
<td>0.51</td>
<td>32.7</td>
</tr>
<tr>
<td>PMAHA</td>
<td>79.64</td>
<td>0.26</td>
<td>20.71</td>
<td>74.08</td>
<td>0.26</td>
<td>19.26</td>
<td>77.1</td>
<td>0.26</td>
<td>20.05</td>
</tr>
<tr>
<td>Tobin’s Q_{at}</td>
<td>1</td>
<td>0.266</td>
<td>0.266</td>
<td>1</td>
<td>0.266</td>
<td>0.266</td>
<td>1</td>
<td>0.266</td>
<td>0.266</td>
</tr>
</tbody>
</table>

Note: Est. indicates a point estimate of each covariate in Table 3. Point estimates in Column (1) come from Column (1) and (2) in Table 3, those in Column (4) are from Column (3) and (4) in Table 3, and those in Column (7) come from Column (5) and (6) in Table 3. Tobin’s Q_{at} is the interaction term between acquirer’s and target firm’s Tobin’s Q.
Finally, we examine the goodness-of-fit of our matching model. To this end, we compare the acquirer-target pairs in a stable matching equilibrium with those in observed matching. When the stable matching assignments are similar to the realized merger pairs, the empirical matching model has a predictive power. The procedure of generating predicted matches from our model is as follows. First, we use the estimated coefficients reported in Column 2 of Table 3 to compute all the possible merger values. Then, deferred acceptance algorithm based on these match values is applied to matching games in all the merger markets to find pairwise stable matching assignments.

Table 5: Year-by-Year Goodness-of-Fit

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Mergers</th>
<th>Predicted Match (1)</th>
<th>Prediction Rate (%)</th>
<th>Average Rank</th>
<th>Predicted Match (2)</th>
<th>Prediction Rate (%)</th>
<th>Average Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>5</td>
<td>0</td>
<td>0%</td>
<td>72%</td>
<td>1</td>
<td>40%</td>
<td>75%</td>
</tr>
<tr>
<td>1997</td>
<td>21</td>
<td>6</td>
<td>29%</td>
<td>58%</td>
<td>8</td>
<td>40%</td>
<td>74%</td>
</tr>
<tr>
<td>1998</td>
<td>18</td>
<td>10</td>
<td>56%</td>
<td>70%</td>
<td>12</td>
<td>68%</td>
<td>66%</td>
</tr>
<tr>
<td>1999</td>
<td>37</td>
<td>7</td>
<td>19%</td>
<td>69%</td>
<td>8</td>
<td>41%</td>
<td>74%</td>
</tr>
<tr>
<td>2000</td>
<td>29</td>
<td>18</td>
<td>62%</td>
<td>62%</td>
<td>16</td>
<td>55%</td>
<td>75%</td>
</tr>
<tr>
<td>2001</td>
<td>30</td>
<td>9</td>
<td>30%</td>
<td>65%</td>
<td>12</td>
<td>47%</td>
<td>67%</td>
</tr>
<tr>
<td>2002</td>
<td>22</td>
<td>8</td>
<td>36%</td>
<td>71%</td>
<td>7</td>
<td>41%</td>
<td>75%</td>
</tr>
<tr>
<td>2003</td>
<td>16</td>
<td>11</td>
<td>60%</td>
<td>76%</td>
<td>11</td>
<td>60%</td>
<td>81%</td>
</tr>
<tr>
<td>2004</td>
<td>15</td>
<td>6</td>
<td>40%</td>
<td>70%</td>
<td>9</td>
<td>50%</td>
<td>76%</td>
</tr>
<tr>
<td>2005</td>
<td>17</td>
<td>13</td>
<td>76%</td>
<td>71%</td>
<td>10</td>
<td>75%</td>
<td>77%</td>
</tr>
<tr>
<td>2006</td>
<td>14</td>
<td>8</td>
<td>57%</td>
<td>68%</td>
<td>7</td>
<td>73%</td>
<td>75%</td>
</tr>
<tr>
<td>Total</td>
<td>224</td>
<td>96</td>
<td>43%</td>
<td>68%</td>
<td>101</td>
<td>45%</td>
<td>74%</td>
</tr>
</tbody>
</table>

Note: Predicted Match (1) represents the number of observed matches consistent with equilibrium matches driven by the match values computed using estimates in Column (1) of Table 3. Predicted Match (2) represents the number of observed matches consistent with equilibrium matches driven by the match values computed using estimates in Column (2) of Table 3. Average Rank indicates the percentile of realized merger matches relative to values of all the counterfactual matches.

Table 5 shows the goodness-of-fit of our model by year. Finally, we compare the merger matches in the stable matching equilibrium and those observed in the data. Our model predicts 101 mergers among 224 transactions, indicating 45% of prediction rate. Except for 1996 and 1999, the merger prediction rate of the model is more than 50%.
When it comes to the highest value, there are 117 mergers having the merger value higher than all counterfactual mergers. This implies that some acquirer purchases a target firm with lower match value. It is because the acquiring firm’s potential target with the highest value is matched to another acquirer who provides a higher offer to the target.

4.2 Model Extension

4.2.1 Alternative Market Definition

The first extension is on the specific merger market definition used in our benchmark model. In this robustness check, we define the merger market as the combination of acquirer’s industry types and merger transaction year. We report the results from this alternative market definition in Column (3) and (4) of Table 3. Encouragingly, they are qualitatively similar to the results in Column (1) and (2) of Table 3. The coefficients of CR and PCR are positive and significant in Column (1), and the coefficients of MAHA and PMAHA are positive and significant in Column (2). Both model specifications suggest that technology spillover and product market synergies create merger value.

4.2.2 Predetermination of Acquirer and Target Sets

Columns (5) and (6) in Table 3 reports the estimation results for this robustness check. The coefficient of PMAHA is positive and significant, suggesting that complementarity in merging firms’ products increases merger value. Further, the coefficient of CR is positive and significant. However, the percentage of stable equilibrium inequalities satisfied only 71.68% in this robustness check, which is lower than 91.12% in the benchmark model. These results indicate that our benchmark model is more appropriate to explain the merger partner choices than the model using extended sets of acquirers and target firms. We interpret these results as the choice of being either acquirer or target is driven by acquirer- or target-specific characteristics rather than match-specific characteristics.
4.2.3 Merging or Staying Independent

The third model extension is to include non-merging firms into the sample. Before choosing a merger partner, a firm decides whether to merge or to stay alone. Then, it chooses to merge with a firm that is expected to achieve synergies. By including stand-alone firms in our sample, we alleviate the endogeneity problem caused by the correlation between unobservables driving merger partner choice and merger decision.

The following example shows how to construct maximum score inequalities in this case. Suppose that there are 5 firms in a merger market, 2 acquirers \( a \) and \( \tilde{a} \), 2 targets \( t \) and \( \tilde{t} \) and a nonmerging firm \( s \). Their matching outcomes are \((a, t), (\tilde{a}, \tilde{t}) \in \mu \) and \( s \in SA \), where \( SA \) represents a set of stand-alone firms. For two realized merger pairs \((a, t)\) and \((\tilde{a}, \tilde{t})\), we use the inequality (5) to determine whether they belong to stable matching equilibrium. However, to compare match value between observed merger pairs and a stand-alone firm, we impose the following assumptions. First, we assume that a non-merging firm’s similarity and complementarity of technology and product are zero. It is because those distances cannot be defined for a stand-alone firm. Second, we set the interaction term of R&D intensity and Tobin’s Q to individual firm’s characteristics. Based on these assumptions, a stable matching inequality can be written as

\[
V(a, t) + V(s, 0) \geq V(a, 0) + V(s, t),
\]

(12)

where \((s, 0)\) and \((a, 0)\) represent stand-alone firms. Even though a stand-alone firm \( s \) plays a role as an acquirer in Equation (13), it can also be acquired by another firm. Thus, we can construct an additional inequality

\[
V(a, t) + V(0, s) \geq V(a, s) + V(0, t).
\]

(13)

When it comes to two non-merging firms \( s_1 \) and \( s_2 \), they prefer to be stand-alone firms rather than merging with each other. This implies the following inequality

\[
V(s_1, 0) + V(s_2, 0) \geq V(s_1, s_2).
\]

(14)
Taken together, our maximum score objective function becomes

\[
Q(\alpha) = \sum_{m=1}^{n} \left\{ \sum_{s,s_1,s_2 \in SA_m} \sum_{(a,t),(\tilde{a},\tilde{t}) \in \mu_m} 1 \left[ \{q_1(\alpha) \geq 0\} \cap \{q_2(\alpha) \geq 0\} \right] + 1 \left[ \{q_3(\alpha) \geq 0\} \cap \{q_4(\alpha) \geq 0\} \right] + 1 [q_5(\alpha) \geq 0] + 1 [q_6(\alpha) \geq 0] \right\},
\]

(15)

where

\[
q_1(\alpha) = V(a, t|\alpha) + V(\tilde{a}, \tilde{t}|\alpha) - V(a, \tilde{t}|\alpha) - V(\tilde{a}, t|\alpha),
\]

\[
q_2(\alpha) = V(a, t|\alpha) + V(s, 0|\alpha) - V(a, 0|\alpha) - V(s, t|\alpha),
\]

\[
q_3(\alpha) = V(a, t|\alpha) + V(0, s|\alpha) - V(a, s|\alpha) - V(0, t|\alpha),
\]

\[
q_4(\alpha) = V(\tilde{a}, \tilde{t}|\alpha) + V(s, 0|\alpha) - V(\tilde{a}, 0|\alpha) - V(s, \tilde{t}|\alpha),
\]

\[
q_5(\alpha) = V(\tilde{a}, \tilde{t}|\alpha) + V(0, s|\alpha) - V(\tilde{a}, s|\alpha) - V(0, \tilde{t}|\alpha),
\]

\[
q_6(\alpha) = V(s_1, 0|\alpha) + V(s_2, 0|\alpha) - V(s_1, s_2|\alpha).
\]

Columns (7) and (8) of Table 3 present the results for the model including stand-alone firms into the sample. Being consistent with our benchmark estimation results, the coefficient of MAHA is positive and significant, suggesting that complementarity in merging firms’ technologies plays a positive role in selecting to merger and whom to merger with. More importantly, containing stand-alone firms into the sample allows us to pin down the effect of technology complementarity on merger value more precisely. As a result, we obtain a larger estimate of MAHA relative to the estimate in Column 5 of Table 3.

4.3 Counterfactual Analysis

In this sub-section, we perform counterfactual experiments exploring changes in merger value function when technology and product complementarities are assumed to have no effect on merger value function. In other words, our counterfactual experiments examine characteristics of the matches in a stable equilibrium if firms do not consider similarity or complementarity in technology and product as a determinant of merger value function.

Table 6 shows the results of these counterfactual experiments. First, we turn the
<table>
<thead>
<tr>
<th></th>
<th>(1) CR</th>
<th>(2) MAHA</th>
<th>(3) PCR</th>
<th>(4) PMAHA</th>
<th>% drop in match value</th>
<th>(6) Prediction rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline Model (1)</td>
<td>0.471</td>
<td>0.5</td>
<td>0%</td>
<td>42.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{CR} = 0$</td>
<td>0.259</td>
<td>0.487</td>
<td>46.1%</td>
<td>39.1%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{PCR} = 0$</td>
<td>0.387</td>
<td>0.292</td>
<td>14.8%</td>
<td>40.2%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{CR} = 0 &amp; \alpha_{PCR} = 0$</td>
<td>0.244</td>
<td>0.243</td>
<td>51.7%</td>
<td>34.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline Model (2)</td>
<td>1.042</td>
<td>0.416</td>
<td>0%</td>
<td>45.1%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{MAHA} = 0$</td>
<td>0.809</td>
<td>0.454</td>
<td>66.8%</td>
<td>30.4%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{PMAHA} = 0$</td>
<td>0.995</td>
<td>0.229</td>
<td>24.5%</td>
<td>38.1%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{MAHA} = 0 &amp; \alpha_{PMAHA} = 0$</td>
<td>0.690</td>
<td>0.188</td>
<td>75.2%</td>
<td>21.6%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note:* $\alpha_{CR}$, $\alpha_{MAHA}$, $\alpha_{PCR}$ and $\alpha_{PMAHA}$ indicate an estimated coefficient for CR, MAHA, PCR and PMAHA respectively. We do each counterfactual experiment by setting corresponding parameter estimate in the baseline model to 0 and finding stable equilibrium matches based on deferred acceptance algorithm. CR, MAHA, PCR and PMAHA are the averages of those measures of all the equilibrium matches in each counterfactual experiment. % drop in match value represents % decrease in sum of match values from equilibrium matches in each counterfactual experiment compared to value sum of equilibrium matches in our baseline model.
coefficient of MAHA to zero and compute the stable equilibrium matches. The average of technology similarity in equilibrium matches decreases from 0.402 in the benchmark model to 0.259 in this counterfactual experiment, and the average of technology complementarity in equilibrium matches decreases from 0.975 in the benchmark model to 0.712 in this counterfactual experiment. The reductions of CR and MAHA in equilibrium matches from the benchmark and this counterfactual experiment are 0.14 and 0.26, which are equivalent to 46% and 44% of one standard deviation of those measures, respectively. Firms select merger partners with less complementary technologies if technology complementarity does not appear in the merger value function. More importantly, when it comes to a decrease in match values in this counterfactual experiment, it shows about 46.1% reduction in value sum of equilibrium matches relative to value sum from baseline equilibrium matches. The prediction rate of our model for observed merger decreases from 64.7% to 41.1%. These results suggest that the inclusion of technology complementarity is significantly important to explain merger partner choices.

Second, we turn the coefficient of PMAHA to zero and compute the stable equilibrium matches. The reductions of PCR and PMAHA in equilibrium matches from the benchmark and this counterfactual experiment are 0.06 and 0.05, which are equivalent to 13% and 15% of one standard deviation of those measures, respectively. Firms select merger partners with less complementary products if they do not concern about product complementarity in the merger value function. Moreover, the counterfactual model generates 14.5% lower merger value and predicts 7.6% fewer realized matches among entire observed matches. These results imply that product complementarity also plays a crucial role in merger partner choices.

4.4 Post-Merger Outcomes

The choice of merger partner is made under the expectation of mutual gain. The probability of merger between firms with complementary technologies and products is higher because they expect a greater synergy from combining those resources. An important aspect of merger synergy for creating value is the post-merger innovation. Thus,
the merger value is expected to be positively related to those post-merger outcomes if the anticipated merger synergy realized. Such relationship also provides a support for the specification of our model.

In this sub-section, we regress the post-merger outcomes on the estimated merger value. The regressions also control for year and industry fixed effects as well as acquirer- and target-specific attributes. Thus, the post-merger outcome equation is

\[
Y_i = \beta_1 V_i + X_{a_i} \beta_2 + X_{t_i} \beta_3 + \nu_{\text{year}} + \xi_{\text{industry}} + \epsilon_i, \tag{16}
\]

where \(Y_i\) represents a merged firm \(i\)'s post-merger outcome variables. \(V_i\) is the firm \(i\)'s estimated merger value. \(X_{a_i}\) and \(X_{t_i}\) are acquirer- and target-specific characteristics, respectively. \(\nu_{\text{year}}\) represents year fixed effects, \(\xi_{\text{industry}}\) represents industry fixed effects, and \(\epsilon_i\) is an unobserved error term.

Table 7 reports the relationship between post-merger outcomes and estimated merger value, where the estimated merger value is based on Column (5) of Table 3. First, we examine how the merger value relates to post-merger valuation in stock market. We use two different types of Tobin’s Q to measure the merged firm’s short- and long-run valuations based on the expectation of discounted present value. The coefficients in Column (1) and (2) are positive and significant, suggesting that the merger value has positive influences in the firm’s valuation in the merger year and over the three-year period after the merger, respectively. Taken together, the merger value positively relates to the merged firm’s short- and long-run valuations.

Next, we turn to the relationship between estimated merger value and post-merger innovation outcomes. The coefficients on the merger value are positive and significant in Columns (3) to (4) of Table 7. These results indicate that the larger the merger value, the more patents and citations after the merger. In addition, the coefficient in Column (5) is positive, suggesting that the merger value is more related to innovation quality than innovation quantity.

The estimates of match value are positive and significant in Columns (6) and (7). It suggests that the merger value is positively correlated with originality and generality of
### Table 7: Post-Merger Outcomes

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Match Value</strong></td>
<td>0.0439</td>
<td>0.0405*</td>
<td>0.503***</td>
<td>0.573***</td>
<td>0.0552*</td>
<td>0.0418*</td>
<td>0.0364*</td>
<td>0.0568*</td>
</tr>
<tr>
<td></td>
<td>(0.0267)</td>
<td>(0.0161)</td>
<td>(0.107)</td>
<td>(0.120)</td>
<td>(0.0299)</td>
<td>(0.0163)</td>
<td>(0.0179)</td>
<td>(0.0274)</td>
</tr>
<tr>
<td><strong>Acquirer</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>0.122</td>
<td>0.0724</td>
<td>-0.711</td>
<td>-0.997</td>
<td>-0.239</td>
<td>0.0664</td>
<td>0.120</td>
<td>-0.309*</td>
</tr>
<tr>
<td></td>
<td>(0.148)</td>
<td>(0.0892)</td>
<td>(0.589)</td>
<td>(0.662)</td>
<td>(0.165)</td>
<td>(0.0896)</td>
<td>(0.0985)</td>
<td>(0.151)</td>
</tr>
<tr>
<td>Tobin’s Q</td>
<td>-3.735***</td>
<td>-3.458**</td>
<td>0.500</td>
<td>-0.298</td>
<td>-0.276</td>
<td>-0.471</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.087)</td>
<td>(1.222)</td>
<td>(0.304)</td>
<td>(0.165)</td>
<td>(0.182)</td>
<td></td>
<td>(0.278)</td>
<td></td>
</tr>
<tr>
<td><strong>Target</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>0.0719</td>
<td>0.0723</td>
<td>-0.194</td>
<td>-0.126</td>
<td>0.0894</td>
<td>0.0131</td>
<td>-0.0150</td>
<td>0.131</td>
</tr>
<tr>
<td></td>
<td>(0.0667)</td>
<td>(0.0401)</td>
<td>(0.265)</td>
<td>(0.298)</td>
<td>(0.0741)</td>
<td>(0.0403)</td>
<td>(0.0444)</td>
<td>(0.0678)</td>
</tr>
<tr>
<td>Tobin’s Q</td>
<td>0.335</td>
<td>0.339</td>
<td>0.0677</td>
<td>0.132</td>
<td>0.140</td>
<td>0.164</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.712)</td>
<td>(0.801)</td>
<td>(0.199)</td>
<td>(0.108)</td>
<td>(0.119)</td>
<td>(0.182)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year effects</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Industry effects</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Observations</td>
<td>224</td>
<td>224</td>
<td>224</td>
<td>224</td>
<td>224</td>
<td>224</td>
<td>224</td>
<td>224</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.235</td>
<td>0.242</td>
<td>0.225</td>
<td>0.382</td>
<td>0.653</td>
<td>0.421</td>
<td>0.461</td>
<td>0.072</td>
</tr>
</tbody>
</table>

**Note:** Robust standard errors are in parentheses. We use OLS estimation in all the columns. The dependent variables are as follows. Tobin’s Q in a merger year (TOBINQ) in Column (1). The average of post-merger Tobin’s Q (AVERQ) in Column (2). The logged number of patents (PAT) in Column (3). The logged number of citation-weighted patents (CWP) in Column (4). The ratio of citation counts to patent counts (CITINT) in Column (5). The 90 percentile of originality of patents (ORIG) in Column (6). The 90 percentile of generality of patents (GENERAL) in Column (7). The standard deviation of CWP during 3 years after merger (STDV) in Column (8). The Match Value is computed using the estimated parameters in Column (6) of Table 3.

$\dagger \; p < 0.10, \; * \; p < 0.05, \; ** \; p < 0.01, \; *** \; p < 0.001$

Further, since Table 4 reports that technology complementarity (i.e. MAHA) and product complementarity (i.e PMAHA) are two important elements in the merger value function, we examine their economic impacts on the post-merger outcomes. We rank the observed mergers according to their MAHA and PMAHA values. Then, we examine the post-merger outcomes for the group of mergers with MAHA and PMAHA in first quarter and the group of mergers with MAHA and PMAHA in last quarter. We interpret mergers with higher MAHA and PMAHA values as good matches, whereas mergers with lower MAHA and PMAHA values as bad matches.

Table 8 shows the difference in post-merger outcomes between two merger groups with technological diversity, and patenting volatility.
### Table 8: Merger Value and Post-Merger Outcomes by Different Similarity

<table>
<thead>
<tr>
<th></th>
<th>(1) Match Value</th>
<th>(2) TOBINQ</th>
<th>(3) AVERQ</th>
<th>(4) PAT</th>
<th>(5) CWP</th>
<th>(6) CITINT</th>
<th>(7) ORIG</th>
<th>(8) GENERAL</th>
<th>(9) STDV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Difference between High and Low CR group</strong></td>
<td><strong>64.82</strong>*</td>
<td>0.261**</td>
<td>0.307***</td>
<td>0.685*</td>
<td>0.554</td>
<td>-0.078</td>
<td>0.065</td>
<td>0.014</td>
<td>0.207†</td>
</tr>
<tr>
<td></td>
<td>(2.41)</td>
<td>(0.11)</td>
<td>(0.09)</td>
<td>(0.40)</td>
<td>(0.48)</td>
<td>(0.13)</td>
<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.08)</td>
</tr>
<tr>
<td><strong>Difference between High and Low PCR group</strong></td>
<td><strong>42.46</strong>*</td>
<td>0.356**</td>
<td>0.332***</td>
<td>-0.439</td>
<td>-0.503</td>
<td>-0.022</td>
<td>0.037</td>
<td>-0.072</td>
<td>0.071</td>
</tr>
<tr>
<td></td>
<td>(3.35)</td>
<td>(0.09)</td>
<td>(0.07)</td>
<td>(0.37)</td>
<td>(0.48)</td>
<td>(0.15)</td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.08)</td>
</tr>
<tr>
<td><strong>Difference between High and Low MAHA group</strong></td>
<td><strong>164.80</strong>*</td>
<td>0.160*</td>
<td>0.187*</td>
<td>1.779***</td>
<td>1.816***</td>
<td>0.056</td>
<td>0.125*</td>
<td>0.065</td>
<td>0.200*</td>
</tr>
<tr>
<td></td>
<td>(8.04)</td>
<td>(0.09)</td>
<td>(0.08)</td>
<td>(0.40)</td>
<td>(0.50)</td>
<td>(0.15)</td>
<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.09)</td>
</tr>
<tr>
<td><strong>Difference between High and Low PMAHA group</strong></td>
<td><strong>104.42</strong>*</td>
<td>0.058</td>
<td>0.082</td>
<td>0.219</td>
<td>0.087</td>
<td>-0.153</td>
<td>-0.070</td>
<td>-0.026</td>
<td>0.150*</td>
</tr>
<tr>
<td></td>
<td>(12.07)</td>
<td>(0.09)</td>
<td>(0.07)</td>
<td>(0.40)</td>
<td>(0.48)</td>
<td>(0.14)</td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.09)</td>
</tr>
</tbody>
</table>

*Note:* Robust standard errors are in parentheses. Merger value and post-merger outcomes in each group of mergers are the average of 56 observations in each group.

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
high and low MAHA and that between two merger groups between high and low PMAHA. Column (1) reports that the merger value is greater for merger with a higher technology complementarity. Column (3) shows that the group of mergers with high MAHA has average Tobin’s Q by 14% points higher than the group of mergers with lower MAHA over three-year periods after the merger. Moreover, most of the post-merger innovation outcomes are significantly larger for the group of mergers with higher MAHA. These results suggest that a better innovation outcome is a source of merger synergy for merger driven by complementary technologies between merging partners. Further, when it comes to the comparison between the mergers with high PMAHA and low PMAHA, the former group of mergers has average Tobin’s Q by 10% points higher than the latter group of mergers over three-year periods after the merger (see Column 3). However, there is no significant difference for post-merger innovation outcomes between high and low PMAHA groups. We suggest that mergers driven by complementary products between merging firms may seek synergy in pricing coordination and cost reduction.

5 Conclusion

This paper examines the effects of complementarities between firms’ technology and product on merger value creation. We find that firms prefer to match with the other firm that has complementary technologies and produces complementary products. All these results suggest that merging firms perceive complement technologies and products as sources of merger synergy. Technology and product complementarities contribute a substantial portion of value creation from merger and improve the predictive power of our model. Post-merger innovation quantity, innovation quality, and firm valuation are both higher for mergers with a higher estimated merger value, suggesting mutual benefits for both the merging firms from assortative matching in complementary technologies and products.

The managerial implication of our analysis highlights the importance of merging with the right partner in addition to merging with a good partner. While our analysis does not
imply that mergers are in general patent and value creating, it does suggest that firms within a merger market tend to sort into merger pairs in order to maximize post-merger performance. Mergers between firms with complementary technologies and products are expected to achieve synergy because there is a considerable boost in post-merger performance. Since divestiture and consolidation after merger are costly processes, managers would be wise to consider technology and product complementarities as two additional factors for deciding a potential merger.

References


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