Inventor Mobility and Value Creation in Mergers and Acquisitions

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Version: April 17, 2022

Abstract: This paper examines the impacts of inventor mobility in value creation in mergers and acquisitions (M&As). We employ a two-sided matching model for acquirers and targets that allows them to choose whom to merge with. Applying this model, we examine how inventor mobility affects value creation in M&As in the manufacturing sector. Inventors exchanged between inventing firms have been interpreted as a mechanism of knowledge transfer. For firms in the M&A market, it can be seen as (1) an indicator of compatibility and therefore a predictor of M&A, (2) a search and screening strategy for identifying a potential merger partner's compatibility, (3) or laying the groundwork for a successful merger. We measure inventor mobility by the turnover of inventors between acquirer and target before the merger. Based on a sample of 348 mergers of the U.S. manufacturing firms during 1980-2015, we find that an exchange of inventors between firms increases the value of their merging, which in turn increases their merger likelihood. After instrumenting for inventor mobility, the positive relationship between mobility and merger likelihood remains, suggesting at least some of mobility's effect on merger likelihood is causal ((1) and (3)).

Keywords: Inventor, Innovation, Merger, Matching

JEL codes: G34, L13, 031, 032

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1. Introduction

Mergers and acquisitions (hereafter, M&As) have become a major strategy for firms' growth in technology industries. Since the merger process is costly, a successful merger depends on whether the merger can create value (Haspeslagh and Jemison, 1991). A firm in a technology industry can use a merger to create value by renewing and reconfiguring its resource portfolio, leveraging its knowledge, and sharing know-how and intellectual property rights with its merger partner (Karim and Mitchell, 2000; Ahuja and Katila, 2001; Puranam and Srikanth, 2007).

However, the hoped-for value from an M&A may never materialize. Prior studies report that less than 40 percent of firms accomplished their goals from M&A transactions (Shrivastava, 1986; Sirower, 1997; Larsson and Finkelstein, 1999; Bogan and Just, 2009; Thelisson, 2020). Studies have found that mergers are more likely to fail when the merging partners are distant in their technological domains and organizational characteristics (Desyllas and Hughes, 2010; Phillips and Zhdanov, 2013; Bena and Li, 2014; Haucap et al., 2019). It is of policy and managerial interest to explore factors that facilitate value creation of merger.

This paper examines the role of inventor mobility in creating merger value in the technology sector. Inventor mobility is surprisingly common in the years leading up to a merger. We find 31.6% of M&As (see section 4.4 below) are preceded by at least one instance of inventor sharing. Because inventors tend to specialize by technology (Jones, 2009), if we see inventors on patents of two firms, we can infer the firms have R&D programs in common, a predictor of merger value. Similarly, inventor sharing between two firms may represent a collaboration that is exploiting a technological complementary between the two firms. Observing this collaboration on a published patent means that such a collaboration has borne fruit possibly signaling to both firms the potential for additional complementaries to be realized via merger. In addition to revealing merger value, inventor mobility may create merger value. Mobile inventors transfer skills and knowledge which can help a firm absorb stimuli and information from outside the firm (Arrow, 1962; Levin et al. 1987; Stephan, 1996; Almeida and Kogut, 1999; Kim and Marschke, 2005). Also, mobile inventors allow the two merging firms to share "cognitive elements," such as administrative and cultural practices (Wagner and Goossen, 2018), which with technological transfers reduce informational asymmetries between them. This paper tests whether greater inventor mobility – inventors moving between firms – creates more value from a merger and hence increases the probability of a merger.

Our empirical analysis is based on a structural model of two-sided matching between acquirer and target. In this model, firms are heterogeneous. The same acquirer matches with different targets creating different merger values, and the merger market is in a pairwise stable equilibrium (Roth and Sotomayor, 1992). That is, two observed acquirer-target pairs cannot gain by forming counterfactual mergers. Since our paper focuses on inventor mobility as a source of merger value creation, we postulate that inventor mobility is a part of the merger value function. Here, we measure inventor mobility using inventor information in the U.S patent records. We define inventor sharing as any overlap of inventors between the two merging firms before the merger. In addition to inventor sharing, our specification of the merger value function contains as controls technological similarity, geographical proximity, an interaction term of two merger partners' Tobin's Q, and an interaction of their R&D intensity.

We then estimate the merger value function using a maximum score estimator approach with the necessary conditions derived from the stable matching equilibrium (Fox, 2010; 2018). The estimated parameters in the merger value function 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 changing merger partners. Our modeling approach has several advantages. First, true merger values driving the decision to merge are unobserved. Our structural model recovers the merger value, especially the valuation impact of inventor mobility. Second, a merger transaction not only affects the merging firms but also influences the rest of the firms in the same merger market. Once a firm is acquired, it is excluded from the choice set of other acquirers. Accordingly, every merger within the same merger market is interdependent with each other. In contrast to a standard discrete choice model, our structural model accounts for such strategic interaction among firms competing within a merger market.

Our empirical results show that inventor mobility between an acquirer and a target is an important determinant in creating merger value. Taking advantage of the structural estimation, we conduct counterfactual experiments to examine the importance of inventor mobility in creating merger value. If inventor mobility in the merger value function was ignored, the merger value would fall by about four-fifths compared to the benchmark case, and the model prediction rate, a measure of goodness-of-fit, would fall by about 14.9 percentage points.

We also consider a quasi-natural experiment to ensure the causality of inventor mobility by using temporal and geographical variation in non-compete law as an instrument for mobility: We use Bishara (2010) index of non-compete covenant enforcement to instrument for inventor sharing. This allows us to interpret the coefficient on the instrumented inventor sharing measure as describing the causal effect of sharing on merging.

Finally, we perform robustness checks. First, we extend our model to include a condition that an observed acquirer cannot gain by acting as a target in any counterfactual merger, and vice versa. Second, we extend our model to include the decision whether to enter the M&A market. The first two checks aim to examine the assumption that our model only allows firms to choose their merging partners, but not their roles as an acquirer or a target and not their decision to merge. Finally, we test the robustness of our main results by using an alternative measure of inventor mobility, considering impact power of inventors, examining various time windows, and including alternative a control variable. Encouragingly, our model is robust to those checks.

Our paper first contributes to the empirical literature using a two-sided matching model to examine merger partner choices. Akkus et al. (2015), Ozcan (2015) and Linde and Siebert (2020) are three papers that are close to ours in that they use the two-sided matching model with transferable utility. We extend this literature by exploring the role of inventor mobility in generating merger value, and by exploring how the merger value relates to post-merger innovation. Also, we extend the two-sided matching model for mergers to allow firms to choose their roles as acquirer or target and to choose merger or not. Second, we contribute to a growing literature that examines how an innovation relationship between a pair of firms affects their merger decision. Gavrilova (2021) finds that a firm is more likely to acquire another firm if its patents have cited the other firm's patent. Our paper differs from hers in examining the inventor mobility between a pair of firms instead of the patent citation between them as their innovation relationship.

The remaining sections of this paper are organized as follows. Section 2 develops hypotheses. Section 3 and 4 describe the empirical strategy and data, respectively. Section 5 and 6 report the empirical results. Section 7 concludes.

2. Hypothesis Development

Inventors are more likely to transfer from one another when the two firms operate in the same technology space (Rhodes-Kropf and Robinson, 2008; Hoberg and Phillips, 2010; Linde and Siebert, 2020). Frequent relocation of inventors between the merging firms demonstrates their ex-ante technology similarities. Learning-by-hiring is useful when a firm hires inventors having technologically distant knowledge (Rosenkopf and Almeida 2003; Song et al., 2003), though firms are less likely to hire away inventors whose knowledge is complementary to the knowledge embedded in their current firm (Palomeras and Melero 2010).

Hypothesis 1: Inventor mobility between potential merger firms indicates existing benefits from merging, so should be positively associated with the likelihood of a merger.

Increased ex-ante technology familiarity translates to a higher relative absorptive capacity that allows the merging firms to better identify and evaluate their technologies (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998). Inventor mobility between merging firms may increase the relatedness of human capital of those two firms. A higher human capital relatedness can facilitate communication and collaboration between workers with similar skill sets (Corredoira and Rosenkopf, 2010). A higher human capital relatedness also bridges the cultural and organizational differences between merging firms because mobile inventors typically maintain ties to their former employer and transfer cognitive elements acquired from their prior and current employer (Wagner and Goossen, 2018).

Hypothesis 2: Inventor mobility between potential merger firms cause mergers.

3. Model and Estimation

We consider an M&A as a two-sided matching problem (Roth and Sotomayor 1992). Previous studies examine the determinants of M&A with the standard discrete choice models such as probit or logit (Ornaghi, 2009; Bena and Li, 2014; Chondrakis, 2016). Nonetheless, there are two major drawbacks of the discrete choice models in a merger analysis. First, the discrete choice models cannot derive the underlying merger value driving the decision to merge but only derive the probability of the merger decision. Second, standard discrete choice models do not capture the determinants of merger partner selection because it assumes an independence among error terms in all merger observations. However, a two-sided matching merger may affect other firms' merger decisions because a merger decision of two firms in a market reduces the likelihood that the rest of firms in the market will find a proper merger partner.

A merger market is defined by the 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 one merger market is independent of a merger deal made in another market.[5] Further, we assume the matching is one-to-one because a target disappears after the merger, so that it cannot merge with more than one acquirer.

3.1 Model

There are two sets of merger firms 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. Firms are heterogeneous. 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 is called a matching $\mu_m \subset M_m$. Hence, an acquirer *a* is denoted by $\mu_m(a)$, and a target *t* 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 measured at the time of the 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, $V_a(a, t) = V(a, t) - p_{at}$,

[5] 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.

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 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, a matching μ is pairwise stable if the following inequalities hold:

$$V(a,t) - p_{at} \geq V(a,\tilde{t}) - p_{a\tilde{t}} , \quad (1)$$

$$V(\tilde{a},\tilde{t}) - p_{\tilde{a}\tilde{t}} \geq V(\tilde{a},t) - p_{\tilde{a}t} , \quad (2)$$

$V(a,t)$ and $V(\tilde{a},\tilde{t})$ are match values of realized mergers in μ, where $\tilde{a} \in A/a$ and $\tilde{t} \in T/t$. The above inequalities require 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.

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

$$V(a,t) - p_{\tilde{a}t} \geq V(a,\tilde{t}) - p_{a\tilde{t}} , \quad (3)$$

$$V(\tilde{a},\tilde{t}) - p_{a\tilde{t}} \geq V(\tilde{a},t) - p_{\tilde{a}t} . \quad (4)$$

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

$$V(a,t) + V(\tilde{a},\tilde{t}) \geq V(a,\tilde{t}) + V(\tilde{a},t) \quad (5)$$

In other words, the total value of realized mergers is weakly greater than the total value of counterfactual mergers formed by exchanging merger partners.

Even though a firm can either be an acquirer or a target, acquirers and targets show inherent differences in our data. For instance, the total asset of acquiring firms is about $25 billion which is 2.5 times greater than the total asset of target firms (about $ 10 billion) on average. Also, the employment size of acquirers (44,763) is 2.12 times greater than that of targets (21,078). Therefore, taking these differences into account, we employ the model in this section as the benchmark case, i.e., the role of firms is predetermined. We check this assumption in a robustness check.

3.2 Estimation

In this subsection, we discuss the specification of the merger value function. Since we explore the impacts of inventor mobility on the value creation of mergers, we assume that the merger value function depends on inventor mobility between potential merging partners. We specify the merger value function $V(a,t)$:

$$V(a,t|\,\beta) = \beta_1 INV_{at} + \beta_2 TS_{at} + \beta_3 PS_{at} + \beta_4 SameState_{at} + \beta_5 (Tobin\ Q_a \times Tobin\ Q_t) + \beta_6\,(R\&D_a \times R\&D_t) + \varepsilon_{at}, \quad (6)$$

where ε_{at} represents an unobserved error term for the merger between a and t. INV_{at} is measured by the number of ex-ante inventor mobility between a pair of firms to the number of employees of those two firms. The parameter of interest is β_1. A positive and significant β_1 supports *Hypothesis 1*.

Equation (6) includes four control variables. First, we control the effects of technology similarities (TS_{at}) and product line similarities (PS_{at}) on merger value creation. Previous studies find firms with similar technology and product lines can increase the value-creating opportunities through M&As (Makri et al. 2010; Bena and Li, 2014; Ozcan, 2015; Cefis et al., 2015; Rao et al., 2016; Linde and Siebert, 2020). Second, we control geographical proximity by including $SameState_{at}$. Previous studies suggest that when two firms are located close to each other, they are more likely to merge and create merger value (Erel et al., 2012; Ozcan, 2015; Cai et al., 2016). Third, we capture the impacts of merging firms' stock valuation on merger value creation. The property rights theory suggests that two firms with similar valuations of assets are more likely to merge and realize the benefits of complementary assets (Grossman and Hart, 1986; Rhodes-Kropf and Robinson, 2008; Savor and Lu, 2009). Fourth, the merger value function includes the interaction term of R&D intensity between acquirers and targets. The existing studies suggest R&D intensity is the main determinant of M&As (Blonigen and Taylor, 2000; Bertrand, 2009; Desyllas and 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 instance, in 1998, Hewlett-Packard acquired Heartstream, a maker of automated external defibrillators, which has an R&D intensity about 30 times higher than itself.

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

In practice, we apply the maximum score estimation to the merger value function. See Appendix A for estimation details.

4. Data

4.1 Data Sources and Sample Selection

Our empirical analysis combines several data sources. We collect M&A transactions from the Securities Data Company's (SDC) US Mergers and Acquisitions database. We select 348 mergers and acquisitions announced between 1981 and 2015 where both acquirer and target firms are public firms.[6] We focus on the firms in manufacturing industries with two-digit SIC codes between 20 and 39 because manufacturing firms are more technology- and product-dependent than firms in other industries, and thus innovation and the role of inventors are more crucial issues to manufacturing firms (Hsu et al., 2014).

According to the model assumptions, an M&A occurs between firms within a single merger market. Our basic idea for a merger market construction as follows. Following the approach of Bena and Li (2014) and Ozcan (2016), we convert the 4-digit SIC codes of firms in the SDC database to 3-digit NAICS (North American Industry Classification System) subsector codes.[7] However, some subsectors have too few M&A transactions to estimate a pairwise stable matching equilibrium during the sample period. Therefore, for the subsector codes that have less than ten M&A transactions, we changed the code to closest higher subsector code.[8] We continue this process until each subsector contains more than ten acquisitions during

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[6] Andrade et al. (2001) explain that mergers as instruments for market discipline did not appear until 1980s often called as the era of hostile takeovers. Since there was no M&A case which contains necessary data in 1980, we start from 1981.

[7] The NAICS sub-sector codes place codes between two industries close to each other if they have similar characteristics.

[8] Manufacturing sectors are classified by NAICS 2-digit codes (31-33) within 3-digit NAICS subsectors listed in order of similar products (311-339).

the sample period. For instance, we merge Food Manufacturing (NAICS: 311) with Beverage and Tobacco Product Manufacturing (NAICS: 312).

In addition, we adjust merger markets to construct more realistic merger markets by observing M&A records. First, we merge the Machinery Manufacturing subsector (NAICS: 333) and the Electrical Equipment, Appliance, and Component Manufacturing subsector (NAICS: 335) which are interrelated in the M&A history. Second, we separate the pharmaceutical-related M&As from the Chemical Manufacturing subsector (NAICS: 325). The M&A transactions in the pharmaceutical industry account for a significant portion of the total merger transactions. In addition, pharmaceutical firms rarely merge with other chemical firms. Third, we separate the Surgical and Medical instruments from the Machinery Manufacturing subsector (NAICS: 333), the Computer and Electronic Product Manufacturing subsector (NAICS: 335), and the Electrical Equipment, Appliance, and Component Manufacturing subsector (NAICS: 335). Fourth, if a market does not have at least five acquisitions at the coarsest level, then we drop that market from the sample. For example, we exclude M&A deals of the Apparel subsector and the Leather subsectors (NAICS: 315, 316, respectively), the Non-metallic Mineral product Manufacturing subsector (NAICS: 327), and the Furniture subsector (NAICS: 337), which have no M&A record with other subsectors. Finally, for the SIC codes which are related to two NAICS subsectors (e.g., Food Products Machinery (SIC: 3556) or Industrial Trucks and Tractors (SIC: 3537)), we refer to the acquirer's SIC code and the similar firms' M&A records.

We identify 104 merger markets of 348 M&A deals for empirical analysis. Table 1 shows these M&As classified by target firm's industry type and transaction year. Our M&A samples cover nine industry types, namely *Chemical, Computer & Semiconductor, Food, Machinery, Medical Instruments, Metal, Paper, Pharmaceutical,* and *Transportation.*[9]

[Table 1 about here]

[9] The detailed descriptions of SIC codes in those nine industries are shown in Appendix B.

We match this M&A sample with the Compustat database. We obtain year-end data of total assets, stock market capitalization, book value, research and development (R&D) expense, and sales of all public firms listed in three major US stock exchanges (New York Stock Exchange, American Stock Exchange, and National Association of Securities Dealers Automated Quotations). We use that information to construct control variables used in our merger value function.

To construct the inventor mobility variable (INV) and the post-merger outcome variables, we observe the patent application and publication records collected from the United States Patent and Trademark Office (USPTO) PatentsView database. The database contains US patent grant date, application date, citation, patent class, a unique identifier for each assignee and each inventor.

4.2 Inventor Mobility

Inventor mobility is our main variable which counts the number of inventors moving from previous firm *j* to the present firm *i* during the period t-5 to t-1. To identify inventor mobility, the prior studies observed inventor information on patent records (Hoisl 2007, Corredoira and Rosenkopf 2010, Wagner and Goossen 2018) [10]. We observe the unique inventor code on patent application records of both firms during the period t-5 to t-1. Specifically, if an inventor who assigned patent applications of previous firm *j* assigns multiple patent applications to different firm *i*, then we consider that the inventor changed employer from the firm j to the subsequent firm *i*. If more than two consecutive patent applications are observed by the same subsequent firm, then the inventor is inferred to have continued with the same employer until t-1. The merging firms are composed of patenting firms and non-patenting firms. We assume that a merger with non-patenting firms have zero inventor mobility. Since the number of inventors

[10] A commingled patent which is produced by inventors coming together form the acquired and acquiring firms can occur before an M&A, which we infer arises from inter-organizational collaboration such as an alliance. Chen et al. (2020) reports that only 1.1% of pre-acquisition patents are commingled in their USPTO PatentsView sample in 1976-2014.

may vary by the firm's size of employment, we divide the number of inventors by the number of employees of the firm.

4.3 Control Variables

First, we measure technological similarity by Mahalanobis distance (MAHA) between firms' vectors of patent shares following Bloom et al. (2013). The USPTO categorizes all the granted patents into 642 technology-based classes. A firm i's vector of patent shares over those patent classes is represented by F_i = $(F_{i,1}, F_{i,2}, \ldots, F_{i,642})$, where $F_{i,c}$ is the firm i's ratio of patent counts in class to the total number of patents. The MAHA is the weighted correlation between firms' patent class distributional vectors where the weight is defined by the correlation among all the patent classes. That is,

$$MAHA = \tilde{F}' W^m \tilde{F} ,$$

where $\tilde{F}$ is a matrix of all firms' normalized vectors of patent shares in patent classes and W^m is a weighting matrix of correlation between patent classes.[11] As Bloom et al. (2013) point out that the MAHA has an advantage in that it can reflect technology relatedness across different patent classes across complementary products. The average of technological distance variables, MAHA is 4.319 (see Table 2).

Second, we measure the product line proximity following using the structure of 6 digit-NAICS code, following Ozcan (2015). The NAICS code structure consists of a two to six digit hierarchy of classifications with five levels of details. We measure the product line proximity score by matching each digit of the NAICS codes of two merging firms. Our approach increases the score by matching the numbers from the first digit to the last two digits. For instance, the product line proximity score is 1 if the NAICS codes are 32123 and 33123 and the score is 4 if the codes are 311211 and 311221. If all the digits of NACIS are same, the product distance is five. Table 2 shows that product market distance has an average

[11] See Appendix C for an example for computing MAHA.

of 3.463, implying that on average the acquirers and the targets have the different one- or two-digit NAICS codes[12]. Third, $SameState_{at}$ is a proxy variable for the geographical distance between merging firms. It equals 1 if an acquirer and a target firm are in the same state, and zero otherwise. Table 2 reports that 20.1% of our mergers have the acquirer and target located in the same state. Fourth, we measure the stock valuation of merging firms with Tobin's Q, which is measured by the ratio of stock market value to the total asset. Fifth, R&D intensity equals the ratio of a firm's R&D expenditure to sales.

4.4 Descriptive Analysis

Table 2 reports the descriptive statistics.[13] Target firms show a higher R&D intensity than acquirers, which is consistent with the results in Blonigen and Taylor (2000). The average Tobin's Q of targets is slightly higher than that of acquirers, which means that highly valued firms are acquired.[14] The average of acquirers' stock market value before the merger is about $32.4 billion, whereas the average of targets' stock market value is approximately $10.1 billion. The composition of targets' industry is similar to that of acquirers' industry because most of the deals are horizontal mergers. In particular, more than 40% of mergers belong to the *Computer & Semiconductor* industry and the *Pharmaceutical* industry.

[Table 2 about here]

In addition, we provide some reduced-form evidence to suggest inventor mobility is relevant for merger decision. Table 3 compares the share of matches having at least one inventor mobility between observed mergers and counterfactual matches. We focus on Panel A, which generates the counterfactual matches

[12] https://www.naics.com/sic-naics-crosswalk-search-results/

[13] All financial variables are adjusted to dollar values in 2000 using consumer price index (CPI).

[14] Similar to prior studies which conducted the early 2000s, our data shows that the acquirer's Tobin's Q exceeds the target's Tobin's Q before 2010 (Andrade et al., 2001; Jovanovic and Rousseau, 2002). However, the merger and acquisitions after 2010 witness greater Tobin's Q of targets than that of acquirers. We suggest that the M&As in our data after 2010 are concentrated in the industries where even target firms are active in stock trading such as *Pharmaceutical, Machinery, and Computer and Semiconductors*. Moreover, a target firm's price rises in pre-announcement period due to the leakage of information or an anticipation of some good news. (Adnan and Hossain, 2016; Tang and Xu, 2016)

based on Inequality (5). 31.6% of observed mergers experience inventor mobility whereas less than 10% of counterfactual matches do. Also, the ratio of mobile inventors to total employees (*INV*) of observed mergers are higher than that of counterfactual mergers. It suggests that inventor mobility is positively associated with the merger likelihood.

[Table 3 about here]

Further, despite the drawbacks of the discrete choice models which we mentioned in Section 3, we estimate a probit model of whether inventor mobility affects the merger. We consider this analysis to be largely descriptive and serve as the robustness of our two-sided matching analysis. Nonetheless, the discrepancies between this analysis and our two-sided matching analysis highlight the importance of our model considering the mechanism of equilibrium matching. Specifically, we employ the following specification:

$$Y^*{}_{at} = \beta_1 INV_{at} + \beta_2 TS_{at} + \beta_3 PS_{at} + \beta_4 SameState_{at} + \beta_5 (Tobin\ Q_a \times Tobin\ Q_t) + \beta_6\, (R\&DINT_a \times R\&DINT_t) + \varepsilon_{at},$$

where Y_{at}= 1 if $Y^*{}_{at} > 0$, otherwise Y_{at}= 0. Thus, we construct the dependent variable Y_{at}= 1 if a merger is an actual merger and Y_{at}= 0 if a merger is a counterfactual combination. The error term ε_{at} follows a standard normal distribution, i.e., $\varepsilon_{at} \sim \mathrm{N}(0,1)$.

Table 4 reports that inventor mobility (*INV*) has significantly positive impacts on the probability of merger. Technology similarity, product similarity, and geographic distance between the merging firms positively affects the probability of merger. Conversely, the interaction term of two merging firms' Tobin's Q and the interaction term of two merging firms' R&D intensity are not significantly correlated with merger probability.

[Table 4 about here]

5. Empirical Results

5.1 Merger Value Creation

This sub-section discusses the results of the merger value function reported in Table 5. Column (1) reports that the coefficients for INV are positive and significant. This result suggests that inventor mobility between merging firms creates merger value and supports *Hypothesis 1*.

[Table 5 about here]

Turning to the control variables, our results show

Turning to the control variables, our results show that firms with technology proximity insignificantly relates to the probability of merger. Also, we find that the coefficient of product similarity is positive and significant. This result is in line with prior studies such as Ozcan (2015) and Linde and Siebert (2020). Further, the positive impact of R&D intensities on the merger value creation suggests that access to external knowledge is the main motivation of the merger (Blonigen and Taylor, 2000; Bertrand, 2009; Desyllas and Hughes, 2010; Phillips and Zhdanov, 2012). Moreover, the coefficient of Tobin's Q interaction between acquirer and target is positive and significant. Merging firms with a similar level of Tobin's Q can create larger synergies through the merger (Rhodes-Kropf and Robinson, 2008). Finally, we normalize the coefficient of $SameState_{at}$ to +1 considering the coefficient of $SameState_{at}$ is positive and significant in Table 4. Since any positive monotone transformation of coefficients does not affect inequalities, the normalizing allows us to compare the relative importance of covariates. This is supported by the result that we obtain a higher percentage of maximum score inequalities satisfied by setting the coefficient of $SameState_{at}$ to +1 instead of -1. It implies that merging firms in the same state can create larger synergies through the merger.

Table 6 measures the relative importance of each covariate in creating merger value because the coefficient of $SameState_{at}$ is normalized to +1. We multiply one standard deviation of each covariate to its corresponding point estimate reported in Table 5 for comparison. Panel (1) in Table 6 shows that an increase of INV by one standard deviation (1.435) raises the merger value by 133.205. The impact of INV on merger value is the largest compared to the impacts of other variables in the merger value function. For instance, the effect of INV on merger value is about three times that of the interaction terms of R&D intensities.

[Table 6 about here]

Finally, we evaluate the goodness-of-fit of our matching model by using a prediction rate. 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 predictive power. The procedure of generating predicted matches from our model is as follows. First, we use the estimated coefficients reported in Table 5 to compute all the possible merger values. Then, a deferred acceptance algorithm based on these merger values is applied to matching games in all the merger markets to find pairwise stable matching assignments. Another way of evaluating the model fit is to compare estimated merger values from realized matches with those of all matches (Akkus et al., 2015).

Table 7 shows the goodness-of-fit of our model (see Model 1). Our model predicts 197 mergers among 348 transactions, indicating 56.6% of prediction rate. For the realized mergers, their merger value is at 59.9 percentiles of all combination of firms, on average. It suggests that the estimated merger values are informative to explain observed mergers.

[Table 7 about here]

5.2 Counterfactual Analysis

In this subsection, we perform counterfactual experiments exploring how inventor mobility (INV) affects merger value function. Specifically, our counterfactual experiments examine characteristics of the matches in stable equilibrium if firms do not consider inventor mobility as a determinant of the merger value function.

Panel (1) in Table 7 shows the results of these counterfactual experiments which turn the coefficient of INV to zero and compute the stable equilibrium matches. The average of INV in equilibrium matches decreases by 0.534 units (from 0.894 in the benchmark to 0.360 in this counterfactual experiment). It is equivalent to about 37.2% of one standard deviation of that measure. Firms select merger partners with less inventor mobility if inventor mobility is omitted in the merger value function. More importantly, from the baseline result to this counterfactual experiment, the merger value reduces by 73.7% and the prediction rate of our model for observed mergers decreases from 56.6% to 41.7%. These results suggest that the inclusion of inventor mobility is important to explain merger value creation.

5.3. Quasi-Natural Experiment

To move us closer toward causal inference, we rely on an exogenous policy shock: noncompete clauses (NCC). Covenants not to compete are legal contracts employers use to restrain ex-employees from joining a firm or starting a business in competition with them in a specific geographical area for a period of time. In technology intensive industries, non-competes are widely used to protect firms' intellectual properties. (Marx, 2011). The NCC would create a negative shock to the level of inventor mobility between two firms, which is exogenous to firms' M&A decisions. This provides an ideal setting for a natural experiment under which merger values could be attributed to inventor mobility.

States have taken different stances on their enforcement. California and North Dakota courts do not enforce non-competes at all. (Bishara, 2010). Other states enforce them though the criteria of "reasonableness" and the strength of enforcement varies across states and within states over time.

Studies report variation in non-compete law explains variation in job mobility among inventors (Fallick et al. 2006; Marx et al. 2009; Garmaise 2011; Chen et al. 2018).

We measure the NCC score by observing the information of the relative strength of the NCC enforcement across the US during 1991-2009 from a survey database of Bishara (2010). The survey asks seven questions to the fifty states and the District of Columbia. Each question awards a possible high score of 10 to a state which has maximum enforcement. Appendix D shows the score which is distributed from 0 to 470 in 1991 and 2009, respectively.

To measure the relevant NCC level of a merger, we sum the scores of the two states of the acquirer and the target in year *t-1*, where *t* is the merger year. In our empirical setup, we conduct a two-stage maximum score estimation (2SMS) analysis during 1992-2010. It involves the following set of equations:

First Stage: $INV_{at} = \alpha_1 NCC_{at} + Z_{at}\alpha_2 + Year + Ind_a + Ind_t + \epsilon_{at}$

Second Stage:

$$V(a,t|\beta) = \beta_1 I\widehat{N}V_{at} + \beta_2 TS_{at} + \beta_3 PS_{at} + \beta_4 SameState_{at} + \beta_5 (Tobin\ Q_a \times Tobin\ Q_t) + \beta_6 (R\&D_a \times R\&D_t) + \varepsilon_{at},$$

where a vector, Z_{at}, includes the control variables such as TS_{at}, PS_{at}, $Tobin\ Q_a \times Tobin\ Q_t$, and $R\&D_a \times R\&D_t$ and $I\widehat{N}V_{at}$ is the predicted value computed from the first stage regression. Panel A in Table 8 describes the results of the first stage regression. The sign of coefficient of NCC_{at} is significant and negative. It implies that strict noncompete enforcement is more likely to reduce inventor mobility between firms. Panel B in Table 8 describes the second stage regression results. In Panel B, the first column shows that the coefficient of $I\widehat{N}V_{at}$ is positive and significant. We compare the result to our baseline model with the sample period 1992-2010. The signs of coefficients of $I\widehat{N}V_{at}$ and INV_{at} are both positive and significant. In Panel C in Table 8, we measure the relative importance of $I\widehat{N}V_{at}$ and INV_{at} in creating merger value to compare the impact sizes of the two variables. To sum, including the effects of NCC to our analysis, we can assure the causality of inventor mobility to merger value creation even though the size of effects decreases.

[Table 8 about here]

6. Robustness Checks

6.1 Flexible Roles of Acquirer and Target

Our benchmark analysis follows the existing literature to assume the sets of acquirers and targets are separate, i.e., there is no overlapping firm in both sets. However, the decisions on whether a firm merges with another firm, and whether a firm is an acquirer, or a target are not predetermined. Rather, they are parts of the merger decision.

Hence, we extend the inequality condition (5) with two sets of inequalities that incorporate actual acquiring firms into the set of potential target firms and vice versa. Since the actual acquirer might be purchased by another actual acquiring firm before the realized merger between and t, we consider the following inequalities in the stable matching equilibrium.

$$V(a,t) - p_{at} \geq V(a,\tilde{a}) - [\mathrm{V}(\tilde{a},\tilde{t}) - p_{\tilde{a}\tilde{t}}], \tag{8}$$

$$p_{at} \geq V(t,\tilde{t}) - p_{\tilde{a}\tilde{t}}, \tag{9}$$

$$\mathrm{V}(\tilde{a},\tilde{t}) - p_{\tilde{a}\tilde{t}} \geq V(\tilde{a},a) - [\mathrm{V}(a,t) - p_{at}], \tag{10}$$

$$p_{\tilde{a}\tilde{t}} \geq V(\tilde{t},t) - p_{at}. \tag{11}$$

Then, by adding the inequalities (6) and (7) or adding the inequalities (8) and (9), we obtain the following inequality condition for the stable matching equilibrium.

$$V(a,t) + V(\tilde{a},\tilde{t}) \geq V(a,\tilde{a}) + V(t,\tilde{t}). \tag{12}$$

This inequality condition implies that actual acquirers (targets) cannot gain from mergers with another acquirer (target). For implementation, we estimate this model with inequalities (5) and (12). From Table

3 to Table 7, we report the results of this model under Model 2. This model generates more counterfactual matches than the benchmark model because firms can choose to be acquirers or targets in counterfactual matches.

Table 4 shows that INV is positively correlated with the probability of merger. Table 5 reports a positive relationship between inventor mobility and merger value creation. Table 6 finds that the influence of INV on merger value is the largest. Table 7 reports that INV is still an important factor for the merger values due to the largest estimated coefficients. Furthermore, Table 7 also shows that Model 2 reports a lower prediction rate at 139/348 (= 39.9%) than Model 1. For the realized mergers, their merger values are ranked at 48.7 percentile of all combinations, on average. This implies that the estimated merger values of Model 2 are still informative to explain observed mergers. Again, these results suggest that the inclusion of inventor mobility is important to explain merger value creation.

6.2 Inclusion of Standalone Firms

This subsection extends the structural model to allow firms to decide whether to merge or to be standalone. The following example shows the set of inequalities capturing the decision of whether to merge. Their matching outcomes are $(a,t),(\tilde{a},\tilde{t}) \in \mu$ and $s,\ \tilde{s} \in SA$, where μ and SA represent a set of merging and standalone firms, respectively. For two realized merger pairs (a,t) and $(\tilde{a},\tilde{t})$, we use the inequalities in (5) and (12) to determine whether they belong to a stable matching equilibrium.

A stable matching inequality for a pair of merging firms and a standalone firm can be written as

$$V(a,t) + V(s,0) \geq V(a,0) + V(s,t), \tag{13}$$

where $(s,0)$ and $(a,0)$ represent self-matches of standalone firms s and a, respectively. Even though the standalone firm s acts as an acquirer in (13), it can also be acquired by another firm. Thus, we construct an additional inequality

$$V(a,t) + V(0,s) \ \geq \ V(a,s) \ + \ V(0,t), \tag{14}$$

When it comes to two standalone firms s and $\tilde{s}$, they prefer to be standalone rather than merging with each other. This implies the following inequality

$$V(s,0) + V(\tilde{s},0) \ \geq \ V(s,\tilde{s}) \tag{15}$$

This inequality condition implies that actual merging firms cannot gain from being standalone firms. For implementation, we estimate this model with inequalities (5), (12), and (15). From Table 3 to Table 7, we report the results of this model under Model 3. This model generates more counterfactual matches than the previous two models because firms can choose to be standalone in counterfactual matches. Encouragingly, the results from this model are consistent with those of the previous models.

6.3 Alternative Measure of INV

In our main analysis, we define INV by dividing the number of inventors who were transferred before the merger by the number of employees of the firms. However, the number of employees might reflect the size of the firm, which might make the impacts of INV on merger value obscured. We perform a robustness check to define INV as only the number of inventors who were transferred before the merger without dividing the number of employees. Column (1) of Table 9 reports that the result from INV without the number of employees is close to our main results, suggesting that our results are robust to an alternative measure of INV.

[Table 9 about here]

6.4 INV with Impact Power

The impact of mobility of each inventor may differ by his/her experience, knowledge, and skills. That is, simply counting the number of inventors may not properly reflect the knowledge spillover effect. For instance, the knowledge spillover effects of the turnover of an inventor with hundreds of citations would be greater than those of five young inventors who have just completed their degree.

We consider the impact power of each inventor's mobility by multiplying the number of inventors who were transferred before the merger by the number of inventors the number of citations that the inventors have received, and dividing by the number of employees of the firms (i.e., $\frac{INV \times number\ of\ citations}{number\ of\ employees}$). Column (2) of Table 9 reports that the result from INV with impact power is consistent with our main results.

6.5 Alternative Time Windows

The baseline analysis is based on INV which counts the number of transferred during the period t-5 to t-1. This subsection provides various robustness checks of the result of Model 1 by alternating the time windows.

In Column (3) of Table 9, we control for a shorter time window by counting INV from patent application records of both firms during the period t-3 to t-1. Also, in Column (4) of Table 9, we measure INV from patent application records of both firms during the period t-7 to t-1.

There might be a concern in our data about whether the applicants are updated before the patent issues on a pre-merger filing date. Column (5) of Table 9 shows the robustness of our results by counting INV from patent application records of both firms during the period t-5 to t-3. Furthermore, in Column (6) of Table 9, we control test a time window by counting INV from granted patent records of both firms during the period t-5 to t-1 instead of using patent application records. All of the results in Column (3)-(6) of Table 9 are consistent with those of the Model 1. We report the number and the share of M&A of the sample of each time window, which has at least one inventor mobility in Appendix E.

6.6 Alternative Measure of Technology Similarity

Instead of MAHA, we employ an alternative measure of technology similarity by the correlation (CR) between pre-merger patent distribution vectors of two firms to measure technology similarity between firms as follows (Jaffe 1986):

$$CR(F_A, F_T) = \frac{Cov\ (F_A, F_T)}{\sqrt{Var(F_A) \cdot Var(F_T)}} \quad ,$$

where F_A (F_T) represents acquirer A's (target T's) vector of patent shares over patent classes. Two firms have more similar technologies before their merger when CR is higher. In contrast, CR is zero if two firms have no patent filed in overlapping classes. We repeat the empirical analysis by replacing MAHA with CR and report the results in Appendix F. Overall, the empirical results are consistent with our benchmark results.

7 Conclusion

This paper examines the effects of inventor mobility on merger value creation. We find that mergers between firms with inventor mobility create values. Our empirical results are robust to alternative extensions of the structural model, alternative measures of technology, and alternative market definition.

The managerial implication of our analysis highlights the importance of merging with the right partner in addition to merging with a good partner. For the choice of merging partner for technology firms, they may consider a firm having inventor turnover with them. Such a choice may ease consolidation and facilitate collaboration among divisions between the merging firms. However, our empirical analysis raises a policy issue that a merger between firms with inventor mobility may dampen the innovation effort.

Tables

Table 1. Merger Industry Categories

Year	CHEM	COM	FOOD	MACH	MED	METAL	PAPER	PHARM	TRANS	Total
1981	0	0	2	2	0	0	0	0	0	4
1982	0	0	2	0	0	0	0	0	0	2
1983	0	0	0	0	0	0	0	0	0	0
1984	0	0	0	0	0	0	0	0	0	0
1985	0	0	0	0	0	0	0	0	4	4
1986	0	2	2	0	0	0	0	0	4	8
1987	0	0	0	0	0	0	2	0	2	4
1988	0	0	0	0	0	0	0	0	0	0
1989	0	0	0	2	0	0	0	3	0	5
1990	0	0	0	0	0	0	2	0	0	2
1991	0	0	0	0	0	0	0	0	0	0
1992	0	0	0	0	0	0	0	0	0	0
1993	0	0	0	0	0	0	0	0	0	0
1994	0	0	0	0	0	0	0	3	0	3
1995	0	0	2	0	0	0	0	0	0	2
1996	3	4	0	0	2	0	0	2	2	13
1997	0	5	3	4	0	0	2	0	6	20
1998	4	5	0	3	5	2	0	0	2	21
1999	4	8	0	3	5	0	3	4	3	30
2000	3	9	3	4	0	2	3	5	4	33
2001	3	6	4	0	3	0	0	2	0	18
2002	0	2	0	0	0	2	0	0	2	6
2003	0	0	0	0	0	2	0	4	2	8
2004	0	3	3	0	2	0	0	3	0	11
2005	0	3	0	4	2	0	0	3	0	12
2006	0	4	0	3	7	0	0	7	3	24
2007	0	5	0	2	5	3	0	0	0	15
2008	2	0	0	2	2	0	0	5	0	11
2009	0	3	0	0	0	0	0	6	0	9
2010	0	3	0	2	2	0	0	3	0	10
2011	0	3	0	0	2	0	0	0	0	5
2012	0	3	0	5	2	2	0	4	0	16
2013	3	0	0	3	0	0	0	4	0	10
2014	3	5	2	2	0	0	0	6	0	18
2015	2	7	3	3	2	0	0	7	0	24
Total	27	80	26	44	41	13	12	71	34	348

Note: CHEM includes chemicals except drugs; COM includes computer and semiconductor; FOOD includes food and tobacco; MACH includes industrial machinery and electronics; MED includes medical instruments; METAL includes primary metal and fabricated metal products; PAPER includes textile mill products, paper, printing, and publishing; PHARM includes drugs and pharmaceutical preparations except other chemicals; TRANS includes Transportation equipment including vehicles, ships, aircrafts, and space vehicles.

Table 2. Descriptive Statistics for Merging Firms

Variable	Description	Mean	S.D.	N
Acquirer				
R&D intensity	R&D expenditure/ Sales	0.108	0.283	348
Tobin's Q	Stock market value /Total asset	2.255	2.847	348
CHEM	Chemicals except drugs	0.095	.	348
COM	Computer and Semiconductor	0.219	.	348
FOOD	Food	0.071	.	348
MACH	Industrial Machinery and electronics	0.080	.	348
MED	Medical Instruments	0.089	.	348
METAL	Primary metal and fabricated metal products	0.043	.	348
PAPER	Textile mill products, paper, printing, and publishing	0.022	.	348
PHRM	Drugs and pharmaceutical preparations except other chemicals	0.240	.	348
TRANS	Transportation Equipment	0.142	.	348
Target				
R&D intensity	R&D expenditure/ Sales	1.093	10.738	348
Tobin's Q	Stock market value /Total asset	2.355	3.112	348
IND1	Chemicals except drugs	0.077	.	348
IND2	Computer and Semiconductor	0.230	.	348
IND3	Food	0.075	.	348
IND4	Industrial Machinery and electronics	0.126	.	348
IND5	Medical Instruments	0.118	..	348
IND6	Primary metal and fabricated metal products	0.037	.	348
IND7	Textile mill products, paper, printing, and publishing	0.035	.	348
IND8	Drugs and pharmaceutical preparations except other chemicals	0.204	.	348
IND9	Transportation Equipment	0.098	.	348
Match-Specific Characteristic				
INV	The number of inventors who were transferred before the merger x1,000/ the number of employees	0.510	2.785	348
MAHA	Mahalanobis distance	4.319	5.198	348
CR	Correlation	0.319	0.288	348
PS	Product Similarity	3.463	1.602	348
Same State	Dummy variable for same state	0.201	0.401	348
R&D intensity	R&D intensity of acquirer x R&D intensity of target	0.215	1.850	348
Tobin's Q	Tobin's Q of Acquirer x Tobin's Q of Target	9.818	44.581	348

Table 3. Number of Matches with INV

	Number of Matches (Number, %) With INV > 0	Average of INV	Total
Model 1			
Observed mergers	110 (31.6%)	0.510	348
Counterfactual Matches	44 (4.4%)	0.003	992
Total	154 (11.5%)	0.135	1,340
Model 2			
Observed mergers	110 (31.6%)	0.510	348
Counterfactual Matches	339 (8.0%)	0.045	4,238
Total	449 (9.8%)	0.081	4,586
Model 3			
Observed mergers	110 (31.6%)	0.510	348
Counterfactual Matches	339 (6.9%)	0.039	4,916
Total	449 (8.5%)	0.070	5,264

Note: This table compares the real merger match group and the hypothetical match group for the share of matches with at least one mobile inventor of all matches in each group.

Table 4. Probit Model

	Model 1	**Model 2**	**Model 3**
INV	5.566***	0.092***	0.095***
	(1.507)	(0.031)	(0.031)
MAHA	0.019*	0.031***	0.044***
	(0.010)	(0.006)	(0.006)
PS	0.144***	0.138***	0.071***
	(0.034)	(0.026)	(0.022)
$\text{Tobin's Q}_a \times \text{Tobin's Q}_t$	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Same State	0.376***	0.237***	0.342***
	(0.126)	(0.079)	(0.078)
$\text{R\&D}_a \times \text{R\&D}_t$	-0.010	-0.006	-0.005
	(0.022)	(0.006)	(0.005)
Constant	-0.215	-1.241***	-1.277***
	(0.509)	(0.329)	(0.306)
Number of Mergers	348	348	348
Number of Observations	1,340	4,586	5,264

Note: We use probit estimation in all columns. Robust standard errors are in parentheses. The dependent variable is an indicator variable which is equal to 1 if two firms are merged with each other. p*<0.1, p**<0.05, p***<0.01.

Table 5. Maximum Score Estimation

	Model 1	**Model 2**	**Model 3**
INV	92.100**	91.380**	70.779**
	[53.275, 99.354]	[58.870, 98.531]	[1.057, 89.362]
MAHA	0.068	2.410	0.234**
	[-0.016, 4.867]	[-1.911, 27.333]	[8.362, 65.598]
PS	0.263**	0.494**	0.309
	[0.179, 46.265]	[0.399, 23.514]	[-12.236, 67.191]
Same State	1**	1**	1**
	Normalized	Normalized	Normalized
$\text{Tobin's Q}_a \times \text{Tobin's Q}_t$	0.281**	0.790**	0.007
	[0.272, 4.353]	[0.628, 4.357]	[-0.202, 8.071]
$\text{R\&D}_a \times \text{R\&D}_t$	18.154**	8.090**	2.603
	[12.091, 86.360]	[4.257, 89.554]	[-25.782, 62.150]
Number of Inequalities	515	2,293	20,030
% of Inequalities satisfied	84.9%	53.5%	0.05%
Number of Merger markets	104	104	104
Number of Mergers	348	348	348
Number of Observations	1,340	4,586	6,320

Note: We use maximum score estimation in all columns and run the estimation by setting the coefficient for the Same State to +1. We then select the vectors of parameter estimates that maximize the maximum score objective function. Model 1 assumes that each merging firm does not change their role. Model 2 allow merging firms to switch their roles. Model 3 adds standalone cases to Model 2. 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. p*<0.1, p**<0.05, p***<0.01.

Table 6. Relative Importance of Covariates in Match Value

Model 1	Estimate	S.D.	Estimate x S.D.
INV	92.100	1.435	132.164
MAHA	0.068	4.352	0.296
PS	0.263	1.526	0.401
Same State	1	0.355	0.355
$\text{Tobin's Q}_a \times \text{Tobin's Q}_t$	0.281	38.408	10.793
$\text{R\&D}_a \times \text{R\&D}_t$	18.154	2.041	37.052
Model 2	Estimate	S.D.	Estimate x S.D.
INV	91.380	1.099	100.427
MAHA	2.410	4.239	10.216
PS	0.494	1.493	0.738
Same State	1	0.349	0.349
$\text{Tobin's Q}_a \times \text{Tobin's Q}_t$	0.790	36.347	28.714
$\text{R\&D}_a \times \text{R\&D}_t$	8.090	11.119	89.953
Model 3	Estimate	S.D.	Estimate x S.D.
INV	70.779	0.693	49.050
MAHA	0.234	5.142	1.203
PS	0.309	1.895	0.589
Same State	1	0.436	0.436
$\text{Tobin's Q}_a \times \text{Tobin's Q}_t$	0.007	84.166	0.589
$\text{R\&D}_a \times \text{R\&D}_t$	2.603	12.263	31.921

Note: Estimate indicates point estimates of each covariate in Table 5. Observed and counterfactual mergers are included to compute standard deviation, thus those figures are different from those reported in descriptive statistics. Model 1 assumes that each merging firm does not change their role. Model 2 allow merging firms to switch their roles. Model 3 adds standalone cases to Model 2.

Table 7. Counterfactual Analysis

Model 1	INV	Average of merger values	Prediction rate
Table 5	0.894	91.798	56.6%
β_1=0	0.360	11.049	41.7%
Model 2	INV	Average of merger values	Prediction rate
Table 5	1.226	140.444	39.9%
β_1=0	0.448	30.906	28.2%
Model 3	INV	Average of merger values	Prediction rate
Table 5	1.331	140.163	37.9%
β_1=0	0.188	10.561	32.5%

Note: β_1 indicates an estimated coefficient for INV in Table 5. 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. INV is the average of the measure of all the equilibrium matches in each counterfactual experiment. Average of merger values represents the sum of merger values from equilibrium matches in each experiment.

Table 8. Quasi Natural Experiments: Noncompete Clause (NCC)

Panel A. First-Stage	**Dependent Variable: INV**
NCC	-0.001*
	(0.000)
MAHA	0.024***
	(0.007)
PS	0.021
	(0.021)
$\text{Tobin's Q}_a \times \text{Tobin's Q}_t$	0.000
	(0.000)
$\text{R\&D}_a \times \text{R\&D}_t$	0.032
	(0.049)
Constant	0.036
	(0.171)
R-squared	0.039
Number of Observations	957

Panel B. Second-Stage	**2SMS**	**Baseline**
$\widehat{\text{INV}}$	29.324**	
	[4.129, 71.452]	
INV		95.323**
		[16.625, 96.631]
MAHA	1.612**	0.418
	[0.668, 45.605]	[-2.153, 64.657]
PS	0.691**	1.538
	[0.122, 66.792]	[-5.709, 67.271]
Same State	1**	1**
	Normalized	Normalized
$\text{Tobin's Q}_a \times \text{Tobin's Q}_t$	0.098	0.519**
	[0.025, 57.391]	[0.010, 57.795]
$\text{R\&D}_a \times \text{R\&D}_t$	5.081	17.005
	[-28.431, 67.962]	[-26.181, 70.564]
Number of Inequalities	374	374
% of Inequalities satisfied	75.1%	85.7%
Number of Merger markets	71	71
Number of Mergers	245	245
Number of Observations	968	968

Panel C. Relative Importance of Covariates in Match Value	$\widehat{\text{INV}}$ in **2SMS**			INV Baseline		
	Estimate	S.D.	Estimate x S.D.	Estimate	S.D.	Estimate x S.D.
	29.324	1.196	35.072	95.323	1.196	113.339

Note: In Panel A, we use an OLS. Robust standard errors are in parentheses. The dependent variable is INV. Panel B compares the results of the 2SLS estimation to our baseline model for the period, 1992-2010. In Panel C, estimate indicates point estimates of $\widehat{\text{INV}}$ and INV in Panel B and S.D. means the standard deviations of $\widehat{\text{INV}}$ and INV, respectively. p*<0.1, p**<0.05, p***<0.01.

Table 9. Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Without employees	**Impact Power**	**3 years**	**7 years**	**2-5 years**	**Grant years**
INV	95.792**	23.620**	93.078**	91.919**	91.510**	66.955**
	[31.393, 99.354]	[11.988, 81.660]	[36.577, 96.500]	[43.917, 96.785]	[31.945, 94.348]	[1.940, 86.791]
MAHA	4.539	7.419	0.387	0.525	0.292	0.400
	[-4.659, 53.086]	[-4.477, 63.957]	[-2.372, 51.775]	[-1.547, 54.664]	[-1.285, 62.647]	[-2.108, 65.064]
PS	23.208**	39.008**	4.659**	4.121**	3.816**	1.320**
	[14.065, 82.876]	[12.078, 86.115]	[3.827, 77.681]	[3.439, 70.056]	[2.118, 68.827]	[1.118, 68.677]
Same State	1**	1**	1**	1**	1**	1**
	Normalized	Normalized	Normalized	Normalized	Normalized	Normalized
$\text{Tobin's Q}_a \times \text{Tobin's Q}_t$	2.073**	2.645**	1.135**	0.249**	0.105**	0.387**
	[1.720, 46.915]	[2.346, 67.533]	[0.533, 30.754]	[0.030, 42.913]	[0.032, 57.481]	[0.016, 65.924]
$\text{R\&D}_a \times \text{R\&D}_t$	77.861	78.687	37.117	21.726	13.064	11.600
	[-8.129, 89.433]	[-12.773, 94.178]	[-18.704, 84.421]	[-15.619, 76.231]	[-24.253, 69.758]	[-26.313, 71.040]
Number of Inequalities	515	515	515	515	515	515
% of Inequalities satisfied	83.5%	83.4%	84.1%	85.8%	84.1%	76.7%
Number of Merger markets	104	104	104	104	104	104
Number of Mergers	348	348	348	348	348	348
Number of Observations	1,340	1,340	1,340	1,340	1,340	1,340

Note: We use maximum score estimation in all columns and run the estimation by setting the coefficient for the Same State to +1. We then select the vectors of parameter estimates that maximize the maximum score objective function. Model 1 assumes that each merging firm does not change their role. Model 2 allow merging firms to switch their roles. Model 3 adds standalone cases to Model 2. 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. p*<0.1, p**<0.05, p***<0.01.

Appendices

Appendix A: Maximum Score Estimation

The maximum score estimator developed by Manski (1975) has been used to estimate inequalities derived from necessary conditions for pairwise stability. Fox (2010, 2018) develop a matching maximum score estimator which has no potentially high dimensional integral for structural revenue functions over unobservable characteristics of firms in a merger market. Our computationally simple function requires only evaluating merger value functions by checking whether an inequality is satisfied and conducting pairwise comparisons for any guess of the structural parameters. Due to the computational advantages, several authors apply this methodology to their merger analyses (Akkus et al., 2015; Ozcan, 2015; Linde and Siebert, 2020).

A.1 Model 1: Benchmark Model

Let the merger value function between acquirer a and target t be $F(a,t) = V(a,t) + \varepsilon_{at}$, where $V(a,t)$ refers to observable merger values and ε_{at} represents an unobserved merger-specific error term. Suppose that there are two realized mergers, $(a,t),(\tilde{a},\tilde{t}) \in \mu$. Also, according to inequality (5), we define

$$q_1(\beta) = V(a,t|\beta) + V(\tilde{a},\tilde{t}|\beta) - V(a,\tilde{t}|\beta) - V(\tilde{a},t|\beta),$$

where represents a vector of parameters to be estimated in the observable part of the merger value function. Thus, $q_1(\beta)$ 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, 2010, 2018), the only necessary condition to identify parameters in the merger value function using maximum score estimation is the following rank order property:

$$q_1(\beta) \geq 0 \ \ if\ and\ only\ if\ Prob\,\{(a,t),(\tilde{a},\tilde{t}) \in \mu\} \geq Prob\,\{(a,\tilde{t}),(\tilde{a},t) \in \mu\}$$

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 β can maximize

$$Q(\beta) = \sum_{m=1}^{n}\{\sum_{(a,t),(\tilde{a},\tilde{t}) \in \mu_m} 1[q_1(\beta) \geq 0]\}, \qquad \text{(A1)}$$

over the parameter space in a stable matching equilibrium, where $Q(\beta)$ is the number of holding inequality (5) in all merger markets.

The objective function in (A1) 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 the unobservables in the objective function. This estimator only requires a set of inequalities necessary to derive a stable matching equilibrium. 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 inequality conditions in (A1) do not uniquely determine estimated values of parameters, we run the estimation repeatedly by using 20 different starting values of point estimates and selecting the coefficient vector that maximizes the number of equilibrium inequalities satisfied.

A.2 Confidence Intervals

To generate confidence intervals for point estimates from the maximum score estimation, we employ subsampling procedures suggested in the literature (Kim and Pollard 1990; Politis and Romano, 1994; Delgado et al., 2001). First, we set the subsample size to be 116 observations, which is $1/3$ of the entire sample size, i.e. 348 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 $\tilde{\alpha}_{sub} = \left(\frac{116}{348}\right)^{\frac{1}{3}} (\hat{\alpha}_{sub} - \hat{\alpha}) + \hat{\alpha}$ for each subsample. Our maximum score estimates converge to the sampling distribution of $\tilde{\alpha}_{sub}$ at the rate of $\sqrt[3]{348}$.[15] We compute 95% confidence intervals from the 2.5 percentile and 97.5 percentile of this empirical sampling distribution.

A.3 Model 2: Flexible Role as Acquirer or Target

According to the inequalities (5) and (12), we maximize the following objective function to estimate the parameters

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

where

$$q_1(\beta) = V(a,t|\beta) + V(\tilde{a},\tilde{t}|\beta) - V(a,\tilde{t}|\beta) - V(\tilde{a},t|\beta)$$

$$q_2(\beta) = V(a,t|\beta) + V(\tilde{a}, \tilde{t} \,|\, \beta) - V(a,\tilde{a}|\, \beta) - V(t,\tilde{t}|\, \beta)$$

The estimation procedure of this model follows subsection A.1 and A.2.

A.4 Model 3: Inclusion of Standalone Firms

According to the inequalities (5), (12) and (15), we maximize the following objective function to estimate the parameters

$$Q(\beta) = \sum_{m=1}^{n}\{\sum_{(a,t),\,(\tilde{a},\tilde{t}) \in \mu} 1\,[\ \{q_1(\beta) \geq 0\} \cap \{q_2(\beta) \geq 0\} \cap \{q_3(\beta) \geq 0\} \cap \{q_4(\beta) \geq 0\} \cap \{q_5(\beta) \geq 0\} \cap \{q_6(\beta) \geq 0\}],$$

where

[15] Kim and Pollard (1990) reported that a general class of *M*-estimators converge at rate $n^{1/3}$ rather than at the standard rate $n^{1/2}$ because for non-smooth estimators, the standard asymptotics tend to break down and the rate of convergence often slows to $n^{1/3}$. Also, Delgado et al. (2001) assume $n = {}^{b}/_{k}$, where ${}^{b}/_{k} \to 0$ and $b \to 0$ as $k \to \infty$. Following their assumption, we take n = ${}^{1}/_{3}$.

$$q_1(\beta) = V(a,t|\beta) + V(\tilde{a}, \tilde{t} \mid \beta) - V(a,\tilde{t}| \beta) - V(\tilde{a},t| \beta)$$

$$q_2(\beta) = V(a,t|\beta) + V(\tilde{a}, \tilde{t} \mid \beta) - V(a,\tilde{a}| \beta) - V(t,\tilde{t}| \beta)$$

$$q_3(\beta) = V(a,t|\beta) + V(\mathrm{s},0 \mid \beta) - V(a, 0| \beta) - V(\mathrm{s}, t| \beta)$$

$$q_4(\beta) = V(a,t\,|\beta) + V(0, s|\beta) - V(a, s\,|\beta) - V(0,t\,|\beta)$$

$$q_5(\beta) = V(\tilde{a}, \tilde{t}\,|\beta) + V(s,0|\beta) - V(\tilde{a}, 0\,|\beta) - V(s,\tilde{t}\,|\beta)$$

$$q_6(\beta) = V(\tilde{a}, \tilde{t}\,|\beta) + V(0, s|\beta) - V(\tilde{a}, s\,|\beta) - V(0,\tilde{t}|\beta)$$

$$q_7(\beta) = V(s, 0\,|\beta) + V(\tilde{s}, 0|\beta) - V(s,\tilde{s}|\beta)$$

The estimation procedure of this model follows subsection A.1 and A.2.

Appendix B: SIC code and Industry Categories in Our Sample

Industry	SIC code	Number of Mergers	Description
Chemical	2819	4	Industrial Inorganic Chemicals
(27 mergers)	2821	5	Plastics Materials and Resins
	2844	1	Toilet Preparations
	2851	3	Paints and Allied Products
	2865	2	Cyclic Crudes and Intermediates
	2869	3	Industrial Organic Chemicals
	2873	1	Nitrogenous Fertilizers
	2879	2	Agricultural Chemicals
	2891	1	Adhesives and Sealants
	2899	3	Chemical Preparations
	3052	1	Rubber and Plastics Hose and Beltings
	3069	1	Fabricated Rubber Products
Food	2011	2	Meat Packing Plants
(26 mergers)	2013	2	Sausages and Other Prepared Meats
	2023	1	Dry, Condensed, Evaporated Foods
	2032	1	Canned Specialities
	2033	1	Canned Fruits and Specialities
	2041	2	Flour and Other Grain Mill Products
	2043	2	Cereal Breakfast Foods
	2045	1	Prepared Flour Mixes and Doughs
	2047	2	Dog and Cat Food
	2051	1	Bread, Cake, and Related Products
	2052	2	Cookies and Crackers
	2062	1	Cane Sugar Refining
	2084	1	Wines, Brandy, and Brandy Spirits
	2086	3	Bottled and Canned Soft Drinks
	2087	1	Flavoring Extracts and Syrups
	2099	1	Food Preparations
	2111	2	Cigarettes
Machinery	3264	1	Procelain Electrical Supplies

(44 mergers)	3491	2	Industrial Valves
	3494	1	Valves and Pipe Fittings
	3511	3	Turbines and Turbine Generator Sets
	3531	1	Construction Machinery
	3533	6	Oil and Gas Field Machinery
	3537	1	Industrial Trucks and Tractors
	3545	1	Machine Tool Accessories
	3546	1	Power-driven Handtools
	3556	1	Food products Machinery
	3559	2	Special Industry Machinery
	3561	2	Pumps and Pumping Equipment
	3562	1	Ball and Roller Bearings
	3565	1	Packaging Machinery
	3569	2	General Industrial Machinery
	3585	4	Refrigeration and Heating Equipment
	3589	2	Service Industry Machinery
	3592	1	Carburetors, Pistons, Rings, Valves
	3594	1	Fluid Power Pumps and Motors
	3625	1	Relays and Industrial Controls
	3633	1	Household Laundry Equipment
	3643	1	Current-carrying Wiring Devices
	3645	1	Residential Lighting Fixtures
	3694	2	Engine Electrical Equipment
	3699	1	Electrical Equipment and Supplies
	3822	2	Environmental Controls
	3825	1	Instruments To Measure Electricity
Medical Instruments	3821	2	Laboratory Apparatus and Furniture
(41 mergers)	3826	5	Analytical Instruments
	3841	21	Surgical and Medical Instruments
	3842	2	Surgical Appliances and Supplies
	3843	1	Dental Equipment and Supplies
	3844	2	X-ray Apparatus and Tubes
	3845	8	Electromedical Equipment
Metal	3312	3	Blast Furnaces and Steel Mills
(13 mergers)	3317	1	Cold Finishing of Steel Shapes
	3324	1	Steel Investment Foundries
	3334	2	Primary Aluminum
	3357	2	Nonferrous Wiredrawing and Insulating
	3429	1	miscellaneous metal products
	3452	2	Bolts, Nuts, Rivets, and Washers
	3482	1	Small Arms Ammunition
Paper	2611	1	Pulp Mills
(12 mergers)	2621	4	Paper Mills
	2631	1	Paperboard Mills
	2673	1	Bags: Plastic, Laminated and Coated
	2675	1	Die-cut Paper and Board
	2676	2	Sanitary Paper Products
	2678	2	Stationery Products
Pharmaceutical	2833	1	Medicinals and Botanicals
(71 mergers)	2834	48	Pharmaceutical Preparations
	2835	4	Diagnostic Substances
	2836	18	Biological Products, Except Diagnostic

Computer and Semiconductors (80 mergers)	3571	8	Electronic Computers
	3572	8	Computer Storage Devices
	3577	4	Computer Peripheral Equipment, Nec
	3651	2	Household Audio and Video Equipment
	3661	5	Telephone and Telegraph Apparatus
	3663	8	Radio and T.v. Communications Equipment
	3669	4	Communications Equipment, Nec
	3674	35	Semiconductors and Related Devices
	3679	3	Electronic Components, Nec
	3823	2	Process Control Instruments
	3861	1	Photographic Equipment and Supplies
Transportation (34 mergers)	3621	1	Motors and Generators
	3711	1	Motor Vehicles and Car Bodies
	3714	6	Motor Vehicle Parts and Accessories
	3721	4	Aircraft
	3724	4	Aircraft Engines and Engine Parts
	3728	1	Aircraft Parts and Equipment
	3731	1	Shipbuilding and Repairing
	3761	1	Guided Missiles and Space Vehicles
	3764	1	Space Propulsion Units and Parts
	3769	1	Space Vehicle Equipment
	3812	10	Search and Navigation Equipment
	3829	3	Measuring and Controlling Devices

Appendix C: MAHA calculation

We explain the calculation of technological similarity by Mahalanobis distance (MAHA). A firm i's vector of patent shares over those patent classes is represented by $F_i = (F_{i,1}, F_{i,2}, \dots, F_{i,438})$, where $F_{i,c}$ is the firm i's ratio of patent counts in class c to the total number of patents. We refer to the 438 patent classes from https://www.uspto.gov/web/patents/classification/selectnumwithtitle.htm. The way to construct this measure is as follows. First, form a matrix of every firm's vector of patent shares over technology classes. That is, the $438 \times N$ matrix, $F = [F_1', F_2', \dots, F_N']$, is the matrix of all the firms' patent distributional vectors over 438 classes, where F_i is the firm i's 1×438 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 $\tilde{F} = [\frac{F_1'}{(F_1 F_1')^{\frac{1}{2}}}, \frac{F_2'}{(F_2 F_2')^{\frac{1}{2}}}, \dots, \frac{F_{438}'}{(F_{438} F_{438}')^{\frac{1}{2}}}]$. Third, form a $N \times 438$ matrix $C = \left[F_{(,1)}', F_{(,2)}', \dots, F_{(,438)}'\right]$, where $F_{(,c)}$ is the class c's $1 \times N$ vector of patent shares over N firms. Then, $\tilde{C} = [\frac{F_{(,1)}'}{\left(F_{(,1)} F_{(,1)}'\right)^{\frac{1}{2}}}, \frac{F_{(,2)}'}{\left(F_{(,2)} F_{(,2)}'\right)^{\frac{1}{2}}}, \dots, \frac{F_{(,438)}'}{\left(F_{(,438)} F_{(,438)}'\right)^{\frac{1}{2}}}]$ is the normalized $N \times 438$ matrix of C. Thus, a 438×438 matrix, $CCORR = \tilde{C}'\tilde{C}$, indicates a uncentered correlation between vectors of all the classes' patent shares across firms. Finally, to capture technology similarity between different patent classes, use a $N \times N$ matrix $TECHSPILL = \tilde{F}' \times CCORR \times \tilde{F}$. Hence, each element of the $TECHSPILL$ matrix is a Mahalanobis distance between two corresponding firms. That is, Mahalanobis distance is the weighted correlation between firms' patent class distributional vectors where the weight is defined by the correlation among all the patent classes ($CCORR$). That is,

$$MAHA = \tilde{F}' W^m \tilde{F},$$

where $\tilde{F}$ is a matrix of all firms' normalized vectors of patent shares in patent classes and W^m is a weighting matrix of correlation between patent classes.

We illustrate the computation of MAHA with the following example. Suppose that there are 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 $F_T = (0, 0.8, 0.2)$. To compute MAHA, we take the following steps. Consider $F = [F'_A, F'_T] = \begin{bmatrix} 0.1 & 0 \\ 0.4 & 0.8 \\ 0.5 & 0.2 \end{bmatrix}$, so that $\tilde{F} = [\frac{F'_A}{(F_A F'_A)^{\frac{1}{2}}}, \frac{F'_T}{(F_T F'_T)^{\frac{1}{2}}}] = \begin{bmatrix} 0.15 & 0 \\ 0.62 & 0.97 \\ 0.77 & 0.24 \end{bmatrix}$. Moreover, $C = [F'_{(,1)}, F'_{(,2)}, F'_{(,3)}] = \begin{bmatrix} 0.1 & 0.4 & 0.5 \\ 0 & 0.8 & 0.2 \end{bmatrix}$, and $\tilde{C} = [\frac{F'_{(,1)}}{\left(F_{(,1)} F'_{(,1)}\right)^{\frac{1}{2}}}, \frac{F'_{(,2)}}{\left(F_{(,2)} F'_{(,2)}\right)^{\frac{1}{2}}}, \frac{F'_{(,3)}}{\left(F_{(,3)} F'_{(,3)}\right)^{\frac{1}{2}}}] = \begin{bmatrix} 1 & 0.45 & 0.93 \\ 0 & 0.89 & 0.37 \end{bmatrix}$. 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$_{AT}$) corresponds to diagonal elements in the $TECHSPILL$ matrix, 1.56.

Appendix D: NCC Score and Rank by States

State name	Score (1991)	Rank (1991)	Score (2009)	Rank (2009)	State name	Score (1991)	Rank (1991)	Score (2009)	Rank (2009)
Alaska	251	47	196	49	Montana	257	46	259	46
Alabama	373	12	373	19	North Carolina	335	28	335	35
Arkansas	220	49	230	48	North Dakota	0	51	0	51
Arizona	296	38	316	36	Nebraska	281	43	281	44
California	39	50	31	50	New Hampshire	361	16	361	24
Colorado	360	19	360	26	New Jersey	385	11	425	9
Connecticut	418	4	435	3	New Mexico	409	6	409	12
District of Columbia	310	33	310	38	Nevada	309	36	342	33
Delaware	318	32	360	27	New York	310	34	295	42
Florida	435	1	470	1	Ohio	340	26	355	31
Georgia	290	39	285	43	Oklahoma	267	45	248	47
Hawaii	286	40	358	30	Oregon	361	17	361	25
Iowa	352	20	425	7	Pennsylvania	335	29	365	23
Idaho	336	27	434	4	Rhode Island	299	37	314	37
Illinois	410	5	430	5	South Carolina	285	42	310	39
Indiana	370	13	370	21	South Dakota	367	15	410	11
Kansas	397	9	455	2	Tennessee	361	18	373	20
Kentucky	395	10	415	10	Texas	350	21	350	32
Louisiana	285	41	380	13	Utah	428	2	428	6
Massachusetts	405	7	375	18	Virginia	335	30	310	40
Maryland	348	22	379	15	Vermont	310	35	379	17
Maine	345	23	370	22	Washington	400	8	380	14
Michigan	367	14	379	16	Wisconsin	319	31	300	41
Minnesota	340	24	340	34	West Virginia	281	44	281	45
Missouri	425	3	425	8	Wyoming	251	48	360	29
Mississippi	340	25	360	28					

Appendix E: Number of Matches with INV

	Number of Matches With INV > 0 (Number, %)	Average of INV	Total
5 years (Baseline)			
Observed mergers	110 (31.6%)	0.510	348
Counterfactual Matches	44 (4.4%)	0.003	992
Total	154 (11.5%)	0.135	1,340
3 years			
Observed mergers	101 (29.0%)	0.420	348
Counterfactual Matches	27 (2.7%)	0.002	992
Total	128 (9.5%)	0.111	1,340
7 years			
Observed mergers	116 (33.3%)	0.551	348
Counterfactual Matches	59 (5.9%)	0.004	992
Total	175 (8.5%)	0.146	1,340
2-5 years			
Observed mergers	80 (23.0%)	0.270	348
Counterfactual Matches	35 (3.5%)	0.002	992
Total	115 (8.6%)	0.072	1,340
Grant years			
Observed mergers	40 (11.49%)	0.066	348
Counterfactual Matches	37 (3.7%)	0.002	992
Total	77 (5.8%)	0.019	1,340

Note: This table compares the real merger match group and the hypothetical match group for the share of matches with at least one mobile inventor of all matches in each group.

Appendix F: Empirical Results with the use of CR

This appendix reports the results of Table 4-Table 7 using CR instead of MAHA. The follow table reports the correspondence between the tables in main text and those in this appendix.

Tables in Main Text		Tables in this Appendix
4	→	D1
5	→	D2
6	→	D3
7	→	D4
8	→	D5
9	→	D6

Overall, the results of CR are consistent with those of MAHA. For example, F.1 and F.2 report positive coefficients of CR in probit and matching models, respectively. These results are consistent with the positive coefficients of MAHA in Table 4 and 5, respectively.

F.1 Probit Estimation

	Model 1	Model 2	Model 3
INV	5.387***	0.084***	0.090***
	(1.475)	(0.029)	(0.028)
CR	0.502***	0.760***	0.989***
	(0.171)	(0.113)	(0.105)
PS	0.129***	0.112***	0.045**
	(0.035)	(0.027)	(0.022)
$\text{Tobin's } Q_a \times \text{Tobin's } Q_t$	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Same State	0.365***	0.213***	0.292***
	(0.126)	(0.080)	(0.081)
$R\&D_a \times R\&D_t$	-0.015	-0.009	-0.009
	(0.023)	(0.014)	(0.014)
Constant	-0.259	-1.313***	-1.371***
	(0.509)	(0.331)	(0.309)
Number of Mergers	348	348	348
Number of Observations	1,340	4,586	6,320

Note: We use probit estimation in all columns. Robust standard errors are in parentheses. The dependent variable is an indicator variable which is equal to 1 if two firms are merged with each other. p*<0.1, p**<0.05, p***<0.01.

F.2 Maximum Score Estimation

	Model 1	Model 2	Model 3
INV	84.209**	54.439**	69.938**
	[41.800, 95.325]	[52.349, 93.781]	[48.698, 97.370]
CR	2.489	0.023	3.367
	[-8.337, 68.709]	[-0.482, 3.999]	[-3.980, 29.467]
PS	0.292**	0.892**	0.755**
	[0.121, 74.277]	[0.281, 54.839]	[0.215, 34.213]
Same State	1**	1**	1**
	Normalized	Normalized	Normalized
$\text{Tobin's } Q_a \times \text{Tobin's } Q_t$	0.447**	0.821**	1.047**
	[0.241, 18.643]	[0.613, 5.852]	[0.455, 3.121]
$R\&D_a \times R\&D_t$	14.715	7.690**	9.797**
	[-5.697, 79.257]	[5.270, 92.910]	[5.256, 85.616]
Number of Inequalities	515	2,293	20,030
% of Inequalities satisfied	86.0%	52.0%	0.05%
Number of Merger markets	104	104	104
Number of Mergers	348	348	348
Number of Observations	1,340	4,586	6,320

Note: We use maximum score estimation in all columns and run the estimation by setting the coefficient for the Same State to +1. We then select the vectors of parameter estimates that maximize the maximum score objective function. Model 1 assumes that each merging firm does not change their role. Model 2 allow merging firms to switch their roles. Model 3 adds standalone cases to Model 2. 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. p*<0.1, p**<0.05, p***<0.01.

F.3 Relative Importance of Covariates in Match Value

Model 1	Estimate	S.D.	Estimate x S.D.
INV	84.209	1.435	120.840
CR	2.489	0.262	0.652
PS	0.292	1.526	0.446
Same State	1	0.355	0.355
$\text{Tobin's Q}_a \times \text{Tobin's Q}_t$	0.447	38.408	17.168
$\text{R\&D}_a \times \text{R\&D}_t$	14.715	2.041	30.033
Model 2	Estimate	S.D.	Estimate x S.D.
INV	54.439	1.099	59.828
CR	0.023	0.253	0.006
PS	0.892	1.493	1.332
Same State	1	0.349	0.349
$\text{Tobin's Q}_a \times \text{Tobin's Q}_t$	0.821	36.347	29.841
$\text{R\&D}_a \times \text{R\&D}_t$	7.690	11.119	85.505
Model 3	Estimate	S.D.	Estimate x S.D.
INV	69.938	1.026	71.756
CR	3.367	0.247	0.832
PS	0.755	1.513	1.142
Same State	1	0.329	0.329
$\text{Tobin's Q}_a \times \text{Tobin's Q}_t$	1.047	34.067	35.668
$\text{R\&D}_a \times \text{R\&D}_t$	9.797	10.740	105.220

Note: Estimate indicates point estimates of each covariate in Table 5. Observed and counterfactual mergers are included to compute standard deviation, thus those figures are different from those reported in descriptive statistics. Model 1 assumes that each merging firm does not change their role. Model 2 allow merging firms to switch their roles. Model 3 adds standalone cases to Model 2.

F.4 Counterfactual Analysis (CR)

Model 1	INV	Average of merger values	Prediction rate
Table 5	0.908	87.010	55.7%
β_1=0	0.376	11.378	43.1%
Model 2	INV	Average of merger values	Prediction rate
Table 5	1.087	71.935	56.6%
β_1=0	0.188	14.575	31.6%
Model 3	INV	Average of merger values	Prediction rate
Table 5	1.255	105.744	39.1%
β_1=0	0.259	17.877	32.8%

Note: β_1 indicates an estimated coefficient for INV in Table 5. 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. INV is the average of the measure of all the equilibrium matches in each counterfactual experiment. Average of merger values represents the sum of merger values from equilibrium matches in each experiment.

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