Innovation and Acquisition:
Two-Sided Matching in M&A Markets

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Abstract

This article investigates the determinants of pairing decisions in M&A activity of knowledge-intensive firms. Using standard patent-based metrics from novel data on 2,378 M&A deals, I show that there is a positive assortative sorting on acquirer and target innovation output quality; conditional on participating in M&A activity, high quality targets pair with high quality acquirers. The positive sorting on innovation quality is consistent with the view that external innovation complements internal innovation output of firms. I also show that the pairing probability in an acquisition decreases with distance between the acquirer and the target firm in technology, product market, and geography. Furthermore, I show that sorting on innovation quality in acquisition of private firms is weaker than in public firms. This difference has implications for acquirer returns in public-private acquisitions.

Keywords: Innovation, Acquiring Innovation, Mergers and Acquisitions, Matching

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1 Introduction

Does the quality of internal innovation play a role in a firm's pairing decision in acquiring outside innovation through Merger and Acquisition (M&A) activity? With the proliferation of open innovation models in corporate research and development (R&D) activities, the relationship between innovation and M&A activity has recently received considerable attention. In this literature a major tool incumbents use is acquisitions of startup firms, which provide the incumbents access to external innovation as a supplement to R&D activities and strategic alliances. However, mostly due to data limitations on private firms, little is known about the acquisition of innovation through M&As outside of the public-public acquisitions. Do firms prefer targets or acquirers with higher quality innovation? Do similarities in technology, product markets, and geography matter in the pairing decisions? In this study, I frame the M&A markets as two-sided matching markets, and using unique data on the census of patents transferred through M&As from 1986 to 2007, I analyze the determinants of acquirer - target pairings in M&A activities of knowledge-intensive firms.

The estimation of the impact of quality on partner choice is an inherently challenging task due to the two sides of the market: the acquirers have a choice among the targets, and the targets also have a choice among the acquirers. I model the M&A markets as two-sided matching markets with endogenously-determined side-payments, and then I adopt the matching maximum score estimator recently developed by Fox (2010). The main identifying assumption of the model is the pairwise stability of the observed distribution of the M&A transactions. Pairwise-stable allocation occurs when there do not exist two firms that would both benefit by deviating from the observed allocation and forming a different acquisition transaction with a possible side payment in the process. Under the pairwise stability assumption, I obtain revealed preference inequalities, which I then use in estimating the matching maximum score estimator to analyze the relative importance of various factors in the sorting of firms in the M&A markets.

The main result of the paper is that the probability of pairing in acquisition increases in the acquirer and target innovation quality, where innovation quality is proxied by standard patent-based metrics. In other words, I find that mergers of high innovation quality acquirers with high innovation quality targets create more value. This is different from the relative quality levels of targets with respect to acquirers: the targets have, on average, higher quality patents than the acquirers. However, there is considerable heterogeneity with a significant portion of acquirers having a higher quality than the targets they acquire. I also find that increases in the technology distance, product market distance, and geographic distance between the acquirers and targets decrease the value created through the merger.

The data used in this study is the result of a major data-linking effort, and thus is novel. It is constructed by linking the Securities Data Company's (SDC) Mergers and Acquisitions data module to newly constructed USPTO patent data. The patent data used is constructed from xml and text files of patents granted by the United States Patent and Trademark Office (USPTO) between 1976 and 2010. The newly constructed data covers four more recent years than NBER patent data files, the standard data source for many studies on patents.

There are several reasons to use this data. Firstly, this data suits my goal of analyzing long-term trends and factors more comprehensively than prior research: the length of time covered is novel, as is the completeness of the census of patented activity and related mergers during this period, including the activities of both publicly traded and private firms. In addition, the new data contains standardized patent assignee names that enable linking patent data to the M&A data and track the transferred patents through M&As.

This study is mainly related to the literature on innovation and acquirer performance, a strand of the literature investigating the acquisitions of incumbent firms and pre-, post-acquisition stock price and R&D performance of acquirers.[1] I differ from the prior literature in that I combine the demand- and supply-side of the merger market, hence mitigating the simultaneity bias inherent in reduced-form demand or reduced-form supply analyses. The standing methodological approach in this literature is the conditional logit model, which can take the characteristics of both sides into consideration. However, the *Independence of Irrelevant Alternatives (IIA)* property of the conditional logit model creates very limiting substitution patterns. The problem is exacerbated with the choice sets that vary in size due to differences in market conditions across industries and over time. Imposing correlated error structures, such as a Conditional Probit model, to remedy the IIA issue creates computational issues and is not feasible in a setting with numerous choices. The two-sided matching model approach with the maximum score estimator takes the choices of the two sides of the market into account, and does not suffer from a computational curse.

Furthermore, by using the census of patenting and M&A activity, I provide the most comprehensive coverage across industry, time and ownership (public and private firms). Though the cited studies contribute to the literature in important ways, many utilize the M&A data of only the public firms, and applying the filter for public firms may limit the generalizability of the results due to the exclusion of private firms from the data (Netter et al. (2011), Ali, Klasa, Yeung (2009)). Therefore, inclusion of private firms in the sample is necessary to avoid a selection bias. By using a census of M&A activity in my sample, I am able to mitigate this problem.

Another contribution of my paper is through my focus on the sorting on innovation quality instead of quantity or intensity. I first show that using the average levels of patent quality in the data, one may conclude that acquirers are quality laggards. I then move on to show the heterogeneity in patent quality across M&A transactions and its implications for our understanding of the innovation laggard versus innovation leader behavior.

My empirical results motivate an open question at the theoretical level: the direction of the relationship between the internal innovation efforts and the acquisition behavior of firms. Does external innovation substitute or complement internal innovation efforts of acquirer firms? One strand of the literature finds that the acquiring firms are laggards in their innovation activities, and uses acquisition of external innovation to substitute for internal innovation in an attempt to catch up with the technology frontier (Zhao (2009), Bena and Li (2014), Sevilir and Tian (2012)).

[1] See, among others: Ransbotham and Mitra (2010, MS), Philips and Zhdanov (2012), Higgins and Rodriguez (2006), Hall (1988), Zhao (2009), Sevilir and Tian (2012), Blonigen and Taylor (2000), Ahuja and Katila (2001).

Even though there is a considerable body of the literature that finds evidence for this catch-up behavior on some industries, the studies have been limited to specific subsets (an industry, or public firms) or to the acquirer or the target side. Using both the demand and the supply side for the ideas market, and the universe of patents transferred through M&As, I do not find supportive evidence for the substitutes theory.

On the other hand, I find evidence supporting the complements theory. According to the complements theory, technology leaders acquire external innovation to fill in the gaps in their internal innovation outputs in a timely manner. The complements theory implies that firms with high quality internal innovation would have an advantage in acquiring outside innovation, implying high-quality acquirers pairing up with high-quality targets. My main finding, the positive assortative sorting on innovation quality, is consistent with this view. Unifying the substitutes theory, for which there is considerable evidence in the literature, with the complements theory, for which I provide the evidence, is an open question that the empirical results of this paper call for, and is left for future work.

The remainder of the paper is organized as follows. Section 2 provides background on the innovation activity in M&A setting. Section 3 introduces the deterministic matching model. Section 4 discusses the theoretical background. Section 5 presents the sources of the data, sample selection, and main trends in M&A markets. Section 6 outlines the empirical methodology and discusses the results. Section 7 provides a conclusion.

2 Patents and M&A Activity

The acquisition of innovative startups has been a trend of the last two decades, during which Cisco, Microsoft, IBM, HP, Oracle, and Intel have made more than 50 acquisitions each. These are not isolated instances, but rather are symptoms of the widespread M&A activity, which I will discuss in detail in the data section below. In this section, I provide a brief overview.

Between 1986 and 2007, there are 2378 acquisitions in which each target and acquirer firm has at least one patent. These acquisitions have targets from 270 6-digit NAICS industries (or twenty seven 3-digit NAICS industries), 46 US states, and they result in the transfer of more than 87 thousand patents, which constitute more than 16% of the acquirers' patent portfolios.

Cisco Inc. is the poster child of acquirers during this era with twenty six acquisitions in my sample chronicled in Table 1. Founded in 1984, Cisco designs, manufactures, and sells information technology and networking equipment, and is classified under NAICS 314119. The targets of Cisco, on the other hand, span ten different 6-digit NAICS industries, with only two targets from the same 6-digit NAICS as Cisco. Even at the 3-digit NAICS level, only thirteen of the twenty six targets are in the same industry as Cisco.

The targets also exhibit considerable disbursement across geography. A majority of the targets are from Cisco's home state, California. However, even though Cisco is known for targeting firms geographically close to its headquarters, eight of the targets are from five other states from across the nation, including Massachusetts, Texas, and Ohio.

Between 1986 and 2007, the period of M&A activity considered in this study, Cisco has received 5,767 patents, which makes Cisco the 53$^{\text{rd}}$ largest innovator in the nation. On the other hand, through the twenty six acquisitions, Cisco has acquired 777 patents, which corresponds to more than 13% of Cisco's internal production over the same period. The patents Cisco creates are from a range of 77 technology classes that USPTO assigns to patents. The patents from the target firms also span 69 technology classes, 57 of which overlap with Cisco's patents, with an additional 12 classes new to Cisco.

The targets are mostly young firms, between 2 to 6 years since their first patent applications. There are also a few old firms, such as Scientific Atlanta, the then 53-year old Georgia-based telecommunications and broadband equipment manufacturer, which has made its first patent application 30 years before its acquisition by Cisco.

The disbursed characteristics of target firms Cisco has acquired are obtained across the M&A activity, with firms acquiring targets from other product market industries, other states, and patent portfolio age and quality levels. These observations motivate the main questions of this paper. How does various characteristics of acquirers and targets impact the pairing decision in the M&A markets? Do firms prefer targets or acquirers with higher quality innovation? Do similarities in technology, product markets, and geography matter in the pairing decisions? In this paper, I model the merger markets as two-sided matching markets to disentangle the impact of various factors on the pairing decision in mergers.

2.1 Related Literature

This paper is mainly related to the various strands of the innovation, mergers and acquisitions, and entrepreneurship literature. First, this paper is related to the literature on the motivations of mergers. Many motivations have been suggested, including the existence of complementary assets (Coase, 1937), Grossman and Hart, 1986), redeployment of assets (Capron, 1999), Healey et. al., 1992, Jensen and Ruback, 1983), gaining market power (Baker and Bresnahan, 1985, Mueller, 1985), and agency issues (Mock, Shleifer, and Vishny, 1990). With the prevalence of open access models in the recent decades, the trade-off between conducting internal research or acquiring external research has also been considered as a potential motivation for merger activity.

The M&A activities motivated by innovation may be considered as part of the strategies under open innovation, which is discussed extensively by Chesbrough (2003). The theory takes various approaches in explaining innovation as a motivation for M&A, including contracting (Aghion and Tirole, 1994), internal capital markets and project risk (Robinson, 2008), product market competition (Fulghieri and Sevilir, 2009), and internal ability to innovate (Chesbrough, 2003), Sevilir and Tian, 2012, Hall, 1988A, Hall, 1988B).

In this paper, I build upon the branch of the literature that canvasses the internal ability to innovate, where two views prevail based on whether external innovation substitutes or complements internal innovation. According to the first view, the external innovation is a substitute for internal innovation: the acquirers fall behind in their innovation efforts, and acquire other firms to catch-up with the technology frontier. There is a considerable body of literature that provides evidence for this catch-up behavior. Higgins and Rodriguez (2006) find that deteriorating internal R&D productivity in biopharmaceutical firms may be the motivation for acquisitions. Philllips and Zhdanov (2012) suggests that small firms optimally decide to innovate more when they can sell out to larger firms, while large firms conduct less R&D because they can obtain access to innovation through acquisition. Sevilir and Tian (2012), Zhao (2009), and Blonigen and Taylor (2000) are other studies providing evidence for the catch-up behavior of incumbent firms.

According to the second prevailing view on internal ability, external innovation complements internal R&D, and the innovation leaders acquire other firms to fill in their research gaps in a timely manner. Chesborough (2003) discusses the absorptive capacity theory of Cohen and Levinthal (1989), and concludes that independent of a firm's access to outside research, the firm should continue to conduct internal research. The internal research then increases the firm's ability to absorb external research. In this paper, I provide evidence for the existence of a positive relationship between the internal innovation and acquisition of external innovation, which can be interpreted as supporting evidence for the complements theory. Observing empirical evidence for both the substitutes and complements theory, the question of how to unify these theories in a single framework remains open.

In addition to the motivations of mergers literature, the target firms in this study are connected to the entrepreneurship literature. M&As constitute a form of exit for startup firms alongside IPOs.[2] Modeling the M&A markets as a two-sided matching game enables a departure from the existing entrepreneurship literature that hones the choices of both entrepreneurs and established firms. The open innovation models have important implications for the entrepreneurship literature (Kaplan and Lerner, 2010). Prior studies have analyzed the matching of start-up firms to investors (Sorensen, 2007), and the exit decisions of start-ups between M&A or IPO (Egan, 2012). However, these studies consider the decisions of either the entrepreneurs, or the incumbents, but not both. By combining the two sides of the market, I enable a unified approach to the acquirer and target choices.

This paper is also related to the market for ideas framework of Gans et. al. (2002). Considering the M&A markets as a mechanism of innovation transfer, I construe the startups as constituting the supply side of the market for ideas, while the acquirers constituting the demand side. Conditional on deciding to be acquired, the startups face a choice between willing incumbent firms. At the same time, conditional on deciding to outsource the innovation through acquisition, the incumbents face a choice between the startup firms with successfully completed innovations. The Gans et. al. (2002) framework considers the strength of intellectual property rights, transaction costs, and sunk costs as determinants of value created through start-up and incumbent cooperation. My paper can be

[2] Smith, Pedace and Sathe (2011) show that M&A success is 60% to 80% as important as IPO success in explaining VC performance. Gompers, Lerner (2000) considers M&As as the second best exit option after IPOs. Gao, Ritter, Zhu (2012), Egan (2012), and Bayar and Chemmanur (2011) look at start-up firms' exit choice between selling the firm to an incumbent (M&A) or conducting an Initial Public Offering (IPO).

construed as infusing the quality of the innovation into this framework.

3 Matching Model

The main analyses in this paper is based on a recent matching estimator developed by Fox (2010). Matching games constitute a relatively new area of empirical research, and the main goal of the empirical matching models is to estimate the preferences of agents over the characteristics of potential matching partners using data on realized matches. These games have found applications mainly on marriage and labor markets. Only recently these models have started to appear in other settings, including Venture Capital and startup firm matches (Sorensen 2007), licensing in biotechnology firms (Levine, 2009), and bank mergers (Akkus and Hortacsu, 2007). Fox (2009) provides a review of the literature on the empirical estimation of matching games.

The model I develop in this paper utilizes the maximum score estimator of matching games developed by Fox (2010). In the merger setting, acquirer firms constitute one side of the market, while the target firms constitute the other side; and using the revealed preferences of firms on both sides of the market, I investigate the role of the match-specific characteristics on the pairing decisions of both acquirer and target firms. In the remainder of this section, I first construct the maximum score matching model from Fox (2010), and then discuss the adaptation of the estimator to the mergers and acquisitions setting.

3.1 Deterministic Model

Let M_I be the number of acquisitions in a merger market, and I and J be the set of all target and acquiring firms, respectively. I then denote a merged pair as (i, j) where $i \in I$, and $j \in J$. In each M&A market, a 1-to-1 matching occurs between the acquirers and the targets: each acquirer acquires one target, and each target is acquired by only one acquirer.As a result of the merger, the acquirer receives a value $V_i(i, j)$ from the merger and pays a price p_{ij} to the target. The return to the target is merely the price it receives from the acquirer. Hence the acquirer and target returns are:

$$\begin{aligned} V_i(i,j) &= f(i,j) - p_{ij}, \\ V_j(i,j) &= p_{ij}, \end{aligned}$$

respectively. Consequently, the total value created from the merger is

$$f(i,j) = V_i(i,j) + V_j(i,j).^3$$

Upon observing merger pairs (i, j), the pairwise stability condition implies that the acquirer i receives a higher return from acquiring target j than acquiring any alternative j' available in the

[3] The choice of the value function $f(i, j)$ changes with the research setting; and we will discuss the particular value function used in Section 6.

same market. Hence, we obtain

$$V_i(i,j) \geq V_i(i,j') \text{ for any } j' \in J,\ j' \neq j,$$
$$f(i,j) - p_{ij} \geq f(i,j') - p_{ij'}. \tag{1}$$

On the target side, we know that the target j' receives a payoff $p_{i'j'}$ from some buyer i'. If the acquirer i were to buy target j, the acquisition price cannot be less than $p_{i'j'}$, else j' would not prefer i. On the other hand, any value above $p_{i'j'}$ would reduce the return to the acquirer, hence acquirer i would also pay $p_{i'j'}$ to target j'; in other words, we would have $p_{ij'} = p_{i'j'}$. Therefore, inequality 1 becomes

$$f(i,j) - p_{ij} \geq f(i,j') - p_{i'j'}. \tag{2}$$

From the observed merger pair (i',j'), we infer the symmetric inequality:

$$f(i',j') - p_{i'j'} \geq f(i',j) - p_{ij}. \tag{3}$$

Adding inequalities 2 and 3 gives:

$$f(i,j) - p_{ij} + f(i',j') - p_{ij} \geq f(i,j') - p_{i'j'} + f(i',j) - p_{i'j'},$$

Notice that any side payments made by the acquirer to the seller is cancelled out in the equation, and hence we do not need to observe the acquisition prices for our empirical analyses:

$$f(i,j) + f(i',j') \geq f(i,j') + f(i',j). \tag{4}$$

The final inequality we obtained in 4 simply states that the total value from any two observed matches exceeds the total value from the counterfactual matches created by exchanging the targets in these matches.

One important observation from inequality 4 regarding identification is the cancellation of terms that are not interacted in a linear merger value function $f(i,j)$. If a characteristic of acquirer is not interacted with a characteristics of the target, then it will cancel out from the inequality, leaving only the interacted terms. As a result, the model is not able to identify the impact of not interacted covariates.

3.2 Maximum Score Estimator

The data generating process in the matching game is that we observe data from many independent matching markets that has the same merger value function. The independence of markets imply that the target firms in one market cannot be bought by acquirers in another market. In the M&A setting, I use the time and product market of firms as the bases for constructing the markets: each

4-digit NAICS code each year is considered to be a separate merger market.[4] The markets each have a finite number of acquirers and targets, and the number of firms in a market varies across markets.

In Section 3 I have constructed the revealed preference inequalities implied by the observed matches. In this section I construct the maximum score matching merger estimator, which uses these inequalities that are necessary conditions for pairwise stability. The estimator is semi-parametric: the unobservables are not modeled except the finite vector of parameters in the merger value function. I impose a rank order condition that relates different equilibrium assignments to the pairwise stability inequalities stated in Equation 4. Using the pairwise stability condition on the matches, and the rank order condition on the error terms, Fox (2010) shows the consistency of the maximum score estimator. The rank order property also breaks the curse of dimensionality by eliminating the need to integrate the value function on unobservables, rendering the application of the estimator feasible on previously prohibitively large data sets.

Let ε_{ij} be the match specific error. Then, we denote the observed match value as follows:

$$F(i,j) = f(i,j) + \varepsilon_{ij}.$$

Notice that if we assume ε_{ij} follows a Type I Extreme Value distribution, and that the acquirer receives the entire return, the problem becomes the familiar multinomial logit for the acquirer. However, the current setting does not lend itself to the multinomial logit model because the Independence of Irrelevant Alternatives (IIA) assumption is too restrictive for the current setting. In addition, multinomial logit requires the same number of choices in each market, whereas different merger markets may include different number of agents, which then biases the results.[5] An alternative to the logit model is the probit model, which requires integration over the errors, and becomes computationally infeasible even with few observations and covariates.

Therefore, I use the maximum score estimator developed by Fox (2010). Let $f(i,j|\beta)$ be the parametric form of the merger value function, and let

$$q(\beta) = f(i,j|\beta) + f(i',j'|\beta) - f(i',j|\beta) - f(i,j'|\beta).$$

Then, define the score function $Q(\beta)$ as follows:

$$Q(\beta) = \sum_{y=1}^{Y} \sum_{i=1}^{I_Y-1} \sum_{i'=i}^{I_Y} 1_{[q(b)\geq 0]},$$

where $1_{[.]}$ is the indicator function equal to one if the inequality is satisfied, and zero otherwise. Given the parametric form of value function $f(i,j|\beta)$, and the score function $Q(\beta)$, the maximum

[4] I use various definitions of markets to ensure that the results are not dependent on the construction of merger markets. The market construction is discussed in more detail in Section 6.

[5] For a detailed discussion of the impact of varying choice sets on inference in multinomial logit model, see Yamamoto (2014).

score matching estimator uses the revealed preference inequalities, and chooses the parameter estimates that maximizes the number of correctly predicted matches in the data. In other words, the maximum score matching estimator is defined as follows:

$$\widehat{\beta} = \arg\max_{\beta} Q(\beta).^{6}$$

Fox (2010b) discusses the identification of the maximum score matching estimator. The main assumption is the Rank Order Property assumption for the errors, a structure, that breaks the dimentionality curse by eliminating the need for integration over errors. The Rank Order Condition states that

$$q(\beta) \geq 0 \Longleftrightarrow P(i \text{ acquires } j \text{ and } i' \text{ acquires } j') \geq P(i \text{ acquires } j' \text{ and } i' \text{ acquires } j).$$

The Rank Order Property simply states that the deterministic part of the value function is driving the mergers we observe, and the error is small relative to the deterministic part of the function. Fox (2010b) shows that under the Rank Order Condition, and the pairwise-stability assumption, the maximum score matching estimator $\widehat{\beta}$ is a consistent estimator of β.

The Rank Order Property connects the stochastic structure of the model and the equilibrium selection rule. Let an assignment be the set of markets we observe in each market. An equilibrium is the assignment that maximize the sum of merger values across matches across markets. The objective function takes only integer values, and there may be multiple equilibria.[7] The rank order property compares two identical assignments, A_1 and A_2, that differ only in two matches of one market, where the two targets of these matches are swapped. The rank order property simply states if the deterministic part of the merger value function is higher in assignment A_1, then the probability of observing A_1 in the data is higher.

The inequalities provide an ordinal comparison of covariates, as a result, any positive monotone transformation of β preserves the inequalities. Therefore, following the literature, I normalize the first element of β, the coefficient on technology distance as discussed below, to ± 1, and then pick -1 as it provides the most number of inequalities satisfied. I choose to normalize the coefficient of technology distance because we know from the prior literature that technology distance has an impact on the acquisition decision. This is also confirmed with the conditional logit models on my data in Section 6.2.

In this setup, the model identifies the relative importance of observables that impacts the value function $f(.)$, but does not identify the nominal levels of these impacts. For example I will be able to state how important the technological proximity between the acquirer and the target is relative to the geographical proximity between the two; however, I will not be able to state how important

[6] Notice that the objective function does not include integrating over unobservable characteristics. As a result, even at the global maximizer $\widehat{\beta}$, or at the probability limit of the objective function, not all inequalities will be satisfied. This is what distinguishes the maximum score estimator from a moment inequality estimator (Pakes, Porter, Ho, and Ishii, 2006 via Fox, 2010).

[7] Fox (2010) shows inexistence of equilibrium is highly infrequent.

the technological proximity is in nominal terms.

The data does not include the set of potential matches, neither this data is necessary for the maximum score matching estimator: for two identical assignments A_1 and A_2 that differ only in two matches as above, the set of unrealized matches is identical, and therefore do not have a bearing on the inequality.

The objective function takes on only integer values, and, despite not including integrals or nested solutions, its optimization is still fairly computationally intensive. I use the differential evolution algorithm, and repeat the estimation using 20 different initial points, and choose the vector that satisfies the maximum number of inequalities.[8] My estimation program is built upon the toolkit provided by Fox, Santiago (2008) for matching maximum score estimation.

3.3 Confidence Intervals

The asymptotics of the maximum score matching estimator is in the number of markets we observe, and the consistency of the maximum score matching estimator under the assumptions discussed is shown by Fox (2010). The sampling distribution of the estimator is obtained using subsamples of markets drawn without replacement from the data. I select 100 random subsamples that contain three quarters of the markets in the sample: for example, in the 105 NAICS-4 based markets, each subsample has 79 markets. For each subsample, I estimate $\widehat{\beta}_{subsample}$ that maximizes the number of implied inequalities by the subsample. Then, the approximate distribution of $\widehat{\beta}_{full}$ can be obtained using the following for each subsample:

$$\widetilde{\beta}_{subsample} = \left(\frac{n_s}{N}\right)^{\frac{1}{3}} \left(\widehat{\beta}_{subsample} - \widehat{\beta}_{full}\right) + \widehat{\beta}_{full},$$

where n_s is the subsample size, and N is the full sample size.[9] Taking the 5^{th} and 95^{th} percentile of the empirical distribution gives us the 90% confidence interval.

4 Theoretical Background

In this Section, I develop the theoretical underpinnings of the acquirer-target pairing decisions in the market for ideas. The fundamental issues are matching on innovation output quality, and on distances in technology, product market, and geography.

The main focus of this paper is the innovation output quality of acquirers and targets. There are two prevalent theories on the pairing of acquirer innovation quality with that of the target. The first view suggests that the acquiring firms are laggards in their innovation activities, and use acquisition as a substitute for internal innovation in an attempt to catch-up with the technoogy

[8] Fox (2010b) discusses that using a sufficiently large subset of the inequalities in the estimation process still yields consistent estimators. In my estimations I use all the implied inequalities from pairwise switches of targets.

[9] See Politis and Romano (1992) and Delgado et. al. (2001) for more on subsampling and the approximate distribution of the maximum score estimator.

frontier.[10] In this view, acquirers would have low quality innovation, and the lower the internal quality, the higher their willingness to pay due to the higher distance to the innovation frontier. Targets with higher quality innovation would be more valuable, implying low-quality acquirer and high-quality target pairings in the M&A markets.

Alternatively, external innovation can be viewed as complementing internal innovation. Along these lines, Cohen and Levinthal's (1989) absorptive capacity theory states "while R&D obviously generates innovations, it also develops the firm's ability to identify, assimilate, and exploit knowledge from the environment-what we call a firm's 'learning' or 'absorptive' capacity." This implies that firms with high quality internal innovation would have an advantage in acquiring outside innovation: as the distance to the innovation frontier decreases, the integration costs would be lower, the ability to identify targets would increase, and the targets' willingness to be acquired would be higher. Therefore, under the complements theory, as the distance to the innovation frontier decreases, the cost of acquisition to the acquirer goes down, implying high-quality acquirer and high-quality target pairing in M&A markets.

Given the opposite direction of the quality pairings in the two alternative theories, the question of which effect dominates is an empirical one. To shed light on these theories, I proxy the innovation quality by standard patent-based metrics, the construction of which I discuss below in the data section. I differ from the prior literature in that I use the quality of the innovation output, as opposed to the R&D expenditures or simple patent counts. Zhao (2009) also utilizes the quality of innovation output based on patent-citation-based metrics, but analyzes only the acquirer side. My analyses combine both the acquirer and the target sides of the market. A second departure from Zhao is my use of the declining balance formula to reflect that as time goes by the value of innovations goes down due to obsolescence. The details of the patent-based quality metric, and the declining balance formula are discussed in the data section below.

I use the quality of innovation output, as opposed to R&D input or simple patent counts, for multiple reasons. First, data on R&D spending or sales is not available for private firms, hence it is not possible to operationalize an R&D input intensity measure for a sample that includes private targets. Furthermore, data on firm sizes is also not available, and using simple patent counts may capture not only innovativeness, but also the size of the firm. Using the quality of a firm's patent portfolio is both feasible, and has the added benefit of being comparable across firms, hence avoiding potential confoundings with the impact of firm size. The quality of the innovation output I use is calculated relative to the quality of all innovation output in the same technology in the same year, the details of which are discussed in the data section.

In acquisitions motivated by access to external innovation, the relatedness of the research activities of the acquirers and the targets would play an important role. Ahuja and Katila (2001) show that the relatedness of the acquirer and target knowledge bases has a substantial impact

[10] Zhao (2009), Bena and Li (2014), Sevilir and Tian (2012) consider acquisitions as a catch-up mechanism. Strategic alliances are another mechanism through which external innovation is used to catch-up with the technology frontier (Robinson, 2008).

on the subsequent innovation output of the firms participating in M&As. Bena and Li (2014) also show that the existence of technological overlaps between any two firms has a positive effect on post-merger innovation output. I follow this literature and conjecture that the value created through a merger would increase with the technological relatedness of the acquirer and target firms. Note that technologically close portfolios may be complements or substitutes, and both may imply relatedness in the research space. The technology distance is agnostic to this distinction.

In addition to the technological activities of firms, product markets are also found to have an impact on the merger decisions of firms (Hoberg, Phillips (2010), Seru (2011)). In this study, I explicitly distinguish the innovative activities of firms from their product market activities. The patents are classified based on their underlying technology, which may be useful in multiple product markets. Schmookler (1966) illustrates this by noting that patents regarding a toothpaste tube and manure spreader are both listed under the same patent subclass: dispensing of solids. Similarly, two substitute products may be developed using drastically different technologies. The solid state disk drives and the hard disk drives constitute such an example: the two are almost perfect substitutes for the end user as computer storage devices; however, the underlying technology each utilize is drastically different from the other.[11]

Building on the distinction between product markets and technology markets, I include a product market distance metric in my estimations to account for the product market proximity in merger value creation.[12] Seru (2011) finds that higher product market distance between the acquirer and the target results in smaller number and less novel post-merger innovations. Building on this, I also conjecture that when the distance in product markets increase, the value created through merger would decrease.

Geographic location is another important factor in firms' R&D and M&A activities. The R&D spillover literature shows geographic localization as one of the main drivers of innovation spillovers (Jaffe, Trajtenberg, Henderson, 1993). The geographic distance has also been used as a proxy for the information asymmetries or better information sharing between the parties (Ragozzino Reuer, 2011, Ang, Wu, 2013). Furthermore, Dyer et. al. (2004) suggests that acquirers are interested in keeping the employees of target firms, and the probability of keeping target firm employees is higher when the two firms are located close to each other. Following these studies, I conjecture that the merger of firms that are geographically close to each other would create a higher value.

The generalizability of the results I draw depends on the comprehensiveness of the data sources I use. Though there is a considerable body of literature that explores innovation and acquisition activities in various contexts, the studies are mostly limited to a single industry (ex: Higgins, Rodriguez (2006)), to one side of the M&A markets (Zhao, 2009) or to firms for which detailed data is available, namely public firms. I discuss the issues caused by limiting the study to only one side of the M&A markets below. Similarly, results from data limited to public firms may also not be

[11] For other examples of modelling the product markets separate from the innovation markets, see: Bloom, Schankerman, Van Reenen, 2013, Gambardella, Giarratana, 2013.

[12] For examples of product market distance, see: Cuypers, Cuypers, Martin, 2007, Capron and Pistre 2002; Uhlenbruck, Hitt and Semadeni, 2006.

generalizable. Netter et al. (2011) shows that aggregate inference on the scope of corporate activity and investment changes when private firms are included in the sample of M&A firms involved. Ali, Klasa, and Yeung (2009) report that industry concentration measures that use public firms data from COMPUSTAT are poor proxies for concentration measured that use United States Census data, which includes private firms. Asker et. al. (2012) also document the differences between the investment behavior of public and private firms. Ransbotham and Mitra (2010) also show that target private status has an impact on the value the acquirers capture. I use the census of activity in the M&A markets, as well as the census of patents from the USPTO, which helps mitigate any selection issue created due to the filtering of the data. Furthermore, I investigate my hypotheses in two subsets of the data separately, one including only the private targets, and the other only the public targets.

5 Data and Summary

The data used in this study is the result of a major data linking effort, and thus is novel. I constructed the data by linking the Securities Data Company's (SDC) Mergers and Acquisitions data module to newly constructed USPTO patent data from 1976 to 2010. Through this linked data I am able to identify the patent portfolio of firms that have participated in M&As either as acquirers or as targets, hence I can track the patents that are transferred to incumbent firms through acquisition of other firms. In the remainder of this Section, I discuss the data sources, and the construction of key variables.

5.1 Patent Data

Patents are one of the most utilized sources of information in the innovation literature. The use of patent data as a proxy for economic activity dates back to Schmookler (1951) and Griliches (1990), and since then an extensive literature on using patents as indicators of innovative activity has developed.[13] Here I follow this literature and use the granted patents by the United States Patents and Trademark Office (USPTO) between 1976 and 2010 as a proxy for the innovative activity of the patent owners. The standard source for patent data in the innovation literature has been the NBER patent data file. However, the NBER data does not provide the full name of patent assignees, which is used to link the patent data to other data sources.[14] Therefore, I resort to the raw USPTO files to construct an updated patent data file, and to enable linking the patent data to the M&A and IPO data. Appendix A describes the construction of the patent data in more detail.

Linking the patent data to the M&A data has been touted as a potentially fruitful avenue.[15] However, the linking process is not a trivial task because there is no unique firm identifier across data files, and due to various misspellings, human errors, or minor changes in firm names over time,

[13] See, e.g., Griliches (1990) and Nagaoka et al. (2010), Lerner et. al. (2011).

[14] The NBER Patent Data File has standardized assignee names, at the pdpass (unique firm identifier) level, whereas the USPTO Patent Data Files have raw assignee names at the individual patent level, a finer level than pdpass.

[15] See ex: Zhao (2009) for a discussion on the benefits of identifying the patents of M&A targets.

there is not a trivial method to identify the patents of a firm. I use an innovative two-step method involving an automated computer algorithm followed by crowd-sourced manual checks. The details of the linking algorithm is provided in Appendix B.[16]

5.2 M&A Sample Selection

I use M&A activity as a measure of the demand for patented technology from other firms. I identify the acquisitions using the Securities Data Company's M&A data module, which includes SEC filings, firms' press releases, news articles, and a variety of other public sources. The data covers all US corporate transactions, public and private, since 1979. An M&A deal is included in the sample if it involves at least 5% of the ownership of the target company, and for the pre-1992 period if the deal valuation is at least $1 million (all deal values are included for the post-1992 period). The data also includes deals in which the deal value is undisclosed. Reported items include the identities of acquiring and target companies, their industry codes, and deal-specific information including the deal value whenever available.

Using the linked M&A and patent data, I identify M&A deals between 1979 and 2010 in which both the target and the acquirer have at least one patent between 1976 and 2010. I use the citations received by patents as a proxy for patent quality, and to allow for the accumulation of citations, I drop the M&A deals taking place during the last three years of my patent data (after 2007). After identifying the deals with at least one patent on both the acquirer and the target sides, I eliminate deals that are not of interest, including incomplete deals, rumors, and repurchases. In this way I keep completed M&A deals that have one of the following forms: merger, acquisition, acquisition of majority interest, acquisition of assets, and acquisition of certain assets. I also drop deals in which the target or the acquirer is in the financial industry (SIC codes 6000 to 6999) or is a utility firm (SIC codes 4900 to 4999). In addition, I drop deals in which the target is a subsidiary. I then manually examine the remaining deals and drop repurchases, or self-acquisitions of a subsidiary that are not already identified by the variables in the SDC data. These steps identify 5082 M&A transactions in which both acquirer and target firm have patents.

Furthermore, to allow for the patent portfolio of firms to accumulate from 1976 onwards, I restrict the data to deals that take place on or after 1986; this step also ensures the data integrity in the SDC M&A data.[17] Finally, I drop firms that did not apply for any new patents in the three years leading to the M&A deal, considering them inactive in the innovation ecosystem. The resulting 2,378 M&A deals between 1986 and 2007 constitute the data sample for the remainder of the study.

The target patent portfolio sizes vary considerably across transactions, from a minimum of one patent to a maximum of 9,355 patents. There are 69 acquisitions with more than 200 patents at the time of the acquisition, and 53 of these acquisitions have US acquirers. Given the sheer

[16] The linking of M&A data to the patents data is a by-product of a larger data linking endeavor, in which I link USPTO patent data to data on Venture Capital backed firms, IPO firms, M&A acquirers and targets, COMPUSTAT and CRSP public markets data. This paper utilizes only the M&A-USPTO links.

[17] Bena and Li (2014) reports that the SDC M&A data is more reliable for the post-1983 period.

size of targets in these transactions, I suspect that the motivation in these acquisitions may be confounded with various other factors, including macroeconomic factors, and I do not include these 69 observations in the main specifications below. In addition, I limit the sample to domestic acquirers for the majority of the paper by excluding the 307 acquisitions conducted by a foreign firm. I discuss the impact of these exclusions in Section 6.

I am concerned that M&A is not the only channel for transferring ownership of patents between firms. Licensing of patents and outright sale of patents are two other channels, and both provide additional information about the market demand for ideas.[18] Serrano records that 13.5% of all granted patents are traded over their life-cycle; and I obtain a similar scale of transfer (10%) through M&A activity. Ozcan, Ersahin (2014) shows that these two sets have no more than 25% overlap, indicating that the total number of patents that change hands through sales or mergers is around 20% of the US patent stock. Identifying the acquirers of individual patent sales requires repeating the name linking algorithm described in Appendix B on the patent sales data, which is a major undertaking and is beyond the scope of this paper. However, comparison of the 10% of M&A transactions with the total transactions of 20% leads me to believe that merger is a good proxy for demand.

5.3 Main Trends

The main sample used in this study constitutes of 2,378 acquisition targets being acquired by 1,366 unique acquirers between 1986 and 2007. In each transaction both the acquirer and the target firm has at least one US patent application within three years leading to the M&A activity. Of these transactions, only 260 are acquired by acquirers that conduct multiple acquisitions within 3 years of each other; the remaining 2,118 acquisitions are isolated from any other acquisition activity of the acquirer for at least the three previous years.

Figure 1 plots the M&A and target patent counts over time. As expected, the M&A activity exhibits an upward trend towards the 2000 dot-com bubble, followed by a sharp decrease in the total amount of activity, averaging 59 acquisitions per year in the first half of the data, and 157 in the second half. The number of patents that change hands through M&A activity follows a similar trend to the acquisition counts.[19]

Table 2 provides a breakdown of acquisition activities by acquirer and target public market status. The transactions with both public acquirers and public targets constitute 31% of the activity, and results in the transfer of 68% of the total transacted patents changing hands. Even though a majority of acquisitions are conducted by public acquirers, the private firms conduct 17% of the acquisition activity, and acquire 16% of the transacted patents. On the other hand, with 1,157 deals, the private targets constitute the majority of the transactions, though the private targets only possess 19% of the transacted patents.

[18] See Arora and Gambardella (2010) and Serrano (2010).

[19] The transferred patent counts exclude two mergers that are of considerably different size than the others. The first is the Cingular and AT&T merger in 2004, with 8,956 patents transferred. The second is the Alcatel and Lucent merger in 2006, resulting in 9,300 patents changing hands.

5.3.1 Geographic Distribution

Geographically, both the acquirers and targets are distributed across the nation, with clusters in California, the Northeast, the Midwest, and Texas. Figure 2 maps the location of target firms, with each circle proportional to the number of targets from that state. California is the leading supplier of targets, with presence in 657 transactions. The second most active region in supplying targets is the New England states,[20] with a combined targets of 267. The Midwest States[21] is as large as the New England states, with 268 target firms. New York, New Jersey, and Pennsylvania region follows with 182 target firms. Other notable centers supplying target firms are Texas, Washington State, and Florida.

Figure 3 maps the acquirer locations in my sample. The acquirers also span the major metropolitan areas of the nation, with California, and Massachusetts as the largest sources of demand. However, their dominance is attenuated slightly with respect to the supply, with New York, Illinois, Pennsylvania, and Minnesota acquiring significantly more than their target supply. This is also suggestive of another important observation from the acquirer-target locations: there is considerable amount of out-of-state acquisitions that I document in Table 3. In fact, the median distance between the acquirers and targets in the sample are 729 miles. Furthermore, this out-of-state activity is not restricted to demand from California, or Massachusetts only. Table 3 also presents the ratio of acquisitions by companies based in California: on average 74% of targets are acquired through cross-state acquisitions, and only 29% of this is due to acquisitions by firms located in CA, suggesting that cross-state activity is considerable.

5.3.2 Product Market Distribution

My data spans the census of acquisition activity over a period of 22 years from 1986 to 2007. It is only expected that companies we are familiar from the popular press also appear in our list of acquirers with 10 or more acquisitions presented in Table 4. The first key observation from Table 4 is the the variety in the industries the acquirers span: there are acquirers from machinery manufacturing (Illinois Tool Works), to chemical manufacturing (Pfizer Inc), to telecommunications (Lucent Technologies). Though the overall sample seems slightly more weighted towards electronics and computing, with acquirers including Cisco, Medtronic, Motorola, and Intel.

Recall that our sample includes acquisitions in which both the target and the acquirer has applied for at least one patent within three years up to the acquisition. We can understand how this restriction impacts the sample by observing the top acquirer in our sample: Cisco. We can say that Cisco is the poster child of acquiring companies, which has received considerable attention from both the industry and academia. In their homepage, the company states they have acquired 119 companies during our sample period.[22] Of the 119, the targets that has at least one patent within

[20] The New England states are Maine, Massachusetts, New Hampshire, Vermont, Rhode Island, and Connecticut.

[21] The Midwestern States that had at least one target in the sample are as follows: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Ohio, Wisconsin.

[22] Cisco Inc. homepage, Acquisitions section. `http://www.cisco.com/web/about/doing_business/corporate_development/acquisitions/ac_year/about_cisco_acquisition_years_list.html` Last accessed: October 19,

three years prior to its acquisition is 26, which are reported in Table 1. Again, as in the top acquirers list, the first key observation from the list of Cisco targets is the multiple industries spanned. In fact this is true for not only the targets of Cisco, but also for the entire sample: the distribution of targets across industries varies considerably (Table 5). Though the manufacturing industries dominate the M&A markets to some extent in our sample, the data also include considerable activity from other industries, including Information, Professional Services, and Administrative Support NAICS groups.

5.4 Variables and Summary Statistics

In this section, I provide a brief overview of variable construction, and discuss the summary statistics for key variables.

The main objective of this study is to disentangle the relative importance of various factors on the pairing decisions of firms. Four classes of factors can be introduced in this context: firm-specific, match-specific, industry-specific factors, and macro conditions of the overall economy. As a result of the matching approach this paper takes, I use the product market industries and M&A years to construct the matching markets. Therefore, industry-specific characteristics, and time-dependent macro-characteristics, which would be the same for all the firms in a same matching market, would be washed out in the estimations, hence cannot be identified. Similarly, firm-specific factors need to be interacted with a characteristic of the firm on the opposite side of the market, otherwise, the firm-specific character would cancel out in the moment inequalities in Equation 4. As a result, I identify the relative impact of interacted firm-specific factors, the innovation quality, and the match-specific factors, the technology, product market and geographic distance, in the estimations. Table 6 provides the summary statistics for the key variables.

The quality of the patent portfolio of the acquirer and the target firms is one of the key variables. I use the patents from the most recent three years prior to the M&A activity as each firm's portfolio, and I use the citations a patent receives from other patents as a proxy for its quality. I then apply the fixed-effects normalization suggested by Hall. et. al. (2001) to account for the changes in citation behavior across industries and years. I also discount citations to older patents using the declining balance formula to account for the depreciating value of patents over time. Appendix C provides the details of the quality measure calculation. The resulting quality measure, the per-patent, fixed-effects-adjusted, time-discounted citations a firm's patent portfolio receives, is the relative position of the firm's patent portfolio in the ranking of all firms. A quality level of one implies that the firm's patents are all at the average quality level in their respective technology class and industry year.[23]

The summary statistics for the quality variable is provided in Table 6. In the sample of acquisitions, the acquirers have an average quality level of 1.7, implying their patents are of higher quality than an average patent in the economy. However, the targets have a quality level of 2.4, which

2014.

[23] I repeat my analyses using various other quality measures, which are discussed in Appendix C.

is even higher than that of acquirers. This is consistent with the extant literature: Bena and Li (2014) states that the acquirers in their sample are more R&D intensive compared to the average firm in COMPUSTAT, but have lower R&D expenses than the targets.

The technology distance between acquirers and targets is the first match-specific factor I use. Identifying the research activities of each firm is not possible. Instead, I observe the patents, the innovation output, of each firm, and the technology class of each patent that USPTO assigns. Using the technology classes to proxy a firm's location in the research space and the proximity between firms is common practice (Jaffe 1986, Benner Waldfogel 2008). Two widely used measures of technology distance are the citations made from one firm's patents to the other, and the distance in the technology space. In this study, I consider the distance in the technology space as citations are observed over time, and the use of citation-based distance would necessitate the truncation of the M&A data for the recent years. The distance in the technology space is based on the technology classes listed by USPTO for each granted patent, which differ from the widely used product market classifications (NAICS, SIC) and are based on the underlying technology. The USPTO technology classes may not necessarily overlap with the product market use of the patent. Using the patent classifications, I construct a vector $T_i = (t_{i,1}, ..., t_{i,H})$ for each firm, with each $t_{i,h}$ indicating the share of the firm's patent portfolio in technology field h, where H is the total number of technology classes USPTO use. To illustrate, consider a firm with 3 patents in biotechnology and another 9 in chemicals. In a world with only two technology classes, the technology vector for this firm would be $(0.25, 0.75)$ because one quarter of its patents are in the biotechnology class. Consider a second firm with 3 patents in biotechnology, and no patents in chemicals, which would have the technology vector $(1, 0)$.

The technological distance between these two firms would then be the Euclidean distance between these two vectors:[24]

$$tech_{i,j} = \sqrt{\sum_{h=1}^{H} (t_{i,h} - t_{j,h})^2}\,.$$

The acquisitions also exhibit considerable variation in the technology distance metric, ranging from the theoretical minimum of zero, to the theoretical maximum of 1.41, with an average level of 0.67.[25]

To capture the product market distance, I check whether the acquirer and the target are in the same industry. I discretize the product market distance by increasing the measure by one for

[24] Jaffe (1986) use an alternative technology distance metric: the angle between the two technology vectors:

$$tech_{i,j} = \frac{\sum_h (t_{i,h} * t_{j,h})}{\sqrt{\sum_h t_{i,h}^2 \sum_h t_{j,h}^2}}.$$

Using the angular distance in my setting gives similar results.

[25] For the technology distance, a value of zero is the theoretical minimum, and happens when both firms have patents in the same technology classes, and the share of each class within the firm's portfolio is the same across the two firms. A value of 1.41 (i.e. $\sqrt{2}$) is the theoretical maximum, which happens when each firms has all its patents in a single technology class, and this class is different between the two firms.

each different digit in the 4 digit NAICS code of the acquirer and the target. To illustrate, the distance between a firm in NAICS 334111 and a firm in NAICS 334119 would be zero because the first four digits in the NAICS code are the same. On the other hand, the product market distance between these codes and NAICS 335911 would be two, because only two of the first four digits are the same.[26] The product market distance also varies between its minimum level of zero, to its maximum level of four, with an average of 1.83, implying that on average the acquirers and the targets have the same 3 or 4 digit NAICS codes. This is simply a re-statement of our observation from Table 5 that the 3-digit NAICS level cross-industry acquisition rate is 49% across the sample.

I include the geographic distance between the acquirer and the target, calculated as the bird's fly distance between the zip codes of the two entities. In a quarter of the acquisitions both the acquirer and the target are in the same state. The average bird's fly distance in our sample is 995 miles, roughly the distance between San Francisco and Albuquerque, NM, or the distance between Boston and Chicago.[27]

The majority of the acquirers, 83%, are public firms, and a majority of the targets, 66%, are private firms. Table 2 breaks down the public-private status of firms further. The public firms acquire 84% of the transacted patents. The private targets, though numerous in size, provide only 19% of the patents transacted.

The patent portfolios of targets are considerably smaller than the acquirers', with a median size of 7 against 93. Both distributions are quite skewed, with some large firms driving the averages up; though the targets have smaller portfolio's than the acquirers. Table 7 provides a finer breakdown based on target patent portfolio sizes. There are only 13 transactions in which the target has more than 1000 patents at the time of the M&A, but these firms command approximately 46% of the patents transacted. When we reduce the threshold to more than 200 patents, we observe only 53 transactions, corresponding to 65% of the patent transactions. Thus, targets with 200 or less patents at the time of the acquisition correspond to 97% of the transactions, and command roughly 35% of the patents transacted. I consider the 53 transactions with more than 200 patents to have confounded motivations: in addition to the hypothesized acquisition of the innovative assets of the targets, the merger may include other concerns including increasing the market share, access to employees, processes, and other assets of the target firms. Therefore I drop these 53 transactions from my sample in the model estimations.

Finally, a quick look at the patent portfolio ages (years since the first patent of the firm) reveals, not surprisingly, that the target firms are on average considerably younger than the acquirer firms: an average target has its first patent 8.5 years before the acquisition, whereas an average acquirer

[26] I am using the primary NAICS code listed by the SDC in the calculation of the product market distance. This may overstate the difference for big acquirers such as GE or GM, as these firms have activities in a variety of product markets, and restricting these firms to a single NAICS code would increase the distance to their target firms on average. To remedy this issue, I am currently working on organizing all the NAICS codes listed for each firm (up to 10 codes), and will repeat the analyses by taking the minimum of the distance between any NAICS code of the acquirer and any NAICS code of the target firm.

[27] The average distance is calculated using the domestic targets and domestic acquirers, excluding the foreign acquirers.

applied for its first patent 15 years before the acquisition. Given the differences in the portfolio sizes of targets and acquirers, this age differential is expected.

6 Empirical Methodology and Results

In this section I first discuss reduced-form descriptive results from the conditional logit model of the M&A matching markets. I then describe the empirical model I use to rationalize the firm choices given the observed acquisition behaviors and firm characteristics in the M&A markets. Operationalizing the 2-sided matching model, I discuss the positive assortative sorting acquirers and targets exhibit on patent portfolio quality, and the negative sorting on distances in technology, geography, and product markets.

I define a matching market using the acquisition years, and industry classification codes of acquisition targets. Conditional on firms participating in acquisition activity in a market, I look for which exogenous characteristics of targets and acquirers are predictors of a match within each market. The exogenous characteristics include acquirer and target patent portfolio quality, the technology, geography, and product market distances between acquirers and targets. I then move on to subsamples of the transactions based on the public and private status of target firms. To disentangle the impact of various characteristics, I use the 2-sided matching model developed by Fox (2010).

I first employ the standing model in the literature, the McFadden (1978) conditional choice model, which is utilized by Bena and Li (2014) in the M&A context. I then describe the violations in the conditional logit model in the M&A setting, which necessitates the matching model. In the conditional logit model, each observation is a potential acquirer and potential target pairing, with the dependent variable equal to one if the paired firms are involved in an actual acquisition, and zero otherwise. In the following analyses, I assume that the observed acquisitions are the results of the highest combined acquirer and target values to an acquisition involving the two parties.

6.1 Market Construction

The matching estimator uses markets as the bases of estimation. I operationalize the matching market concept in the data using the acquisition year, and the product market industry of the target firms. The M&A sample contains an average of 86 acquisitions each year, and the targets are spread across more than two hundred 6-digit NAICS industries. As my preferred market construction I consider a 4-digit NAICS industry within a calendar year as a matching market. In some years the 4-digit NAICS buckets spread the M&A activity too thin. For buckets containing less than five acquisitions, I follow Bena and Li (2014) and move one level up in the product market classification and merge the buckets under the same 3-digit NAICS level in the same year. I continue this process until each merger market contains at least five acquisitions. If a market does not have at least five acquisitions at the coarsest level, then I drop that market from the sample. This process results in 105 merger markets for the 4-digit NAICS based construction.

To ensure that the results are not an artifact of the market construction, I repeat the analyses using other market buckets, including the 58 markets based on 2-digit NAICS, 114 markets based on 2-digit SIC, and 135 markets based on a hybrid of 4-digit NAICS and 2-digit SIC codes.[28] The main results are qualitatively same across these varying definitions of matching markets.

6.2 Descriptive Results

In this section I use logistic regression to investigate the determinants of firm pairings in M&As.[29] I posit that acquirers (targets) within each matching market have a choice across all targets (acquirers) within the same matching market. Conditional on participating in an M&A activity, the logistic model estimates the impact of acquirer and target characteristics on matching probability. One of the main assumptions of the estimation is the fixed alternatives: the matching between a potential acquirer - potential target pair is determined by assuming the matching of the other acquirer-target pairs as fixed. The results presented here are qualitatively very similar to the results from the full matching model below. However, quantitatively, the logistic model gives a higher estimated impact of acquirer-target quality interaction, and geographic and product market distances on matching probability than the matching model.

In the conditional logit setting a matching market is defined as a product market - acquisition year bucket, as detailed in Section 6.1. A potential acquirer is any acquirer that has made an acquisition in the given product market in the same year. A potential target is any target that was acquired in the same year in the same product market. An observation is a potential acquirer - potential target pair, and the regressors are interactions of acquirer and target firm characteristics. The dependent variable is a dummy which equals one if the potential acquirer has actually acquired the potential target, and zero otherwise. For example, there are 4 acquisition in 2006 in which the target is in the product market NAICS 4234. In this market, there would be 16 observations pairing all acquirers with all targets, with the dependent variable equal to 1 for the four actual acquisitions, and zero for the twelve counterfactuals.

In Section 3.2, we denote the match value as

$$F(i,j) = f(i,j) + \varepsilon_{ij},$$

where ε_{ij} is the match specific error. Let $f(i,j) = X_{ij}\beta$, where X_{ij} stand for the characteristics of the jth target for acquirer i, and β be the corresponding parameter vector, . If we assume the errors ε_{ij} to be iid Type I Extreme Value, then, we obtain the conditional logit model, with the probability that acquirer i acquirers target j as

$$P_{ij} = \frac{\exp\left(X_{ij}\beta\right)}{\sum_{J} \exp(X_{ij}\beta)},$$

[28] The industry classification system has changed from SIC to NAICS in 1998. The mapping between SIC and NAICS is a many-to-many mapping. The SDC M&A data reports both SIC and NAICS values for each transaction. In the hybrid classification, I use the target firm SIC codes pre-1998, and the NAICS codes post-1998.

[29] For prior uses of conditional logit in matching settings, see Levine (2009) and Bena and Li (2014).

where J is the set of alternatives available to acquirer i.[30]

Notice that the characteristics of targets that do not change across acquirers drop out of the probability. Therefore, the model can estimate the match-specific factors (interacted terms, or distance between acquirer and target), but cannot identify target-specific factors (target size or location).

I operationalize the match value function with the variables constructed from the M&A and patent data. The regressors include the interaction of acquirer and target patent portfolio qualities, and technology, product market, and geography distances, and market fixed effects. Table 8 reports the estimates from the conditional logit models: Panel A reports the parameter estimates, Panel B reports the odds ratio estimates, and Panel C reports the implied changes by a one standard deviation change in the covariate, where the implied change by technology distance is normalized to -1.

Column 1 reports the estimation from the 4-digit NAICS based markets. Increasing the technology, product market or geographic distance all decrease the probability of matching, whereas increasing the acquirer or target quality increases the probability of matching. Changes in the technology distance has the highest impact on acquisition probability: a one standard deviation increase in technology distance results in a 53% decrease in the probability of a match. The direction of this impact is consistent with the previous literature. The second highest impact comes from the changes in the product market distance: a one standard deviation increase from the average level of 1.83 to 3.36 results in a 37% decrease in matching probability. The geographic distance is also an important factor in the acquisition decisions, with a one standard deviation increase in the distance resulting in a 3.8% reduction in matching probability.

Patent portfolio quality of the targets and acquirers is the only trait that shows a positive impact on the probability of acquisition. The acquirer and target quality variables are interacted in the model, therefore, it gives us the differential impact of changes in one variable holding the other constant. Panel B of Table 8 reports that holding the target quality fixed at its average level, a one standard increase in acquirer quality results in a 2.2% increase in acquisition probability. On the other hand, holding the acquirer quality constant at its mean, and increasing the target quality by one standard deviation results in a 4% increase in the probability of a match. Though these impacts may seem modest compared to the impact of other covariates in the model, consider a one standard deviation increase in both the acquirer and the target patent portfolio qualities: the probability of acquisition increases by 9.2%. If we normalize the impact of technological distance to -100%, then the impact of the quality is 17.4%.

Each column in Table 8 reports the estimates from a different market construction, ranging from 4 digit NAICS-based markets in column 1, to 4-digit NAICS and 2-digit SIC hybrid markets in column 4. The estimated parameters are quantitatively very close across different definitions of markets, which suggests the independence of results from market definition.[31]

[30] For details on Conditional Logit, and a comparison to multinomial and mixed logit models, see Hoffman, Duncan (1988).

[31] Only the estimates on the impact of the product market distance exhibits fluctuations across markets. Such a

The positive impact of patent quality on the probability of acquisition is consistent with the absorptive capacity theory, where acquirers with higher internal production quality acquire targets with higher quality. Two potential underlying mechanisms for the positive assortative sorting on quality are i) high quality firms may have access to a wider set of potential targets through target preferences, and thus are able to pick the better targets, or ii) high quality firms have the ability to identify high quality counterparts. Even though I am not able to distinguish between these two mechanisms in the conditional logit models, the existence of a statistically significant, positive relationship that is robust to market definition hints that complementarities between internal and external innovation may play a role in the M&A markets.

6.3 The Matching Model

The conditional logit model assumes independent errors, choice sets of the same size, and one-sided decision making. In this section I discuss the implications of these assumptions on the conditional logit parameter estimates in the M&A setting, and how the 2-sided maximum score matching model works around these problems.[32]

The conditional logit regressions I estimated above take into account the choice problem of only the acquirer, whereas the acquisition decision is two-sided: the acquirers choose among the alternative targets, and the targets also choose among alternative acquirers. The omission of the simultaneous decision results in inconsistent estimates.

In the conditional logit regressions the independence of error terms across alternatives creates the independence of irrelevant alternatives (IIA) property: the ratio of acquisition probabilities of any two targets by an acquirer depend only on the characteristics of those two targets. The error structure ensures that changes in the characteristics of other alternatives in the choice set does not change the ratio of acquisition probabilities for the two alternatives at hand (the classical red bus, blue bus problem). The IIA assumption is especially problematic in the M&A setting because not only the characteristics of the alternatives change from market to market, but also the size of the choice sets change considerably in the M&A markets due to both variations across industries, and over time.

It is possible to remedy the issue by relaxing the independence assumption and assuming multivariate normal correlated error terms and the resulting conditional probit model. However, computational intensity of the multinomial probit model increases exponentially in the number of alternatives, and estimation becomes infeasible very quickly.

The maximum score matching estimator solves both the computation and simultaneity problems: it takes into account the preferences of both the acquirers and the targets in the moments

fluctuation is expected because the construction of the markets and the product market distance both depend on the product market industry of the target firms: the impact of product market distance is highest in the coarsest matching market definition (column 2), and lowest in the finest matching market definition (column 4), and increases monotonically with the granularity of the matching market definition.

[32] For other applications of empirical matching models, see, among others: Akkus and Hortacsu (2007), Levine (2009), Yang et. al. (2009), Mindruta (2009).

constructed, and solves the curse of dimentionality through a rank-order assumption on the error terms, rendering computation feasible even with very large choice sets.

6.4 Matching Model Estimates

In the matching estimates, matching markets consists of target firm product market - year buckets, as described in Section 6.1. The potential acquirers are any acquirer that has conducted an acquisition in the same market, and potential targets are the set of acquisition targets in the same market. The estimates are then based on the maximum score matching estimator developed in Section 3.2, with the match value function defined as follows:

$$f(i,j|\beta) = \beta_1 * TechDist_{ij} + \beta_2 * AcqQual_{ij} * TgtQual_{ij} + \beta_3 * PMDist_{ij} + \beta_4 * GeoDist_{ij},$$

where the covariates technology distance, product market distance, geographic distance and patent portfolio quality are as constructed in Section 5.4. Recall that the identification of the parameters is up to a scale, therefore I follow the literature on matching maximum score estimators, and normalize β_1. I estimate the model with $\beta_1 = 1$, and with $\beta_1 = -1$, and then pick the model that maximizes the number of inequalities satisfied, which happens when $\beta_1 = -1$ in my setting. The negative impact of technology distance is also consistent with the negative coefficient estimates from the conditional logit models in Section 6.2. Given this normalization, the coefficient on geographic distance is interpreted as follows: conditional on firms participating in a merger deal in a given market, β_4 is the ratio of increase in value when the acquirer and target are one mile further apart from each other to the increase in value when the firms are one unit further apart in technology distance.

The estimation results from the estimation on 4-digit NAICS based markets are reported in Table 9. Panel A reports the point estimates and 90% confidence intervals. I consider an estimate to be statistically significant if the confidence region for the estimate does not contain zero. Panel B reports the implied level changes in the merger value with a one standard deviation change in the covariate relative to the impact of 1 standard deviation change in technology distance.

The estimates show that sorting happens on all four measures: increases in technology distance, product market distance, and geographic distance all reduce the merger value, whereas increases in the acquirer or target patent portfolio quality increase the merger value. The technology distance has the highest impact on firm pairing decisions; in Panel B of Table 9 I normalize the implied merger value change by one standard deviation change in technology distance to -1. The second highest impact is created by the product market distance, at -21%, followed by the geographic distance at -1.92%.

Recall that the quality covariate is an interaction of acquirer and target quality levels: the impact of a one standard deviation increase in target patent quality at the mean level of acquirer quality is 0.25%. This impact dramatically increases at higher levels of target quality. For the targets at the top percentile of the quality distribution, the impact of portfolio quality on merger value is twice as much as the impact of geographic distance. The sorting impact gets higher when we increase both the acquirer and target quality: increasing both from their mean by one standard deviation results in a 0.75% increase relative to the technology distance, which is the same as 39% of the implied change relative to the geographic distance.

The matching maximum score estimates presented so far are based on the 4-digit NAICS based merger markets. In order to ensure that the results presented are not an artifact of the 4-digit NAICS based markets, I repeat the analyses using various other market constructions. Table 10 reports the estimates of the full model from four different market constructs based on varying target product market levels. Results from different markets do not contradict the main results based on the 4-digit NAICS markets: there is positive assortative sorting on the interaction of acquirer and target patent portfolio quality, and negative sorting on distances in technology, product market, and geography.

The estimations in Tables 9 and 10 are based on the sample of acquisitions conducted by domestic acquirers buying domestic targets with 200 or less patents at the time of the acquisition. In unreported analyses, I find that the inclusion of the 307 acquisitions with foreign acquirers do not change the results, with or without the geographic distance in the specification.

The inclusion of the 53 acquisitions with large targets does not change the results on the distance metrics, but reverses the sign on the quality interaction term. This switch may be the result of a variety of confounding factors: in addition to the acquisition of the innovative assets of the targets, mergers with large targets may include other concerns including increasing the market share, access to employees, processes, and other assets of the target firms.

The literature provides evidence that innovation laggards acquire other firms to catch up with the innovation frontier. This would imply an antiassortative sorting on innovation quality. Instead, using the matching maximum score estimator on the census of transferred patents, I find a positive assortative sorting on patent quality, which constitutes evidence for alternative mechanisms in M&A activity other than the laggard theory. The positive sorting is consistent with the view that quality leaders acquire other firms to complement their internal research pipelines. The same pattern would also emerge if quality leaders were acquiring other high quality firms to reduce competition. I leave the construction of a unifying theory that places these theories into a framework for future work.

6.5 Public-Private Subsets

This section explores whether the observed impact of innovation quality on pairing decisions vary between public and private target firms.

Prior research shows that exclusion of private firms from the data may change the inference on a number of outcome variables. Netter et al. (2011) shows that aggregate inference on the scope of corporate activity and investment changes when private firms are included in the sample of M&A firms involved. Ali, Klasa, and Yeung (2009) report that industry concentration measures that use public firms data from COMPUSTAT are poor proxies for concentration measured that use United States Census data, which includes private firms. Asker et. al. (2012) also document the differences between the investment behavior of public and private firms. Ransbotham and Mitra (2010) also show that target private status has an impact on the value the acquirers capture. Fuller et. al. (2002) finds that the returns to acquirers are positive for private targets, and negative for public targets.

The data sample used in Section 6.4 contains both public and private targets and acquirers. Table 2 provides a breakdown of acquisition activities by acquirer and target public market status. The transactions with both public acquirers and public targets constitute 31% of the activity, and results in the transfer of 68% of the total transacted patents changing hands. Even though a majority of acquisitions are conducted by public acquirers, the private firms conduct 17% of the acquisition activity, and acquire 16% of the transacted patents. On the other hand, with 1,157 deals, the private targets constitute the majority of the transactions, though the private targets only possess 19% of the transacted patents.

I repeat the matching analyses of Section 6.4 on two subsets of the data based on the public-private status of the target firms. Table 11 reports the results from the full sample in Column 1, the sample with private targets in Column 2, and the sample with public targets in Column 3.

The first observation from Table 11 is that the impact of patent portfolio quality on the pairing decision is highest when both the acquirer and the target are public firms, and the impact is statistically indistinguishable from zero for the private targets. As a result, it cannot be the case that in public-public acquisitions a higher fraction of firms use external innovation as a substitute to internal innovation.

The coefficient estimate of the product market distance is very close in all three columns, ranging from 25% to 28% of the impact of the technology distance. The impact of geography distance is also similar in the full sample, and the private targets sample, but doubles in size in the public targets sample.

To the extent that higher quality innovation is associated with higher value creation, the difference in quality sorting between public and private targets limits the interpretation of the sorting on innovation quality. Recall that the acquirer returns are higher for private targets (Fuller et. al., 2002), yet I find that the sorting on quality is lower for private targets. One potential explanation for this discrepancy is that the public targets may be in a better position to extract value from the merger, reducing the returns to the acquirers even when more value is created through merger. An alternative explanation is that the role of innovation quality in the mechanism of value creation in public-public acquisitions is different from the role in public-private acquisitions, resulting in different acquirer returns.

6.6 Acquirer Returns (Work in Progress)

The differences in the sorting strength, hence value creation between the public targets and private targets in the matching model has motivated further scrutiny of the heterogeneity in the data. In this section, I focus on the returns by extending the revealed preference arguments. In Section 3.1, I have used the revealed preferences by exchanging the target firms between two acquisitions to create the inequalities I use in the estimation:

$$f(i,j) + f(i',j') \geq f(i,j') + f(i',j),$$

where (i,j) and (i',j') are observed acquisitions, and f is the merger value function. Akkus and Hortacsu (2007) build on the Fox estimator, and extends the inequalities with the acquisition prices. Let acquirer i pay p_{ij} to target j. Then, from the revealed preferences of acquirer i, we have

$$f(i,j) - p_{ij} \geq f(i,j') - p_{ij'}.$$

For target j' to prefer any other acquirer then i', the price $p_{ij'}$ must be equal to or higher than $p_{i'j'}$, or else the target would have a higher return by choosing acquirer i. On the other hand, if $p_{i'j'} > p_{ij'}$, then acquirer i' could reduce $p_{i'j'}$ by ε, increasing its own return by the same amount. Hence, in equilibrium $p_{ij'} = p_{i'j'}$. Substituting this into inequality yields:

$$f(i,j) - p_{ij} \geq f(i,j') - p_{i'j'}.$$

The acquisition prices p_{ij} and $p_{ij'}$ are available for a subset of the M&A data. In addition, I have the abnormal stock returns to the publicly traded acquirers. Therefore, I can build upon Akkus and Hortacsu (2007) using the transaction and stock returns data.

Estimation with the new inequalities enables easier interpretation of the estimates, but loses the identification arguments of the Fox estimator. Therefore, I am in the process of running Monte Carlo simulations to compare the performance of the estimator with the new moments to that of the Fox estimator under various error structures. The easier interpretation of estimates with the new moments stems from the fact that the inequalities are based on the dollar amounts, hence any coefficient can be interpreted in terms of total dollar effect induced by changes in the covariate. Another benefit of the new moments is the ability to include individual, uninteracted effects in the estimation, such as the acquirer size, and the target size.

The analyses discussed in this section are in progress, and the results are to be included in the future versions of the paper.

7 Conclusion

In this paper I investigate an important dimension of the market of ideas, namely, the pairing decisions of firms in M&A deals. Using novel data on the census of M&A and patenting activity, I find that the innovative activities of firms have a substantial impact on the pairing decision. First, there is a positive assortative sorting on the patent portfolio quality of the acquirer and target firms: firms with high-quality patent portfolios acquire firms with high-quality target firms. Second, the impact of the innovation quality is higher for public targets than it is for private targets. I also find that firms prefer pairing with like-firms in technology, product markets, and geography. Increases in distances in technology, product markets, and geography between the acquirer and target firms reduce the probability of pairing.

Besides utilizing a novel data, this paper introduces a new methodological approach to the study of innovation and M&As. Estimating the impact of quality on partner choice is an inherently challenging task due to the two sides of the market. To overcome the simultaneity issue in reduced-form demand- and supply- analyses, I model the M&A markets as two-sided matching markets and estimate the Fox maximum-score matching estimator. The empirical strategy in this paper takes into account the preferences both sides of the market, the acquirers and the targets. The model also avoids the limiting substitution patterns resulting from IIA assumption without sacrificing from computational feasibility.

The findings in this paper frame an open question on the theory of acquiring external innovation. Prior studies provide considerable evidence that acquiring firms are innovation laggards, and use external innovation as a substitute for internal innovation to catch-up with the technology frontier. On the other hand, my finding of high-quality firms acquiring high-quality targets is consistent with the complements view, in which innovation leaders acquire external innovation to complement their internal innovation in a timely manner. A unifying framework on the substitutes and complements theories is an area ripe for exploration.

The results also draw attention to target heterogeneity in pairing decisions. The effects of innovation quality on the pairing decision is considerably higher for public targets than for private targets. This result is driven by the sum of the acquirer and target merger values from the moment inequalities. Fuller et. al. (2002) finds that the acquirer returns are positive for private targets, and negative for public targets. The differences in the results suggest that total merger value may not directly translate into higher values for both participants, and the distribution of the returns between the acquirers and targets require further scrutiny.

The decision of acquiring innovation through mergers has an intertemporal dimension that the current model does not capture. In addition, the retention of target firm employees may play a role in the decision process. Future work taking into account the dynamic effects in the matching decision, and the role of employees in this process could provide further insights.

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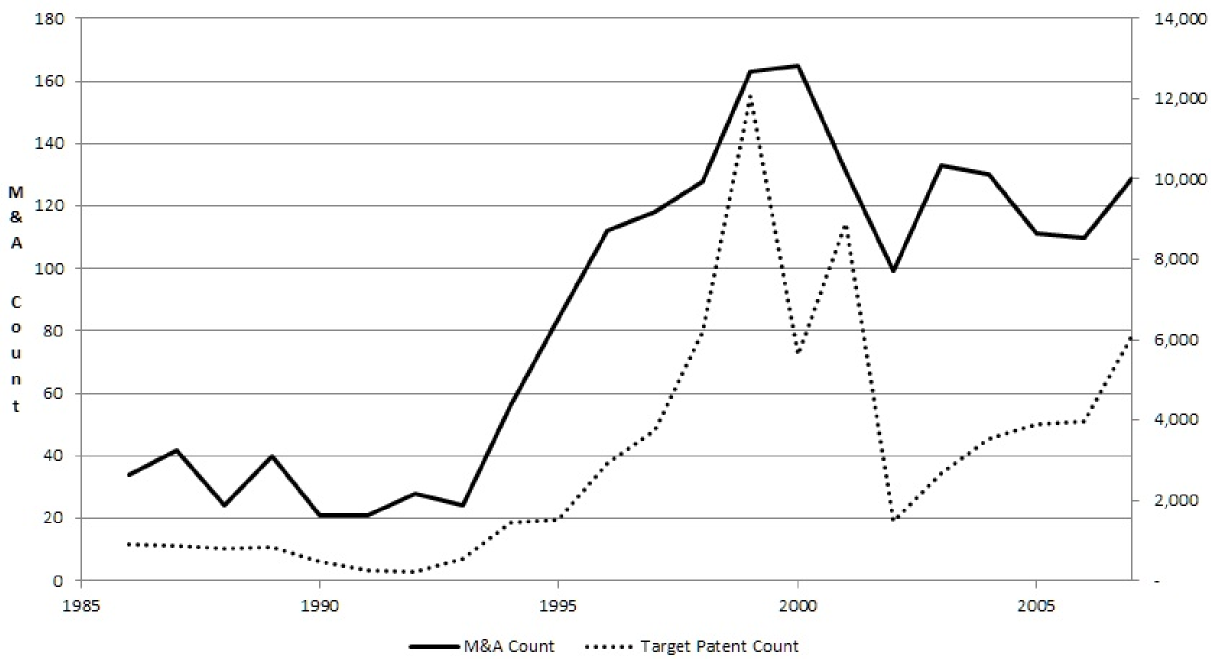
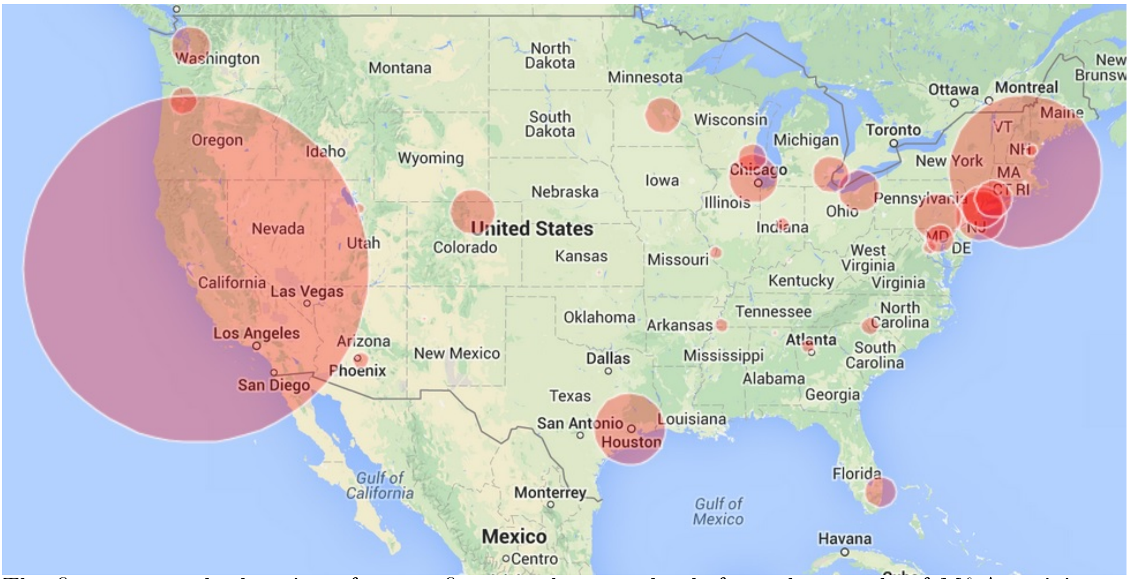
Figure 1: M&A and Transferred Patent Counts by Acquisition Year



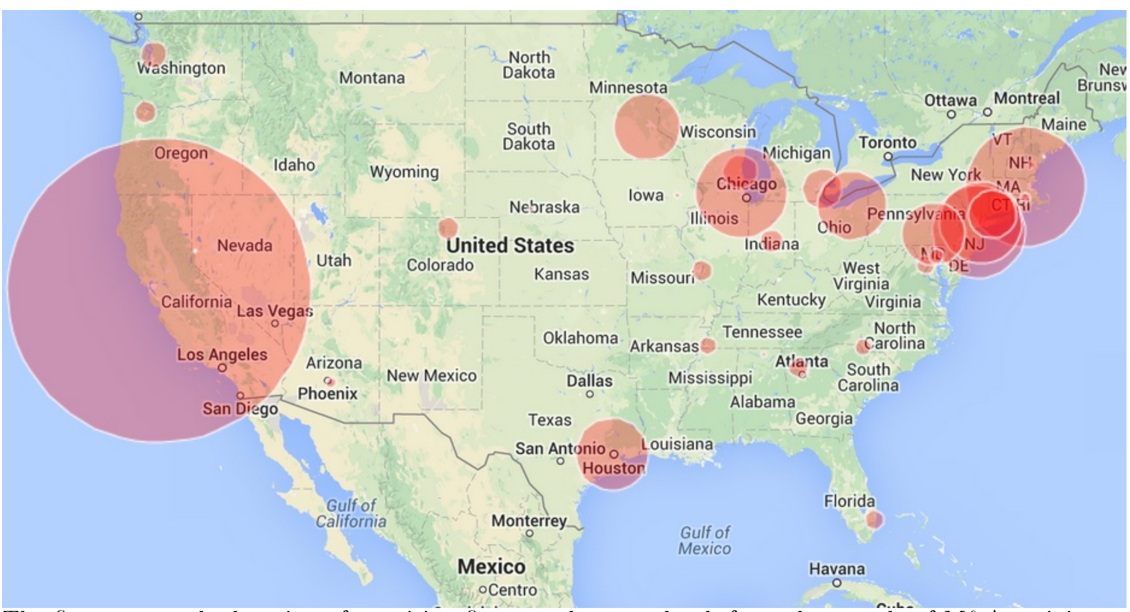
The figure plots the number of M&As and patents transferred through M&As by year from the sample as constructed in Section 5. The sample includes all acquisitions between 1986 and 2007 in which the target has at least one patent in the three years up to the acquisition. Patent count is the total number of target firm patents that are applied for by the acquisition date, and are ultimately granted by USPTO.

Figure 2: Target Locations



The figure maps the location of target firms at the state level, from the sample of M&A activity as constructed in Section 5. The sample includes all acquisitions between 1986 and 2007 in which the target and the acquirer have at least one patent in the three years up to the acquisition. The radius of each circle is proportional to the number of target firms from the state the circle's center is located.

Figure 3: Acquirer Locations



The figure maps the location of acquiring firms at the state level, from the sample of M&A activity as constructed in Section 5. The sample includes all acquisitions between 1986 and 2007 in which the target and the acquirer have at least one patent in the three years up to the acquisition. The radius of each circle is proportional to the number of target firms from the state the circle's center is located.

Table 1: Acquisitions by Cisco Inc.

The table reports the acquisitions conducted by Cisco Inc. in the sample as constructed in Section 5. The sample includes all acquisitions between 1986 and 2007 in which the target has at least one patent in the three years up to the acquisition.

M&A Year	Target Firm	Years Since First Patent	Patent Count	NAICS3	State
1994	Kalpana Inc	3	1	334210	CA
1995	Grand Junction Network Inc	2	1	334111	CA
1996	StrataCom Inc	12	22	334210	CA
1996	Telebit Corp	16	12	334210	CA
1997	Telesend Inc	2	1	541512	CA
1999	GeoTel Communications Corp	4	3	334611	MA
2000	ArrowPoint Communications Inc	2	1	334119	MA
2000	Aironet Wireless Communications Inc	5	13	334220	OH
2000	SightPath Inc	3	1	334611	MA
2002	Psionic Software Inc	3	1	511210	TX
2004	Riverhead Networks Inc	2	2	541512	CA
2004	Procket Networks Inc	2	2	334119	CA
2004	P-Cube Inc	4	15	541512	CA
2004	NetSolve Inc	6	4	541512	TX
2005	Protego Networks Inc	2	2	511210	CA
2005	Airespace Inc	3	18	511210	CA
2005	FineGround Networks Inc	5	5	334611	CA
2005	Sheer Networks Inc	5	6	511210	CA
2006	Scientific Atlanta Inc	30	586	334220	GA
2007	Ironport Systems Inc	7	15	511210	CA
2007	Reactivity Inc	5	4	511210	CA
2007	NeoPath Networks Inc	3	5	541519	CA
2007	WebEx Communications Inc	7	21	561499	CA
2007	Spans Logic Inc	3	2	334413	CA
2007	BroadWare Technologies Inc	10	4	334611	CA
2007	Cognio Inc	6	30	511210	MD

Table 2: Public Private Status of Merger Participants

The table presents the breakdown of M&A activity by acquirer and target public status. The sample includes all M&A transactions in which both the target and the acquirer have at least one patent in the three years up to the acquisition. The sample is restricted to transactions with domestic targets and domestic acquirers.

Public Status		M&A		Transacted Patents	
Acquirer	Target	Count	% Total	Count	% Total
Public	Private	990	52	14,114	16
Public	Public	586	31	59,503	68
Private	Public	60	3	11,251	13
Private	Private	267	14	2,473	3

Table 3: Target Counts by State

The table reports the M&A activity breakdown by target firm location. The sample includes all M&A transactions in which both the target and the acquirer have at least one patent in the three years up to the acquisition. The sample is restricted to transactions with domestic targets and domestic acquirers.

Targets		Acquirer			
		Count		Percent	
State	Count	Intra-State	Inter-State	Inter-State	California
California	657	307	350	53	47
Massachusetts	192	41	151	79	25
Colorado	106	28	78	74	20
New Jersey	66	6	60	91	18
Illinois	62	16	46	74	11
Pennsylvania	62	11	51	82	8
Colorado	59	3	56	95	36
New York	54	9	45	83	20
Ohio	53	9	44	83	11
Connecticut	48	3	45	94	10
Florida	48	3	45	94	21
Michigan	46	10	36	78	13
Washington	45	3	42	93	31
Minnesota	44	11	33	75	14
Maryland	37	2	35	95	19
Other	327	22	302	92	20

Table 4: Top Acquirers by M&A Count

The table reports the acquirers that have conducted ten or more acquisitions in the sample as constructed in Section 5. The sample includes all M&A transactions between 1986 and 2007, in which both the target and the acquirer have at least one patent in the three years up to the acquisition. The sample is restricted to transactions with domestic targets and domestic acquirers. Patent count is the number of target firm patents that are applied for by the acquisition date, and are ultimately granted by USPTO.

M&A Count	Patents Acquired	Acquirer	NAICS3	Industry Description
26	778	Cisco Systems Inc	334	Computer and Electronic Product Man.
25	461	GE	423	Merchant Wholesalers, Durable Goods
20	1,379	Johnson & Johnson	325	Chemical Man.
18	1,161	Boston Scientific Corp	339	Miscellaneous Man.
17	424	Medtronic Inc	334	Computer and Electronic Product Man.
13	1,482	Motorola	334	Computer and Electronic Product Man.
13	235	Intel Corp	334	Computer and Electronic Product Man.
12	630	Pfizer Inc	325	Chemical Man.
12	115	Cadence Design Systems	334	Computer and Electronic Product Man.
11	522	Honeywell Inc	334	Computer and Electronic Product Man.
11	279	Illinois Tool Works Inc	333	Machinery Man.
11	63	Microsoft Corp	334	Computer and Electronic Product Man.
10	144	Abbott Laboratories	325	Chemical Man.
10	403	Texas Instruments Inc	334	Computer and Electronic Product Man.
10	265	Emerson Electric Co	334	Computer and Electronic Product Man.
10	148	Lucent Technologies Inc	517	Telecommunications
10	181	Parker Hannifin Corp	332	Fabricated Metal Product Man.

Table 5: Acquisitions by Target Firm Industry

The table reports the breakdown of M&A activity by target firm 3-digit NAICS indursty code. The sample includes all M&A transactions between 1986 and 2007, in which both the target and the acquirer have at least one patent in the three years up to the acquisition. The sample is restricted to transactions with domestic targets and domestic acquirers.

Targets			Acquirer Industry		
NAICS	NAICS Description	Count	Same as Target	Different from Target	Percent Different
334	Computer and Electronic Product Man.	743	502	241	32
325	Chemical Manufacturing	211	148	63	30
339	Miscellaneous Manufacturing	205	92	113	55
333	Machinery Manufacturing	142	64	78	55
541	Professional, Scientific, and Technical Services	140	15	125	89
511	Publishing Industries (except Internet)	89	28	61	69
335	Elec. Eq., Appliance, Component Man.	72	23	49	68
332	Fabricated Metal Product Manufacturing	60	17	43	72
336	Transportation Equipment Manufacturing	50	29	21	42
	Other	191	56	135	71
	Total	1,903	974	929	49

Table 6: Summary Statistics

The table reports summary statistics of the key variables in the analysis, defined in Section 5. The sample includes all M&A transactions between 1986 and 2007, in which both the target and the acquirer have at least one patent in the three years up to the acquisition. The sample is restricted to transactions with domestic targets and domestic acquirers.

Variable	Mean	Std	Median
Acquirer Patent Quality	1.72	1.21	1.49
Target Patent Quality	2.43	3.16	1.6
Tech Distance (Euclidean)	0.67	0.28	0.64
Product Market Distance	1.83	1.53	2
Geographic Distance (Miles)	995	902	728
Acquirer - Target in Same State	0.25	0.44	0
Acquirer Public	0.83	0.38	1
Target Public	0.34	0.47	0
Acquirer Patent Count	1,428	4,146	93
Target Patent Count	46	341	7
Acquirer Patent Age	14.84	8.4	14
Target Patent Age	8.48	6.56	6

Table 7: M&A and Patent Counts by Target Patent Portfolio Size

The table presents the breakdown of M&A activity by target firm patent portfolio size at the time of the acquisition. The sample includes all M&A transactions in which both the target and the acquirer have at least one patent in the three years up to the acquisition. The sample is restricted to transactions with domestic targets and domestic acquirers.

Target Patent Portfolio Size	M&A count	Patent Count
1	234	234
2	183	366
3	149	447
4	111	444
5	125	625
6-10	350	2,721
11-20	309	4,558
21-30	126	3,102
31-40	83	2,946
41-50	47	2,157
51-100	91	6,541
101-200	42	6,216
201-500	26	7,357
501-1000	14	9,747
1000 or more	13	39,880

Table 8: Conditional Logistic Estimates

The table presents the conditional logit estimates of changes in merger probabilities. A merger market is a year and product market bucket. Each column reports results based on different product market levels, as defined in Section 6.1. A potential acquirer is defined as any firm that has conducted an acquisition from the same merger market. A potential target is defined as any firm that has been acquired within the same merger market. An observation is a potential acquirer - potential target pair. The regressions include product market and year fixed effects, and is conditioned on each acquirer buying one target, and each target being acquired by one acquirer. Panel A reports the coefficient estimates. Panel B reports the odds ratio estimates. The interpretation of an odds ratio estimate on variable A equal to X in panel B is: the odds of merger given a change in characteristic A are X times as large than before the change. Panel C reports the relative odds ratios by normalizing the impact of one standard deviation change in technology distance to -100%. The interpretation of an estimate on variable A equal to X in Panel C is: a one standard deviation change in A changes the probability of acquisition by X% of the change induced by a one standard deviation change in technology distance. In panels B and C, the acquirer quality row reports changes at the mean of target quality; and the target quality row reports the changes at the mean of acquirer quality. $*$, $**$, and $***$ indicate that the estimates are statistically signifcant at the 10%, 5%, and 1% levels.

Panel A: Coefficient Estimates

Column	1	2	3	4
Markets	NAICS 4	NAICS 2	SIC 2	NAICS4 - SIC2
Technology Distance	-2.68***	-2.83***	-2.54***	-2.67***
	(0.11)	(0.11)	(0.11)	(0.11)
Acquirer Quality $*$ Target Quality	0.0073**	0.0079**	0.0074**	0.0072**
	(0.002)	(0.002)	(0.003)	(0.002)
Product Market Distance	-0.31***	-0.47***	-0.25***	-0.22***
	(0.02)	(0.02)	(0.02)	(0.02)
Geographic Distance (1000 Miles)	-0.04**	-0.05***	-0.05**	-0.04**
	(0.01)	(0.01)	(0.01)	(0.01)
N Markets	105	58	114	135
N Observations	35366	96574	33801	27298

Panel B: Odds Ratios

Column	1	2	3	4
Markets	NAICS 4	NAICS 2	SIC 2	NAICS4 - SIC2
Technology Distance	0.47	0.451	0.489	0.472
Acquirer Patent Quality	1.022	1.023	1.022	1.021
Target Patent Quality	1.04	1.044	1.041	1.04
Product Market Distance	0.627	0.488	0.683	0.718
Geographic Distance (1000 Miles)	0.962	0.955	0.96	0.963

Panel C: Change In Acquisition Probability with One Sandard Deviation Change (Percent)

Column	1	2	3	4
Markets	NAICS 4	NAICS 2	SIC 2	NAICS4 - SIC2
Technology Distance	-100	-100	-100	-100
Acquirer Patent Quality	4.1	4.3	4.3	4
Target Patent Quality	7.6	7.9	8	7.5
Product Market Distance	-70.3	-93.2	-62.2	-53.4
Geographic Distance (1000 Miles)	-7.2	-8.3	-7.9	-7

Table 9: Matching Model Estimates

The table presents the estimates of Fox (2010) maximum score matching estimator as parameterized in Section 6.4. A merger market is a year and product market bucket based on 4-digit NAICS codes of target firms. A potential acquirer is defined as any firm that has conducted an acquisition from the same merger market. A potential target is defined as any firm that has been acquired within the same merger market. 90% confidence intervals are presented, and were calculated using subsampling by merger market. Subsampling uses 100 replications, 79 merger markets per replication. An estimate is considered statistically significant if the 90% confidence interval does not include zero. The inequalities used in the estimation come from the pairwise stability assumption of the observed mergers. Inequalities used are constructed by two acquirers that has conducted an M&A from the same merger market switching their targets, and this is repeated for every such acquirer pairs. Panel A reports the coefficient estimates. Panel B reports the relative changes in the merger value function by one standard deviation change in the covariate, after normalizing the impact of technology distance to -100%. The interpretation of an estimate on variable A equal to X in Panel B is: a one standard deviation change in A changes the merger value function by X% of the change induced by a one standard deviation change in technology distance. In Panel B the acquirer quality row reports changes at the mean of target quality; and the target quality row reports the changes at the mean of acquirer quality.

Panel A: Coefficient Estimates

Columns	1	2	3	4
Technology	-1	-1	-1	-1
Distance	normalized	normalized	normalized	normalized
Acquirer Quality	0.00016			0.00013
∗ Target Quality	(0.00012, 0.00148)			(0.00002, 0.00037)
Product Market		-0.0035		-0.0391
Distance		(-0.0046, 0.0004)		(-0.048, -0.0262)
Geo. Distance			-0.008	-0.006
(1000 miles)			(-0.01, -0.008)	(-0.008, -0.003)
N Transactions	1787	1787	1787	1787
N Markets	105	105	105	105
N Inequalities	16790	16790	16790	16790
% Inequalities Satisfied	87.5	88.1	87.8	88.8

Panel B: Change In Value Function with One Sandard Deviation Change (Percent)

Column	1	2	3	4
Technology Distance	-100	-100	-100	-100
Acquirer Patent Quality	0.17			0.14
Target Patent Quality	0.31			0.25
Product Market Distance		-1.9		-21.19
Geo. Distance (1000 Miles)			-2.56	-1.92

Table 10: Matching Model Estimates with Varying Market Levels

The table presents the estimates of Fox (2010) maximum score matching estimator as parameterized in Section 6.4. A merger market is a year and product market bucket. Each column reports results based on different product market levels, as defined in Section 6.1. A potential acquirer is defined as any firm that has conducted an acquisition from the same merger market. A potential target is defined as any firm that has been acquired within the same merger market. 90% confidence intervals are presented, and were calculated using subsampling by merger market. Subsampling uses 100 replications, and three quarters of the merger markets in the sample per replication. An estimate is considered statistically significant if the 90% confidence interval does not include zero. The inequalities used in the estimation come from the pairwise stability assumption of the observed mergers. Inequalities used are constructed by two acquirers that has conducted an M&A from the same merger market switching their targets, and this is repeated for every such acquirer pairs. Panel A reports the coefficient estimates. Panel B reports the relative changes in the merger value function by one standard deviation change in the covariate, after normalizing the impact of technology distance to -100%. The interpretation of an estimate on variable A equal to X in Panel B is: a one standard deviation change in A changes the merger value function by X% of the change induced by a one standard deviation change in technology distance. In Panel B the acquirer quality row reports changes at the mean of target quality; and the target quality row reports the changes at the mean of acquirer quality.

Panel A: Coefficient Estimates

Columns	1	2	3	4
Market Base	NAICS 4	NAICS 2	SIC 2	NAICS4 - SIC2
Technology	-1	-1	-1	-1
Distance	normalized	normalized	normalized	normalized
Acquirer Quality	0.00013	0.00117	0.00197	-0.0000005
∗ Target Quality	(0.00002, 0.00037)	(0.00107, 0.00225)	(-0.00085, 0.00389)	(-0.00298, 0.00011)
Product Market	-0.039	-0.052	-0.024	-0.073
Distance	(-0.048, -0.026)	(-0.068, -0.047)	(-0.026, -0.021)	(-0.114, -0.061)
Geographic	-0.0056	-0.0067	-0.0073	-0.0062
Distance (1000 miles)	(-0.0076, -0.0035)	(-0.0078, -0.0003)	(-0.0094, -0.0031)	(-0.0109, 0.0033)
N Transactions	1787	1787	1728	1765
N Markets	105	58	114	135
N Inequalities	16790	47394	16037	12767
% Inequalities Satisfied	88.8	92.8	86.8	87.8

Panel B: Change In Value Function with One Sandard Deviation Change (Percent)

Columns	1	2	3	4
Market Base	NAICS 4	NAICS 2	SIC 2	NAICS4 - SIC2
Technology Distance	-100	-100	-100	-100
Acquirer Quality	0.14	1.22	2.06	-0.0005
Target Quality	0.25	2.25	3.78	-0.001
Product Market Distance	-21.14	-28.18	-13.01	-39.56
Geographic Distance (1000 miles)	-1.98	-2.36	-2.58	-2.19

Table 11: Matching Estimates with Target Public Market Status

The table presents the estimates of Fox (2010) maximum score matching estimator as parameterized in Section 6.4. A merger market is a year and product market bucket at the 2-digit NAICS level. The first column reports results from the full sample. Column 2 reports from the sample including only M&A deals with public acquirers and private targets. Column 3 reports from the sample including only M&A deals with public acquirers and public targets. A potential acquirer is defined as any firm that has conducted an acquisition from the same merger market. A potential target is defined as any firm that has been acquired within the same merger market. 90% confidence intervals are presented, and were calculated using subsampling by merger market. Subsampling uses 100 replications, and three quarters of the merger markets in the sample per replication. An estimate is considered statistically significant if the 90% confidence interval does not include zero. The inequalities used in the estimation come from the pairwise stability assumption of the observed mergers. Inequalities used are constructed by two acquirers that has conducted an M&A from the same merger market switching their targets, and this is repeated for every such acquirer pairs. Panel A reports the coefficient estimates. Panel B reports the relative changes in the merger value function by one standard deviation change in the covariate, after normalizing the impact of technology distance to -100%. The interpretation of an estimate on variable A equal to X in Panel B is: a one standard deviation change in A changes the merger value function by X% of the change induced by a one standard deviation change in technology distance. In Panel B the acquirer quality row reports changes at the mean of target quality; and the target quality row reports the changes at the mean of acquirer quality.

Panel A: Coefficient Estimates

Columns	1	2	3
Sample	Full Sample	Private Targets	Public Targets
Technology Distance	-1	-1	-1
Acquirer Quality	0.00117	0.0002	0.004
∗ Traget Quality	(0.00107, 0.00225)	(-0.0005,0.0003)	(0.0023,0.0071)
Product Market	-0.052	-0.051	-0.046
Distance	(-0.068, -0.047)	(-0.065,-0.047)	(-0.062,-0.031)
Geographic	-0.0067	-0.006	-0.015
Distance (1000 miles)	(-0.0078, -0.0003)	(-0.006,-0.001)	(-0.023,-0.013)
Market Base	NAICS 2	NAICS 2	NAICS 2
N Transactions	1787	964	491
N Markets	58	50	37
N Inequalities	47394	14434	4577

Panel B: Change In Value Function with One Sandard Deviation Change (Percent)

Columns	1	2	3
Sample	Full Sample	Private Targets	Public Targets
Technology Distance	-100	-100	-100
Acquirer Quality	1.22	0.18	4.22
Target Quality	2.25	0.33	7.76
Product Market Distance	-28.18	-27.79	-25.14
Geographic Distance (1000 miles)	-2.36	-1.77	-4.89

Appendix A: Construction of Patent Data

In this study I use patent data constructed from raw USPTO text files for the period from 1976 to 2010 for a variety of reasons. First, coverage of the NBER data files end in 1999 for the inventor variables, and in 2006 for the remainder of the data; our newly constructed data set goes to 2010. In addition, the NBER data does not include the original names of patent assignees; instead it provides assignee names that have gone through a series of standardizations. I use the original names from the newly constructed data in the process of linking the patent data to the M&A data as described below.

Each week the USPTO makes available a new XML file, which can be accessed on its FTP site, containing bibliographic information for the patents granted within the prior week. In addition, the USPTO makes historical files available through the Google Patents Bulk Downloads site. In this study we supplement the NBER patent data period with the XML files that go back to 2001, and the yearly hierarchical text files that cover the 1976-2001 period, resulting in the utilization of 474 weekly XML files and 26 yearly text files.[33] The newly organized data includes information on granted utility patents applied for and granted between 1976 and 2010, including the application year, grant year, patent technology class, patent assignee name, location, and type.

In order to verify the data quality, I conduct extensive comparison of the newly compiled data against NBER patent data files for the overlapping period. In addition, I compare various aggregate statistics against the USPTO aggregate patent statistics. Table A1 presents patent counts by grant year from our data and the USPTO aggregate statistics page. As observed in the table, the two datasets follow each other very closely. Comparisons on other patent properties follow similar close trends.

In addition to the main bibliographic items, the USPTO assigns a primary technology class and a number of secondary technology classes to each patent at the time of grant. The classification system may be modified over time due to advances in technologies or other reasons. The USPTO updates the technology classes of all patents granted since 1790 and publishes them in the US Patent Grant Master Classification File (MCF) once every two months. My data includes classifications from the December 2010 version of this product.

As in prior work, I take advantage of citations. The patent data contains the citations made by the granted patents between 1976 and 2010 to other granted patents in earlier periods. This information is used in controlling for the heterogeneity in patent value, which has a highly skewed distribution.[34] Prior studies have documented a strong, positive correlation between the value of a patent and the number of citations it receives. [35]

The main pillar of this study is the patent ownership composition, which is constructed using the share of granted patents to each unique assignee. However, the newly compiled USPTO patent data

[33] Between 1976 and 2010 the data format changed dramatically, once in 2002 and again in 2005. Some minor changes were also made in 2006. The corresponding variables from various years were matched using the relevant version of the Redbook documentation from the USPTO website.

[34] Harhoff et al. (1999), Pakes and Schankerman (1984).

[35] See, e.g. Harhoff et al. (1999).

does not contain a unique assignee identifier (akin to NBER's pdpass variable) that is consistent across different patents and across time. The main assignee identifier is the firm name, which is a long string and is susceptible to errors in links due to potential misspellings, different spelling of foreign firms, and differences in abbreviations. To address the lack of unique firm identifiers, I developed a methodology to link different name strings representing the same entity to each other. I discuss the details of this algorithm and a comparison to NBER's unique identifiers in Appendix B.

Appendix B: Firm Name Linking Algorithm

The newly compiled USPTO patent data does not contain a unique assignee identifier that is consistent across time. The main assignee identifier is the firm name, which is a long string and is susceptible to errors in links due to potential misspellings, different spelling of foreign firms, and differences in abbreviations (such as "corporation," "co." and "co"). To address the lack of unique firm identifiers, I developed a methodology to link different name strings representing the same entity to each other.[36]

I use the same methodology in linking the patent data to the M&A data. Even though the M&A data has better firm identifiers (such as CUSIP numbers), there is no common variable in both the M&A and patent data that can be used to link them, other than the firm name strings. As the process of linking the firm name strings is not trivial, prior merger studies usually use a small sample and link different sources manually.[37] Using the firm names from both datasets and the algorithm discussed below, I am able to identify M&A and IPO deals in which the parties involved have patents.

The linking algorithm consists of two stages: an automated stage and a human intelligence stage. In the automated stage, a computer program standardizes the firm names using common abbreviations and misspellings identified from the data, such as corp, corporation, corpooration, etc. The program then conducts a linking based on common words in company names. Although this program captures a significant portion of actual matches across datasets, it also produces false positives. An example of a false positive would be flagging "ABC Business Solutions" and "XYZ Business Solutions" as the same company due to the common "Business Solutions" phrase. To work around this problem I conduct a human intelligence stage. In this stage the matches identified by the computer program are fed into a crowd-sourcing website, Amazon's Mechanical Turk, for manual human verification that will un-flag the false positives, and leave only the actual matches for use in the data linking.[38]

[36] This new variable will assume the role of the NBER patent data's pdpass variable in my dataset.

[37] Ouimet, Zarutskie (2010) uses only the mergers in which the target is a public company; Kerr and Fu (2008) focuses on firms that are in the National Science Foundation's Industry R&D Survey.

[38] Crowdsourcing sites enable the outsourcing of simple tasks to a large group of workers on demand. In the context of this paper, workers see a pair of company names matched by the computer program, and are asked to simply choose "yes" or "no" to indicate whether the two companies are the same companies, or not. Outsourcing the linking process to a large workforce and using standard quality control techniques facilitate the timely completion of the task

As a quality check of this process I compare the results to the NBER patent data files, which address the same issue only within the patent data, and mapped 322,783 names into 243,800 unique entities. A comparison of the results from my algorithm on a sample of 70,000 firm names to the NBER patent data file suggests that my results are as good as the NBER matches, if not better.

Differences exist between the two algorithms, partly due to random errors and partly due to the difference in what is considered a unique entity. Table A2 provides an illustration through a subset of names for the Sony Corporation. In this list, each line represents a different entity (different pdpass) in the NBER data, whereas all are considered part of the same entity in our data. The three versions of "Sony Electronics Inc" being assigned to different entities in the NBER data give an example of random errors in the matching process.[39] However, designating "Sony Corp of America" and "Sony Electronics Inc" as different entities highlights differences in what I consider a firm. In this assignment I believe that firms create different subsidiaries for a variety of reasons, including tax blueprint, legacy, and other managerial or strategic issues. However, I conjecture that two such firms would go through patent infringement issues only under very extreme, unlikely conditions; therefore I consider them the same entity.

Appendix C: Quality Measure

This appendix describes the construction of the patent portfolio quality variable.

The set of patents a firm has is easily available from the linked USPTO patent data file. However, everything else equals, older patents would not have the same value as patents obtained in more recent years for two reasons. First, over time the technology a patent protects becomes obsolete to a certain degree. Second, the patent protection duration decreases over years, with older patents providing protection for fewer years, reducing the value of the patent to the owner. Therefore, instead of using simple patent counts in constructing the patent portfolios of firms, I follow the extant literature, and calculate the depreciated counts of active patents.[40,41,42] To be more precise, let firm i possess $stock_{i,t-1}$ patents at the beginning of period t, and apply for $flow_{i,t}$ number of patents during year t. Then, the patent stock of firm i by the end of period t is defined as in Equation 5:

$$stock_{i,t} = (1-\delta)stock_{i,t-1} + flow_{i,t} = \sum_{k=0}^{19}\left((1-\delta)^k flow_{i,t-k}\right). \tag{5}$$

at a reasonable cost.

[39] Similar cases where a match missed by my algorithm is captured by the NBER also exist in the data. Table A2 does not indicate superiority of my algorithm over NBER's.

[40] I consider a patent to be active for 20 years starting with the patent filing year, or for 17 years starting from the patent grant year, whichever comes later.

[41] The patent term for applications before June 8, 1995, expire at the later of (i) 17 years from the issue date, or (ii) 20 years from the application date. For applications on or after June 18, 1995, the patent term is 20 years from the filing date. These two definitions are equivalent for my sample period ending in 2010.

[42] For earlier use of the declining balance method, see Hall and MacGarvie (2010).

In my calculation I set δ, the depreciation rate, to 15%.

I follow a long strand of innovation literature and use the citations a patent receives from other patents as a proxy for its quality.[43] However, simple citation counts pose problems due to varying propensity to cite across industries, potentially changing propensity to cite over time, as well as truncation issues towards the end of the sample period. To remedy these issues, I adopt the fixed-effects adjustment introduced by Hall. et. al. (2001): I divide the number of citations a patent receives by the average number of citations received in the same technology class and the same application year.[44,45] One can interpret the fixed-effects adjusted citations as the relative location of the patent among the set of patents from the same year and technology class.

In the calculation of the quality proxy of a firm's innovation, I use the patents from the most recent three years.[46] Moving from the quality of individual patents to the quality of a portfolio of patents involves the depreciated sum of the fixed-effects adjusted citations, as in the calculation of the patent stock above. Recall that $flow_{i,t}$ denotes the number of new patent applications firm i has submitted in year t. Let $Flow_{i,t}$ be the set of the new patent applications that firm i applies for in year t that are ultimately granted; and let $c_{i,t}$ be the number of all citations that patents in $Flow_{i,t}$ receive.[47] Then, the quality of the patent portfolio of firm i at period t is the ratio of the depreciated citation stock to its depreciated patent stock, both from the previous three years:

$$quality_{i,t} = \frac{\sum_{k=1}^{3} \left((1-\delta)^k c_{i,t-k}\right)}{\sum_{k=1}^{3} \left((1-\delta)^k flow_{i,t-k}\right)}.$$

The quality of a portfolio is then the relative position of the firm's patent portfolio in the ranking of all firms, with a value of 1 indicating an average quality firm. [48]

[43] Harhoff et al. (1999) and Hall et al. (2005), among others, show a significant relation between the value of patents and the number of citations they receive.

[44] I use the patent application year as the date of the patent, as opposed to the patent grant year. The application year is closer to the time of the actual innovation than the grant year (Griliches et. al. 1987). The patent grant dates exhibit significant, and idiosyncratic, delays due to issues not-related to the innovative activities of the patent applicant firm. Cockburn, MacGarvie (2009) also find evidence that the application of a patent matters more than its grant on a variety of funding and liquidity events.

[45] One may suspect that the use of application date may contaminate the data for acquired firms. Zhao (2009) states that if a patent is applied for by a firm, and the firm was acquired before the patent was granted, the patent would still be issued to the original applicant. Therefore, the use of application date does not contaminate the data.

[46] Using patent portfolios from longer periods yields qualitatively similar results.

[47] There is an implicit assumption in the calculation of patent quality using citations. The econometrician observes the ex-post citations made to the patents, but at the time of the M&A activity, the agents involved in the merger markets do not observe the citations made after the M&A deal. I implicitly assume that the agents involved have the information to gauge the quality of the innovation at the time of the M&A deal, and that the information is revealed to the econometrician through the citations over time.

[48] In addition to the per-patent fixed effects adjusted citations a firm's patents receive, I repeat the analyses using various other quality measures. I construct three ratio variables, indicating the share of a firm's portfolio that are of high quality. In other words, I divide the total number of patents a firm has in the top 10%, 25%, and 50% quality levels in their respective technology class and application years, to the total number of patents the firm has. These measures are highly correlated with each other, and the estimation results do not change qualitatively across measures, though the magnitude and statistical significance of estimates vary slightly.

Table A1: Granted Utility Patents

Grant Year	USPTO	XML	Difference
2010	219,614	219,909	295
2009	167,349	167,553	204
2008	157,772	157,894	122
2007	157,282	157,502	220
2006	173,772	173,922	150
2005	143,806	143,927	121
2004	164,290	164,413	123
2003	169,023	169,104	81
2002	167,330	167,424	94
2001	166,035	166,158	123
2000	157,494	157,595	101
1999	153,485	153,592	107
1998	147,517	147,576	59
1997	111,984	112,019	35
1996	109,645	109,653	8
1995	101,419	101,431	12
1994	101,676	101,696	20
1993	98,342	98,384	42
1992	97,444	97,473	29
1991	96,511	96,557	46
1990	90,365	90,421	56
1989	95,537	95,566	29
1988	77,924	77,937	13
1987	82,952	82,967	15
1986	70,860	70,865	5
1985	71,661	71,669	8
1984	67,200	67,215	15
1983	56,860	56,860	0
1982	57,888	57,878	10
1981	65,771	65,766	5
1980	61,819	61,812	7
1979	48,854	48,839	15
1978	66,102	66,084	18
1977	65,269	65,200	69
1976	70,226	70,190	36
Total	3,911,078	3,913,051	2,293

Notes: Patent counts by grant year from USPTO aggregate patent statistics and our newly constructed sample from USPTO XML and text files. Source: U.S. Patent Statistics Chart, Patent Technology Monitoring Team (PTMT), USPTO.

Table A2: Assignee Names for SONY Corp.

NBER pdpass	NBER Assignee Name
11297047	SONY AUSTRALIA PTY LTD
11277610	SONY BROADCAST & COMMUNICATION
11958546	SONY CHEM CORP
13040458	SONY CHEM CORP NEAGARI PLANT
12059716	SONY CINEMA PROD CORP
12104210	SONY COMPUTER ENTERTAIMENT INC
12805945	SONY COMPUTER ENTERTAINMENT AM
13147302	SONY CORP ENTERTAINMENT AMERIC
11205194	SONY CORP OF AMERICA
13171917	SONY CORPORATIOM
21878152	SONY ELECTONICS INC
21589106	SONY ELECTRONIC INC
11399266	SONY ELECTRONICS INC

Notes: A sample of different spellings of Sony Corporation in the Patent and M&A data. Each row, identified by the pdpass column, is considered as a separate entity in the NBER patent data.