Specialized Investments and Firms' Boundaries: Evidence from Textual Analysis of Patents*

Jan Bena
University of British Columbia

Isil Erel
Ohio State University, NBER, and ECGI

Daisy Wang
Ohio State University

Michael S. Weisbach
Ohio State University, NBER, and ECGI

August 14, 2021

Abstract

Inducing firms to make specialized investments through bilateral contracts can be challenging because of potential hold-up problems. Such contracting difficulties have long been argued to be an important reason for acquisitions. To evaluate the extent to which this motivation leads to mergers, we perform a textual analysis of the patents filed by the same lead inventors of the target firms before and after the mergers. We find that patents of inventors from target firms become 28.9% to 46.8% more specific to those of acquirers' inventors following completed mergers, benchmarked against patents filed by targets and a group of counterfactual acquirers. This pattern is stronger for vertical mergers that are likely to require specialized investments. There is no change in the specificity of patents for mergers that are announced but not consummated. Overall, we provide empirical evidence that contracting issues in motivating specialized investment can be a motive for acquisitions.

* We are extremely grateful to Ben Hermalin, Weiling Song, and René Stulz, as well as participants in seminars at Ohio State, Georgetown, South Carolina, Porto, HKU, and the Virtual Corporate Finance Seminar for helpful suggestions.

1. Introduction

Investments specific to a particular business relationship, more valuable in that relationship than elsewhere, can be difficult to manage through arms-length contracting. This difficulty arises because the return to the investments one party makes can be captured by the other party via its bargaining power (*e.g.*, a credible threat to walk away from the deal, leaving the investing party with an asset of little value). The celebrated Grossman-Hart-Moore "incomplete contracts" theory of the firm uses this logic to argue that firms should be structured so that the parties engaging in relationship-specific investments be part of the same firm (see for example Chapter 2 of Hart, 1995). An important implication of this theory is that when two firms enter a business relationship that requires substantial specialized investments, they are likely to merge to avoid the contracting challenges arising from potential hold-up problems.[1] In this paper, we provide a test of this implication, which suggests that merging firms' investments do become more specialized following acquisitions. The implication of this result is that facilitating specialized investment can be a motive for acquisitions.

There are a number of examples of acquisitions that appear to have been motivated by a desire to avoid holdup problems, perhaps the most famous being General Motors' 1926 acquisition of Fisher Auto Body.[2] Yet there has been little work evaluating the theory's key prediction that each firm in a merger will be more likely to engage in investments specialized to their mutual relationship following the merger. While there is an enormous literature on the various reasons motivating mergers and acquisitions, there is little work studying the extent to which contracting problems arising from relationship-specific investments motivate acquisitions in the real world.[3] Most likely, this prediction has not been more extensively tested because doing so requires

[1] The idea that hold-up problems create "quasi-rents" that can be appropriated and that merging potentially solves this problem dates to Klein, Crawford, and Alchian (1978).
[2] See Klein, Crawford, and Alchian (1978) and Klein (1988) for a discussion of the deal and how it evolved because of potential hold-up problems. It is used as an example of hold-up problems affecting acquisition decisions in Williamson (1985), Tirole (1986), Hart (1995), Carlton and Perloff (1994), and Hermalin and Katz (2009). However, the importance of the holdup problem in motivating even the Fisher deal is not universally accepted (see Coase (2000)).
[3] For example, the most recent survey of mergers and acquisitions surveys 181 papers about mergers, none of which addresses the idea that specialized investment can motivate mergers (see Mulherin, Netter, and Poulsen (2017)).

detailed data on the investments done by targets not only when they are independent but also post-merger as a part of the combined firms.

This paper evaluates the hypothesis that firms increase the likelihood of making relationship-specific investments following acquisitions using textual analysis of the firms' patents to measure the specificity of particular research efforts. We consider a sample of mergers between publicly traded U.S. firms between 1976 and 2012. Our focus is on the research that the companies do, as reflected in the patents they file. Two attributes of patents make them ideal to evaluate the importance of relationship specificity in merger decisions. First, patents are filed under the name of the inventors, so it is possible to tell, even after an acquisition is consummated, whether a particular patent was filed by an inventor who worked at the acquirer or at the target prior to the deal. Second, the patent contains details of the actual research, so that an outsider can understand the nature of the invention and assess the extent to which it is specific to a particular relationship.

We use textual analysis to characterize the nature of the patents. Our approach is to compare the similarity of the patents produced by the acquirer and target firms both before and after the acquisition. If the merger enables the target and acquirer to make relationship-specific investments, then the patents should become more similar to one another following the merger than they were before it occurred.

We follow Kelly, Papanikolaou, Seru, and Taddy (2020) in using a term frequency-inverse document frequency (*tf-idf*) textual analysis technique to measure the similarity of patents. This technique presumes that a patent's terms that are less common across the sample of patents represent unique features of that patent. If two patents share an "uncommon" term, then we consider them to be more similar than two randomly chosen patents. The technique measures patent pairwise commonality by overweighting the terms that are more unique to individual patents while underweighting the terms that are more common across patents in the entire sample. Through this procedure, each patent becomes represented by a vector of word counts in the technological space. The similarity between two patents is determined by the cosine similarity of their corresponding word-count vectors.

Assessing whether an increased similarity in patents between acquiring and target firms reflects an improved ability to make specialized investments without fear of holdup requires evidence that such R&D investments would not have been made in the absence of the merger. We attempt to capture the notion of specialized investment defined by Klein, Crawford and Alchian (1978) as the gap in the value of an asset to the actual customer and to the customer with the second highest valuation. We construct the investment specificity of the target by benchmarking the target-acquirer similarity against the similarity between the target and a group of counterfactual acquirers.

Making use of the inventor identity, we identify those patents that are potentially attributable to a target's post-merger specialized, innovative efforts to overcome the fact that that target and the acquirer could file patents under the joint entity. However, this approach of observing the change in specialized investment before and after the merger suffers from a potential endogeneity issue because the matching of target firms with acquirers is not random. It is possible that our sample deals occurred because the two companies were in the process of developing related products, and that their inventions would have become similar to one another even if there were no acquisition. Consistent with this notion, Bena and Li (2014) document that targets tend to be similar to acquirers in the nature of their technology. To ensure that any observed change in the similarity of patents does not occur because the matching of acquirers and targets, and thus affecting our innovation specificity measure, we follow Seru (2014) and consider a sample of deals that were announced but subsequently withdrawn, usually for reasons related to financing or anti-trust. By comparing our sample of completed deals to ones that failed because of reasons unrelated to innovation, we control for underlying unobservable trends that led to the matching of targets and the acquirers, and also could have affected the similarity of targets' and acquirers' patents.

We find that targets of completed deals produce patents that are 28.9% to 46.8% more specific to acquirers' patents in the post-merger period than prior to the deal, as benchmarked against the similarity with counterfactual acquirers. Prior to the acquisition, the specificity between acquirer and target patents is roughly constant for both withdrawn and completed deals. This pattern suggests that there is not a trend of the two

firms' research moving together pre-acquisition, so the selection issue does not appear to be driving the difference in the specificity of the patents. This finding provides evidence that the acquisitions in our sample enabled the firms to make relationship-specific investments that they were unable to make for contractual reasons prior to the deal.

The original discussions of the way in which contracting costs could motivate acquisitions focused on firms with vertical relationships (see Klein, Crawford, and Alchian (1978)). However, vertical relationship are not the only ones in which hold-up problems can impede efficient contracting. Innovative firms interact in ways that could have contracting difficulties when they engage in cross-licensing agreements, set standards, provide complementary value to each other's patents, and commercialize their ideas. Nonetheless, contracting problems would be particularly severe in a vertical relationship, in which one firm makes intermediate goods used by the other for production. In other words, specializing on an intermediate good for one partner makes the product less attractive to other potential partners. For this reason, we expect the treatment effect of a merger on the specialized innovation to be particularly stronger for vertical acquisitions.

We consider a subsample of vertical deals using the vertical integration measure suggested by Frésard, Hoberg, and Phillips (2020). We compare the change in the specificity of patents for those deals to the change for the non-vertical deals in our sample. We find that the patents from vertical targets become more specific to their acquirers' patents than those from the non-vertical targets in our sample. Mergers play a more important role in alleviating contractual frictions and motivating specialized investment when the target and acquirer are related in a supply-chain relationship.

Finally, we present a number of tests to evaluate alternative interpretations of our findings. One possibility is that the increase in similarity between the target's and the acquirer's patents after the merger occurs from the two using the same lawyer. Since each lawyer potentially has a different approach to writing patents, the observed post-acquisitions similarity could reflect writing styles rather than the underlying technology of the patent. To understand the extent to which the identity of lawyers can explain our findings, we re-estimate the equations using a subsample of patents in which the lawyers on the target and the acquirer

patents remain different following the acquisition. For this subsample, the estimates are similar to those on the full sample.

Another possibility is that mergers lead to the combination of research teams, leading the patents filed by former acquirer and target employees to become more similar. In addition, it is possible that there are informational externalities due to teams working in a common facility leading to target and acquirer teams conducting similar research. To address this potential explanation, we re-estimate our equations using a subsample, where the target and acquirer inventor teams do not add individuals from the partner firm following the merger and also they are physically located in different cities post merger. The estimates using this subsample are also similar to those from the full sample.

Finally, we evaluate the possibility that the increase in specificity between the target and acquirer is purely driven by a transitory selection where the acquirers select targets with similar ongoing projects at the time of merger, which will revert to the mean in the future. We find that the observed effects on target and acquirer patent specificity are persistent over a five year window following the acquisition, alleviating this possible concern transitory selection.

This work extends the literature in a number of ways. First, we provide empirical evidence on the way in which contracting problems can lead to acquisitions. Klein, Crawford and Alchian (1978) proposed that common ownership can mitigate hold-up problems, so that a merger of two firms with a prior business relationship can lead to efficiencies from specialization of the firms' investments. Williamson (1971, 1979) presents related arguments in which common ownership can be beneficial because it leads to more efficient reactions to unforeseen contingencies. Grossman and Hart (1986) and Hart and Moore (1990) develop a theory of firm boundaries in which incentives to invest in specialized complementary assets is the primary determinant of ownership.

There have been a number of studies that address this argument empirically, including Monteverde and Teece (1982), Woodruff (2002), Acemoglu et al (2010), and Frésard, Hoberg and Phillips (2020). These

studies used information about firms and their contractual relationships to predict whether vertical integration will occur. In contrast, this paper examines post-merger information to evaluate whether firms appear to make more relationship-specific investments following acquisitions.

Our paper also contributes to the literature on the relationship between M&A and innovation. Prior work has documented that acquirers tend to purchase firms with a relatively large overlap with its own technology base (Bena and Li, 2014), and with high R&D intensity (Phillips and Zhdanov, 2013). After acquisitions, acquirers with overlapping knowledge base with target produce more patents (Bena and Li, 2014), encourage more collaboration between inventors and are associated with more valuable patents (Li and Wang, 2020). While existing work focuses on the effects of mergers on the quantity and quality of patents, this paper evaluates the way in which the direction of innovation changes following mergers. One paper that focuses on the nature of post-merger patents is Mei (2019), which finds that if acquirer and target are less technologically overlapped before the merger, the combined firms are more likely to engage in innovations different from either of the parties.

Finally, our paper is among the early applications of vector space textual analysis methods in patent research (Younge and Kuhn, 2016, Kelly et al, 2018, Gentzkow et al. 2019, Mei, 2019). As suggested by Hall, Jaffe and Trajtenberg (2005), subsequent studies on patents and innovation use either the vector of patents from various technological classes or the vector of citations from such classes to measure the technological proximity (Bena and Li, 2014, Bloom et al. 2013, Li et al, 2019). Measures constructed by such methods are usually only available at the firm level, while the use of vector space methods on patent texts enables comparisons between any patents at more granular level in addition to providing more flexibility to the researcher in aggregating the measure to the firm level.

2. Sample Construction

2.1. Identifying Target Firms' Investments Using their Patents

To test the hypothesis that firms increase their relationship-specific investments following mergers, we need to be able to track target firms' investments after their acquisitions take place and evaluate the extent to which such post-acquisition investments are relationship-specific. A major difficulty, however, is that data on investments made by former target firms after mergers, as well as information that would allow to measure the relationship specificity of the investments, are unobservable using publicly available financial information. We circumvent this challenge by focusing on R&D investments. Specifically, we rely on the outcomes of R&D that are thoroughly recorded in patent documents. Patents provide information on inventors – the individuals who contribute to the invention – that can be used to identify investments made by target firms following the acquisition. Furthermore, we are able to use textual analysis of patent claims – texts that define what subject matter the patent protects and the scope of the protection conferred – to construct measures of the relationship-specificity of R&D investments.

While a target and an acquirer typically file new patents post-merger under a combined entity, we can distinguish R&D investments that originate from the former target or acquirer by using the identities of inventors listed on the patents. Specifically, we focus on "staying inventors," the inventors who file patents under either the target or the acquirer prior to a merger, and continue to file patents under the combined entity after the merger is completed. Pre-merger patents help us identify the affiliations of the inventor, and, by tracking the patents filed by this inventor after the merger, we attribute her R&D activities to the part of the combined firm which she is affiliated with. Since it is possible that a target firm's inventor is reassigned to an acquirer firm's research team after the merger, in which case such inventor's patents may reflect the acquirer's research agenda instead of that of the target's, we focus on patents whose lead inventors – the first inventors listed on patent documents – are the staying inventors. Each patent in our data is, therefore, identified using the identity of the "staying lead inventor", and staying lead inventors of target firms in the merger are the main cross-sectional units of our analysis. We use the staying lead inventors' patents filed pre- and post-deal to discern investments, through which former target firms contribute to the merged firms' R&D efforts, and to measure the specificity of these investments.

2.2 Data Sources and Sample Construction

We obtain our sample of acquisitions from the SDC Platinum database, which covers deals since 1976. Because the link table we use to match patents to firms stops in 2017, and we require all acquisitions to have a five-year post-merger period, over which we measure innovation output, our sample ends in 2012. Our sample deals are classified as a "merger", an "acquisition of assets" or an "acquisition of major interests" and are considered "friendly;" they have status of either "complete" or "withdrawn." We first match our sample firms with CRSP by 6-digit CUSIP and obtain the corresponding PERMCO. To construct deal and firm characteristics, we further use the CRSP-Compustat Merged Link Table to obtain the GVKEY for those firms. Since we use PERMCO as an identifier to obtain patent portfolios, we remove some rare cases where the acquirer and target have the same PERMCO. These deals were presumably not mergers, but restructurings that were included by the SDC in the same category. For deal characteristics, we use the latest fiscal year-end information that is available before the deal announcement date. After this step, out sample contains 8232 deals, of which 7125 are completed and 1107 are withdrawn.

To construct our measure of specialized investment by target firms, we use data on texts of patent claims together with patent inventor and assignee information, provided by USPTO *PatentView*. To match patents to our sample of merging firms, we rely on the link table from Kelly, Papanikolaou, Seru, and Stoffman (KPSS, 2017) that relates patents to PERMCOs from CRSP by matching patent assignees. We further supplement this link table by inferring the PERMCO-assignee information from KPSS link table by forward filling patents that are not in the existing link table. Using this link table, we extract all the patents a target and an acquirer filed before and after the merger. We require the target and acquirer to have at least one patent in the five-year window preceding the deal announcement date. After imposing this requirement, our sample, for which both parties are active in innovation before the merger, includes 1,148 completed deals and 170 withdrawn deals.

To construct our estimation sample, we use patents filed by staying lead inventors of target firms to create a panel database on innovation activities of these inventors around the time of M&A deals. Specifically,

first we extract the lead inventor's affiliation before the merger by examining the set of patents that targets and acquirers filed in the entire pre-merger period (not restricted to a 5-year window). We identify a lead inventor to be a target (acquirer) lead inventor if he is listed as lead inventor on a patent that the target (acquirer) filed before the merger. In cases where the same inventor appears in both side of the merged firm, we use the latest patent filed before the merger to identify her affiliation. We identify lead inventors if she leads at least one patent in both the pre- and post-merger period, and include in the sample all the patents for which she is the lead inventor. To salvage cases where the target pre-merger lead inventors stay in the firm but become a non-lead in the post-merger period, we supplement the sample with such staying lead inventors as well as the patents led by her pre-merger and filed by her post-merger as long as they are not led by an acquirer lead inventor. We define a lead inventor to be a "staying" lead inventor if she is identified in the second or the third step, and measure R&D investment specificity by examining similarity between the target and acquirer's patents by such staying lead inventors.

Our measure of target-acquirer investment specificity imposes two more conditions on our sample. First, targets and acquirers (of both completed and withdrawn deals) present in our sample have to have at least one staying lead inventor. After this step, our sample includes 511 completed deals and 70 withdrawn deals.[4] Second, for each acquirer (of both completed and withdrawn deals) present in our sample, we need to construct a set of firms that serve as counterfactual acquirers – an acquirer benchmark group, and obtain patents by these counterfactual acquirers' lead inventors. Instead of restricting to *staying* lead inventors as in the real acquirer and target case where one needs to identify inventor affiliation in the combined entity, we use *all* lead inventors because there is no mixing between target and counterfactual acquirer inventors since these deals never actually occurred.

The final sample requires each target team to have at least one target team-acquirer firm level observations, using deal announcement/resolution dates as cutoff. After imposing patenting requirements by

[4] We do not need staying lead inventors' identity to distinguish target and acquirer R&D activity outcomes for withdrawn deals, as there is no real mixing of R&D forces for withdrawn deals, but we used the same lead inventor methodology for consistency.

acquirers' and counterfactual acquirers' lead inventors, our sample includes 2,809 staying lead inventors coming from 350 completed deals and 1,212 staying lead inventors from 41 target firms of withdrawn deals.

2.3. Summary Statistics

Table 1 presents summary statistics on the final sample of mergers. The acquirer and target characteristics are calculated using the latest available financial data before the deal announcement date. Acquirers tend to be larger and older than targets, have higher market to book ratios, profitability, payout ratios, but similar leverage and average patent age and lower sales growth. On the other hand, targets tend to have higher R&D than acquirers, suggesting the target has engaged in more intensive R&D activities before the merger. The completed and withdrawn deal acquirers are generally similar, with completed acquirers having lower leverage and profitability but higher sales growth.

Panel A of Table 2 provides summary statistics on inventor teams that are led by acquirer and target firms' staying lead inventors to provide comparison across acquirer/target firms in completed/withdrawn deals over time. The *number of teams* refers to the number of unique staying lead inventors the acquirer or target has. The *average team size* refers to the average number of team members for patents filed under the same lead inventor, while *average number of patents* is the total number of patents the team filed in the 5-year window before/after the merger. The latter two variables are first calculated at the team level, then aggregated to deal level by taking averages across teams. Finally, we report medians of all three variables across deals because of the high skewness in the innovation data across firms.

This panel indicates that acquirers of completed deals average 13 inventor teams, while the acquirers of the withdrawn deals average 5 inventor teams. The average team size and team productivity measured by the average number of patents per team are generally similar across acquirer/target firms in both completed/withdrawn deals, with a generally small decline in team productivity and small increase in team size from pre- to post-merger period. The targets are in general smaller than the acquirer with 2 inventor teams. The average team size is similar to that of the acquirer, while the team productivity is slightly lower than that of the acquirer.

The difference in the number of teams between completed and withdrawn deals could be due to the difference in either size or innovativeness. To delineate the source of difference, in Panel B of Table 2 we compare the difference in sales, size and logarithm of R&D scaled by total assets. While the first two variables capture firm size, the last variable captures the innovativeness. The t-statistics on the difference between the completed and the withdrawn group indicates that acquirers of the two groups mainly differ in size but not innovativeness.

To evaluate whether staying lead inventors characterize the entire team behind patents around the mergers, Panel C of Table 2 provides a breakdown of patenting activity by staying inventors of target firms in all completed deals in the post-merger period, regardless of whether they survive other filtering criteria and remain in our final sample. We focus on patents filed by merged firm in completed deals since withdrawn deals do not incur any mixing of inventors. Within completed deals, we extract all patent-inventor pairs within the five-year post-merger window, the inventor of which is affiliated with the target firm before the merger. We find 35,023 such unique patent –inventor pairs, of which 88% of these patent-inventor pairs are from patents that do not include any acquirer inventor. These patent-inventor pairs are from 20,884 unique patents. Of the 13% remaining unique patents that do include acquirer inventors, another 35% of them are led by a target lead inventor, and 31% of the them have target inventors as the majority of the team. Overall, Panel C of Table 2 shows that the target inventor team composition tends to remain stable after the target firm is acquired, with target firm's inventors mostly continuing to work with one another following the acquisitions.

3. Measuring Innovation Investment Specificity

This section describes how we construct the measure of the specificity of target firms' innovation investments with respect to those of acquirers. We first describe how we compute the similarity of any two patents using textual analysis. Second, we show how we aggregate similarity of individual patents to measure

the closeness of the target firm's innovation investments with the acquirer's. Finally, we explain how we adjust this closeness measure using counterfactual acquirer' investments to create a measure of specificity.

3.1 Pairwise Similarity of Patents

We use textual analysis to compute the similarity of patents' principal claims. We focus on a patent's principal claims because they define the invention, for which the Patent Office has granted protection, while the rest of the patent document facilitates understanding of the claimed invention. The principal claim, as the first and foremost claim of the sequence of the claims listed in a patent, reflects the most important features of the invention.

We start by representing the principal claim of each patent using a vector of word counts applying the term frequency-inverse document frequency (*tf-idf*) weighting scheme. In the *tf-idf* scheme, the word (i.e., term) count in each principal patent claim is offset by the number of such claims in the corpus[5] that contain the word, which adjusts for the fact that some words appear more frequently in general. Formally, we define the corpus as the set of all principal claims of patents filed in the same calendar year ($corpus_t$), and we define the total collection of words used in principal claims of patents in our sample as W. The "Term Frequency", TF_{pwt}, is the count of word w in the principal claim of patent p filed in calendar year t. The "Inverse Document Frequency" is defined as

$$IDF_{wt} = \log\left(\frac{total\ number\ of\ documents\ in\ corpus_t}{number\ of\ documents\ in\ corpus_t\ using\ word\ w}\right).$$

By allowing IDF_{wt} to vary over time we adjust for the change of relevancy of terms over our long time-series sample.[6] As a result, each patent is represented by vector $TFIDF_{pwt} = TF_{pwt} \cdot IDF_{wt}$, that is, the

[5] The term "corpus" in Natural Language Process literature refers to the set of documents that one use as a training set to provide a context of how the language is naturally used. In our study, the corpus refers to the set of patent claims we use to calculate *IDF* vector.

[6] For example, the use of term "Internet" in patents filed in 1990 is far less prevalent compared to 2012. Therefore, the use of term "Internet" should be considered more relevant/important/informative for comparisons across patents filed in 1990 compared to 2012.

dot product of TF_{pwt} and IDF_{wt} with the length of $TFIDF_{pwt}$ vector being equal to the size of vocabulary W. After applying this technique to every patent, as the last step, we calculate the pairwise similarity between patents i and j using the cosine similarity between the two $TFIDF_{pwt}$ vectors, $TFIDF_i$ and $TFIDF_j$:

$$TFIDFsimilarity_{ij} = \frac{TFIDF_i \cdot TFIDF_j}{\|TFIDF_i\| \|TFIDF_j\|}.$$

3.2 Measuring the Closeness of a Target's Innovation Investments to the Acquirer's

To measure the similarity of target firm's innovation investments to the acquirer's investments, we focus on examining the closeness of innovation output between target and acquirer inventor teams that are led by staying inventors. To do so, we first compute the average $TFIDFsimilarity$ of all pairs of patents filed by the same target inventor team-acquirer inventor team pair in the same relative year, and we repeat this calculation for every target inventor team-acquirer inventor team pair for all the relative years in our sample.[7] We define relative year using the dates that are 5, 4, 3, 2, 1 continuous years before the deal announcement dates as cutoff dates for pre-merger period and 1, 2, 3, 4, 5 continuous years after the deal completion date as cutoff dates for post-merger period. The use of relative year in classifying patents provides a more precise timeline than calendar year in capturing any time-variation in treatment effects.

Second, for each target inventor team in each relative year, we create the empirical distribution of the average $TFIDFsimilarity$ with every possible acquirer inventor team computed in the first step. From this distribution, we take the 90th-percentile highest average $TFIDF\ similarity$ to be the target inventor team's similarity with the acquirer – a measure that reflects how each target inventor team is close to the acquirer in each year. We denote this measure $TARGETcloseness_{v,a,t}$, where v denotes the target inventor team, a denotes acquirer, and t is relative year.

[7] For each target inventor team-acquirer inventor team pair, if the target inventor team has *N* patents and the acquirer inventor team has *M* patents, the resulted similarity matrix will be of size *N* by *M*, and the target-acquirer inventor team-wise similarity is the average of such N times M similarity scores.

The reasoning behind this approach to aggregation is twofold. First, acquirers tend to be larger and more diverse firms, while target teams are usually smaller and their innovation is more focused on specific fields. If target inventor teams specialize their innovation investments to facilitate synergies with the acquirers, what should matter is whether their investments are similar to *any* of the acquirer's investments, not whether the target team's investment is similar to the *average* of the acquirer's investments. For this reason, we consider the target firms' investments to be similar if there is a high similarity score between the target's teams and any of the acquirer's teams. Based on this aggregation approach, we consider the target's innovation output to be similar to that of acquirer in situations where alternative approaches might incorrectly consider the output to be different from the acquirer. We illustrate this point graphically in Figure 1.

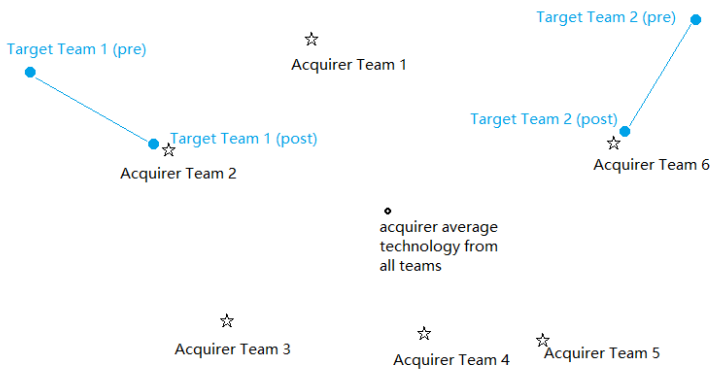

Figure 1: In this illustrative example, the acquirer has six inventor teams, each of which is far from the "center dot" representing the "average" technological position of all six inventor teams of the acquirer. Target firm's inventor Team 1 produces a very similar innovation to acquirer's inventor Team 2 following the merger, even though it is far from the acquirer's average technological position. The same applies to target firm's inventor Team 2 that becomes close to acquirer's inventor Team 6 post M&A.

Second, we use the 90th-percentile highest of all target-acquirer inventor team similarity scores as a measure of target's inventor team to acquirer firm-wise similarity. Potentially, one could use the highest target-acquirer inventor team similarity to reflect the intuition above, however, for a very large and technologically diversified acquirer such as Google, whose research teams are scattered throughout the entire technological space, no matter where the target is located, there will almost surely be at least one team that is in its neighborhood. Therefore, in this case, using the highest target-acquirer team similarity score is not informative as the similarity would likely be uniformly small and the change in similarity would be minimal. On the other

hand, if the target indeed gets closer to the fields of research that acquirer does, the target will still be close to the acquirer teams at 90th-percentile, while if a target is accidently close to only one team of acquirer's, it might not be as close to the 90th-percentile.

To understand this argument, consider an example of a target whose single inventor team specializes in Virtual Reality (VR) for which there are two potential acquirers: acquirer A is a firm that also specializes in VR with 8 inventor teams in VR and 2 teams in software development, while acquirer B is mainly a pharmaceutical firm with 9 teams in biotech and only 1 team in VR. If one compares the similarity between the target and the closest acquirer team from A and B, in both cases the similarity score will not be noticeably different because both acquirers have one inventor team in VR. In contrast, comparing the similarity at 90th-percentile yields a different implication: for acquirer A, the target is compared with one of A's teams in VR, the similarity of which is still relatively high; while, for acquirer B, 90th-percentile rule means comparing a biotech team with the target specializing in VR, which will result in a very low similarity. Using our approach, in this example, the target will be much closer to acquirer A compared to acquirer B.

3.3 Target-Acquirer Innovation Investment Specificity Measure

Klein, Crawford, and Alchian (1978) argue that the gap in value between the actual customer and the potential customer with the second highest valuation defines the extent to which the specialized investment is vulnerable to appropriable quasi rents. In our setting, the idea that hold-up problems can lead to acquisitions relies on the notion that there are multiple potential firms for which target's innovation activities may be useful if they become specialized, and the acquisition facilitates specialization toward a specific acquirer. Following this reasoning, identifying alternative acquirers and benchmarking the closeness of the target to the acquirer relative to how close the target is to the set of alternative acquirers is necessary for measuring the way in which specialized investment can lead to acquisitions.

We construct the innovation investment specificity measure of a given target inventor team toward the acquirer, $TARGETspecificity_{v,a,t}$, as a way of comparing the closeness of the target inventor team v to the

acquirer a with the closeness of this target inventor team to the counterfactual acquirers for acquirer a. Specifically, we define

$$TARGETspecificity_{v,a,t} = \frac{TARGETcloseness_{v,a,t} - \overline{TARGETcloseness_{v,counterfactual\ acquirers\ for\ a,t}}}{\sigma_t},$$

where $TARGETcloseness_{v,a,t}$ denotes how target's inventor team v is close to actual acquirer a as defined in the prior section, $\overline{TARGETcloseness_{v,counterfactual\ acquirers\ for\ a,t}}$ denotes the average closeness between team v and the set of counterfactual acquirers for acquirer a, and σ_t denotes the standard deviation of the closeness measures between team v and both the actual and counterfactual acquirers. The intuition behind this measure – similar to the intuition behind constructing z-statistics of any variable – is to adjust for the cross-sectional differences in the compactness of the closeness measure between actual acquirer and counterfactual acquirer.

3.4 Set of Counterfactual Acquirers

We construct a set of counterfactual acquirers for each deal by matching on observable characteristics. Specifically, for each acquirer of the deal announced in calendar year t, we find the ten closest firms using Mahalanobis distance matching[8] from Compustat, using the information on the patent closeness with the target in windows [t-6,t-4] and [t-3,t-1], R&D and total assets at year t-5, t-3, and t-1, growth of total assets and R&D over the 5 year window, the number of patents filed within the 5 year window, as well as the total number of patents filed up to year t-1. Since the counterfactual acquirers are meant to represent the closest peers to the actual acquirer in terms of innovation activities, the matching variables we select are more related to the acquirer's R&D and patenting and less to other variables such as the market to book ratio or profitability. We use information that spans the entire 5-year pre-merger window instead of only at the deal announcement year

[8] The Mahalanobis distance is a measure that captures the multi-dimensional distance between two points using` how many standard deviations away they are along each (matching) dimension. It could be considered as a variation of Euclidean distance where the length along each dimension is normalized by the standard deviation of the corresponding variables.

to ensure the counterfactual acquirers resemble the dynamics of closeness between the real acquirer and the target throughout the pre-merger period.

To capture the supply-chain relationship for vertical integration deals, we develop a refined matching scheme by augmenting the matching methodology described above with the product market similarity measure from Hoberg and Phillips (2016) (the "augmented matching"). Specifically, we add the firm pair-wise product market similarity (TNIC) measure at relative years t-5, t-3, t-1 into the Mahalanobis metric matching and construct the innovation investment specificity measure from Section 3.3 using this set of counterfactual acquirers from the augmented matching. The inclusion of product market similarity increases the chance that the counterfactual acquirers have the same position in the supply chain network as the actual acquirer, and thus the chance that the counterfactual acquirers are vertically related to the target in the same way the acquirer is related to the target. While improving measurement, a drawback of this matching sample is that the TNIC data are only available since 1988. To allow for five years of the pre-merger period, our sample for this matching scheme can only start after 1992, which significantly shortens the length of the sample period. We thus use this augmented matching scheme as a refinement of the baseline matching scheme for a subset of our analyses.

3.5 Validity of the Target-Acquirer Innovation Investment Specificity Measure

Our target-acquirer innovation investment specificity measure is meant to capture the extent to which the target innovation is close to the real acquirer compared to the target's innovation being close to the counterfactual acquirers. If, as we hypothesize, the target of a completed deal becomes closer to the actual acquirer disproportionally more than it does to the counterfactual acquirers after the merger, we should see an increase in the post-merger actual acquirer's similarity relative to the counterfactual acquirers.

To evaluate the validity of our innovation specificity measure, we calculate the average probability of the real acquirer to be within top three in terms of target-acquirer innovation similarity out of the ten counterfactual acquirers. We tabulate the probability for completed and withdrawn deals separately, both for the pre-merger and post-merger period. The probability of acquirers of completed deals being among top three

increases from 17% to 31% from pre- to post-merger period, which is statistically significant at the 1% level. In contrast, while this probability also increases in withdrawn deals from 20% to 28%, the magnitude of the increase is economically small and not statistically significant at conventional levels.

4. Estimates of the Impact of Acquisitions on Patents' Contributions

4.1. Empirical Specification

To what extent do mergers lead target firms to more specialized investments that have complementarities with the acquirer's assets ex post? To measure the post-merger changes in target firm's investments, we rely on textual analysis of the patents produced by inventors coming from the target firm.

We estimate equations explaining the similarity between the patents filed by the inventors of the target and acquirer firms. To account for changes that likely would have occurred had the firm not been acquired or was acquired by a firm with a different set of specialized assets, we benchmark our similarity measure with the same measure calculated using counterfactual acquirers rather than the actual ones. In this way, our dependent variable, $TARGETspecificity_{vat}$, captures the technological proximity between the target and the acquirer, beyond the potential proximity to the acquirer peers for which the innovation is of second highest value, as defined in Section 3.3. Therefore, it represents the relationship-specific innovation efforts by the target towards the acquirer.

We estimate the following equation at the target-team-year level:

$$TARGETspecificity_{vit} = \alpha_0 + \beta\, Complete_i \times Post_{it} + \gamma\, Complete_i + \delta\, Post_{it} + \lambda' X_{it} + \rho' G_i + \theta' H_{jt} + FEs + \epsilon_{ijt}$$

where *v, i,* and *t* index target inventor team, deal, and relative year, respectively. $Complete_i$ is a dummy variable equal to one if the deal has been completed, and zero if withdrawn. $Post_{it}$ is a dummy variable equal

to one for years after the deal resolution date (i.e. relative year = 1 to 5), which is the effective date for completed deals and the withdrawal date for withdrawn deals. The variable of interest is the interactive term, $Complete_i \times Post_{it}$, which captures the difference in technological shift between the complete deals and the withdrawn deals as a result of the merger. The vector G_i is a vector of time-invariant deal characteristics, including *Relative Deal Size* and *Same SIC2*, which is a dummy variable equal to one if the acquirer and target belong to the same 2-digit SIC group. The vector X_{it} consists of time-varying acquirer firm characteristics, including *Acquirer Size, Asset M/B, ROE*, *R&D stock, Firm age, average patent age* and *patent count*. The vector H_{jt} consists of time-varying target team characteristics, including *Patent count* and *Average team size*. For all the variables calculated from Compustat (*Acquirer Size, Asset M/B, ROE*, *R&D stock, Firm age*), we use the values as of the last fiscal year end. We also include a variety of fixed effects including acquirer two-digit industry classification (SIC2), acquirer, deal, and target lead inventor to control for the time-varying common trends affecting both the treatment and the control groups, as well as time-invariant industry, firm, deal or team heterogeneity. We estimate the model using ordinary least squares (OLS) with robust standard errors corrected for clustering of observations at the deal level.

4.2. Estimates of Post-Merger Changes in Innovation Specificity

Table 3 contains estimates of this equation. All columns include time-invariant deal characteristics as well as time-varying acquirer characteristics. Column 1 includes acquirer SIC 2-digit industry fixed effects, and Columns 2, 3, and 4 have acquirer fixed effects, deal fixed effects and target lead inventor fixed effects respectively.

The estimated coefficients on the interaction term $Complete_i \times Post_{it}$ are positive and statistically significantly different from zero in all specifications. This positive coefficient implies that the patents produced by inventors from the target team become closer in their content to those from the acquirer following the acquisition. The effect is large in magnitude: it corresponds to an increase in $TARGETspecificity$ of 0.11 to 0.178 units, equivalent to a 28.9% to 46.8% increase compared with the mean $TARGETspecificity$ of 0.38.

The coefficient on the $Post_{it}$ dummy is not statistically significantly different from zero. In other words, the observed change in research specificity in completed deals does not occur in withdrawn deals. Since deals are normally withdrawn for reasons having nothing to do with the research that will be done subsequent to the mergers, the difference between completed and withdrawn deals provides evidence that the change in research following acquisitions does not occur because of selection. It does not appear that the results are driven by the targets of withdrawn deals moving away from acquirers following the failed merger.

Focusing on the other independent variables, we find that *Total Assets* are negatively correlated with $TARGETspecificity$, which is not surprising given larger firms tend to have a more diverse innovation portfolios. *Asset M/B* is positively related to $TARGETspecificity$, suggesting that target tend to have higher specificity to the acquirer with higher market valuations. When including deal and target lead inventor fixed effects, *Acquirer R&D stock* and *Average patent age* are also negatively correlated with the independent variable -i.e, acquirers' historical innovativeness is negatively correlated with the target specificity measure. The average target team size is positively correlated with the specificity measure, suggesting that the specificity to acquirer of larger target teams are on average bigger than that on smaller teams.

4.3 Vertical vs. Non-Vertical Deals

The idea that hold-up problems in contracting could lead to acquisitions has traditionally been applied to firms in vertical relationships, in which one firm produces inputs to the other's production process (see Klein et al. (1978) and Frésard, Hoberg and Phillips (2020)). As illustrated in models like the one presented in Chapter 2 of Hart (1995), an input that is specialized to the production process can be more efficient than a more general input. If integration makes it easier to reach equilibria in which the supplier produces the specialized input, then integration can be efficient.

However, innovative firms face hold-up problems even when they are not in a supply-chain relationship. They interact in the process of cross-licensing agreements, setting standards, providing complementary value to each other's patents and commercialization (Holgersson et al, 2018). It is during these

processes that the contracting frictions can cause potential hold-up problems. For this reason, we do not restrict our sample to vertical mergers. Nevertheless, the prior literature has focused on the role of hold-up in vertical relationships because these contracting frictions are likely to be particularly severe when firms are in a supply-chain relationship. To evaluate this prediction formally, we split the sample into vertical and non-vertical acquisitions and test the hypothesis that the treatment effect is indeed larger in the subsample of vertical deals. To identify deals that are vertical, we rely on the classification scheme of Frésard, Hoberg and Phillips (2019).[9]

Table 4 presents estimates on these two subsamples. In Column (1) of Panel A, we present coefficients on the *Completed deal* dummy and *Post merger* dummy, as well as on their interaction term, with deal fixed effects and other control variables included. In Column (2), we replace deal fixed effects with target lead inventor fixed effects. In each specification, the estimated coefficient on the interaction term for the vertical integration subsample is larger than for the non-vertical integration counterparts. A test of the cross-equation restriction rejects the hypothesis that the coefficients on vertical and non-vertical deals are the same.[10] This finding support the prediction that vertical acquisitions are especially likely to be motivated by the alleviation of contractual frictions, as was originally suggested by Klein, Crawford, and Alchian (1978).

To capture the dynamics in supply-chain relationships, we develop a refined matching scheme by adding the product market similarity from Hoberg and Phillips (2016) into the existing set of matching variables. The inclusion of product market similarity increases the chance that the counterfactual acquirers have the same position in the supply chain network as the actual acquirer, and thus the chance that the

[9] These authors constructed a direct measure of vertical relatedness between firm-pairs using the BEA Input/Output tables by comparing the product description of firms' 10-Ks with the textual product description of each commodity from the BEA Input/Output table. We used their vertical relatedness measure TNIC at the 10% granularity level to identify the deals that are vertical. We regard a merger deal to be vertical integration either in cases where target is identified as upstream to the acquirer or where the acquirer is identified as upstream to the target.

[10] To compare the statistical magnitude of interaction terms from vertical vs. non-vertical subsamples, we conduct a seemingly unrelated regression (SUR) allowing for covariance structure of error terms across equations. To conduct this test, we first estimate OLS regression for each subsample, and then conduct F-test based on the covariance matrix of stacked error terms from the first step, clustering standard errors at deal level. The test is conducted using Stata package *suest*.

counterfactual acquirers are vertically related to the target in the same way the acquirer is related to the target. Therefore, we expect the treatment effect to be better captured in the augmented matching sample.

In Panel B of Table 4, we present estimates of our equation on the vertical and non-vertical subsamples, using the augmented matching scheme. The estimated coefficients that reflect the change in post-acquisition innovation specificity imply that the effect of vertical deals on innovation specificity is larger than in the previous specification. This larger effect holds both in terms of the magnitude of coefficients and the difference in interaction term between vertical and non-vertical subsamples.

In Figure 2, we plot the dependent variable, $TARGETspecificity,$ across relative years, for both completed and the withdrawn deals. The graph indicates that, except relative year -5 in which the withdrawn deals have very large but noisy level of dependent variable, the completed and the withdrawn deals otherwise are not significantly different from one another and have flat trends in the pre-merger period. The completed deals experience a jump in specificity at time of the deal resolution, and stay persistently higher than the withdrawn deals afterwards. The specificity of the patents between acquirer and target in the withdrawn deals, however, stay at approximately the same level as the pre-merger one.

5. Alternative Interpretations

We have documented that the innovation of merging firms, reflected in the content of the patent they file, moves closer to one another following the consummation of the deals. We interpret this finding as reflective of investment specialization brought upon by the merger. However, there are a number of alternative reasons why this relation could occur in the data. We discuss these potential alternative explanations in this section and evaluate the extent to which they could explain the changing specificity of patents around mergers.

5.1. The Impact of Lawyers

Another possibility is that following the acquisitions, the target begins using the acquirer's law firm. If the lawyers tend to use similar language in all the patents that they file, which differs from one lawyer to another, the acquirer and the target could end up using similar language after the merger when they file patents. This similar language could lead to the increase in our dependent variable, even if the actual research done by the target and acquirer is unaffected by the merger.

This possible explanation of our results would suggest that both vertical and non-vertical deals have similar measured increases in patent similarity, which is in strong contrast to our estimates that suggest that vertical deals have much larger increases in patent similarity. However, to provide additional insight into the extent to which the propensity of law firms to use similar language across patents explains the post-merger increase in similarity, we reestimate our equation on a subsample where the patents filed by the target and acquirer are filed by different lawyers following the deal. To construct this subsample, in the post-merger period, we identify the earliest year in which the target and the acquirer start to share an overlapping lawyer and drop years of observations on or after that.

Table 5 presents the estimates on the lawyer-screened subsample using the augmented matching approach. The coefficients on the $Complete \times Post$ interaction for the vertical subsample remain significantly positive. This finding suggests that changes in law firms induced by the merger is not the primary factor leading to the observed post-merger increase in innovation specificity for vertical deals.

One might argue the choice of lawyer could also be an endogenous decision based on the technological integration of the target and the acquirer post-merger. However, in such case, the deals in which the target and the acquirer producing more similar innovations are more likely to hire the same lawyer, which works against finding our results.

5.2. The Impact of Knowledge Spillovers and Collaboration

When two firms merge, the two firms sometimes combine their research efforts. Such combinations could potentially affect the patents that their inventors file. If inventors from one merging firm joins research

teams from the other and patents are attributed to individual inventors, then there could an observed increased similarity of target and acquirer patents, even if the only change with the merger is the names on the patent applications rather than the actual research. Of course, the reassignment of inventors to teams from merging firms is itself a result of contracting efficiencies brought on by mergers, since it is extremely unlikely that the same arrangement in which one firm's researchers work on another firm's projects could be accomplished via arm-length contracting.

In addition, even if acquirer and target researchers remain on the same teams as they were pre-merger, there are likely to be knowledge spillovers through contact between acquirer and target inventors. If close proximity to one another following the merger leads inventors from the two firms to share ideas and exchange know-hows, then it would be likely that their inventions become more similar to one another. Consequently, knowledge spillovers could lead to the pattern we document above, with target and acquirer post-merger patents being more similar than they were pre-merger.

We evaluate whether the changing composition of research teams or knowledge transfers are the reason for the post-merger changes in the composition of patents. To do so, we consider the subsample of inventor teams which do not add individuals from the partner firm following the merger, and which are physically located in different places from their partner firm. Specifically, for each target patent, we require the target patent to not include any inventor that worked for the acquirer prior to the merger deal. Moreover, for each target patent, we restrict the sample to the inventors that are not located in a city where any of the acquirer inventors has been located, using data from acquirer patents filed before the merger and within 5 years after the merger. We conduct the same screening procedure on acquirer patents. Using the subsample of patents from target and acquirer that satisfy these conditions, we reestimate the equations from Table 4.

Table 6 contains estimates for this subsample, again using counterfactual acquirers based on our augmented matching. The screening process significantly reduces the sample size, but the coefficients on the $Complete \times Post$ interaction term is still positive and statistically significantly different from zero for the

vertical integration subsample, with magnitudes even larger than those from Table 4. The finding suggests that the results in our paper are not driven by more frequent collaboration or knowledge spillovers after the merger.

5.3. Year by Year Changes in Innovation Specificity

An alternative interpretation of our findings is that merger deals are more likely to be completed if the target and acquirer have relatively high overlaps in technology. An implication of this matching argument is that the target and acquirer will be more likely to show high similarities in patents in the immediate years around the merger deal. Over the long run, the similarity of target and acquirer will revert back to the mean. On the contrary, if the merger leads to specialized investment, one should expect to see more persistent treatment effects in the post-merger period.

To test this idea formally, we replace the $Post_{it}$ dummy with a set of dummies indicating each year after the merger. The interaction of these dummies with the $Complete_i$ variable represents the difference in target specialized investment level between the completed and withdrawn deals estimated in each post-merger year.

Table 7 presents estimates of this specification on the vertical integration sample using augmented matching. The interaction term for the year immediately before the deal resolution is not significantly different from zero, suggesting there is not a noticeable difference between the target specificity between the complete and the withdrawn deals prior to the merger. The interaction term for the year immediately after the deal resolution is positive and statistically significantly different from zero. This finding suggests that the target team's patents become closer to the acquirer's in that year, which may be partially driven by a selection effect of the merger. However, the treatment effects do not die out – estimated using the most stringent target lead inventor fixed effect specification, the treatment effects are actually the strongest in the fourth year after deal resolution, suggesting a highly persistent effects of merger on the merging firms.

6. Summary and Discussion

The notion that mergers occur to facilitate specialized investment has been accepted by the literature since at least Klein, Crawford, and Alchian (1978), and is the central idea of the leading explanation for why firms exist. Yet, knowing whether specialized investments are an important factor affecting the boundaries of real-world firms is difficult because detailed information about firms' investments and the extent to which they are specialized to a particular relationship is not easily observable to an outsider. While there has been some work measuring the likelihood of an acquisition as a function of variables observed pre-merger, no one has examined the investments of firms subsequent to mergers and evaluated whether these investments become more specialized with those of their merging partner.

This paper considers this hypothesis on a sample of mergers of publicly-traded US corporations using textual analysis of patent data. Patents are unique among firms' investments in that their filings are under the individual inventor's name, and contain detailed information about the invention itself. We use the inventor's name to determine whether a particular patent was filed by the part of the merged company that was target or the acquirer, and term frequency-inverse document frequency (*tf-idf*) textual analysis to evaluate the extent to which any two patents are similar to one another.

Our main finding is that target and acquirer patents become more similar to one another following acquisitions. Our interpretation of this finding is that the merger leads the firm to make investments that are more specialized than would have been possible had the firms attempted to have a business relationship through bilateral contracts. One potential alternative interpretation is that the mergers in our sample occurred in firms that were starting to do business in related lines before the merger, which could lead their patents to become increasingly similar to one another even if they are not specialized to the particular relationship. Because of this possibility, we measure the change in innovation specificity relative to that of a sample of acquisitions that were announced but not completed, presumably for exogenous reasons, using a difference in differences specification. The change in specificity of patents occurs in deals that did occur but not in the

withdrawn deals, which suggests that the finding does not occur because of the nonrandom set of firms that choose to merge.

While innovative firms face a number of contracting issues that are potentially subject to hold-up problems whenever they have a business relationship, these issues are likely to be particularly difficult in the case of vertical relationships, in which one firm produces an intermediate good for another firm's production. Therefore, we evaluate whether vertical deals are particularly associated with a change in patenting behavior following the acquisition. Empirically, we find that the increase in the specificity of patent following acquisitions is higher when the firms are in a vertical relationship than in other deals.

We consider a number of alternative explanations for our findings. We consider the possibilities that our findings could occur because of information flows within post-merger firms, the assignment of target inventors to collaborate on projects that acquirer firms had been researching on (or vice versa), or the possibility that the law firms filing the documents tend to use similar language. None of these explanations appear to be the reason why patents in targets and acquirers become closer to one another following the mergers.

Despite the enormous literature on mergers, we still do not know much about what actually happens in the post-merger combined firms, and therefore, cannot really say what factors motivated the deals in the first place. The analysis of patents is one way to finesse this issue, since patents are filed by individual inventors whose pre-merger affiliation is traceable, and the content of the patents is publicly available. We use these patent data to help understand the way that contracting can influence acquisitions. Patent data will likely allow for fruitful analysis of related issues in the future.

References

Acemoglu, Daron, Philippe Aghion, Rachel Griffith, and Fabrizio Zilibotti. 2010. "Vertical Integration and Technology: Theory and Evidence." *Journal of the European Economic Association* 8(5): 989–1033.

Aghion, Philippe et al. 2013. "Identifying Technology Spillovers and Product Market Rivalry." *Econometrica* 81(4): 1347–93.

Bena, Jan, and Kai Li. 2014. "Corporate Innovations and Mergers and Acquisitions." *Journal of Finance* 69(5): 1923–60.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How much should we trust Differences-in-Differences Estimates?" *Quarterly Journal of Economics*.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen. 2013. "Identifying Technology Spillovers and Product Market Rivalry." *Econometrica* 81(4): 1347–93.

Carlton, Dennis W., and Jeffrey M. Perloff. "Modern industrial organization." *Reading MA* (1994).

Coase, Ronald H. "The acquisition of fisher body by general motors." *The Journal of Law and Economics* 43.1 (2000): 15-32.

Frésard, Laurent, Gerard Hoberg, and Gordon M. Phillips. 2020. "Innovation Activities and Integration through Vertical Acquisitions." *Review of Financial Studies*, forthcoming

Gentzkow, Matthew, Bryan Kelly, and Matt Taddy. 2019. "Text as Data." *Journal of Economic Literature* 57(3): 535–74.

Grossman, Sanford J., and Oliver D. Hart. 1986. "The Costs and Benefits of Ownership: A Theory of Vertical and Lateral Integration." *Journal of Political Economy* 94(4): 691–719.

Hart, Oliver. *Firms, contracts, and financial structure*. Clarendon press, 1995.

Hermalin, Benjamin E., and Michael L. Katz. "Information and the hold-up problem." *The RAND Journal of Economics* 40.3 (2009): 405-423.

Hoberg, G., & Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5), 1423-1465.

Holmstrom, Bengt, and John Roberts. 1998. "The Boundaries of the Firm Revisited." *The Journal of Economic Perspectives* 12(4): 156–70.

Kelly, Bryan T., Dimitris Papanikolaou, Amit Seru, and Matt Taddy. 2018. "Measuring Technological Innovation over the Long Run." *SSRN Electronic Journal* (January).

Klein, Benjamin. "Vertical integration as organizational ownership: The Fisher Body-General Motors relationship revisited." *Journal of Law, Economics, & Organization* 4.1 (1988): 199-213.

Klein, Benjamin, Robert G. Crawford, and Armen A. Alchian. 1978. "Vertical Integration, Appropriable Rents, and the Competitive Contracting Process." *The Journal of Law & Economics* 21(2): 297–326.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2017. "Technological Innovation, Resource Allocation, and Growth." *Quarterly Journal of Economics* 132(2): 665–712.

Li, Kai, and Jin Wang. 2020. "How did Mergers and Acquisitions Foster Innovation? Inventor-Level Evidence," *Working Paper*.

Mei, Danqing. 2019. "Technology Development and Corporate Mergers." *Working Paper.*

Monteverde, Kirk, and David J. Teece. 1982. "Supplier Switching Costs and Vertical Integration in the Automobile Industry." *The Bell Journal of Economics* 13(1): 206–13.

Mulherin, J. Harold, Jeffry M. Netter, and Annette B. Poulsen. "The evidence on mergers and acquisitions: A historical and modern report." *The handbook of the economics of corporate governance*. Vol. 1. North-Holland, 2017. 235-290.

Phillips, Gordon M., and Alexei Zhdanov. 2013. "R&D and the Incentives from Merger and Acquisition Activity." *Review of Financial Studies* 26(1): 34–78.

Seru, Amit. 2014. "Firm Boundaries Matter: Evidence from Conglomerates and R&D Activity." *Journal of Financial Economics* 111(2): 381–405.

Sevilir, Merih, and Xuan Tian. 2012. "Acquiring Innovation." *SSRN Electronic Journal* (812).

Tirole, Jean. "Procurement and renegotiation." *Journal of Political Economy* 94.2 (1986): 235-259.

Williamson, Oliver E. 1971. "The Vertical Integration of Production: Market Failure Considerations." *The American Economic Review* 61(2): 112–23.

Williamson, Oliver E. 1979. "Transaction-Cost Economics: The Governance of Contractual Relations." *Journal of Law and Economics* 22: 112–23.

Williamson, Oliver E. 1985. *The Economic Institutions of Capitalism: Firms, Markets, and Relational Contracting*, Free Press.

Woodruff, Christopher. 2002. "Non-Contractible Investments and Vertical Integration in the Mexican Footwear Industry." *International Journal of Industrial Organization* 20(8): 1197–1224.

Younge, Kenneth A., and Jeffrey M. Kuhn. 2016. "Patent-to-Patent Similarity: A Vector Space Model." *SSRN Electronic Journal*.

Figure 2. Target Specificity for Completed and Withdrawn Deals: Parallel Trends

This figure plots our dependent variable, $TARGETspecificity_{vit}$, which measures the technological proximity (similarity) between the target team and the acquirer firm, using a term frequency-inverse document frequency (*tf-idf*) textual analysis technique. We normalize this similarity measure by benchmarking it with the same measure calculated using counterfactual acquirer (see Appendix A for the exact definition). The $TARGETspecificity$ is presented, for completed and withdrawn merger deals separately, over five years before the deal announcement date and after the deal resolution date, which is the effective date for completed deals and the withdrawal date for withdrawn deals.

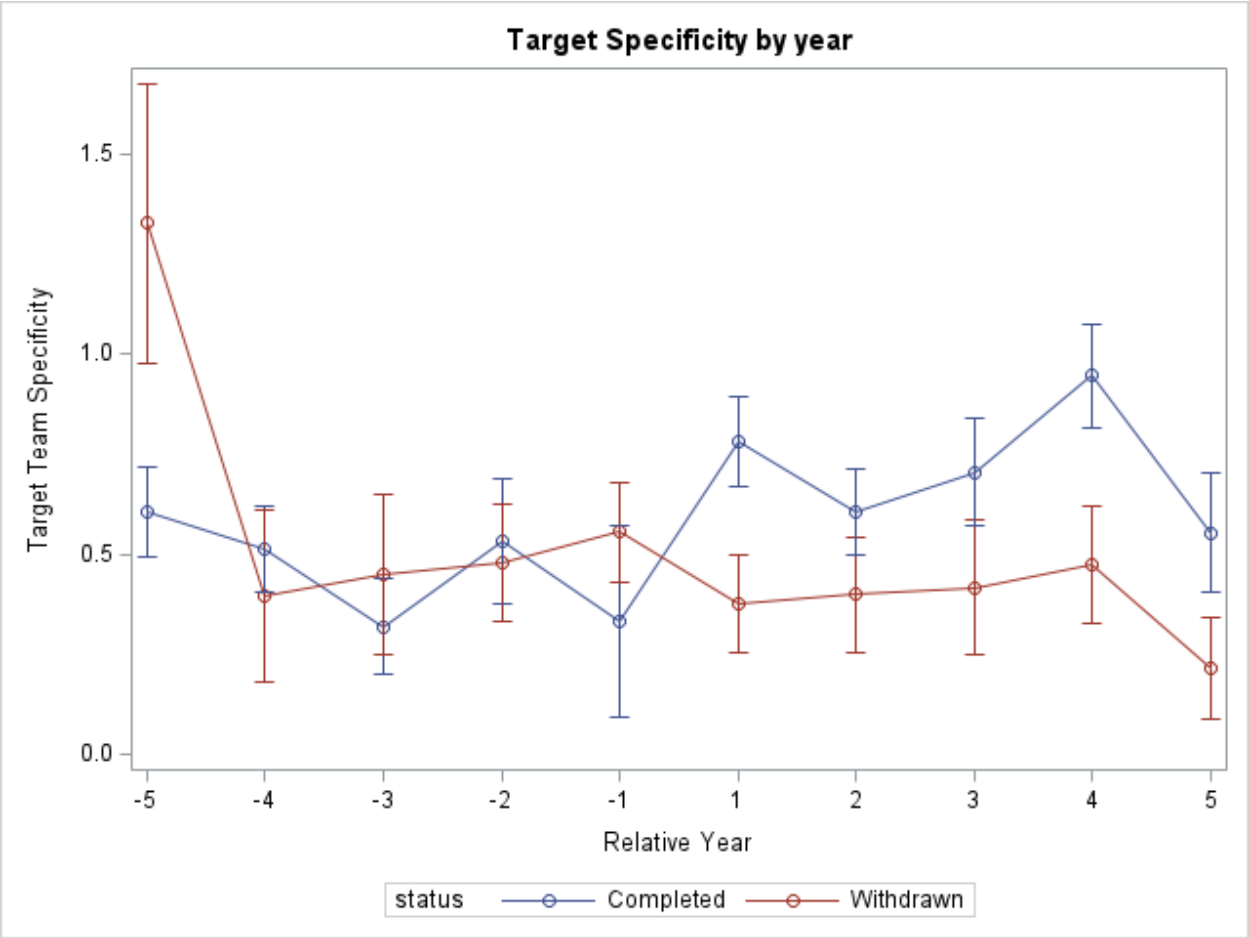

Table 1. Summary Statistics

This table presents summary statistics of dependent variable as well as independent variables of deal, acquirer, and target characteristics. The summary statistics are presented at team-relative year level, for all mergers in our sample as well as for completed and withdrawn deals separately. Refer to Appendix A for the detailed definition of variables.

	Whole Sample			Completed			Withdrawn		
	Nobs.	Mean	Stdev.	Nobs.	Mean	Stdev.	Nobs.	Mean	Stdev.
Dependent Variable:									
Target Specificity	12972	0.38	0.98	8957	0.36	0.99	4015	0.41	0.95
Deal Characteristics:									
Relative Deal Size	12972	0.47	0.44	8957	0.42	0.41	4015	0.57	0.48
Same SIC2	12972	0.55	0.50	8957	0.64	0.48	4015	0.34	0.47
Toehold	12972	0.54	3.52	8957	0.79	4.22	4015	0.00	0.00
All Cash	12972	0.22	0.42	8957	0.31	0.46	4015	0.02	0.12
All Stock	12972	0.43	0.49	8957	0.34	0.47	4015	0.63	0.48
Acquirer Characteristics:									
Total Assets	12972	9.79	1.80	8957	9.49	1.59	4015	10.45	2.05
Asset M/B	12972	1.90	1.47	8957	2.05	1.60	4015	1.55	1.05
Leverage	12972	0.23	0.14	8957	0.19	0.11	4015	0.32	0.15
ROE	12972	0.18	0.19	8957	0.16	0.18	4015	0.22	0.19
Payout	12685	0.17	0.11	8713	0.16	0.12	3972	0.19	0.09
R&D	12972	0.07	0.11	8957	0.08	0.13	4015	0.06	0.05
Sales Growth	12970	0.13	0.39	8955	0.15	0.45	4015	0.08	0.18
R&D Stock	12972	0.21	0.15	8957	0.23	0.16	4015	0.17	0.14
Avg. Patent Age	12972	8.58	4.26	8957	8.71	4.49	4015	8.30	3.69
Firm Patent Count	12972	165.69	218.36	8957	138.49	180.35	4015	226.37	275.99

(Continued on next page)

(Continuing from last page)

	Whole Sample			Completed			Withdrawn		
	Nobs.	Mean	Stdev.	Nobs.	Mean	Stdev.	Nobs.	Mean	Stdev.
Target Characteristics:									
Total Assets	8152	8.27	1.84	4436	7.59	1.96	3716	9.07	1.29
Asset M/B	8141	1.70	1.62	4425	1.90	1.93	3716	1.46	1.10
Leverage	8141	0.22	0.14	4425	0.21	0.16	3716	0.23	0.11
ROE	7910	0.05	1.10	4236	0.03	0.81	3674	0.07	1.36
Payout	7428	0.14	0.15	3773	0.13	0.20	3655	0.15	0.08
R&D	8139	0.10	0.62	4423	0.13	0.84	3716	0.05	0.05
Sales Growth	8099	0.25	2.95	4384	0.37	4.00	3715	0.12	0.26
R&D stock	8152	0.23	0.20	4436	0.27	0.23	3716	0.18	0.14
Avg. Patent Age	7946	8.83	4.07	4242	9.33	4.32	3704	8.26	3.68
Team Patent Count	12972	1.55	1.08	8957	1.55	1.09	4015	1.54	1.06

Table 2. Inventor Statistics

The tables present summary statistics of patent inventor. Panel A reports the team summary statistics defined by staying lead inventor. The sample includes all teams identified by staying lead inventors, whether or not they appear in final sample, as well as the deal that contains them. The *number of teams* refers to the number of unique staying lead inventors ("the team") the acquirer or target has. The *average team size* refers to the average number of team members each team has for all the patents filed under the same lead inventor, while *average number of patents* is the total number of patents the team filed in the 5-year window before/after the merger. The latter two variables are first calculated at team level, then aggregated to deal level by taking average across teams. All variables are reported as the median across deals. Panel B provides firm characteristics of the acquirer for pre- and post-merger, from completed and withdrawn deals separately. Acquirer sales, size, and log(R&D/Total Assets) are calculated using the latest financial data before the deal announcement date. Panel C tracks the target inventor patenting activities of complete deal in the post-merger period, whether or not they appear in final sample. The percentage of each value to the corresponding group total is reported in parenthesis.

Panel A: Team statistics

	Completed		Withdrawn	
	pre	post	pre	post
Acquirer				
Number of teams	13	13	5	5
Average team size	2.35	2.50	2.00	2.11
Average number of patents	2.41	2.16	2.20	2.00
Target				
Number of teams	2.00	2.00	2.00	2.00
Average team size	2.00	2.33	1.94	2.00
Average number of patents	1.80	1.83	1.97	2.00

Panel B: Acquirer firm characteristics

	Completed	Withdrawn	t-stat on diff
Sales	8,096.27	4,566.49	2.39
Size	7.65	6.41	4.94
log(R&D/Total Assets)	0.14	0.12	0.62

Panel C: Target inventor post-merger statistics of completed deals

	non-mix with acquirer			mix with acquirer		
unique patent-inventor pairs	30,848			4,175		
% from total	88%			12%		
unique patents	18,192			2,692		
% from total	87%			13%		
	Lead inventor identity					
	Target	Acquirer	Other	Target	Acquirer	Other
Unique patents	12,310	0	5,882	942	1,138	612
% from group total	68%	0%	32%	35%	42%	23%
	Majority of inventor identity					
	Target	Acquirer	Other	Target	Acquirer	Other
Unique patents	12,702	0	5,490	841	1,034	1,246
% from group total	70%	0%	30%	31%	38%	46%

Table 3. Estimates of Acquirer and Target Innovation Specificity Following Mergers

This table presents estimates of *Post-Merger Changes in Innovation Specificity* using ordinary least squares (OLS) regressions at the *deal (i), target team (v), and relative year (t) level.* The dependent variable, $TARGETspecificity_{vit}$, captures the technological proximity (similarity) between the target team *v* and the acquirer of the deal *i*, benchmarked with the same measure calculated using counterfactual acquirers. $Complete_i$ is a dummy variable equal to one if the deal has been completed, and zero if withdrawn. $Post_{it}$ is a dummy variable equal to one for years on or after the deal resolution date, which is the effective date for completed deals and the withdrawal date for withdrawn deals. Variable definitions for the various deal, acquirer, and target-level controls are in Appendix A. Standard errors, corrected for clustering of observations at the deal level, are reported in parentheses.

	$TARGETspecificity_{vit}$			
VARIABLES	(1)	(2)	(3)	(4)
Complete * Post	0.143*	0.111	0.156**	0.178***
	(0.0775)	(0.0734)	(0.0700)	(0.0626)
Complete	-0.0589	-0.158		
	(0.148)	(0.110)		
Post	0.0365	-0.0146	-0.0405	-0.0450
	(0.0740)	(0.0633)	(0.0647)	(0.0626)
Relative Deal Size	-0.0901	0.347**		
	(0.0949)	(0.136)		
Same SIC2	-0.178*	-0.416***		
	(0.101)	(0.0937)		
Total Assets	-0.0270	-0.123**	-0.197***	-0.197***
	(0.0358)	(0.0605)	(0.0645)	(0.0647)
Asset M/B	0.0720***	0.0356*	0.0405**	0.0258
	(0.0264)	(0.0184)	(0.0180)	(0.0176)
ROE	-0.0667	-0.0287	-0.108	-0.0791
	(0.141)	(0.0909)	(0.0811)	(0.0834)
Firm Age	0.000475	0.0113	0.0125	0.0190
	(0.00314)	(0.0233)	(0.0209)	(0.0186)
R&D Stock	0.203	-0.495	-0.853**	-0.589*
	(0.303)	(0.346)	(0.335)	(0.315)
Avg. Patent Age	0.00617	-0.0104	-0.0409**	-0.0393**
	(0.0122)	(0.0102)	(0.0192)	(0.0185)
Target Team #Patents	-0.0143	-0.00424	0.000534	0.00500
	(0.0132)	(0.0103)	(0.00974)	(0.00874)
Acquirer Firm #Patents	-0.000159	-0.000212	-0.000278*	-0.000313**
	(0.000201)	(0.000157)	(0.000161)	(0.000158)
Target Team Avg. Size	0.0314***	0.0294***	0.0289***	-0.00441
	(0.0103)	(0.00836)	(0.00829)	(0.00738)
Constant	0.459	1.222	2.051	1.766
	(0.349)	(1.423)	(1.314)	(1.198)
Observations	12,972	12,972	12,972	12,972
R-squared	0.065	0.202	0.269	0.570
Calendar Year FE	YES	YES	YES	YES
Acq SIC2 FE	YES	NO	NO	NO
Acquirer FE	NO	YES	NO	NO
Deal FE	NO	NO	YES	NO
Target Lead Inventor FE	NO	NO	NO	YES

Table 4. The Effect of Vertical Integration on Innovation Specificity

This table presents estimates of *Post-Merger Changes in Innovation Specificity* using ordinary least squares (OLS) regressions at the *deal (i), target team (v), and relative year (t) level.* The dependent variable, $TARGETspecificity_{vit}$, captures the technological proximity (similarity) between the target team *v* and the acquirer of the deal *i*, benchmarked with the same measure calculated using counterfactual acquirers. $Complete_i$ is a dummy variable equal to one if the deal has been completed, and zero if withdrawn. $Post_{it}$ is a dummy variable equal to one for years on or after the deal resolution date, which is the effective date for completed deals and the withdrawal date for withdrawn deals. Panel A reports estimation results based on the baseline matching scheme while Panel B reports the results based on the augmented matching scheme with inclusion of product market similarity measure. The Chi-squared and p-value from the SUR test of difference between interaction terms from non-vertical vs. vertical deals are reported. Variable definitions for the various deal, acquirer, and target-level controls are in Appendix A. Standard errors, corrected for clustering of observations at the deal level, are reported in parentheses.

Panel A: Baseline Matching

	(1)		(2)	
VARIABLES	Non-Vert.	Vert.	Non-Vert.	Vert.
Complete * Post [A]	0.0986	0.497***	0.141*	0.435***
	(0.0900)	(0.111)	(0.0846)	(0.114)
Post	-0.0509	-0.147*	-0.0456	-0.200*
	(0.0899)	(0.0865)	(0.0878)	(0.104)
Acq. Size	-0.234***	-0.0428	-0.240***	-0.0244
	(0.0715)	(0.149)	(0.0698)	(0.160)
Acq. Asset M/B	0.0239	0.0268	0.00550	0.0314
	(0.0197)	(0.0658)	(0.0200)	(0.0681)
Acq. ROE	-0.0531	-0.407	-0.0160	-0.328
	(0.0867)	(0.267)	(0.0811)	(0.294)
Acq. Firm Age	0.0101	0.0648	0.0123	0.0809
	(0.0199)	(0.0688)	(0.0162)	(0.0654)
Acq. R&D Stock	-0.863**	-1.000	-0.544	-1.114
	(0.364)	(0.711)	(0.332)	(0.751)
Acq. Avg. Patent Age	-0.0439*	-0.0269	-0.0397**	-0.0327
	(0.0229)	(0.0328)	(0.0194)	(0.0350)
Target Team #Patents	0.00347	-0.00499	0.00672	2.00e-05
	(0.0130)	(0.0111)	(0.0110)	(0.0142)
Acquirer Firm #Patents	-0.000219	-0.000294	-0.000241	-0.000405
	(0.000230)	(0.000250)	(0.000220)	(0.000251)
Target Team Avg. Size	0.0287***	0.0286	-0.0127	0.0151
	(0.00945)	(0.0181)	(0.00873)	(0.0113)
Constant	2.524**	-2.684	2.497**	-3.678
	(1.251)	(4.663)	(1.084)	(4.632)
SUR [A] coefficient [Non-Vert.=Vert.]				
$\chi 2$	7.89		4.63	
p-value	0.0050		0.0314	
Observations	9,286	3,685	9,286	3,685
R-squared	0.300	0.191	0.590	0.526
Calendar Year FE	YES	YES	YES	YES
Deal FE	YES	YES	NO	NO
Deal Inventor FE	NO	NO	YES	YES

Panel B: Augmented Matching with Product Market Similarity

	(1)		(2)	
VARIABLES	Non-Vert.	Vert.	Non-Vert.	Vert.
Complete * Post [A]	-0.156	0.643***	-0.0760	0.550***
	(0.126)	(0.126)	(0.128)	(0.127)
Post	0.105	-0.228**	0.132	-0.283**
	(0.122)	(0.107)	(0.119)	(0.110)
Acq. Size	-0.132	-0.309*	-0.178*	-0.235
	(0.100)	(0.174)	(0.103)	(0.193)
Acq. Asset M/B	0.0191	0.0110	0.00278	-0.00291
	(0.0203)	(0.0461)	(0.0208)	(0.0558)
Acq. ROE	-0.0696	-0.947***	-0.0466	-0.848***
	(0.0982)	(0.279)	(0.0909)	(0.286)
Acq. Firm Age	0.0136	-0.113	0.0177	-0.0995
	(0.0208)	(0.0889)	(0.0176)	(0.0869)
Acq. R&D Stock	-0.778*	-2.322**	-0.638	-2.143**
	(0.438)	(0.989)	(0.451)	(1.009)
Acq. Avg. Patent Age	-0.0477**	-0.0879**	-0.0445**	-0.0936**
	(0.0207)	(0.0353)	(0.0215)	(0.0377)
Target Team #Patents	0.00469	0.00444	0.00104	0.00276
	(0.0122)	(0.0135)	(0.0122)	(0.0180)
Acquirer Firm #Patents	-0.000401**	3.88e-05	-0.000455**	-9.08e-05
	(0.000202)	(0.000278)	(0.000200)	(0.000296)
Target Team Avg. Size	0.0296***	0.0421	0.00104	0.00725
	(0.00882)	(0.0258)	(0.00981)	(0.0139)
Constant	1.592	11.80*	1.880	10.46*
	(1.435)	(6.004)	(1.326)	(5.838)
SUR [A] coefficient [Non-Vert.=Vert.]				
$\chi 2$	20.42		10.82	
p-value	0.0000		0.0010	
Observations	6,211	3,645	6,211	3,645
R-squared	0.301	0.200	0.571	0.571
Calendar Year FE	YES	YES	YES	YES
Deal FE	YES	YES	NO	NO
Deal Inventor FE	NO	NO	YES	YES

Table 5. Impact of Lawyer

This table presents estimates of *Post-Merger Changes in Innovation Specificity* using ordinary least squares (OLS) regressions at the *deal (i), target team (v), and relative year (t) level*, based on a subsample of patents with separated inventors. The dependent variable, $TARGETspecificity_{vit}$, captures the technological proximity (similarity) between the target team *v* and the acquirer of the deal *i*, benchmarked with the same measure calculated using counterfactual acquirers based on augmented matching. $Complete_i$ is a dummy variable equal to one if the deal has been completed, and zero if withdrawn. $Post_{it}$ is a dummy variable equal to one for years on or after the deal resolution date, which is the effective date for completed deals and the withdrawal date for withdrawn deals. Variable definitions for the various deal, acquirer, and target-level controls are in Appendix A. Standard errors, corrected for clustering of observations at the deal level, are reported in parentheses.

	(1)		(2)	
VARIABLES	Non-Vert.	Vert.	Non-Vert.	Vert.
Complete * Post [A]	-0.234	1.413***	-0.208	1.365**
	(0.221)	(0.515)	(0.256)	(0.592)
Post	-0.00757	-1.151**	0.167	-1.245**
	(0.215)	(0.466)	(0.244)	(0.502)
Acq. Size	-0.125	-0.385	-0.0320	-0.0773
	(0.171)	(0.348)	(0.228)	(0.370)
Acq. Asset M/B	0.0387	-0.157	0.0701**	-0.159
	(0.0286)	(0.125)	(0.0279)	(0.152)
Acq. ROE	-0.432	-1.269***	-0.654**	-1.232**
	(0.280)	(0.430)	(0.304)	(0.577)
Acq. Firm Age	-0.00577	0.506	0.00565	0.540*
	(0.00940)	(0.314)	(0.0108)	(0.312)
Acq. R&D Stock	-0.855	-2.972	0.0158	-2.310
	(0.844)	(1.894)	(1.104)	(1.812)
Acq. Avg. Patent Age	-0.0769	-0.0487	-0.0807	0.00358
	(0.0598)	(0.0402)	(0.0676)	(0.0440)
Target Team #Patents	-0.00456	-0.00916	-0.000674	-0.0391
	(0.0134)	(0.0249)	(0.0236)	(0.0305)
Acquirer Firm #Patents	-0.000410	-0.00127**	-0.000922	-0.00114
	(0.000567)	(0.000517)	(0.000634)	(0.000693)
Target Team Avg. Size	0.0246*	0.0297	-0.00115	-0.0925***
	(0.0137)	(0.0365)	(0.0182)	(0.0326)
Constant	2.768	-22.12	1.223	-26.44
	(1.797)	(17.78)	(2.316)	(17.06)
SUR [A] coefficient [Non-Vert.=Vert.]				
$\chi 2$	8.90		4.00	
p-value	0.0029		0.0454	
Observations	2,374	1,473	1,494	907
R-squared	0.357	0.235	0.655	0.682
Calendar Year FE	YES	YES	YES	YES
Deal FE	YES	YES	NO	NO
Deal Inventor FE	NO	NO	YES	YES

Table 6. Impact of Knowledge Spillovers and Collaboration This table presents estimates of *Post-Merger Changes in Innovation Specificity* using ordinary least squares (OLS) regressions at the *deal (i), target team (v), and relative year (t) level*, based on a subsample of patents by geographically and teamwise segregated target and acquirer inventors. The dependent variable, $TARGETspecificity_{vit}$, captures the technological proximity (similarity) between the target team v and the acquirer of the deal i, benchmarked with the same measure calculated using counterfactual acquirers based on augmented matching. $Complete_i$ is a dummy variable equal to one if the deal has been completed, and zero if withdrawn. - $Post_{it}$ is a dummy variable equal to one for years on or after the deal resolution date, which is the effective date for completed deals and the withdrawal date for withdrawn deals. Variable definitions for the various deal, acquirer, and target-level controls are in Appendix A. Standard errors, corrected for clustering of observations at the deal level, are reported in parentheses.

	(1)		(2)	
VARIABLES	Non-Vert.	Vert.	Non-Vert.	Vert.
Complete * Post [A]	-0.0360	0.725**	0.0522	0.864***
	(0.121)	(0.341)	(0.142)	(0.318)
Post	-0.0881	-0.180	-0.129	-0.300
	(0.154)	(0.206)	(0.186)	(0.181)
Acq. Size	0.0609	-0.368	0.0165	-0.511
	(0.130)	(0.350)	(0.133)	(0.361)
Acq. Asset M/B	-0.0173	0.0211	-0.0215	-0.0432
	(0.0291)	(0.173)	(0.0335)	(0.161)
Acq. ROE	0.167*	-1.141	0.187	-0.964
	(0.0930)	(0.905)	(0.133)	(0.903)
Acq. Firm Age	0.0184	-0.416***	0.0800	-0.424**
	(0.0758)	(0.146)	(0.0869)	(0.164)
Acq. R&D Stock	1.587**	-1.031	1.508*	-2.251
	(0.793)	(1.726)	(0.860)	(1.801)
Acq. Avg. Patent Age	-0.00629	0.00604	-0.00346	-0.0200
	(0.0408)	(0.0874)	(0.0499)	(0.0892)
Target Team #Patents	0.0332**	0.0164	0.0433**	0.0456***
	(0.0134)	(0.0198)	(0.0167)	(0.0134)
Acquirer Firm #Patents	0.000533	0.000935	-0.000343	0.000563
	(0.000909)	(0.000712)	(0.00122)	(0.000770)
Target Team Avg. Size	0.0305***	0.0930***	0.00811	0.0340*
	(0.00784)	(0.0167)	(0.0132)	(0.0197)
Constant	-1.794	31.75***	-4.706	34.76***
	(4.821)	(10.26)	(5.331)	(11.56)
SUR [A] coefficient [Non-Vert.=Vert.]				
$\chi 2$	4.60		5.71	
p-value	0.0320		0.0169	
Observations	1,419	1,297	1,419	1,297
R-squared	0.342	0.179	0.658	0.682
Calendar Year	YES	YES	YES	YES
Deal FE	YES	YES	NO	NO
Deal Inventor FE	NO	NO	YES	YES

Table 7. Dynamic Regression

This table presents estimates of *Post-Merger Changes in Innovation Specificity* using ordinary least squares (OLS) regressions at the *deal (i), target team (v), and relative year (t) level.* The dependent variable, $TARGETspecificity_{vit}$, captures the technological proximity (similarity) between the target team *v* and the acquirer of the deal *i*, benchmarked with the same measure calculated using counterfactual acquirers based on augmented matching. $Complete_i$ is a dummy variable equal to one if the deal has been completed, and zero if withdrawn. In this test, the $Post_{it}$ dummy variable is replaced by a set of dummy variables indicating each relative year after merger deal resolution. Control variables includes *Acquirer Total Assets, Asset M/B, ROE, Firm age, R&D Stock, Average Patent Age, Firm Patent Count, Target Team Patent Count,* and *Average Team Size.* Column (1) and (2) also include *Relative Deal Size* and *Same 2-digit SIC dummy*. Variable definitions for the various deal, acquirer, and target-level controls are in Appendix A. Standard errors, corrected for clustering of observations at the deal level, are reported in parentheses.

	$TARGETspecificity_{vit}$			
VARIABLES	(1)	(2)	(3)	(4)
Complete	0.229	0.115		
	(0.353)	(0.0827)		
Complete * (T = Res Year -1)	0.0189	-0.0795	0.115	-0.0674
	(0.211)	(0.248)	(0.211)	(0.241)
Complete * (T = Res Year +1)	0.601***	0.500**	0.702***	0.622***
	(0.224)	(0.228)	(0.190)	(0.194)
Complete * (T = Res Year +2)	0.531**	0.316	0.510**	0.348
	(0.214)	(0.225)	(0.204)	(0.217)
Complete * (T = Res Year +3)	0.880***	0.788***	0.769***	0.538***
	(0.174)	(0.178)	(0.159)	(0.176)
Complete * (T = Res Year +4)	0.750***	0.720***	0.675***	0.638***
	(0.209)	(0.217)	(0.204)	(0.178)
Complete * (T = Res Year +5)	0.537***	0.647***	0.575***	0.537***
	(0.203)	(0.185)	(0.195)	(0.190)
Observations	3,645	3,645	3,645	3,645
R-squared	0.126	0.188	0.205	0.577
One-way Relative Year Variables	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES
Calendar Year FE	YES	YES	YES	YES
Acq SIC2 FE	YES	NO	NO	NO
Acquirer FE	NO	YES	NO	NO
Deal FE	NO	NO	YES	NO
Target Lead Inventor FE	NO	NO	NO	YES

Appendix A. Variable Definitions

Variable	Definition	Data Source
	Dependent Variable	
TARGETspecificity	For each target stable team v, deal i and relative year t, the Z similarity score is calculated as $TARGETspecificity_{vit} = \frac{TARGETsimilarity_{vit} - \overline{TARGETsimilarity_{v,counterfactual\ acquirer\ for\ i,t}}}{\sigma_t}$ Refer to section 3.3 for details.	PatentView
	Deal Characteristics	
Relative Deal Size	Value of transaction over the market value of acquirer. The value of transaction obtained from SDC and the acquirer market value of acquirer obtained from Compustat using the latest available fiscal year end data before deal announcement date.	SDC, Compustat
Acquirer/Target 2-digit SIC (SIC2)	Primarily from Compustat historical SIC (sich) at the latest available fiscal year end data. The variable is coalesced with SIC code from CRSP for the corresponding calendar year if original data is missing. Further populated by acquirer/target primary SIC code from SDC if data are missing from both Compustat and CRSP.	SDC, Compustat, CRSP
Toehold	The percentage of shares owned by acquirers before deal announcement date	SDC
All Stock/Cash	Dummy variable that equals to one if the consideration description is "Cash Only/Stock Only"	SDC
	Firm Characteristics	
Size	Logarithm of (1+total assets in $million)	Compustat
Total Assets	Book total assets in $million	
M/B	The market value of common equity scaled by book value of common equity.	
Book Leverage	Debt divided by total assets	
Payout	Common and preferred dividend over operating income before depreciation	
ROE	Earnings before extraordinary items (IB) over lagged common equity	
Sales Growth	Difference between sales and lagged sales, scaled by lagged common equity	
R&D stock	Logarithm of R&D stock over total assets where R&D stock is calculated Following Bloom et al (2013), using 15% depreciation rate of cumulative R&D expenditure.	
Average Patent Age	The average patent application year of all patents filed before the current calendar year *t*	PatentView
Team Productivity	The number of patents filed in relative year *t*	PatentView