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

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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 acquisitions, we perform a textual analysis of the patents filed by the same lead inventors of the target firms before and after the acquisitions. We find that patents of inventors from target firms become 22% to 33% more specific to those of acquirers' inventors following completed acquisitions. This pattern is stronger for vertical acquisitions that are likely to require specialized investments, while there is no change in the specificity of patents for acquisitions that are announced but not consummated. Overall, we provide empirical evidence that contracting issues in motivating specialized investment can be a motive for acquisitions.

Keywords: Textual Analysis of Patents, Relationship-Specific Investments, Acquisitions

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1. Introduction

Investments specific to a particular business relationship, that is, 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 relationship and thereby leaving the investing party with an asset of little value). The seminal Grossman-Hart-Moore "incomplete contracts" theory of the firm uses this logic to argue that economic activity should be structured so that the firms engaging in relationship-specific investments be under the common ownership (see for example Chapter 2 of Hart, 1995). An important prediction of this theory is that when two firms consider entering into 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] The theory implies that the need to make specialized investment can provide a motive for acquisitions, which in turn implies that the merging firms' investments should become more specialized to their respective relationships following the acquisitions. In this paper, we provide evidence that is consistent with this prediction.

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] A more recent example is Texas Instruments Inc. (TI)'s acquisition of Amati Communications Corp. (Amati) in 1998, which led to the production of Amati xDSL chipset that is

[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)).

specialized for the TI's DSP technology.[3] 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 motives for mergers and acquisitions, there is little evidence on the extent to which contracting problems arising from relationship-specific investments motivate acquisitions in the real world in spite of the prominence of this theoretical argument.[4] Most likely, this theory has not been more extensively evaluated because doing so requires detailed data on the type of investments done by targets not only when they are independent firms, but also subsequent to their acquisitions as a part of the combined firms.

This paper evaluates the hypothesis that firms more likely make relationship-specific investments following acquisitions using textual analysis of the firms' patents to measure the specificity of particular innovation efforts. We consider a sample of mergers and acquisitions between publicly traded U.S. firms in 1976-2014 period. Our focus is on the investments into research and development that the merging firms do, which is reflected in the patents they file. Two attributes of patents make them particularly useful to evaluate the importance of relationship specificity in acquisition decisions. First, patents are filed under the name of the inventors, and it is thus 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, a patent contains detailed description of the actual invention, so that an outsider can understand the characteristics of the

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[3] Amati specializes in a technology named Digital Subscriber Line (xDSL) that vastly accelerates the speed of data transmission over phone lines. In 1998, TI acquired Amati for $395 million to build a specialized xDSL chipset that combines with TI's digital signal processor (DSP) technology. (Source: https://www.zdnet.com/article/ti-to-acquire-xdsl-company-amati/)

[4] For example, the most recent survey of mergers and acquisitions discusses 181 papers, none of which addresses the idea that specialized investment can motivate mergers (see Mulherin, Netter, and Poulsen (2017)).

research and development investment and thereby assess the extent to which the investment is specific to a particular relationship.

We use textual analysis of patents to characterize the nature of the investments. Our approach is to use the similarity of the patents produced by the acquirer and target firms both before and after the acquisition to create a novel measure of innovation investment specificity. Intuitively, if the merger enables the target and acquirer to make relationship-specific investments, then the merged firms' patents should become more similar to one another following the merger compared to before, and also compared to the similarity to other potential acquirers.

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. 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 of patents. In this methodology, each patent is represented by a vector of word counts in the technological space, and the similarity between two patents is determined by the cosine similarity of their corresponding word-count vectors weighted by a measure of how uncommon each word is in the patent data. In simple terms, if two patents disproportionately share "uncommon" terms, they are considered to be more similar than a randomly chosen patent pair. Kelly et al. (2020) document that their technological innovation indicators created using these high-dimensional data extracted from patent documents correlate with existing measures of patent quality while providing useful additional information.

Assessing whether an increased similarity in patents between acquiring and target firms reflects an improved ability to make specialized investments requires evidence that such R&D

investments would not have been made in the absence of the merger and that the patent similarity is with respect the specific firm—the acquirer. Following the intuition of Klein, Crawford and Alchian (1978), we capture the notion of specialized investment as the gap in the value of an asset created by the investment to the actual customer and to the customer with the second highest valuation. To this end, we construct the innovation investment specificity of the target by benchmarking the target-acquirer patent similarity against the similarity between the target and a group of counterfactual acquirers. Further, utilizing inventor identity, we identify the set of patents that are arguably attributable to a target's specialized innovative efforts post-acquisition, overcoming the fact that the target and the acquirer often file patents under the joint entity to be the patent assignee after the acquisition.

The approach of observing the change in specialized investment before and after the merger suffers from a potential endogeneity concern, because the matching of target firms with acquirers is not random. For example, it is possible that our sample deals occurred because the two merging firms were in the process of developing related products, and therefore their inventions would have become similar to one another even if there were no acquisition. To alleviate the concern that the changes in the similarity of patents post-acquisition occur due to endogenous selection of acquirers and targets into deals, we follow Seru (2014) and analyze a sample of deals that were announced but subsequently withdrawn. Typically, the reason for deal withdrawal is related to financing or anti-trust considerations, that is, due to reasons unrelated to innovation. By comparing completed deals to ones that failed, we control for underlying unobservable trends that can impact the matching of targets and acquirers, and also could have affected the similarity of targets' and acquirers' patents post-merger.

We show that targets of completed deals produce patents that are 22% to 33% more specific to acquirers' patents, that is, patents more similar to their respective acquirers when benchmarked against the similarity with counterfactual acquirers, in the post-acquisition periods relative to such specificity prior to the acquisitions. We also find that, prior to the acquisitions, the specificity of targets' patents is approximately constant for both the sample of completed and withdrawn deals in the period leading to acquisition announcements. The result that there is no significant differential trend of the merging firms' innovations moving together prior to acquisition between the two samples suggests that selection does not appear to be driving the dynamics of the specificity of the patents. Overall, these findings provide evidence that is consistent with the argument that acquisitions in our sample enabled the firms to make relationship-specific investments in R&D that they were unable to make for contractual reasons prior to the deal.

Facilitating specialized investment is only one of many motives for acquisitions (Holmström and Roberts, 1998). An increase in innovation specificity could be an outcome of an integration process between firms even in the absence of any contracting issues, for example, due to improved communication between target's and acquirer's inventors. To further examine whether the relationship between the innovation specificity and the ex-ante hold-up risk drives acquisitions, we follow Frésard, Hoberg and Phillips (2019) and split the sample into high vs. low ex-ante hold-up risk targets using the number of firms active in each acquirer's TNIC-3 industry. A small number of acquirer's peers limits target's outside options once it makes acquirer-specific investments, in which case the target faces a higher hold-up risk ex-ante. If the increase in post-acquisition innovation specificity is in response to an alleviated hold-up risk, we should expect the treatment effects to be larger in deals where the target faces a more severe ex-ante hold-up risk. We find that the patents of the targets from the high hold-up risk subsample exhibit a significantly larger increase in specificity than those from the low hold-up risk subsample. This finding further supports the prediction of the theory of the firm that the increase in targets' investment specificity we observe is likely driven by an alleviated hold-up risk.

The original discussion in the literature of the way in which contracting costs motivate acquisitions focuses on firms with vertical relationships (see Klein, Crawford, and Alchian (1978)). However, vertical relationships 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 are likely to be particularly severe in a vertical relationship because an upstream firm makes intermediate products used by the downstream firm as inputs. For example, when a supplier specializes an intermediate good for one downstream manufacturer, this good can become unusable by other potential customers. For this reason, we expect the treatment effect of an acquisition on the innovation specificity to be stronger for vertical deals. To examine this hypothesis, 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 of vertical targets become more specific to their respective acquirers' patents than those from the non-vertical targets. Acquisitions thus play a more important role in alleviating contractual frictions and motivating specialized investment when the target and acquirer are related in an ex-ante 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 target's and the acquirer's patents after the acquisition occurs because the two firms start to use the same patent lawyers. Since each lawyer potentially has a different approach to writing patents, the patterns of post-acquisitions patent similarity could reflect different writing styles rather than changes in the underlying technology of the patents. To understand the extent to which the identity of lawyers can explain our findings, we re-examine our main results using a subsample of patents in which the lawyers of the target's and the acquirer's patents are different. In this subsample, our results are similar to those in the full sample.

Another possibility is that acquisitions lead to combinations of research teams, leading the patents filed by former acquirer's and target's inventors to become more similar. In addition, it is possible that there are informational externalities across research teams, for example, as they work in a common facility, again leading to target's and acquirer's teams conducting similar research. To address this potential explanation, we re-examine our main results using a subsample, where the target and acquirer inventor teams do not add individuals from the partner firm following the acquisition, and also when they are physically located in different cities after the acquisition. The estimates using this subsample are also similar to those obtained using our main sample.

Third, it is possible that the increase in innovation specificity is due to an endogenous selection of inventors who continue innovating with the combined firm and who leave the firm or stop patenting after the acquisition. To explore this possibility, we first gauge the inventor attrition distribution in our sample, and find that of all target lead inventors of five-year pre-merger patents from completed deals, 22% stay in the combined firm after merger and continue patenting ("stayer"), whereas 24% leave the current firm and file patents with another firm ("leaver"), and 52% stop patenting after merger ("stopper"). We compare the similarity of patents led by these different types of inventors with the acquirer patents filed during the same five-year period before the acquisition and find that the stayers' patent similarity is not significantly higher than that of non-stayers' (leavers or stoppers). While the selection of inventors could be based on their potential to innovate in acquirer-specific fields post acquisition, which may not be fully captured by differences in the patent similarity with the acquirer's patents prior to the deal, we argue that our focus on the pre-acquisition patent similarity offers a meaningful test that helps alleviate the concern that the increase in innovation specificity is due to inventor attrition.

Finally, we evaluate the possibility that the increase in innovation specificity is driven by a transitory selection where the acquirers select targets with similar ongoing projects at the time of mergers, which will revert to the mean in the future. We find that the observed effects on innovation specificity are persistent over a five-year window following the acquisition, alleviating such transitory selection concern.

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 boundaries between firms 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 use information about firms and their contractual environment 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 mergers and acquisition activity and innovation. Prior work has documented that acquirers tend to buy 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 targets produce more patents (Bena and Li, 2014), encourage more collaboration between inventors and are associated with more valuable patents (Li and Wang, 2020).[5] 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 corporate innovation changes toward higher target-acquirer specificity following acquisitions. 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. We also contribute to the wider literature on motives for mergers and acquisitions, including but not limited to operational synergies, financial synergies, agency issues, wealth transfers between various stakeholders, and acquiring labor in addition to acquiring technology (see, e.g., two recent review papers, Betton, Eckbo and Thorburn, 2008 and Mulherin, Netter and Poulsen, 2017).

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), recent 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 (Bloom et al., 2013, Bena and Li, 2014, Li et al., 2019). Building on this work, we extend the textual analysis methods by applying them at the patent inventor and inventor team levels and by developing a novel measure of target-acquirer innovation specificity.

2. Sample Construction

[5] Cunningham, Ederer and Ma (2021) consider the possibility that deals occur to allow acquirers to "kill" competing innovations.

2.1. Identifying Target Firms' Investments Using their Patents

To test the hypothesis that firms increase their relationship-specific investments following acquisitions, 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 acquisitions, 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 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 an acquisition and continue to file patents under the combined entity after the acquisition is completed. Pre-acquisition patents help us identify the affiliations of the inventor, and, by tracking the patents filed by this inventor after the acquisition, 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 acquisition, in which case such inventor's patents could 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 acquisition transactions 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 2019 and we require all acquisitions to have a five-year post-acquisition period over which we measure innovation output, our sample ends in 2014. 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, our sample contains 8,232 deals, of which 7,125 are completed and 1,107 are withdrawn.

To construct our measure of specialized investment by target firms, we use data on the text of patent claims together with patent inventor and assignee information, provided by USPTO *PatentsView* database. To match patents to our sample of merging firms, we rely on the link table from Kelly, Papanikolaou, Seru and Stoffman (KPSS, 2017) that assigns 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 acquisition. 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 acquisition, 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 acquisition deals. We first extract the lead inventor's affiliation before the acquisition by examining the set of patents that targets and acquirers filed in the entire pre-acquisition period (not restricted to a 5-year window). We identify a lead inventor to be a target (acquirer) lead inventor if she is listed as the first inventor on a patent that the target (acquirer) filed before the acquisition. In cases where the same inventor appears on both sides of the merged firm, we use the latest patent filed before the merger to identify her affiliation. We retain the lead inventor in our sample if she leads at least one patent in both the pre- and post-acquisition period and include in the sample all the patents for which she is the lead inventor. To salvage cases where the target pre-acquisition lead inventors stay in the firm but become non-lead in the post-acquisition period, we supplement the sample with such staying lead inventors, as well as the patents led by them pre-merger and filed by them post-acquisition, as long as the post-acquisition patents 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.

The construction of our measure of target-acquirer innovation 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. 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 for the counterfactuals. 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 acquirers' and counterfactual acquirers' lead inventors, our sample includes 2,804 staying lead inventors coming from 351 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 acquisitions. The acquirer and target characteristics are calculated using the latest available financial data before each relative year end date. Acquirers tend to be larger than targets, have higher market to book ratios, profitability and payout ratios, similar leverage and average patent age, and lower sales growth. On the other hand, targets tend to have higher R&D than acquirers, suggesting that targets have engaged in more intensive R&D activities before they are acquired. 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 of the acquirer or target firm. 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 average of 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.

Acquirers of completed deals have on average 13 inventor teams, while the acquirers of the withdrawn deals have on 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 differences in either size or innovativeness. To highlight the source of these differences, in Panel B of Table 2 we present the differences in sales, total assets, and logarithm of R&D scaled by total assets. While the first two variables capture firm size, the last one captures innovativeness. The t-statistics on the difference between the completed and the withdrawn group suggest that acquirers of the two groups mainly differ in size but not innovativeness.

To evaluate whether staying lead inventors characterize the entire team behind the patents that are filed around the time of acquisitions, Panel C of Table 2 provides a breakdown of patenting activity by staying inventors of target firms in all completed deals in the post-acquisition 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-acquisition window, the inventor of which is affiliated with the target firm before the acquisition. We find 35,023 such unique patent–inventor pairs, of which 88% 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 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 the 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, representing the first and foremost 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, following Kelly, Papanikolaou, Seru and Taddy (2020). 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. These authors show that, their technological innovation indicators created using these high-dimensional data extracted from patent documents correlate with existing measures of patent quality while providing useful additional information. Specifically, their measures capture the evolution of technology waves over time.

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[6] 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:

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

[6] 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.

By allowing IDF_{wt} to vary over time we adjust for the change of relevancy of terms over our long time-series sample.[7] As a result, each patent is represented by vector $TFIDF_{pwt} = TF_{pwt} \cdot IDF_{wt}$, that is, the dot product of TF_{pwt} and IDF_{wt} with the length of $TFIDF_{pwt}$ vector being equal to the size of vocabulary W. Note that the *TFIDF* is reduced not only due to words that appear infrequently in patent claims (i.e., low TF) but also due to common words that appear in many patents (i.e., low IDF).

After applying the *tf-idf* 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.[8] 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

[7] 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.

[8] 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.

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.

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.

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 maximum 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. A 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. The 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[9] from Compustat, using the information on

[9] 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.

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 five-year window, the number of patents filed within the five-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 five-year pre-acquisition window instead of only at the deal announcement year to ensure the counterfactual acquirers resemble the dynamics of closeness between the real acquirer and the target throughout the pre-acquisition 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 acquisition, we should see an increase in the post-acquisition 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 actual acquirer being in the top three in terms of target-acquirer innovation similarity of the ten counterfactual acquirers. We tabulate the probability for completed and withdrawn deals separately, both for the pre-acquisition and post-acquisition period. The probability of acquirers of completed deals being among top three increases from 17% to 31% from pre- to post-acquisition period, with the increase being 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 small and not statistically significant at conventional levels.

Pr(Real Acq. Among Top 3)	Pre	Post	Pre/Post Difference
Completed	0.17	0.31	0.146***
Withdrawn	0.20	0.28	0.086

4. Acquisitions and Target Innovation Specificity

4.1. Empirical Specification

To examine whether acquisitions lead target firms to do more specialized investments towards acquirers, we estimate the following regression equation at the target-team-year level:

$$TARGETspecificity_{vit} = \alpha_0 + \beta\ Complete_i \times Post_{it} + \gamma\ Complete_i + \delta\ Post_{it} + \lambda' X_{it} + \rho' G_i + \theta' H_{vt} + FEs + \epsilon_{vit}, \quad (1)$$

where *v, i,* and *t* index target inventor team, deal, and year relative to deal announcement/resolution year, respectively. $Complete_i$ is a dummy variable equal to one if the deal has been completed, and zero if it has been withdrawn. $Post_{it}$ is a dummy variable equal to one for years after the deal resolution date (i.e., relative year equal to 1 to 5), which is based on the effective date for completed deals and the withdrawal date for withdrawn deals. The variable of interest is the interaction term, $Complete_i \times Post_{it}$, which captures the difference in technological shift between the complete deals ("treatment group") and the withdrawn deals ("control group") as a result of the acquisition. 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_{vt} 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 inventor team heterogeneity. We estimate Equation (1) using ordinary least squares (OLS) with robust standard errors corrected for clustering of observations at the deal level.

4.2. Changes in Target Innovation Specificity Post-Acquisition

Table 3 contains estimates of Equation (1). All columns include time-invariant deal characteristics and 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. Both the economic magnitude and the statistical significance become stronger as more restrictive specifications are used. In Column (3) and (4) where we have the most restrictive specification, the interaction term is statistically significant from zero. 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 0.09 (Column (1)) to 0.136 (Column (4)) units, equivalent to a 22% to 33% increase compared with the mean $TARGETspecificity$ of 0.41.

The coefficient of $Post_{it}$ dummy is not statistically significantly different from zero. This lack of significance suggests that the observed change in research specificity in completed deals does not occur for withdrawn deals. Since deals are typically 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 suggests that the change in targets' innovation activities following acquisitions does not occur because of selection of firms into merger pairs. Further, the results do not seem to be driven by the targets of withdrawn deals moving away from acquirers following failed mergers.

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 portfolio. *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 is on average bigger than that on smaller teams.

4.3. Ex-Ante Hold-Up Risk

Facilitating specialized investment is only one of many possible motives for acquisitions. If the increase in target post-acquisition investment specificity is due to a change in firms' boundaries that reduces hold-up risk, we should expect the effect to be larger for deals where the target faces a higher hold-up risk. To provide direct evidence on the relationship between hold-up risk and investment specificity, we follow Frésard, Hoberg and Phillips (2019) and measure the ex-ante hold-up risk the target firm faces using the number of firms active in each acquirer's TNIC-3 industry. The fewer acquirer industry peers, the harder it is for the target to find an outside option that values its specialized innovation as high as the acquirer does, leading to a higher hold-up risk the target faces. We split the mergers and acquisitions sample by median number of acquirer TNIC-3 industry peers and define a deal to have a high ex-ante hold-up risk if the acquirer has fewer than the median number of industry peers among all deals and vice versa. We then estimate Equation (1) on the subsamples of deals with *High* and *Low* ex-ante hold-up risk separately.

Table 4 presents the estimates on the two subsamples. In Column (1) and (2), we present coefficients of *Completed deal* dummy and *Post merger* dummy, as well as on their interaction term, with calendar year fixed effects and deal fixed effects, as well as other control variables included. In Column (3) and (4), we replace deal fixed effects with target lead inventor fixed effects. In each specification, the significant increase in target innovation specificity post-acquisition is concentrated in the subsample with high ex-ante hold-up risk, while the coefficient of the interaction term for low ex-ante hold-up risk subsample is not statistically significantly different from zero. A test of cross-equation restrictions rejects the hypothesis that the coefficients of the interaction term between the high and low hold-up risk deals are the same.[10] This finding alleviates the concern that the increase in target specificity is a mechanical outcome of the integration between two parties and supports the prediction that the increase in target innovation specificity is driven by the lower hold-up risk because of the acquisition.

4.4. Vertical vs. Non-Vertical Deals

The argument 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, 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 in our main analysis. Nevertheless, the prior literature has focused on the role of hold-up in vertical relationships because these contracting

[10] To compare the statistical magnitude of interaction terms from high vs. low ex ante hold-up risk 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.

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 effect of acquisition on innovation specificity 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).[11]

Table 5 presents estimates of Equation (1) on these two subsamples. In Column (1) and (2) of Panel A, we present coefficients of *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 (3) and (4), 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 in both specifications. This finding supports the view 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 when we construct the set of counterfactual acquirers. The inclusion of product market similarity ensures that the counterfactual acquirers have similar position in the supply chain network as the actual acquirer, and thus restricts counterfactual acquirers to be vertically related to the target in the similar way the actual acquirer is related to the target. Due to this improved matching,

[11] 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.

we expect the effect of the vertical acquisition to be better captured in the augmented matching sample.

In Panel B of Table 5, we present estimates of Equation (1) on the vertical and non-vertical subsamples that are constructed 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 analogous specification from Panel A. This larger effect holds both in terms of the magnitude of coefficients and the difference between interaction term between vertical and non-vertical subsamples. The cross-equation difference restriction rejects the hypothesis that the coefficients on vertical and non-vertical deals are the same, for both specifications.

In Figure 2, we plot the mean of dependent variable, $TARGETspecificity,$ across relative years, for both completed and the withdrawn deals, with 95% confidence interval. 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.[12] 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

[12] Our findings are robust to dropping year -5 from the analyses.

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 6 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-how", then it could be likely that their inventions become more similar to one another for this reason. 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 7 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. The finding suggests that the results in our paper are not driven by more frequent collaboration or knowledge spillovers after the merger.

5.3. Target Inventor Attrition

Since our sample only includes inventors who stay at the combined entity after the merger and continue patenting in the 5-year post-merger period, a potential concern is that the attrition of target inventors is endogenously determined by the inventor's research focus. Specifically, one might be concerned that inventors who have a higher likelihood to produce more acquirer specific innovations are more likely to stay with the firm ("*stayer*"), while those whose skills are not related to the acquirers might be prompted to leave the firm ("*leaver*") or stop patenting ("*stopper*").

In Panel A of Table 8, we first tabulate the distribution of target inventors in terms of their attrition status. Within the completed deal sample, 22% of target lead inventors in the 5-year pre-merger period stayed in the combined entity and filed at least one patent in the 5 years after the merger ("*stayer*"). Our regression results are solely based on the stayer group. 24% of the target lead inventors leave the firm and filed at least one patent with a different firm after the merger completion date ("*leaver*"). 52% of the target lead inventors never filed another patent after the deal completion date ("*stopper*"). Since the affiliation of the inventors is inferred through the inventor-assignee pair of the patents, we do not know if the stopper inventors stay with the combined entity. There are some inventors who filed at least one patent with the joint entity after the merger, but only after 5-year post-merger window is over (about 2% of the sample). Since our post-merger window is only 5 years long, this group will not enter the regression sample. The distribution of withdrawn deals is generally similar, with the percentage of *stayer* somewhat higher and *leaver* lower.

We explore the possibility that the selection of inventors into different attrition status is endogenously determined by the inventors' potential to specialize in acquirer's area of innovation. For each target lead inventors in Panel A, we calculate the average similarity of all the patents participated by those inventors with patents filed by acquirers in the 5-year pre-merger window. We then examine whether being a *stayer* is positively correlated with a higher similarity with the acquirer's patents. Panel B of Table 7 presents the regression results. Controlling for deal fixed effects, we find no significant difference in similarity with acquirer patents between *stayer* and *leaver/stopper*. The standard error is associated with *stayer* is small both clustered at industry-year or deal level, suggesting the lack of significance is not driven by noisy measures.

More than half of the target lead inventor consists of *stoppers*. This high percentage (52% for completed deals and 51% for withdrawn deals) likely reflects the fact that many inventors stop producing new patents after a certain number of years. For comparison, we measure the natural dropout rate for the universe of inventors through a random sampling approach. We find the 99% confidence interval of average natural dropout rate to be between 58.35% and 58.37%.[13]

[13] We conduct the random sampling over the entire inventor population. To mirror the condition of target lead inventor stoppers who have led at least one patent in the 5-year pre-merger period, or each draw, every year we draw a number of inventors who have led at least one patent in the previous 5 years, and the number of inventors for each year is proportional to the number of deals in the M&A sample. We then calculate the percentage of those selected inventors who file zero

5.4. 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 9 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.

patent after the given year. We repeat the random draw process for 200 times and have a sample of 200 with replacement for each draw.

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*.

Betton Sandra, Espen Eckbo, and Karin Thorburn, 2008, "Corporate takeovers:" *in Handbook of Corporate Finance* 2, 291-429.

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.

Cunningham, Colleen, Florian Ederer, and Song Ma, 2021, Killer Acquisitions, Journal of Political Economy 129: 649-702.

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

Holmström, 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, 2017. "The evidence on mergers and acquisitions: A historical and modern report." *The handbook of the economics of corporate governance*. Vol. 1. North-Holland, 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 1: Illustrative Example of Technological Space between Acquirers and Targets

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.

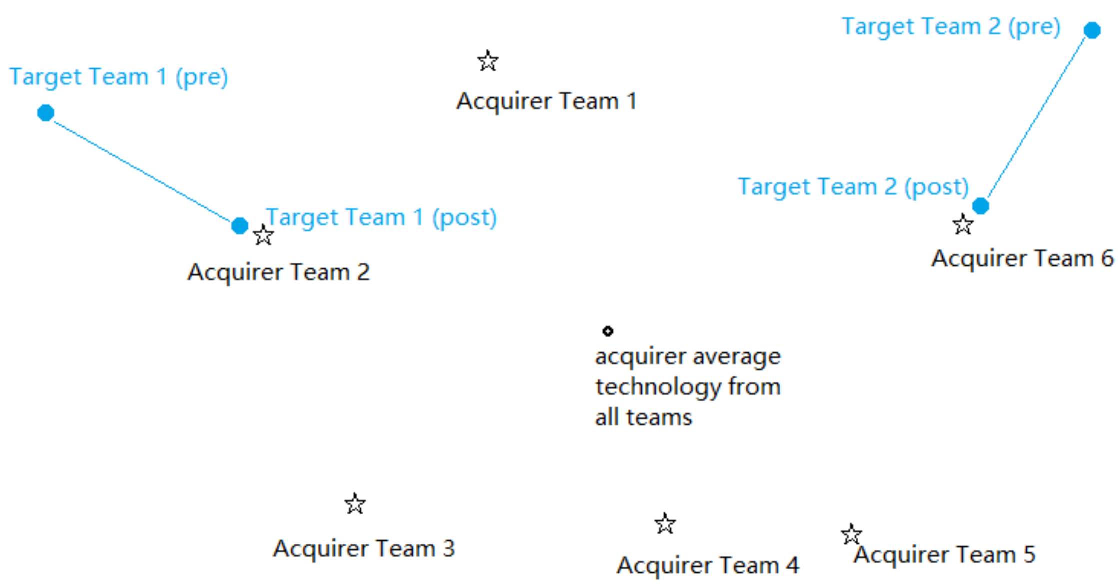

Figure 2. Target Innovation Specificity for Completed and Withdrawn Deals: Parallel Trends

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. The sample includes vertical integration deals from augmented matching scheme with product market similarity. 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. 95% confidence interval is presented around the mean.

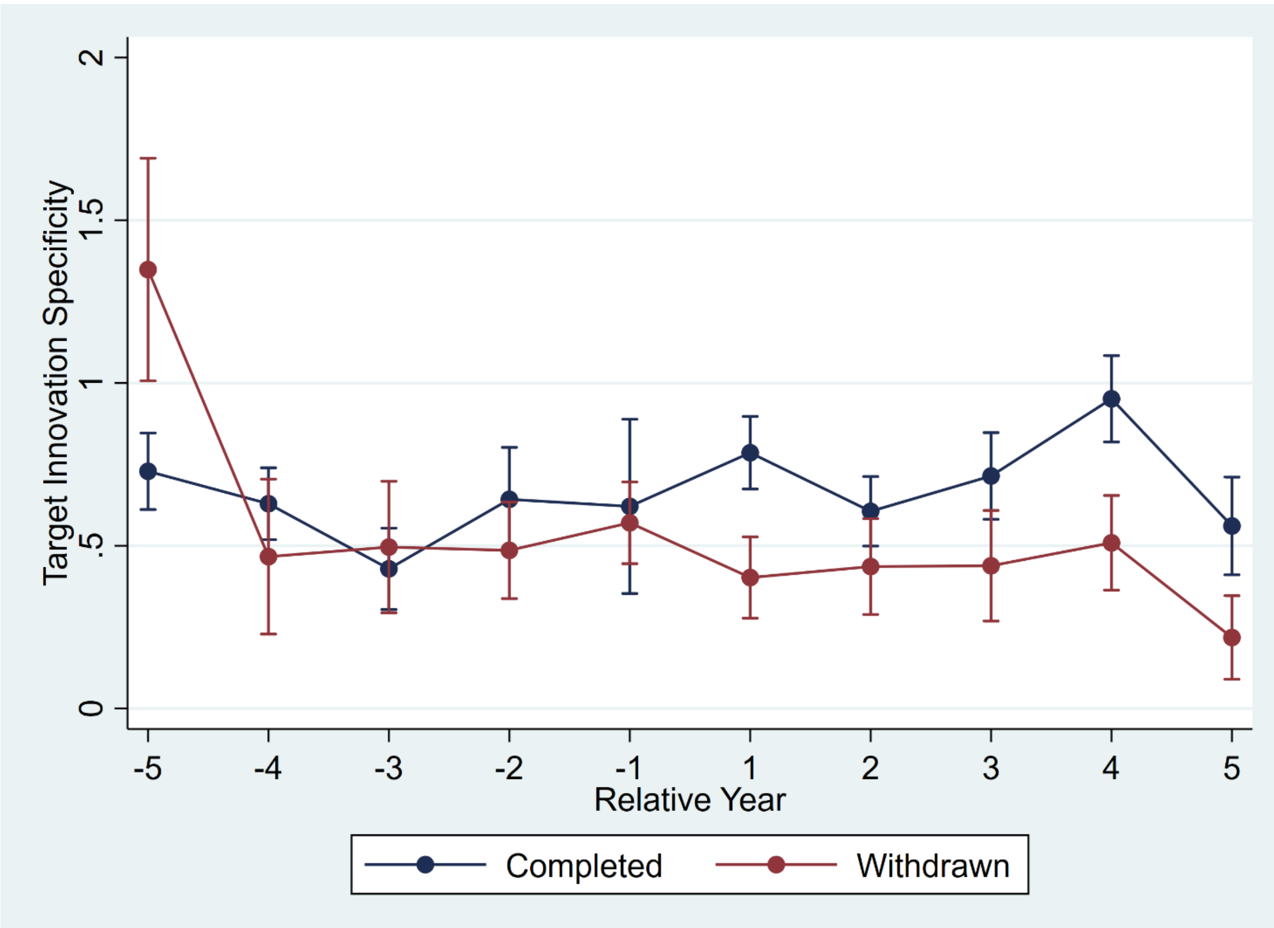

Table 1. Summary Statistics

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		
	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
Dependent Variable:									
Target Specificity	12953	0.41	1.00	8938	0.39	1.01	4015	0.43	0.96
Deal Characteristics:									
Relative Deal Size	12953	0.47	0.44	8938	0.42	0.41	4015	0.57	0.48
Same SIC2	12953	0.54	0.50	8938	0.64	0.48	4015	0.34	0.47
Toehold	12953	0.55	3.53	8938	0.79	4.22	4015	0.00	0.00
All Cash	12953	0.22	0.42	8938	0.31	0.46	4015	0.02	0.12
All Stock	12953	0.43	0.49	8938	0.33	0.47	4015	0.63	0.48
Acquirer Characteristics:									
Total Assets	12953	9.79	1.80	8938	9.49	1.59	4015	10.45	2.05
Asset M/B	12953	1.89	1.47	8938	2.05	1.59	4015	1.55	1.05
Leverage	12953	0.23	0.14	8938	0.19	0.11	4015	0.32	0.15
ROE	12953	0.18	0.19	8938	0.16	0.18	4015	0.22	0.19
Payout	12666	0.17	0.11	8694	0.16	0.12	3972	0.19	0.09
R&D	12953	0.07	0.11	8938	0.08	0.13	4015	0.06	0.05
Sales Growth	12951	0.13	0.39	8936	0.15	0.45	4015	0.08	0.18
R&D Stock	12953	0.21	0.15	8938	0.23	0.16	4015	0.17	0.14
Avg. Patent Age	12953	8.58	4.26	8938	8.70	4.49	4015	8.30	3.69
Firm Patent Count	12953	165.85	218.48	8938	138.66	180.50	4015	226.37	275.99

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	Whole Sample			Completed			Withdrawn		
	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
Target Characteristics:									
Total Assets	8146	8.27	1.84	4430	7.59	1.96	3716	9.07	1.29
Asset M/B	8135	1.70	1.62	4419	1.90	1.93	3716	1.46	1.10
Leverage	8135	0.21	0.14	4419	0.21	0.16	3716	0.23	0.11
ROE	7904	0.05	1.10	4230	0.03	0.81	3674	0.07	1.36
Payout	7422	0.14	0.15	3767	0.13	0.20	3655	0.15	0.08
R&D	8133	0.10	0.62	4417	0.13	0.84	3716	0.05	0.05
Sales Growth	8093	0.25	2.95	4378	0.37	4.00	3715	0.12	0.26
R&D stock	8146	0.23	0.20	4430	0.27	0.23	3716	0.18	0.14
Avg. Patent Age	7940	8.83	4.06	4236	9.32	4.31	3704	8.26	3.68
Team Patent Count	12953	1.54	1.08	8938	1.54	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: Inventor Team Characteristics

	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-Acquisition 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. Target Innovation Specificity Following Acquisitions

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.

	$TARGETspecificity$			
	(1)	(2)	(3)	(4)
Complete × Post	0.0996	0.0718	0.114*	0.136**
	(0.0754)	(0.0708)	(0.0687)	(0.0623)
Complete	-0.0504	-0.128		
	(0.152)	(0.137)		
Post	0.000215	-0.0213	-0.0748	-0.0796
	(0.0750)	(0.0628)	(0.0652)	(0.0646)
Relative Deal Size	-0.110	0.308**		
	(0.0940)	(0.153)		
Same SIC2	-0.162	-0.435***		
	(0.103)	(0.107)		
Total Assets	-0.0504	-0.170***	-0.227***	-0.231***
	(0.0364)	(0.0598)	(0.0623)	(0.0617)
Asset M/B	0.0742***	0.0372**	0.0425**	0.0276*
	(0.0268)	(0.0174)	(0.0167)	(0.0162)
ROE	-0.0491	-0.0339	-0.138*	-0.111
	(0.142)	(0.0836)	(0.0751)	(0.0778)
Firm Age	0.000749	-0.00836	-0.00461	0.00167
	(0.00322)	(0.0229)	(0.0166)	(0.0151)
R&D Stock	0.112	-0.772**	-1.031***	-0.802***
	(0.302)	(0.338)	(0.293)	(0.261)
Avg. Patent Age	0.00554	-0.00713	-0.0292*	-0.0261*
	(0.0131)	(0.00996)	(0.0169)	(0.0144)
Target Team #Patents	-0.0112	-0.00260	0.00308	0.00598
	(0.0134)	(0.0104)	(0.00986)	(0.00864)
Acquirer Firm #Patents	-0.000140	-0.000128	-0.000235	-0.000268*
	(0.000199)	(0.000165)	(0.000151)	(0.000141)
Target Team Avg. Size	0.0282***	0.0273***	0.0283***	-0.00390
	(0.0104)	(0.00830)	(0.00811)	(0.00794)
Constant	0.752**	2.771**	3.231***	2.983***
	(0.357)	(1.387)	(1.087)	(1.006)
Observations	12,953	12,953	12,953	12,953
R-squared	0.062	0.197	0.273	0.571
Calendar Year FE	YES	YES	YES	YES
Acquirer 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. Ex-Ante Hold-Up Risk and Target 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. The column for *High* and *Low* indicates the sample with ex ante hold-up risk measured using the number of acquirer TNIC peers. *The* Chi-squared and p-value from the SUR test of difference between interaction terms from high vs. low ex ante hold-up risk 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.

	(1) High	(2) Low	(3) High	(4) Low
Complete × Post	0.324**	-0.201**	0.310**	-0.111
	(0.127)	(0.100)	(0.119)	(0.115)
Post	-0.287**	0.150	-0.300***	0.187
	(0.126)	(0.117)	(0.114)	(0.120)
Total Assets	0.232	-0.280***	0.213	-0.297***
	(0.157)	(0.0664)	(0.161)	(0.0654)
Asset M/B	0.131***	0.0262	0.123**	0.0112
	(0.0454)	(0.0193)	(0.0481)	(0.0183)
ROE	-0.230**	-0.190	-0.178	-0.176
	(0.102)	(0.122)	(0.127)	(0.121)
Firm Age	-0.0171	0.0985	-0.00631	0.0803
	(0.0140)	(0.0649)	(0.0141)	(0.0626)
R&D Stock	0.922	-1.583***	0.911	-1.364***
	(0.808)	(0.301)	(1.009)	(0.281)
Avg. Patent Age	-0.00394	0.00685	-0.00541	0.000288
	(0.0242)	(0.0275)	(0.0263)	(0.0257)
Team Patent Count	-0.0150	0.0316	-0.0104	0.0263
	(0.0135)	(0.0196)	(0.0146)	(0.0161)
Firm Patent Count	-0.000605**	-7.22e-05	-0.000609**	-0.000146
	(0.000289)	(0.000217)	(0.000270)	(0.000203)
Avg. Team Size	0.0338***	0.0171	0.00837	-0.0214*
	(0.0105)	(0.0118)	(0.0113)	(0.0109)
Constant	-1.162	-0.442	-1.550	0.524
	(2.163)	(2.733)	(2.143)	(2.652)
SUR [Complete × Post] coefficient [High=Low]				
χ2	10.67		6.580	
p-value	0.00109		0.0103	
Observations	5,231	4,873	5,231	4,873
R-squared	0.272	0.277	0.572	0.559
Calendar Year FE	YES	YES	YES	YES
Deal FE	YES	YES	NO	NO
Deal Inventor FE	NO	NO	YES	YES

Table 5. The Effect of Vertical Integration on Target 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) Non-Vert.	(2) Vert.	(3) Non-Vert.	(4) Vert.
Complete × Post	0.0673	0.413***	0.111	0.349***
	(0.0870)	(0.105)	(0.0822)	(0.107)
Post	-0.113	-0.0964	-0.108	-0.158
	(0.0894)	(0.0857)	(0.0878)	(0.0987)
Total Assets	-0.258***	-0.128	-0.267***	-0.119
	(0.0717)	(0.133)	(0.0695)	(0.139)
Asset M/B	0.0306	0.0138	0.0118	0.0178
	(0.0190)	(0.0649)	(0.0188)	(0.0706)
ROE	-0.0889	-0.472*	-0.0541	-0.405
	(0.0830)	(0.241)	(0.0778)	(0.260)
Firm Age	0.00431	-0.0676	0.00602	-0.0513
	(0.0179)	(0.0564)	(0.0147)	(0.0558)
R&D Stock	-1.074***	-1.117*	-0.784***	-1.301*
	(0.329)	(0.651)	(0.286)	(0.687)
Avg. Patent Age	-0.0393*	-0.0243	-0.0345*	-0.0287
	(0.0238)	(0.0279)	(0.0207)	(0.0294)
Target Team #Patents	0.00707	-0.00426	0.00869	-0.000167
	(0.0133)	(0.0111)	(0.0111)	(0.0140)
Acquirer Firm #Patents	-0.000171	-0.000219	-0.000188	-0.000336
	(0.000224)	(0.000237)	(0.000212)	(0.000239)
Target Team Avg. Size	0.0267***	0.0325*	-0.0136	0.0202*
	(0.00924)	(0.0166)	(0.00917)	(0.0115)
Constant	3.111***	6.175	3.134***	5.264
	(1.154)	(3.756)	(1.007)	(3.856)
SUR [Complete × Post] coefficient [Non-Vert.=Vert.]				
χ2	6.565		3.181	
p-value	0.0104		0.0745	
Observations	9,267	3,685	9,267	3,685
R-squared	0.306	0.188	0.590	0.527
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) Non-Vert.	(2) Vert.	(3) Non-Vert.	(4) Vert.
Complete × Post	-0.149	0.547***	-0.0683	0.450***
	(0.124)	(0.123)	(0.128)	(0.125)
Post	0.0589	-0.139	0.0830	-0.202
	(0.121)	(0.133)	(0.118)	(0.131)
Total Assets	-0.167*	-0.464***	-0.215**	-0.382**
	(0.0967)	(0.157)	(0.0997)	(0.168)
Asset M/B	0.0186	-0.00575	0.00278	-0.0288
	(0.0204)	(0.0494)	(0.0200)	(0.0602)
ROE	-0.0824	-0.934***	-0.0583	-0.852***
	(0.0991)	(0.271)	(0.0915)	(0.287)
Firm Age	0.0110	-0.199**	0.0145	-0.176**
	(0.0190)	(0.0857)	(0.0158)	(0.0807)
R&D Stock	-0.899**	-2.209***	-0.779*	-2.046**
	(0.394)	(0.802)	(0.402)	(0.822)
Avg. Patent Age	-0.0496**	-0.0697**	-0.0457**	-0.0693**
	(0.0208)	(0.0324)	(0.0216)	(0.0332)
Target Team #Patents	0.00680	0.00493	0.00313	0.000291
	(0.0125)	(0.0136)	(0.0125)	(0.0187)
Acquirer Firm #Patents	-0.000389*	0.000142	-0.000436**	2.07e-05
	(0.000198)	(0.000263)	(0.000196)	(0.000286)
Target Team Avg. Size	0.0289***	0.0457*	0.000221	0.0113
	(0.00867)	(0.0246)	(0.00989)	(0.0138)
Constant	2.155	18.45***	2.485**	16.40***
	(1.338)	(5.659)	(1.243)	(5.197)
SUR [Complete × Post] coefficient [Non-Vert.=Vert.]				
$\chi 2$	16.06		8.527	
p-value	0.0001		0.00350	
Observations	6,212	3,645	6,212	3,645
R-squared	0.307	0.193	0.573	0.567
Calendar Year FE	YES	YES	YES	YES
Deal FE	YES	YES	NO	NO
Deal Inventor FE	NO	NO	YES	YES

Table 6. Impact of Lawyers

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)	(3)	(4)
	Non-Vert.	Vert.	Non-Vert.	Vert.
Complete × Post	-0.147	1.113**	-0.141	1.030*
	(0.215)	(0.508)	(0.239)	(0.569)
Post	-0.0962	-0.926**	0.102	-0.939*
	(0.216)	(0.464)	(0.238)	(0.489)
Total Assets	-0.161	-0.268	-0.0976	-0.0955
	(0.134)	(0.369)	(0.203)	(0.332)
Asset M/B	0.0342	-0.0757	0.0545*	-0.0736
	(0.0254)	(0.150)	(0.0288)	(0.168)
ROE	-0.508**	-0.882***	-0.712***	-0.997***
	(0.243)	(0.282)	(0.266)	(0.358)
Firm Age	-0.00433	0.256	0.00877	0.367
	(0.00780)	(0.285)	(0.00986)	(0.291)
R&D Stock	-0.867	-1.449	-0.172	-1.710
	(0.664)	(1.584)	(0.954)	(1.426)
Avg. Patent Age	-0.0779*	-0.0408	-0.0828	-0.0156
	(0.0464)	(0.0461)	(0.0568)	(0.0463)
Target Team #Patents	0.0161	0.0261	0.0299	-0.0150
	(0.0114)	(0.0176)	(0.0214)	(0.0225)
Acquirer Firm #Patents	-8.64e-06	-0.00146**	2.66e-05	-0.00137*
	(0.000167)	(0.000579)	(0.000182)	(0.000779)
Target Team Avg. Size	0.0199*	0.0218	0.00516	-0.0695***
	(0.0106)	(0.0271)	(0.0153)	(0.0250)
Constant	3.242**	-8.282	1.925	-14.88
	(1.480)	(15.35)	(2.226)	(15.02)
SUR [Complete × Post] coefficient [Non-Vert.=Vert.]				
$\chi 2$	5.353		3.741	
p-value	0.0207		0.0531	
Observations	3,312	1,910	2,162	1,181
R-squared	0.345	0.256	0.644	0.668
Calendar Year FE	YES	YES	YES	YES
Deal FE	YES	YES	NO	NO
Deal Inventor FE	NO	NO	YES	YES

Table 7. 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) Non-Vert.	(2) Vert.	(3) Non-Vert.	(4) Vert.
Complete * Post	-0.215	0.398**	-0.153	0.415**
	(0.185)	(0.167)	(0.193)	(0.169)
Post	-0.0829	0.0690	-0.0627	0.0563
	(0.176)	(0.203)	(0.187)	(0.203)
Total Assets	0.112	-0.476**	0.0904	-0.419**
	(0.124)	(0.209)	(0.129)	(0.206)
Asset M/B	0.0307	0.172*	0.0153	0.111
	(0.0291)	(0.0922)	(0.0297)	(0.126)
ROE	-0.0728	-1.080***	-0.0248	-1.032***
	(0.0657)	(0.331)	(0.0751)	(0.305)
Firm Age	0.00529	-0.407***	0.0110	-0.354***
	(0.0167)	(0.106)	(0.0146)	(0.103)
R&D Stock	0.0882	-2.021	0.178	-2.399
	(0.548)	(1.759)	(0.567)	(1.463)
Avg. Patent Age	-0.0442*	-0.00260	-0.0277	-0.0146
	(0.0258)	(0.0458)	(0.0258)	(0.0422)
Target Team #Patents	0.0163	0.00359	0.0120	0.0235
	(0.0109)	(0.0185)	(0.0136)	(0.0170)
Acquirer Firm #Patents	-0.000111	0.000158	-0.000327	0.000218
	(0.000409)	(0.000370)	(0.000449)	(0.000461)
Target Team Avg. Size	0.0222***	0.0601**	-0.00564	0.0209*
	(0.00821)	(0.0240)	(0.00782)	(0.0108)
Constant	-0.771	31.74***	-0.944	27.97***
	(1.565)	(7.346)	(1.504)	(7.040)
SUR [Complete × Post] coefficient [Non-Vert.=Vert.]				
$\chi 2$	6.188		5.010	
p-value	0.0129		0.0252	
Observations	2,456	2,166	2,456	2,166
R-squared	0.319	0.183	0.591	0.606
Calendar Year	YES	YES	YES	YES
Deal FE	YES	YES	NO	NO
Deal Inventor FE	NO	NO	YES	YES

Table 8. Inventor Attrition Analysis

This table presents target lead inventor attrition statistics. Panel A illustrates the distribution of attrition status for target lead inventors that have led at least one patent in the 5-year pre-merger period ("pre5"). The target lead inventors are classified into *Stayer* (who participated in at least 1 patent with the combined entity in the 5-year post-merger period), *Leaver* (who filed at least one patent with a different firm after the deal completion date), *Stopper* (who never filed another patent after the deal) and *Other* (who filed with the combined entity after 5-year post-merger period only). The number shows the percentage of corresponding inventor category over all target lead inventors of pre5 patents. The sample includes all inventors from all deals from the merger and acquisition sample, regardless of whether it enters the final regression sample. Panel B represents the ordinary least square regression results of the target lead inventor patent similarity with the acquirer's patents in the 5-year pre-merger period. The dependent variable is the average pairwise similarity between patents the target lead inventor participated in pre5 period and the patents the acquirer filed in pre5 period. The dummy variable *Stayer* equals one if the inventor is a stayer, and zero if the inventor is a leaver or stopper. Both columns also include Deal FE. Standard errors are clustered at industry-year level for Column (1) and deal level for column (2).

Panel A: Distribution of Inventor Attrition Status

	Target Pre5 Lead Inventor	
Attrition Status	Completed	Withdrawn
Stayer (Participated in at least 1 patent with the target-acquirer in Post5)	22%	25%
Leaver (Filed with a different firm after the deal)	24%	22%
Stopper (never filed another patent after the deal)	52%	51%
Other (Filed with the target-acquirer after Post5)	2%	2%

Panel B: Similarity with Acquirer Patents in 5-year Pre-merger Period

	Target Inventor Pre5 Patent Similarity with Acquirer	
VARIABLES	(1)	(2)
Stayer	0.00253	0.00253
	(0.00218)	(0.00161)
Constant	0.0684***	0.0684***
	(0.000519)	(0.000383)
Observations	25,946	25,946
R-squared	0.418	0.418
Deal FE	YES	YES
SE Clustering	Industry-Year	Deal

Table 9. Dynamic Regressions

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* for vertical integration sample using augmented matching scheme with product market similarity. 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.

	$TARGETspecificity$			
	(1)	(2)	(3)	(4)
Complete	-0.223	0.134*		
	(0.206)	(0.0796)		
Complete × (T = Res Year -1)	0.297	0.212	0.388	0.157
	(0.260)	(0.296)	(0.259)	(0.235)
Complete × (T = Res Year +1)	0.561**	0.478**	0.656***	0.538***
	(0.220)	(0.211)	(0.178)	(0.191)
Complete × (T = Res Year +2)	0.442*	0.259	0.439**	0.258
	(0.234)	(0.224)	(0.205)	(0.221)
Complete × (T = Res Year +3)	0.769***	0.698***	0.684***	0.451**
	(0.194)	(0.178)	(0.157)	(0.173)
Complete × (T = Res Year +4)	0.652***	0.640***	0.599***	0.614***
	(0.214)	(0.192)	(0.179)	(0.163)
Complete × (T = Res Year +5)	0.508**	0.630***	0.565***	0.515***
	(0.210)	(0.178)	(0.184)	(0.177)
Observations	3,645	3,645	3,645	3,645
R-squared	0.123	0.185	0.200	0.573
One-way Relative Year Variables	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES
Acquirer 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