Relationship-Specific Investments and Firms' Boundaries: Evidence from Textual Analysis of Patents*

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Abstract

The hold-up problem can impair firms' abilities to make relationship-specific investments through contracts. Ownership changes can mitigate this problem. To evaluate changes in the specificity of human capital investments, we perform textual analyses of patents filed by lead inventors from both acquirer and target firms before and after acquisitions. Inventors whose human capital is highly complementary with the patent portfolios of their acquisition partners are more likely to stay with the combined firm post-deal and subsequently make their investments more specific to the partner's assets. As ownership of another firm results in increasingly specific investments to that firm's assets, contracting issues related to relationship-specific investments is likely a motive for acquisitions.

Keywords: Textual Analysis, Patents, Investment Specificity, M&A, Mergers and 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 firm boundaries should be defined so that the firms engaging in relationship-specific investments be under 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 relationship-specific investments, they are likely to merge to avoid the contracting challenges arising from potential hold-up problems.[1]

In the 21st century, firms are characterized by investments in their human capital by innovative employees and they rely heavily on intellectual property assets. Hart and Moore (1990) model the way in which the incentives of these innovative employees to make firm-specific investments in their human capital evolve in response to ownership of non-human assets by their employers. A key assumption of their model is that there are complementarities between access to non-human assets and investment in human capital. Therefore, an employee’s incentive to make asset-specific investments depends on whether her employer owns assets that are complementary to her human capital. In this paper, we test the prediction of the Hart and Moore (1990) model that inventors with human capital complementary to the patent portfolio of the M&A partner will have incentives to make relationship-specific innovation investments after the deal’s completion when they gain access to the partner’s patent portfolio.

Using state-of-the-art textual analyses over an extensive sample of patents filed by inventors of the US public and private firms involved in mergers and acquisitions (M&A) over the 1976-2014 period, we find that both acquirer and target inventors whose work is complementary to the M&A partner’s patent stock are more likely to remain with the combined firm following the deal’s completion. More importantly, we also find that only those inventors with high complementarities make their investments in new research specific to that of the M&A partner

[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).

once the partner's patents are jointly owned. These findings are consistent with the predictions of Hart and Moore (1990) model and suggest that enhanced incentive to make specific investment arising from joint ownership of assets is one source of merger gains.

While there is a voluminous 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.[2] This idea has not been more extensively tested likely because doing so requires detailed data on the type of investments done by acquirers and targets not only when they are independent firms, but also subsequent to the acquisitions as a part of the combined firms. We finesse this issue by focusing on investments into research and development of the merging firms, which are characterized by the patents they file. Using inventor affiliations before the M&A deal, we identify the inventors who stay with the combined firm following the deal's completion and the patents in which they participate. This approach enables us to attribute specialization to targets or acquirers even though targets' and acquirers' inventors file patents under the combined firm following the deal's completion.

Our empirical analysis is at the inventor level and compares patents filed by inventors affiliated with both acquirers and targets based on the complementarity of their human capital with the new M&A partner's patent stock. Two attributes of patents make them particularly useful to evaluate the importance of relationship specificity in M&A decisions. First, patents are filed under the name of the inventors, allowing us to allocate them to inventors who worked at the acquirer or at the target not only prior to the deal but also after an acquisition is consummated. Second, a patent contains detailed description of the actual invention, so that an outsider can understand the characteristics of the research and development investment and thereby assess the extent to which the investment is specific to a particular relationship.

Methodologically, our work is based on textual analyses that characterize the nature of the investments in human capital as measured by patents. To construct a novel measure of investment specificity in human capital, we first generate dictionaries of words that represent acquirer/target-specific technologies. For each acquirer, we find counterfactual firms using matching that are similar in the technology space and innovation characteristics over the five-year period prior to the M&A deal. We define acquirer-specific terms to be those that are *only* used by acquirer but not

[2] Monteverde and Teece (1982), Woodruff (2002), Acemoglu et al. (2010), and Frésard, Hoberg, and Phillips (2020) are exceptions.

the counterfactual acquirers. Presumably, such words are associated with technologies that are unique to the acquirer when compared to a counterfactual acquirers' benchmark. We follow the same procedure to create dictionaries of target-specific terms using both actual targets and matched counterfactual targets.

Using dictionaries specific to the merging firms, we construct our first measures of relationship-specific innovation, *Innovation Specificity Unique (%)*, as the number of unique acquirer-specific (target-specific) words used by a lead inventor of the target (acquirer) in patents she files each year divided by the total number of unique words in her patents. We employ several alternative approaches to measure specificity based on the total number of occurrences of words from the dictionary (the "term frequency") and the total number of occurrences of words from the dictionary weighted by an inverse document frequency (the "term frequency-inverse document frequency"). The notion behind any weighting scheme is to adjust for the importance of words in the patent document.

The key prediction of Hart and Moore (1990) pertains to the way in which the pre-merger complementarity of an inventor's human capital with the non-human assets of her firm's merging partner influences her incentives to specialize her innovation following the merger. To capture such complementarity in the innovation space, we utilize the *knowledge base overlap ratio* measure introduced by Bena and Li (2014), who document that this measure of technological overlap between firms is a significant predictor of the likelihood and innovation synergies of M&As. We modify this measure to capture the complementarity at the inventor level and focus on *High Complementarity*, which occurs when a target (acquirer) inventor's knowledge base overlap ratio with the counterparty firm in the M&A deal is greater or equal to the 75^{th} percentile of knowledge base overlap ratio for all target (acquirer) inventor's that are involved in this deal.

We first evaluate whether inventors (e.g., target inventors) whose human capital is more closely aligned with patent portfolio of the M&A partner (e.g., the acquirer) are more likely to remain with the combined firm after the deal is completed. We find that inventors with high complementarity are more likely to stay with the combined firm following an M&A transaction than inventors with low complementarity. The estimated effect is large in magnitude, representing a 4.5% greater likelihood of staying compared to the mean for acquirer inventors. The estimated difference in the likelihood of staying more than doubles to 9.5% for target inventors with high complementarity with the acquirer.

Having established that complementarities between inventors' patents and the merged firm's newly expanded portfolio of patents influence inventors' mobility, we next examine the way in which relationship-specific investment in human capital increases following M&A deals. In particular, we consider whether, as suggested by the Hart and Moore (1990) model, this change is driven by inventors with a high complementarity to the M&A partner's patent portfolio.

The approach of observing the change in specialized investment before and after the M&A deal suffers from a potential endogeneity concern, because of the nonrandom matching of target firms with acquirers. To alleviate this concern, we follow the prior literature (Seru (2014) and Bena and Li (2014)) and analyze a sample of deals that were announced but subsequently withdrawn. Most often, the reason for deal withdrawal is related to financing or anti-trust considerations that are unrelated to innovation. By comparing completed deals to ones that failed to consummate, we control for underlying unobservable trends that can impact the matching of targets and acquirers and could also be related to the post-merger specificity of patents of merging firms.

To evaluate whether inventors with human capital complementary to the patent portfolio of the M&A partner pursue relationship-specific innovation investments after the deal's completion, we focus on inventor-level measures of innovation specificity and complementarity. Specifically, we compare the change in innovation specificity of staying lead inventors with high complementarities to the M&A partner's patent portfolio with those having low such complementarities, using the inventors from the withdrawn deals as a control group in a triple-differences estimation setting. Consistent with the predictions of the theory, we find that inventors with high complementarities in completed deals increase specificity of their own inventions after the deal, with a statistically and economically large effect. For acquirer inventors with high complementarities, the estimates represent a 25% (17%) higher innovation specificity due to M&A when evaluated at the mean (standard deviation). The effect is even larger for target inventors.

We also provide results supporting the parallel pre-trends assumption, which is essential for a causal interpretation of our findings. We further document that changes in law firms induced by M&A transactions are unlikely the reason why we observe an increase in innovation specificity for high complementarity inventors following acquisitions. Next, we present a placebo test that rules out the possibility that our findings are driven by innovation similarity rather than specificity. Finally, we also address recent concerns raised by econometrics literature on the staggered difference-in-differences with two-way fixed effects.

Our work extends the literature in a number of ways. 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 contributes to the literature on the relation between mergers and acquisition activity and innovation. Prior work has documented that acquirers tend to buy firms with high R&D intensity (Phillips and Zhdanov, 2013) and with a large overlap with its own technology base (Bena and Li, 2014). 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).[3] While existing work focuses on the effects of acquisitions on the quantity and quality of patents, this paper evaluates the way in which the direction of corporate innovation changes toward higher innovation specificity following acquisitions. One paper that focuses on the nature of post-merger patents is Mei (2019), showing that the combined firms are more likely to engage in innovations different from either of the deal parties if acquirer and target are less technologically overlapped before the merger. We also contribute to the broader literature on motives for mergers and acquisitions, including but not limited to operational synergies, financial synergies, agency issues, wealth transfers between various stakeholders (see, e.g., two review papers, Betton, Eckbo, and Thorburn, 2008 and Mulherin, Netter, and Poulsen, 2017).

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

Our paper also contributes to the literature on the effects of mergers and acquisitions on labor. Existing research evaluates the role of mergers and acquisitions as a way in which firms acquire certain skills (Chen et al., 2020; Ouimet and Zarutskie, 2020), achieve synergies in the labor force (Tate and Yang, 2016; Lee, Mauer, and Xu, 2018; Gehrke et al., 2021), and facilitate technology adoption (Lagaras, 2017; Ma, Ouimet, and Simintzi, 2022). More relatedly, there is work on inventor post-merger turnover and productivity. Fulghieri and Sevilir (2011) outlined an adverse effect of mergers and acquisitions on inventor post-merger innovation incentives, as reduced competition limits inventor's outside option. Empirically, Seru (2014) documents that target inventors experience drop in innovation productivity after diversifying deals. Wang (2023) finds that target inventor productivity decreases after the merger and that they experience larger turnover than the acquirer inventors. Li and Wang (2023) find that post-merger collaboration between target and acquirer inventors enhances the likelihood of creating path-breaking patents. While these studies focus on the inventor productivity change around the merger and its role in determining inventor turnover, this paper relates both inventor turnover and the relationship-specific investments of staying inventors to the key concepts of the theory of the firm.

Finally, our paper is among the early applications of vector space textual analysis methods in patent research (Younge and Kuhn, 2016; Kelly et al., 2021; Gentzkow et al., 2019; Mei, 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 inventor innovation specificity. Our results demonstrate that the innovation specificity measure captures the essence of asset specificity outlined in the theory (Hart and Moore, 1990), and importantly, it is independent of established measures of similarity.

2. Mergers and Acquisitions and Inventors' Asset-Specific Investments

Klein, Crawford, and Alchian (1978) and Grossman and Hart (1986) analyze the impact of hold-up problems, which occur because of contracting costs, on relationship-specific investments and, consequently, on incentives to alter firm boundaries. These models focus on private investments of owner-managers in their human capital. However, our setting concerns inventors, who are employees of the firms. Therefore, we rely on the framework of Hart and Moore (1990), which examines the way in which incentives of employees to make firm-specific investments in their human capital are affected by changes in the ownership of non-human assets by their employers.[4]

This literature assumes that parties cannot write contracts specifying their future investment decisions in human capital. Parties can only contract over who owns, and therefore has control over, non-human assets before making investment decisions in human capital. The allocation of control over non-human assets is important because access to these assets enhances the productivity of investment in human capital. An asset owner can exclude others from using the asset, thereby affecting their employees' incentives to invest in human capital.

In Hart and Moore (1990), employees can make human capital investments that enhance their productivity while using non-human assets owned by employers. A key assumption of their model is that there are complementarities between access to non-human assets and returns on investment in human capital, leading to a higher marginal productivity of such investments when an employee has access to complementary assets. An employee's incentive to make such asset-specific investments depends on whether her employer owns assets that are complementary to her human capital. If the employer owns an asset that complements the employee's human capital, the employee can make investments that increase the value of her capital *vis a vis* this asset. In contrast, if the employer does not own the complementary asset, the employee will be reluctant to make such investments because of potential hold-up problems. Through this mechanism, ownership of non-human assets confers an indirect control/power over employees who depend on such assets while arm's length contracting does not (see Hart and Moore (1990) and Moore (1996), p. 9).

We apply these ideas to acquisitions of innovative firms, where we see inventors as key employees whose investments in their human capital depend on the innovation-related assets owned by their employer. Patents, filed in the name of individual inventors and containing detailed textual information on the protected inventions, can be used to characterize the specificity of inventors' investments in human capital with respect to innovation-related assets owned by firms involved in acquisitions. Additionally, patents can be employed to assess the complementarity of the inventors' human capital with respect to firms involved in acquisitions. Finally, patents also reveal the turnover status of inventors, as different firms are listed as assignees on patents filed by an inventor at various times.

[4] Stole and Zwiebel (1996) and Rajan and Zingales (1998) also discuss the incomplete contracting problem between firms and employees.

To align the predictions of Hart and Moore (1990) with our empirical setting, we consider the inventors of acquirer/target firms as the employees who potentially make specialized investments. We view the patent portfolios of the acquirer/target firm as non-human assets that could be complementary to these investments. Patent portfolios, resulting from the past R&D spending and efforts, can be used to measure the specific technologies that have been pursued by firms and their inventors. Since the commercialization of innovation, and thereby the value of innovations, typically relies on multiple interdependent patents, the value of an inventor's future patents depends on the availability of other complementary patents.[5] Inventors can forego significant rents generated by their own patents if they lack access to complementary patents. Therefore, patent portfolios are important non-human assets, and the access to these assets can affect inventors' investments in human capital. The complementarity of their human capital with respect to a firm's patent portfolio can be measured by comparing the properties of the inventor's patenting output with those of the firm's output.

Figure 1 presents a schematic that illustrates the acquisition of a knowledge-oriented firm (the target firm) by another (the acquirer), along with their inventors and patents. The patent portfolios of these firms reflect their historical accumulation of knowledge. Each inventor employed by these firms has a history of patents, reflecting the nature of the inventor's human capital. We classify the inventors from each firm into three categories: *Stayers*, who file a patent with the firms involved in the transaction in the five years after the transaction; *Leavers*, who file one with a different firm, not involved in the transaction, in the five years after the transaction (presumably indicating a switch away from the transaction firms around the time of the deal); and *Stoppers*, who do not file any in the five years following the transaction, leaving their post-deal employment status unknown. Using the textual analysis of patent claims described in Section 3.2 below, we develop a novel measure to evaluate the innovation specificity of an inventor from one firm in relation to the patents of the other firm involved in the transaction. Additionally, we assess the complementarity of an inventor's human capital from one firm with respect to the patents of

[5] Private Standards Setting Organizations (SSOs), e.g., The Institute of Electrical and Electronics Engineers (IEEE) or European Telecommunications Standards Institute (ETSI), operate in many technology fields to produce technology standard based on pooling patents through licencing of "essential patents". Prior literature has identified additional sources of the interdependence of patents through, for example, innovation spillovers (e.g., Jaffe, 1986; Bloom, Schankerman, and van Reenen, 2013), or the existence of "cumulative" technologies or patent "thickets" (e.g., Shapiro, 2000; Hall and Ziedonis, 2001; Ziedonis, 2004; Hall, von Graevenitz, and Helmers, 2021).

the other firm involved in the transaction, by analyzing the patent citations made by the inventor's patents.

According to the logic of the Hart and Moore (1990) model, inventors are more likely to increase innovations specific to the new patent portfolio they gain access to following an M&A transaction. Inventors whose human capital is highly complementary to the partner firm's patent portfolio are likely to experience a more pronounced change in such innovations, as they gain access to more complementary assets following the M&A transaction. Since inventors whose human capital is complementary to the assets of the M&A partner are more likely to benefit more from the M&A transaction through an improved incentive to make specific investments, we expect acquirer inventors with human capital that is more complementary to the target's patents, and target inventors with human capital complementary to the acquirer's patents (the "highly complementary" inventors) to be more likely *stayers*. Conditional on being a *stayer*, because of the improved access to new complementary patents, we expect the high complementary target inventors to produce patents that are more specific to the acquirer after the M&A transaction is completed, and vice versa for the acquirer inventors. In the reminder of the paper, we develop measures and empirical methods to test these predictions.

3. Sample Construction, Variable Definitions, and Summary Statistics

3.1. Data Sources and Sample Construction

We obtain our sample of merger and acquisition (M&A) transactions of publicly traded US acquirers of public and private targets from the *SDC Platinum* database.[6] Our inclusion criteria cover deals from the 1976-2014 period that are classified as a "merger," an "acquisition of assets," or an "acquisition of major interests," and are considered "friendly." These deals must have a status of either "complete" or "withdrawn." We consider deals where the acquirer is a publicly listed firm and we do not condition on the listing status of the target firms, so that the sample contains a large number of acquisitions of private targets by public acquirers. We match publicly listed firms involved in the M&A deals with the *CRSP* database by 6-digit CUSIP identifiers available in the *SDC Platinum* database using the link table *dsenames* from *CRSP* and obtain PERMCO identifiers for those firms. To obtain firm- and deal-level characteristics from *Compustat*, we rely on the

[6] See Erel, Liao, and Weisbach (2012), who document that 96% of M&As worldwide include private targets, which we include in our sample. Private acquirers, which are not in our sample, represent only 26% of acquirers worldwide.

CRSP-Compustat Merged Link Table available through *WRDS* to obtain GVKEY identifiers for those firms. To construct firm- and deal-level characteristics, we use, for each firm, the latest fiscal year-end information that is available before the deal announcement date. Through this process we end up with an M&A sample containing 77,746 deals, of which 73,454 are completed and 4,292 are withdrawn.

Our analysis employs measures of the types of innovations pursued by inventors from firms involved in M&A deals, which we construct using patent data from the *PatentsView* dataset maintained by the United States Patent and Trademark Office (USPTO). *PatentsView* covers patents issued by USPTO starting from 1976. To link patents issued by the USPTO with firms involved in M&A deals, we match the assignee firm name strings in *PatentsView* with the acquirer/target firm name strings in *SDC Platinum*. Additionally, to identify cases where an acquirer undergoes name changes around the time of the deal, we match assignee firm name strings with the historical firm names of the acquirer, as obtained from the *CRSP* database. Our matching procedure employs fuzzy string matching with Term Frequency – Inverse Document Frequency (TF-IDF) weighting for individual tokens of firm name strings, and we describe the details in Internet Appendix B.

To construct our measure of innovation specificity we rely on a set of counterfactual acquirers for each acquirer in our M&A sample. We use the link table from Kogan et al. (KPSS, 2017), which connects patents issued by the USPTO with publicly listed firms in the *CRSP* database, to link patents to these counterfactual acquirers. The KPSS link table is available for patents with application years up until 2019. Since we measure innovation output over a five-year window following the transaction and use the patent application dates as the dates when the inventions occurred, we include deals that are completed or withdrawn up until 2014.[7]

We require that both the target and acquirer have at least one patent in the five-year window preceding the deal announcement date. After imposing this requirement, our sample, where both parties are active in innovation before the acquisition, includes 5,105 completed deals (including 2,221,582 acquirer inventors and 82,735 target inventors) and 299 withdrawn deals (including

[7] Since we use PERMCO as an identifier to obtain patent portfolios, we exclude the rare cases where the acquirer and target firm of the same M&A deal share the same PERMCO identifier. These deals, coded by *SDC Platinum* as mergers, but are actually corporate restructurings.

44,968 acquirer inventors and 12,674 target inventors). We use this sample ("main sample" thereafter) to analyze inventor attrition around the deal.

The construction of the innovation specificity measure introduces additional restrictions on our sample of M&A deals. To test the hypothesis about innovation specificity, we utilize patents filed by inventors who are *stayers*. To identify staying inventors, we first determine each inventor's pre-deal affiliation by examining the patents filed by the target firms and acquirers during the entire pre-transaction period (not just the five-year window). We focus on lead inventors, identifying them as affiliated with the target (or acquirer) if they are listed as the first inventor on patents filed by that entity before the deal. If an inventor appears as a lead inventor for both the target and acquirer in the same deal, we establish her affiliation based on the firm with which she files the majority of her patents. For each deal, we then retain those lead inventors who are *stayers*, meaning they lead at least one patent in both the pre- and post-transaction five-year windows. We also include inventors who lead at least one patent in the pre-transaction window and stay with the merged firm, even if they become non-lead inventors in the post-transaction window. Following this step, an M&A deal remains in our sample if both the target and the acquirer have at least one staying lead inventor. This process results in 2,159 completed deals and 108 withdrawn deals.

To construct the innovation specificity measure, we use all patents filed by staying lead inventors in the pre-transaction five-year window and those filed by these inventors in the post-transaction five-year window, provided the post-transaction patents are not led by any lead inventor from the other party involved in the deal. The final sample for the innovation specificity analysis requires each staying lead inventor to have at least one observation with a non-missing specificity measure in both the pre- and post-transaction window (the procedure for constructing this measure is described in Section 3.2). For the acquirer inventor innovation specificity analysis, our sample includes 247,546 staying lead inventors from 1,955 completed deals and 4,425 staying lead inventors from 103 withdrawn deals. For the target inventor innovation specificity analysis, our sample includes 10,051 staying lead inventors from 1,688 completed deals and 1,340 staying lead inventors from 78 withdrawn deals. Internet Appendix Table A.1 summarizes the way that sample construction steps described in this section affect the sample size.

3.2. Measures of Relationship Specificity and Complementarity of Innovation

To test the predictions of Section 2, we develop a measure that captures the relationship specificity of innovation. Following the long-standing literature (Griliches, 1998), we use patents to measure innovation and employ textual information from the universe of USPTO utility patents to construct this measure. In broad terms, we analyze the texts of the patents' principal claims using textual analysis to identify "relationship specific" words. We focus on principal claims because they state the novel aspects of the invention, define the scope of patent protection, and play a critical role in patent litigation. We measure the relationship specificity of innovation at the inventor level by assessing the extent to which an inventor's patents use specific words that relate to the patents of the firm with which the inventor's firm is merging. We measure innovation complementarity at the inventor level by adapting the knowledge overlap measure introduced by Bena and Li (2014).

3.2.1. Innovation Specific to Target and Acquirer

To gauge the innovation specificity of an acquirer's inventor in relation to the focal target firm, we identify words in the inventor's patents' principal claims that are specific to the target firm.[8] We define target-specific words as those used in the principal claims of the target firm's patents and not used by the patents of "counterfactual target firms". Counterfactual targets are firms similar to the focal target firm in the technology space and innovation characteristics over the five-year period prior to the acquisition. Specifically, for each target firm involved in an M&A transaction (deal) announced in year $T=0$, we calculate the Jaffe patent class similarity (Jaffe, 1986) between the target's patents and those of every other company assignee in the USPTO data, based on patents filed between years $T=-5$ and $T=-1$. For each target, we retain the top 500 assignees in terms of Jaffe similarity with the target. From this set of assignees close to the focal target firm in the technology space, we select the three closest assignees using Mahalanobis distance matching that we compute based on the patent stock at year $T=-5$ and the total number of patents filed over the period $[T=-5, T=-1]$. We use information covering the entire five-year pre-acquisition window, rather than only the deal announcement year, to ensure that the counterfactual targets mirror the dynamics of closeness with the focal target throughout the pre-acquisition period. Because our sample of targets includes private firms for which we do not observe financial and accounting information, our matching is solely based on innovation variables available for all patenting firms in the US.[9]

[8] To simplify the exposition, we explain our approach to measuring innovation specificity from the perspective of an inventor at the acquiring firm.

[9] In the untabulated covariate balance table, we find that the counterfactual firm matching effectively reduces the standardized differences on the covariates and moves the variance ratios to one.

We define the innovation specificity of a target firm's inventor in relation to that of the focal acquirer analogously. However, since the acquirers are public firms, we conduct the matching within the universe of public firms that have at least one patent using the link table created by Kogan et al. (2017). In robustness checks, we perform matching using alternative methods and find that our main results are not sensitive to the matching method employed.

Central to our measure of innovation specificity are the words contained in the principal claims of patents, which we define as either target- or acquirer-specific. We define specificity this way to capture a set of words unique to either the target firm or the acquirer. For this reason, we require that these words be used by either the target firm or the acquirer, and not by other firms active in a similar technology space (referred to as "counterfactual target firms" for the target and "counterfactual acquirers" for the acquirer, respectively). The diagram in Figure M.1 below illustrates this concept from the perspective of the target firm. Area A in the diagram represents words exclusively used by the focal target firm: "focal target firm' specific words/dictionary." Area C depicts words exclusively used by the counterfactual target firms: "counterfactual target firms' specific words/dictionary." Area B includes words used by both the focal target firm and its counterfactual target firms. Words in area B are either common to most patents in the patent universe or shared between the focal target and its counterfactual targets, representing the common terminology and language of the technology area in which both the focal target and its counterfactual targets are active. By basing our innovation specificity measure on words in area A and excluding words representing common technologies and those that also apply to the counterfactual targets, we focus on the technologies unique to the target. Counterfactual firms are used solely to create a subset of words unique to the focal targets and acquirers to construct our measure of innovation specificity. Beyond this measure construction, these counterfactual firms do not enter our analysis in any other way.

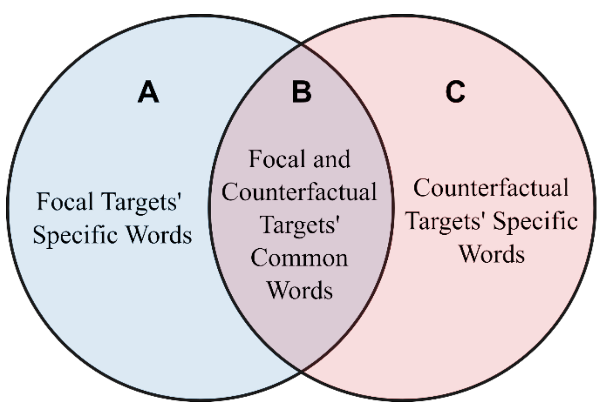

Figure M.1: Target firm-specific words/dictionary

3.2.2. Relationship-Specific Innovation

Using words specific to the target firm, we define the acquirer's inventor's relationship specificity with the target based on the extent to which the inventor uses target-specific words in her patents. If an acquirer's inventor produces patents specific to the target, it is more likely that her patents will use target-specific words. To capture the pre-merger target-specific innovation, we define target-specific words using the patents filed by the target and counterfactual targets within the five-year window preceding the announcement of a deal involving the target. After the deal's completion, we extend this five-year window annually up to year $T=+5$. We then measure the extent to which the acquirer's inventor's patents, filed in each year over the period $[T=-5, T=+5]$ use the target-specific words. In tests where we examine the relationship specificity of each of the target firm's inventors with the acquirer firm, we proceed analogously, using words specific to the acquirer.

We define three dependent variables that capture relationship-specific innovation. Our first variable, *Innovation Specificity Unique (%)*, is defined as the number of unique acquirer-specific (target-specific) words used by a lead inventor of the target (acquirer) divided by the total number of unique words in patents she files within a given year. We define this variable using the *Staying Lead Inventor's Patents* only.[10] We consider years from year $T=-5$ to $T=+5$ with $T=0$ being the deal announcement year, and the variable is defined only in years when the lead inventor files at least one patent.

Our next variable employs the same set of words in both the numerator and the denominator of the ratio. However, instead of counting each word only once, we assign a weight to each word based on the frequency of its usage in the respective lead inventor's patents. The weight for each word is thus its term frequency ("*TF*") and our second variable, *Innovation Specificity TF (%)*, is defined as the TF-weighted sum of acquirer-specific (target-specific) words used by a lead inventor of the target (acquirer) in patents she files each year divided by the TF-weighted sum of all words

[10] The *Staying Lead Inventor's Patents* include both pre-merger patents and post-merger patents. For pre-merger patents, this includes all patents led by the staying lead inventor before the deal announcement date. For post-merger patents, it includes patents led by the focal inventor if she is a lead inventor for at least one post-merger patent. Alternatively, if she is not a lead inventor for any post-merger patents, it includes patents in which the focal inventor participated as a non-leader, provided that the lead inventor of the patent is not from the other firm participating in the deal.

in these patents. This means the variable considers how often the lead inventor uses specific words, not just how many specific words she uses.

To construct our third variable, we augment our second variable by further weighting the term frequency by the inverse document frequency ("*IDF*"), following Kelly et al. (2020). The *IDF* weighting scheme overweights the terms that are more unique to individual patents and underweights the terms that are more common across patents in the entire sample. *Innovation Specificity TF-IDF (%)* is defined as the Term Frequency - Inverse Document Frequency ("*TF-IDF*") weighted sum of acquirer-specific (target-specific) words used by a lead inventor of the target (acquirer) in patents she files each year divided by the TF-IDF-weighted sum of all words in these patents. We discuss the details of the construction of these variables in Internet Appendix C.

3.2.3. Innovation Complementarity

The key prediction discussed in Section 2 pertains to the way in which the pre-merger complementarity of an inventor's innovation with the assets of her firm's merger partner influences her incentives to specialize her innovation following the merger. To capture such complementarity in the innovation space, we utilize the *Knowledge Base Overlap Ratio* measure introduced by Bena and Li (2014) and modify it to capture the complementarity at the inventor level. Specifically, we measure an inventor's innovation complementarity with her firm's merger partner by the extent to which her and the merger partner's pre-merger patents are based on the same overlapping prior knowledge, as indicated by backward citations. Bena and Li (2014) document that this measure of technological overlap between firms is a significant predictor of the likelihood of mergers and the innovation synergies achieved through them.

We compute the measure through the following steps: First, we define a target (or acquirer) firm's knowledge base as the set of patents that have received at least one citation from any of the firm's patents with application dates prior to the deal announcement date. This knowledge base is specific to each transaction and is computed separately for both the target and acquirer firms involved in the transaction. Second, we define an inventor's knowledge base as the set of patents that have received at least one citation from any of the inventor's patents with patent application dates prior to the deal announcement date. Third, we define the common knowledge base as the intersection between a target (or acquirer) firm's knowledge base with that of each acquirer (target) inventor's knowledge base. Fourth, we compute the knowledge base overlap ratio for each target (acquirer) inventor as the ratio of the total number of patents in the common knowledge base over the total number of patents in the target (acquirer) inventor's knowledge base. Finally, we define our main independent variable, *High Complementarity*, as a dummy variable that equals one if a target (acquirer) inventor's knowledge base overlap ratio with the counterparty firm in the M&A deal is greater or equal to the 75th percentile of knowledge base overlap ratio[11] for all target (acquirer) inventor's that are involved in this deal.

3.3. Summary Statistics

Panel A of Table 1 presents summary statistics for acquirers, targets, and deals in the main sample, in which both the target and the acquirer have at least one patent in the five-year window prior to the deal announcement date. The total assets of the acquirer and target are calculated using the latest available fiscal-year-end data before the deal announcement date. The innovation characteristics are constructed using patents filed either in the five-year window prior to the deal announcement date (denoted [$T=-5$, $T=-1$]) or in the five-year window after the deal resolution date (denoted [$T=+1$, $T=+5$]). Approximately half of our sample deals involve firms that are from the same two-digit SIC industry, and almost a quarter of the deals are paid entirely in cash. Public targets constitute 27 percent of the deals in our sample. On average, acquirers and targets have total assets of $11.55 billion and $2.26 billion, respectively, with an average relative deal size ratio of 27 percent. Acquirers are also much larger in terms of their innovative output, filing an average of 453 patents in the period [$T=-5$, $T=-1$], compared to 16.5 patents for targets.

The average asset size of acquirers in completed deals is $11.85 billion, compared to $6.15 billion for those in withdrawn deals. Acquirers of completed deals are also larger in terms of their innovative output compared with those in withdrawn deals. This difference is smaller for targets. Withdrawn deals typically involve merging partners with similar sizes, indicated by an average deal size ratio of 81 percent. In addition, targets in withdrawn deals tend to be larger in terms of innovation output, because withdrawn deals more often involve public targets. The proportion of public-to-public deals is 60 percent for withdrawn deals, compared to 25 percent for completed deals.[12]

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[11] The knowledge base overlap ratio is right skewed with median being zero for both the target and acquirer inventors. Therefore, we choose 75th percentile as the cutoff.

[12] We confirm that the differences in innovative outputs between the completed and the withdrawn acquirers are driven by size differences as opposed to innovativeness. In Internet Appendix Table A.2, we conduct an in-depth analysis of the differences in firms' innovation activities. In Panel A, we confirm that the acquirers of completed deals involve more teams, however, the per-team innovation productivity is similar between the completed and the withdrawn deals.

Panel B of Table 1 presents summary statistics for the inventors in our sample, with the statistics broken down by acquirer and target inventors, and further distinguished based on whether a deal was completed or withdrawn. The average inventor complementarity, as measured by the *Base Overlap Ratio*, is significantly lower for acquirer inventors (0.41%) than for target inventors (8.07%). The main distinction between completed and withdrawn deals is that target inventor complementarity is much smaller in withdrawn deals (2.98%) than in completed deals (8.85%), which suggests that complementarity is an important driver of M&A activity. The patent count and team size in the period [$T{=}-5$, $T{=}-1$] are similar on average for both acquirer and target inventors, with about 2 to 3 patents and 3 to 4 team members, respectively.

Panel C of Table 1 provides summary statistics for our three dependent variables, which capture inventor innovation specificity. These are presented separately for acquirer and target inventors, using the sample of all deals as well as subsamples of completed and withdrawn deals. Innovation specificity is consistently higher for acquirer inventors across all samples. Innovation specificity is greater for inventors involved in completed deals than in withdrawn deals, which is consistent with the predictions outlined in Section 2.

Overall, our sample is similar to those used in prior research studying M&A activity among firms active in innovation. The notable distinction is our inclusion of private target firms. Including private deals leads to a larger sample, but it also amplifies the differences observed between completed and withdrawn deals.

4. Inventor Dynamics Around Mergers and Acquisitions

4.1. Univariate Comparisons

Our analysis centers on inventors who continue patenting under the merged entity after the transaction, who we refer to as *stayer* inventors. A prediction from the discussion in Section 2 is that inventors whose human capital is not complementary to the patents of the merger partner are more likely to leave the combined post-deal firm (*leavers*). Moreover, understanding the selection process of inventors into *stayers*, *leavers*, or those who cease to innovate (*stopper*) inventors, facilitates the interpretation of the results on innovation output post-transaction.

In Panel B, we compare acquirer characteristics before the merger announcement and document that acquirers of completed deals differ from those of withdrawn deals in size measures (*Sales* and *Total Assets* are both significantly different at the 1% level). However, they are not different in terms of innovativeness; the withdrawn acquirers in fact have an insignificantly larger *R&D Stock* to *Total Assets* ratio.

Table 2 presents the percentages of inventors in each of the three categories (*stayer, leaver, stopper*) for both acquirers and targets in our main sample. To discern the extent to which the selection of inventors into these categories is driven by M&A activity as opposed to general trends in inventor innovation, we also present corresponding statistics for counterfactual acquirers and targets.

Table 2 documents that approximately 46% of acquirer inventors and 50% of target inventors who filed a patent with either the target or the acquirer in the five-year period prior to the deal did not file any patents in the subsequent five-year period, so are classified as *stoppers*. The corresponding numbers for counterfactual acquirers and targets are similar, suggesting that a substantial number of inventors do not engage in repeated invention, and the cessation of inventing is unrelated to M&A activity. Another 38% of the acquirer inventors filed another patent with the post-merger entity in the five-year period after the deal so are classified as *stayers*. The proportion of *stayers* for target inventors is smaller; 28% of the target inventors are *stayers*, which suggests that inventors at smaller firms tend to experience more frequent turnovers. Finally, inventor attrition rates are similar between acquirers and counterfactual acquirers.

To assess whether complementarities with the newly acquired assets cause the relatively high rate of departures following M&A deals, we examine our measure of complementarities – *Knowledge Base Overlap Ratio* – between inventors and the newly acquired assets separately for *stayers*, *leavers*, and *stoppers*. We present these comparisons in Figure 2, where the error bar represents the 95% confidence interval. The sample includes completed and withdrawn deals, in which both the target and the acquirer have filed at least one patent in the five-year period leading up to the deal announcement date. Inventors are included if they file at least one patent in the same five-year period.

Figure 2 indicates that complementarities with newly acquired assets are substantially larger for *stayer* inventors than for *leaver* inventors. Specifically, *stayer* inventors in both acquirers and targets exhibit the highest levels of complementarity, while *leaver* inventors in both groups show the lowest. Furthermore, the difference in complementarity between *stayers* and *leavers* is larger than that between *stayers* and *stoppers*. This pattern suggests that M&A deals can lead to significant changes in a firm's labor composition, with employees whose human capital is more closely aligned with that of the acquisition partner being more likely to remain with the combined entity.

Given the stark differences in complementarity between inventor *stayers* and *leavers*, we next ask whether similar disparities exist in productivity among these inventor groups, or if they only differ in the type of innovation they pursue. We explore this question using the deals (both completed and withdrawn) and inventors in the main sample. Figure 3 examines the productivity of inventors who stay or leave relative to those who do not file subsequent patents over a ten-year window surrounding the deal. Specifically, we calculate the average number of patents produced annually by inventors in each category over this period. Panel A details the productivity of acquirer inventors, whereas Panel B describes target inventors. To provide a benchmark, we also present analogous statistics for the inventors associated with counterfactual acquirers and targets.

Figure 3 illustrates that the productivity of both *leaver* and *stayer* inventors exhibits a hump-shaped trend around the time of the deal, with an increase over the five years leading up to the deal announcement and a moderate decline following the deal's resolution. The shifts in productivity are more pronounced for *stayer* inventors. These findings are consistent with the notion that inventors who see larger productivity gains during the initial five years of the observation period are more likely to stay with their current firm. Alternatively, this pattern could reflect strategic timing of patent filings influenced by the deal, which could occur if *stayers* postpone patenting until after the deal's resolution. However, the observation of similar hump-shaped trend among the counterfactual acquirers and targets where there is no deal taking place mitigates concerns regarding strategic patent timing. As for inventors who cease filing patents post-deal, their productivity is significantly lower and flat over the five years leading up to the deal announcement (approximately half a patent for *stoppers* versus one to one and a half patents for *stayers*).

Since we assign a patent's affiliation to either the acquirer or target based on the pre-merger affiliation of the patent's lead inventor, we evaluate the extent to which the affiliation of staying lead inventors represents the affiliation of inventor teams behind patents (i.e., all inventors of a patent) filed after the deal. Table 3 presents statistics on inventor team composition of patents filed by merged firms in completed deals. For this analysis, we trace *stayer* inventors whose affiliation with the acquirer or the target is identified using their pre-merger patents and report the team composition of their post-merger patents. Table 3 presents statistics on inventor team composition of patents participated by at least one staying inventor that are filed in the five-year window following deal resolution.

We report team composition statistics at both unique patent-inventor pair level and unique patent level. For acquirer staying inventors (Panel A), we find 3,861,416 such unique patent inventor pairs, from 1,766,048 unique patents. The vast majority of acquirer inventors do not mix with the target inventors (99.82% by unique patent-inventor pairs and 99.78% by unique patents). For target staying inventors (Panel B), the number is slightly lower but still represents a substantial proportion of the target inventor population (94.18% unique patent-inventor pairs, and 92.04% unique patents). Of the 7.96% post-merger patents filed by target inventors that do include acquirer inventors, 35% of them are led by a target lead inventor, and 29% of them have target inventors comprising the majority of the team. Overall, Table 3 illustrates that inventor team composition tends to remain stable after deals, with target inventors continuing to work with other target inventors and acquirers' inventors working with other acquirer inventors.

4.2. Multivariate Analysis

The comparisons presented in Figure 2 suggest that inventors whose human capital is more closely aligned with that of the acquisition partner are more likely to remain with the combined entity after the deal is completed. We formally test this prediction in Table 4, where we present estimates of a linear probability model predicting the likelihood of an individual inventor staying with the firm following deal resolution. The estimation sample includes inventors from the main sample who are either *stayers* or *leavers*, and the dependent variable is a dummy variable that equals one if the inventor is a *stayer*. Columns (1) and (2) present estimates of this regression model for acquirer inventors, while Columns (3) and (4) present estimates for target inventors.

The independent variable of interest is a dummy variable *High Complementarity* that equals one if the inventor's knowledge base overlap ratio is greater than or equal to 75th percentile of the inventors from the same firm of the deal. In Columns (2) and (4), the regression specifications also include patent count, the average team size and total number of coinventors. These control variables are measured over the five-year window prior to the deal announcement and are based on patents participated by the focal inventor. Columns (3) and (6) further add patent count measured over the five-year window following the deal completion based on patents participated by the focal inventor. All equations include deal fixed effects, and standard errors are corrected for clustering of observations at the deal level.

In each column of Table 4, the coefficient of *High Complementarity* is positive and statistically significant at the 1 percent level, suggesting that inventors with high complementarity are more likely to stay with the firm following an M&A transaction. The estimated effect is large in magnitude. The estimate in Column (2) implies that acquirer inventors with high complementarity with the target firm are 3 percentage points more likely to stay (rather than leave) with the merged firm and innovate within five years after the deal completion, which represents a 4.5% greater likelihood of staying compared to the mean. The estimated likelihood more than doubles to 9.5% for target inventors with high complementarity with the acquirer.

In summary, the existence of complementarities between inventors' patents and the merged firm's newly expanded portfolio of patents—originating from either the acquired firm or the new parent company—appears to influence inventors' mobility. Specifically, we observe that inventors whose human capital is more closely aligned with the patent portfolio of the M&A partner tend to remain with the firm post-acquisition. While this finding applies to inventors from both acquiring and target firms, the effect is about twice as pronounced for those from the target firms.

5. Relationship-Specific Innovation and Mergers and Acquisitions

The prediction of Hart and Moore's (1990) model that we evaluate is that inventors with human capital complementary to the patent portfolio of the M&A partner will have incentives to make relationship-specific innovation investments after the deal's completion when they gain access to the partner's patent portfolio. We evaluate this prediction using the inventor-level measures of innovation specificity and complementarity introduced in Section 3.2.

5.1. Estimates from a Triple-Differences Specification

In our main test, we employ a "triple-differences" specification that compares the change in innovation specificity of staying lead inventors with high complementarities to the M&A partner's patent portfolio with those having low complementarities. This comparison is relative to their own personal inventions prior to the deal, and also to comparable inventors at firms where deals were withdrawn. This specification aims to capture the effect of an M&A deal on innovation specificity because of complementarities. By comparing inventors within the same firm before and after an M&A transaction, we alleviate the possibility that cross-firm heterogeneity might explain the results.

We present the estimates of this triple-difference specification in Table 5. The equations are estimated at the inventor-deal-relative year level, using a sample covering the five years before and after the deal announcement and resolution dates.[13] The dependent variables are the three measures of innovation specificity described in Section 3.2.2: *Innovation Specificity Unique (%)*, *Innovation Specificity TF (%)*, and *Innovation Specificity TF-IDF (%)*. Each measure captures the extent to which acquirer (or target) inventors use specific words extracted from the patents of the target firm (or acquirer firm). *Complete* is a dummy variable that equals one if the deal is completed and zero if withdrawn. *Post* is a dummy variable that equals one for observations from post-merger years. *High Complementarity* is a dummy variable that equals one if the inventor's knowledge base overlap ratio with the M&A partner firm is at or above the 75th percentile compared to inventors from the same firm involved in the deal.

Panel A presents estimates for acquirer staying lead inventors and Panel B for target staying lead inventors. In the odd-numbered columns, we include only the dummy variables that define the triple-differences specification, while the even-numbered columns include additional variables capturing pre-merger time-invariant inventor characteristics. Specifically, we control for the patent count, the average team size and the total number of co-inventors, all measured over the five-year window prior to the deal announcement, based on patents led by the focal inventor who is affiliated with the target/acquirer firm of the deal.[14] All specifications include deal fixed effects, and standard errors are corrected for clustering of observations at the deal level.

The estimates presented in Table 5 indicate that the coefficients of *Complete* × *Post* × *High Complementarity* interaction are positive and statistically significantly different from zero in all specifications for both acquirer and target inventors. The coefficient estimates of the triple interaction term range from 1.04 to 1.09 for the acquirer inventors, which are statistically significantly different from zero at the 1 percent level in all specifications. The economic magnitude is large. The estimates represent a 25.3% to 26.3% higher innovation specificity due to M&A when evaluated at the mean and 17.1% to 20.7% when evaluated at the standard deviation. Similarly, for target inventors, the triple interaction term coefficient estimates range from 0.75 to 0.99, with each coefficient being statistically significantly different from zero at the 5 percent level. The associated economic magnitude is also substantial, representing a 29.1% to 31.5% higher innovation specificity when evaluated at the mean and a 14.7% to 16.9% higher when evaluated

[13] The resolution date is defined as the withdrawal date for the withdrawn deals and effective date for the completed deals.
[14] The details of variable definitions are presented in the Appendix.

at the standard deviation. These positive coefficients imply that inventors with high complementarities in completed deals increase specificity of their own inventions after the deal, relative to other inventors in the same firm with lower complementarities and also relative to comparable inventors in withdrawn deals.

Using *Innovation Specificity Unique (%)* measure for acquirer inventors, Figure 4 illustrates patterns in our data consistent with the triple-differences regression estimates presented in Table 5. In Panel A, we plot the mean innovation specificity over time for high and low complementarity inventors, separating those involved in completed deals from those in withdrawn deals. In Panel B, we present the mean difference in innovation specificity between high and low complementarity inventor groups, separately for those involved in completed and withdrawn deals. In Panel C, we show the mean difference in innovation specificity between inventors involved in completed and withdrawn deals, this time separately for high and low complementarity inventors.

Panel A shows that the specificity of the acquirer inventors' innovations to the target firm's patents remains almost flat prior to the deal announcement, for both high and low complementarity inventors involved in completed as well as withdrawn deals. This flat pattern is particularly evident in the much larger sample of completed deals. Notably, inventors involved in completed deals exhibit higher innovation specificity than those in withdrawn deals. Innovation specificity increases for the inventors involved in completed deals after their completion (as shown in Panel A), and within these completed deals, it increases more for high complementarity inventors than for low complementarity ones (as shown in Panel B). Additionally, Panels A and B document that the increase in innovation specificity for inventors in completed deals occurs shortly after the deal's completion, and this increased specificity does not diminish over time.

Panel B further illustrates that although the difference in innovation specificity between high and low complementarity inventor groups is positive and approximately the same in both completed and withdrawn deals prior to the deal announcement, a noticeable divergence emerges between completed and withdrawn deals after the deal resolution. While this difference approximately doubles in completed deals, it declines to zero in withdrawn deals. Starting from year $T{=}{+}2$ relative to the deal withdrawal date, there is no significant difference in the innovation specificity of high and low complementarity inventors.

As further documented in Panel C, the changing innovation patterns of high complementarity inventors are central to these results. Panel C shows that high complementarity inventors in completed deals significantly increase the specificity of their innovation output following the deal resolution compared to their counterparts in withdrawn deals. In contrast, the difference in innovation specificity between low complementarity inventors in completed and withdrawn deals remains approximately constant over the entire ten-year period before and after the deal.

Figure 5 displays corresponding graphs for target inventors. In each panel, the pattern is similar to that observed for acquirer inventors, with one notable exception: high complementarity target inventors in completed deals experience a more pronounced increase in their innovation specificity following the deal completion.

5.2. Pre-Trends and the Timing of the Effect

A concern with any study relying on a difference-in-differences specifications is that the observed changes in the dependent variable might have occurred even without a change in the independent variable. A way to mitigate this concern is to examine the pre-trends in the dependent variable, in this case, innovation specificity. Presumably, if inventors were already specializing their human capital to patents of future acquirers prior to the deal, it is likely they would continue to do so following the deal.

We examine the pre-trends of one specificity measure, *Innovation Specificity Unique (%)*, in Figures 4 and 5. For both acquirer and target inventors, *Innovation Specificity Unique (%)* appears to follow parallel trends prior to the deal. While *Innovation Specificity Unique (%)* is higher for high complementarity inventors than for low complementarity ones, their trends are parallel. Following the deal, *Innovation Specificity Unique (%)* increases for high complementarity both acquirer and target inventors, and, to a lesser extent, for low complementarity acquirer inventors, but not for low complementarity target inventors. There is no such increase for withdrawn deals. These findings suggest that there is no noticeable pre-trend that could affect the interpretation of the estimates in Table 5.

In Table 6, we estimate the pattern of increases in innovation specificity around the time of our sample deals. The specifications in the columns of Table 6 follow the structure of Table 5, except that we replace *Post* with a dummy variable that equals one for the year immediately prior to the deal announcement ($T=-1$), and with a set of dummy variables for each year following the deal resolution, starting from the first year following the deal resolution ($T=+1$), to five years after ($T=+5$). The years from $T=-5$ to $T=-2$ serve as a comparison group.

For both acquirer inventors (Panel A) and target inventors (Panel B), using all three measures of innovation specificity, we estimate an increase in innovation specificity in the years following the deal completion. This increase starts in year $T=+1$ for acquirer inventors and in year $T=+2$ for target inventors. For both groups, innovation specificity becomes more pronounced over the five-year window following the deal completion. Consistent with the absence of pre-trends documented in Figures 4 and 5, the coefficient of the dummy variable for year $T=-1$ is not statistically significant and is small in magnitude. The results in Table 6 support the parallel trends assumption, which is essential for a causal interpretation of our findings.

5.3. Additional Analysis and Robustness Tests

5.3.1. Potential Impact of Using Common Patent Attorneys

A potential alternative interpretation of our findings is that target inventors could begin using the acquirer's law firm after the deal's completion. If patent attorneys employ similar language in all patent documents they prepare, and if there are language differences from one attorney to another, we could observe an increase in the use of common language following mergers that would have nothing to do with the substance of the patents and the specialization of the inventors when the patents are prepared by the same attorneys. Since our dependent variable, innovation specificity, is based on the text of patent claims, any commonality in language introduced by patent attorneys into the claims could lead to an increase in our dependent variable. This increase could occur even if the direction of innovation of both target and acquirer inventors is unaffected by the deal completion. This mechanism could explain our findings if the same patent attorneys are more likely to prepare patents of high complementarity inventors compared to low complementarity ones after deal completion.

To examine whether the use of the same patent attorneys following deal completion can explain the observed increase in innovation specificity, we reestimate the equations from Table 5 using the subsample of patents filed by target and acquirer inventors after deal completion that are prepared by different patent attorneys. To construct this subsample, for each deal, we identify the earliest year in which target and acquirer inventors begin using the same patent attorney after deal completion, and we exclude all observations from this year onward from the original sample. Compared to Table 5, our sample size decreases minimally due to this additional sample screen.

Table 7 presents estimates obtained using this subsample. The coefficients of *Complete* × *Post* × *High Complementarity* interaction are positive and statistically significant in all specifications we consider. Their magnitudes are comparable to the baseline estimates presented in Table 5. These results suggests that changes in law firms induced by M&A transactions are unlikely the reason why we observe an increase in innovation specificity for high complementarity inventors following acquisitions.

5.3.2. A Placebo Test

A potential alternative explanation for our findings is that rather than high complementarity inventors making investments specific to the innovation-related assets acquired through the deal, these inventors could be creating new patents that resemble these assets after the deal's completion for another reason. For instance, the increase in patent similarity could occur because of more intense knowledge spillovers among inventors within the merged firm. In this scenario, the increase in our dependent variable could reflect an increase in patent similarity rather than an actual increase in their specificity.

To evaluate this possibility, we conduct a placebo test by creating new dependent variables using the same approach as our innovation specificity measures with one key difference: instead of using words specific to the merger partner (i.e., words in region A of the diagram in Figure M.1), we utilize words common to both the acquirer/target and the counterfactual acquirers/targets (i.e., words in region B of the diagram in Figure M.1). If our results were driven by an increase in patent similarity, we would expect to see high complementarity inventors using common words more frequently than their low complementarity counterparts following deals' completions.

Table 8 presents estimates obtained using these alternative dependent variables. The coefficients of *Complete × Post × High Complementarity* interaction are negative, not statistically significant and close to zero in all specifications. This pattern holds for both acquirer and target inventors. The coefficients of *Complete × Post* interaction are positive in all specifications, with a 10 percent level of statistical significance in most specifications for the acquirer inventor group. These results suggest that both high and low complementarity inventors experience an increase in the use of common words following the deal completion; however, there is no differential effect for high complementarity inventors when compared to low complementarity ones. This result suggests that our findings are driven by innovation specificity rather than similarity, and underscores the importance of the comparison between high and low complementarity inventors as predicted by the Hart and Moore's (1990) model.

5.3.3. Stacked Triple-Differences Specification

Our analysis of innovation specificity employs two-way fixed effects in a setting where inventors can participate in multiple deals, thus resembling the staggered difference-in-differences design. Recent research has indicated that this design can yield biased estimates, if units treated earlier are used as controls for units treated later in cases where there is treatment heterogeneity across units or over time (e.g., Goodman-Bacon, 2019; Baker, Larcker, and Wang, 2021).

Since we utilize withdrawn deals, which never undergo "treatment," as the control group and rely on a ten-year balanced event window around each deal, we mitigate some of the concerns associated with the staggered difference-in-differences design through our sample construction procedure. Nevertheless, given that our treated and control units (the completed and withdrawn deals) occur at different times, our specifications do compare completed with withdrawn deals regardless of their timing. This approach may affect our estimates if there are time-varying treatment effects.

To address this potential concern, we follow Cengiz et al. (2019) and create treatment-time cohorts where each cohort includes one treated unit (a completed deal) and control units (withdrawn deals) announced in the same year as the treated unit. We then stack all the cohort-deal-inventor-relative year observations together and estimate a triple-differences regression with cohort-fixed effects and calendar year fixed effects. We cluster the standard errors at the cohort level. Table 9 reports the results. For both the acquirer and the target inventor sample, the coefficients of *Complete* × *Post* × *High Complementarity* interaction are positive and statistically significant at the 1 percent level in all specifications. The magnitudes of the coefficient are similar to our baseline estimates in Table 5.[15]

5.3.4. Other Robustness Tests

In this section, we complement our baseline results with a number of robustness tests. First, we employ two alternative methods to construct our main dependent variable, innovation specificity. In our baseline tests, innovation specificity is calculated as the ratio of the number of acquirer/target-specific words to the total word count, pooling all patents filed by a focal inventor each year. In the first alternative approach, we calculate the measure of specificity for each patent, then average these values at the inventor-year level. Estimates using this measure are reported in

[15] The mean of the dependent variable is smaller than that reported in Table 5. This difference obtains because, in this estimation, a withdrawn deal could be repeated multiple times in different cohorts. Since withdrawn deals tend to have lower unconditional innovation specificity, this sample construction procedure results in a lower mean of the dependent variable. For this reason, we do not include a discussion of the economic magnitudes based on this sample.

Internet Appendix Table A.3. In the second alternative approach, to account for the right-skewness and the presence of many zero values, we apply an inverse hyperbolic sine transformation to our main specificity measure, with estimates using this measure reported in Internet Appendix Table A.4. Both tables confirm the positive and statistically significant estimates of the triple interaction term *Complete* × *Post* × *High Complementarity*, with magnitudes similar to those reported in Table 5.

Second, we introduce an alternative definition of our main independent variable, *High Complementarity*. In our baseline tests, we classify a target (acquirer) inventor as having a high complementarity with the deal's other party by considering the 75^{th} percentile of all target (acquirer) inventors who have filed at least one patent in the five-year window prior to the deal announcement. Alternatively, we redefine *High Complementarity* by focusing on the 75^{th} percentile within target (acquirer) staying lead inventors only, who are inventors included in our sample for the triple-differences innovation specificity tests. The estimates using this alternative definition are reported in Table A.5. This table presents positive and statistically significant estimates of the triple interaction term *Complete* × *Post* × *High Complementarity*, with magnitudes similar to those reported in Table 5.

Third, we restrict our analysis to inventors who remain in leadership roles both before and after the M&A transaction. In our baseline tests, we include inventors who are lead inventors on at least one patent within the five-year window prior to the deal announcement and stay with the merged entity after deal resolution. This includes both inventors who continue as lead inventors after the merger ("continued leaders") and those who, while no longer lead inventors, still contribute to patents led by inventors of the same pre-merger affiliation ("post-merger non-leaders"). Although this approach broadens our sample by not being specific about the selection of inventors into leadership roles post-merger, in this section, we validate the robustness of our main results using only the sample of continued leaders. Internet Appendix Table A.6 presents the results, which are in line with our baseline tests in Table 5.

Finally, we reestimate our main results using a subsample of "clean treatment" deals, which are those completed deals that do not overlap in their event windows with another deal. This refinement reduces the acquirer inventor sample by 97.4% and the target inventor sample by 84.7%. The results are reported in Internet Appendix Table A.7. In the acquirer inventor sample, the estimates of the triple interaction term *Complete* × *Post* × *High Complementarity* are positive and statistically significant, with magnitudes nearly double compared to those in Table 5. In the target inventor sample, the coefficient estimates of this triple interaction term are positive across all specifications and statistically significant at the 5 percent level for *Innovation Specificity Unique (%)*. Since the magnitude of the coefficients are similar to, if not larger than, those reported in Table 5, the absence of statistical significance in the target inventor sample can be attributed to reduced statistical power from the much smaller sample size.

6. Conclusion

The notion that mergers can facilitate specialized investment has been recognized since at least Klein, Crawford, and Alchian (1978), and forms the underpinning of the leading explanation for why firms exist (Grossman and Hart, 1986). However, evaluating whether the desire to facilitate specialized investments is an important determinant real-world firms' boundaries is challenging because detailed information about most investments and the extent to which they are specialized for a particular relationship are not observable to outsiders. While some research has measured the likelihood of an acquisition based on pre-merger observable variables, less is known about the nature of firms' investments following mergers and whether these investments become more specialized to those of their merging partner.

A substantial portion of the investments of modern firms is in intangible capital, often related to firms' R&D. These investments are often initiated by inventors, whose incentives to invest are driven by the extent to which their human capital is complementary with their firm's assets. The model of Hart and Moore (1990) is relevant to this situation since it applies the ideas of incomplete contracts and specialized investments to a firm's employees, such as inventors. The key implication is that employees are more likely to specialize their human capital to assets owned by their firm rather that to contracted assets. This reasoning predicts that inventors whose human capital is complementary to the new assets acquired by a firm will further specialize their capital to better utilize these assets.

Patent data provides an ideal setting to evaluate predictions of this theory. Patents are unique among firms' investments as they are filed under the individual inventor's name and contain detailed information about the invention itself. This paper examines a sample of mergers and acquisitions involving publicly traded and private US corporations that are active in technological innovation and estimates the way in which inventors specialize their capital using textual analysis of patent data. We rely on the inventor's pre-merger affiliation to determine whether a particular patent was filed by the target or acquirer part of the merged company. We then apply textual analysis to assess both the complementarity between an individual inventor's human capital and the assets of the merger partner firm, as well as the way in which this complementarity affects asset-specific investments in innovation following the deal's completion.

Our empirical results suggest that that the complementarity of an inventor's capital with the assets of the merger partner firm affects the likelihood of the inventor remaining with the firm following the deal – inventors from both the acquirer and target who have high complementarity with the new assets are much more likely to stay with the firm than those with low complementarity. Inventors who do stay with the firm and have high complementarity tend to specialize their capital to the firm's new assets, while inventors with low complementarity do not. These findings are consistent with the idea that acquisitions lead to valuable investments that might not be feasible otherwise due to contracting frictions.

Despite the extensive literature on mergers and acquisitions, our understanding of the real changes in combined firms following deals remains limited, obscuring the underlying motivations behind these deals. Analysis of the patents filed by inventors before and after acquisitions is a potential approach to understanding some of what happens in the combined firms, since patents are filed by individual inventors whose pre-merger affiliation can be traced, and their content is publicly accessible. We utilize these patent data to gain insights into how contracting difficulties influence acquisitions. Looking ahead, patent data will likely provide further insights into the economics of corporate mergers and acquisitions.

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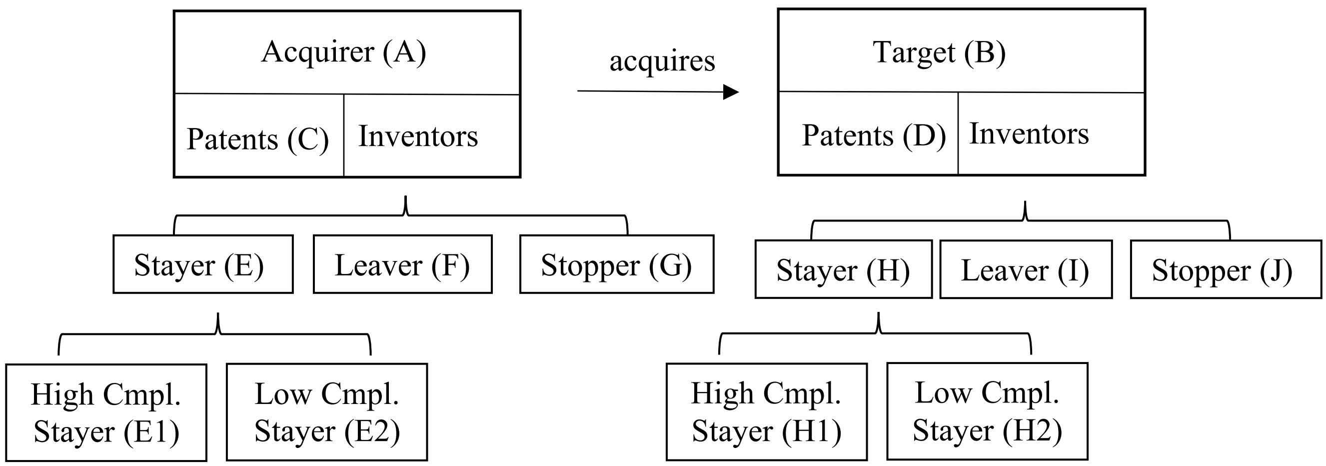
Figure 1. Schematic of an Acquisition of a Knowledge-Based Company

The figure presents the schematic of the theoretical framework that guides the empirical tests of the paper.



Predictions:

1. Inventor staying vs. leaving decision

(a) Using pre-merger patents, inventor E has a higher complementarity (Cmpl) with target B's patents D than inventor F.

(b) Using pre-merger patents, inventor H has a higher complementarity (Cmpl) with acquirer A's patents C than inventor I.

2. Innovation specificity improvement

(a) After merger, inventor E1 has a larger increase in specificity with respect to the target B than inventor E2.

(b) After merger, inventor H1 has a larger increase in specificity with respect to the acquirer A than inventor H2.

Figure 2. Inventor Complementarity by Inventor Attrition

The figure plots the average inventor complementarity measure (*Knowledge Base Overlap Ratio*) calculated based on pre-merger patents, by stayer, leaver, and stopper inventors who are target and acquirer inventors respectively. The sample includes inventors from the main sample. Specifically, the sample only includes deals (both completed and withdrawn) where both the target and the acquirer have at least 1 patent in the five years before the deal announcement date, and the inventors are included if they file at least 1 patent with either the target or the acquirer in the same window. The error bar shows 95% confidence interval. The y-axis on the left indicates the scale for the target inventors while the one on the right indicates the scale for the acquirer inventors.

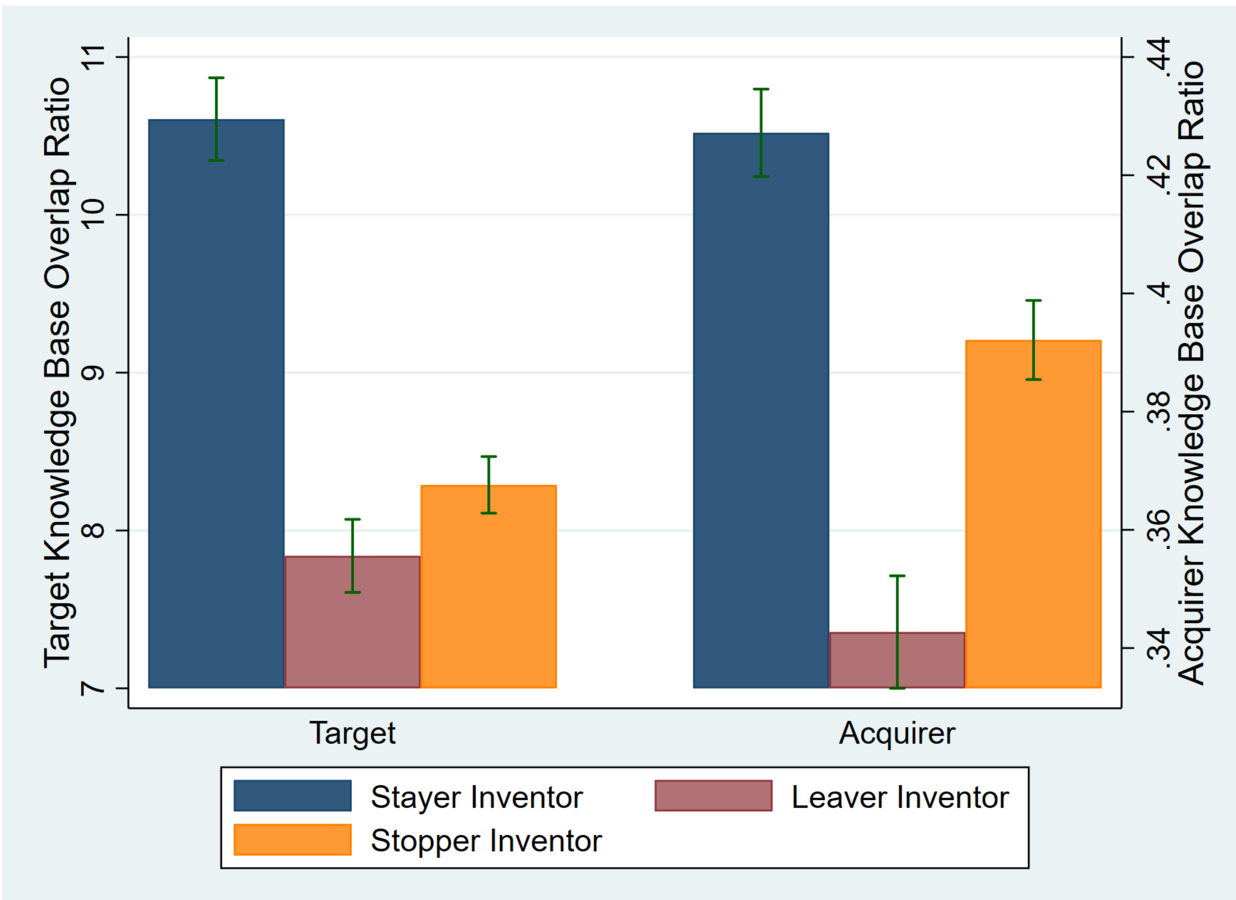
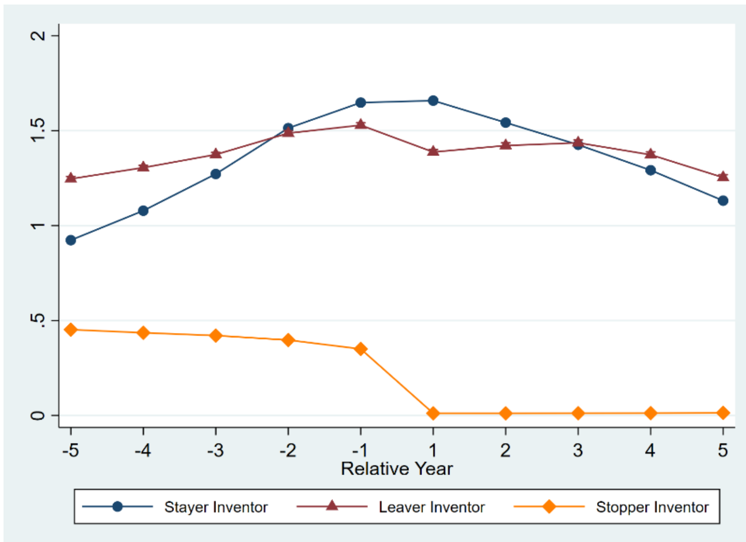
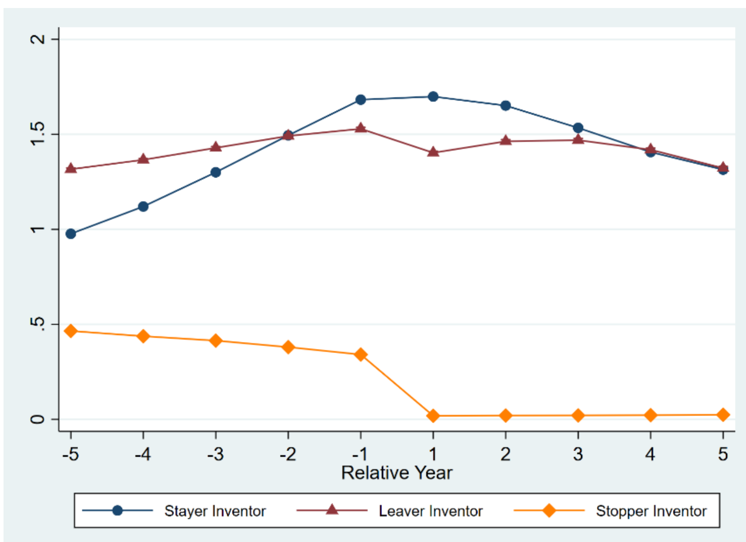


Figure 3. Innovation Productivity by Inventor Attrition

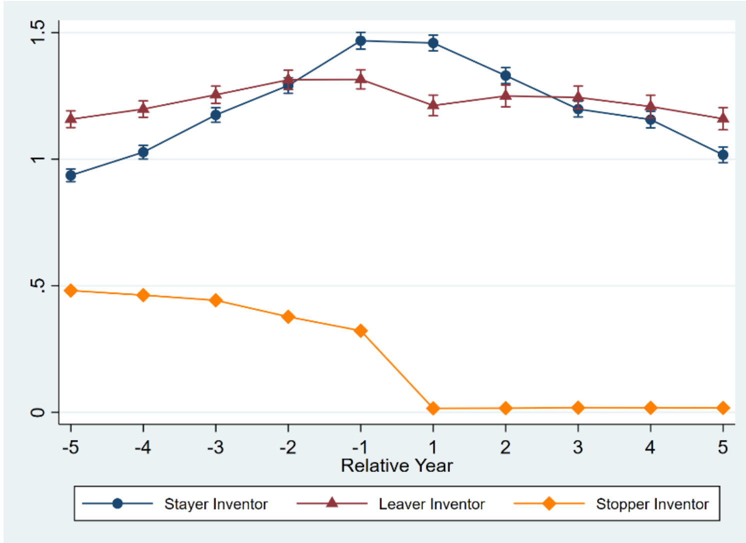
The figure plots the average annual patent count of inventors by different attrition types (stayer, leaver, and stopper) over the relative years. The definitions of different attrition types are presented in Appendix Variable Definitions. The sample includes inventors from the main sample. Specifically, the sample only includes deals (both completed and withdrawn) where both the target and the acquirer have at least 1 patent in the five years before the deal announcement date, and the inventors are included if they file at least 1 patent with either the target or the acquirer in the same window. Panel A shows the statistics for the acquirer and counterfactual acquirer, while Panel B shows that of the target and the counterfactual target. 95% confidence intervals are presented around the mean.

Panel A: Acquirer Inventors (upper graph), Counterfactual Acquirer Inventors (lower graph)





Panel B: Target Inventors (upper graph), Counterfactual Target Inventors (lower graph)



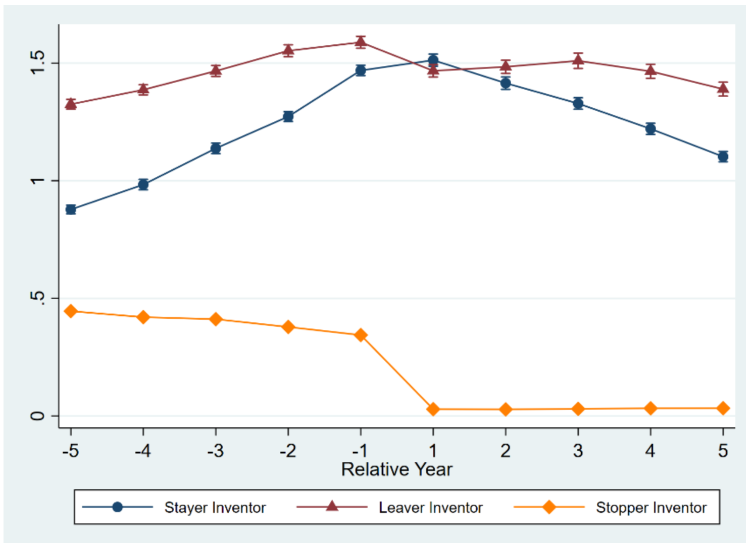
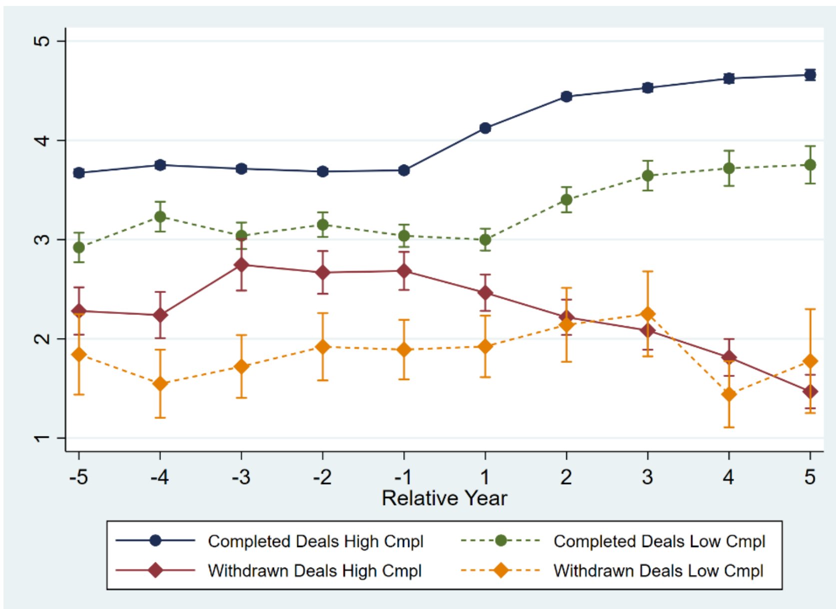


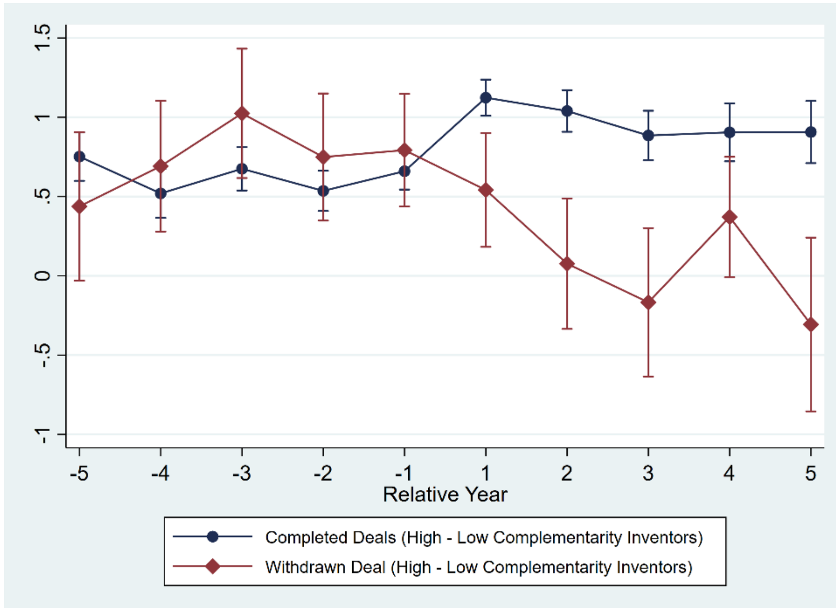
Figure 4. Acquirer Stayer Innovation Specificity by Inventor Complementarity

The figure plots the average acquirer stayer lead inventor *Innovation Specificity Unique (%)* measure over the relative years by deal status and inventor complementarity level, which is the dependent variables for the triple-differences regressions. For Panel A, the statistics are presented by four different inventor groups respectively ("Completed High" represents completed deals and high complementarity inventors, "Completed Low" represents completed deals and low complementarity inventors, "Withdrawn High" represents withdrawn deals and high complementarity inventors, and "Withdrawn Low" represents withdrawn deals and low complementarity inventors.) For Panel B, the statistics are presented as the mean differences between high and low complementarity inventor groups, for completed and withdrawn deals respectively. For Panel C, the statistics are presented as the mean differences between inventors from completed and withdrawn deals, for high and low complementarity inventors respectively. 95% confidence interval is presented around the mean.

Panel A: Innovation Specificity by Deal Status and Inventor Complementarity (Cmpl) Level



Panel B: Innovation Specificity Differences between High and Low Complementarity Inventors, by Deal Status



Panel C: Innovation Specificity Differences between Completed and Withdrawn Deas, by Inventor Complementarity Level

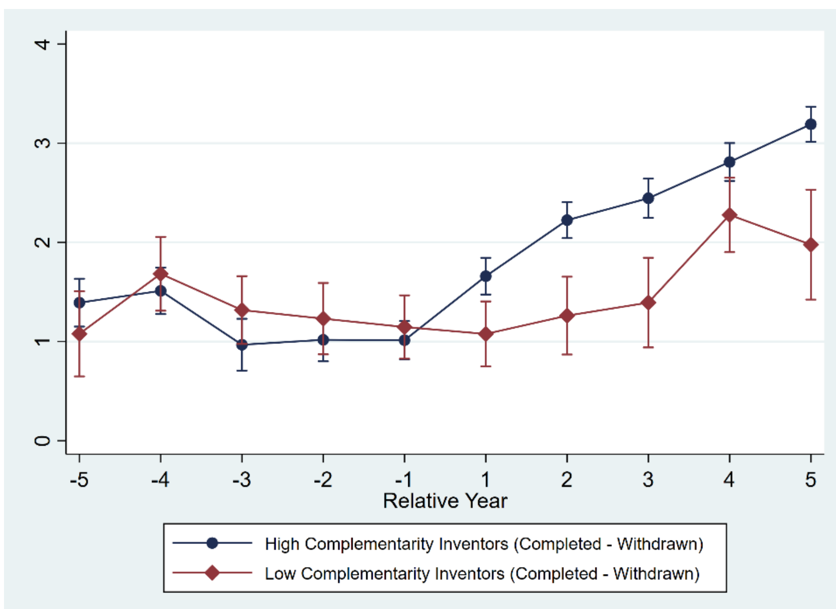
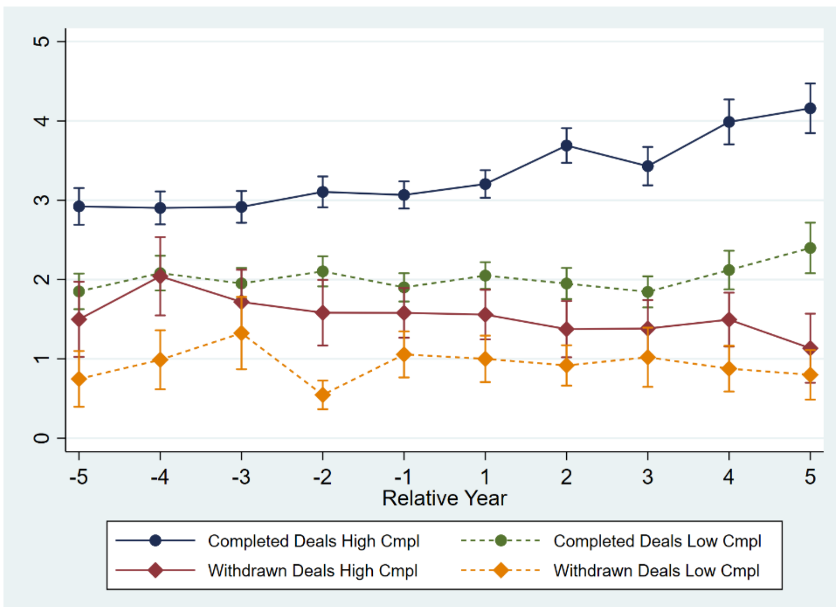


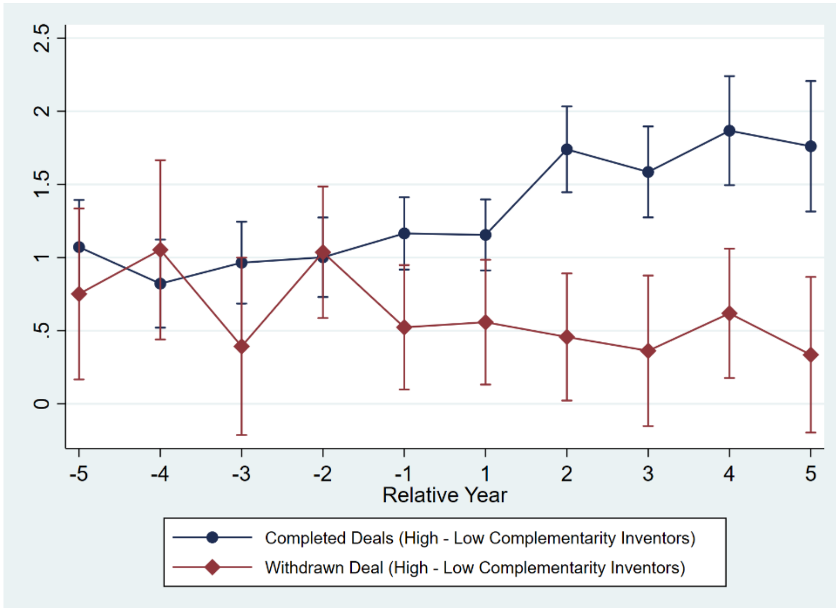
Figure 5. Target Stayer Innovation Specificity by Inventor Complementarity

The figure plots the average target stayer lead inventor *Innovation Specificity Unique (%)* measure over the relative years by deal status and inventor complementarity level, which is the dependent variables for the triple-differences regressions. For Panel A, the statistics are presented by four different inventor groups respectively ("Completed High" represents completed deals and high complementarity inventors, "Completed Low" represents completed deals and low complementarity inventors, "Withdrawn High" represents withdrawn deals and high complementarity inventors, and "Withdrawn Low" represents withdrawn deals and low complementarity inventors.) For Panel B, the statistics are presented as the mean differences between high and low complementarity inventor groups, for completed and withdrawn deals respectively. For Panel C, the statistics are presented as the mean differences between inventors from completed and withdrawn deals, for high and low complementarity inventors respectively. 95% confidence interval is presented around the mean.

Panel A: Innovation Specificity by Deal Status and Inventor Complementarity (Cmpl) Level



Panel B: Innovation Specificity Differences between High and Low Complementarity Inventors, by Deal Status



Panel C: Innovation Specificity Differences between Completed and Withdrawn Deals, by Inventor Complementarity Level

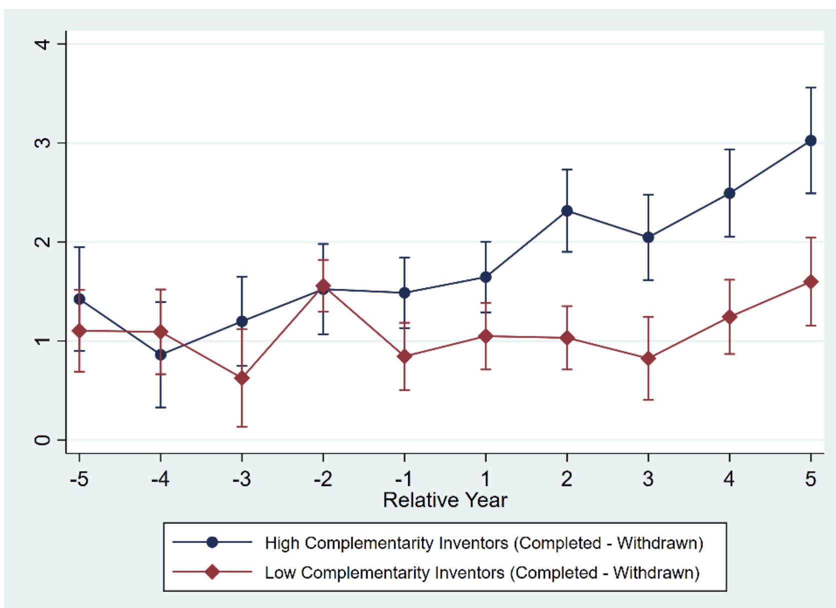


Table 1. Summary Statistics

The table presents summary statistics of the sample. Panel A provide the deal, acquirer and target firm characteristics of deals from the main sample, where both the target and the acquirer have at least 1 patent in the 5 years before the deal announcement date. Panel B provides characteristics of inventors from the main sample, which are from the same deals as Panel A, and additionally require the inventors to have at least 1 patent with the firm in the 5 years before the deal announcement date. The patent statistics are based on patents inventor participated with the focal target/acquirer firm. Panel C provides statistics for the inventor specificity measures, and are from the sample where the inventors are stayer lead inventors and have at least one non-missing specificity observations.

Panel A: Firm and Deal Characteristics

	All Deals			Completed			Withdrawn		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Acquirer Characteristics									
Total Assets ($ Million)	5,190	11,547	50,376	4,910	11,855	51,228	280	6,147	31,522
Avg. Patent Age (Years)	5,404	6.63	4.69	5,105	6.70	4.73	299	5.43	3.70
All Patents [-5,-1]	5,404	452.89	1393.04	5,105	470.34	1424.71	299	154.84	569.62
Stayer Patents [-5,-1]	4,278	366.50	1074.78	4,079	378.02	1095.54	199	130.51	417.64
Stayer Patents [+1,+5]	4,260	303.37	829.46	4,062	312.00	843.43	198	126.40	420.13
Target Characteristics									
Total Assets ($ Million)	1,321	2,259	30,116	1,156	2,401	32,149	165	1,268	4,415
Avg. Patent Age (Years)	5,404	4.83	3.54	5,105	4.84	3.57	299	4.64	3.13
All Patents [-5,-1]	5,404	16.46	101.75	5,105	15.14	98.51	299	38.88	144.84
Stayer Patents [-5,-1]	2,419	16.64	97.1	2,281	15.73	97.19	138	31.62	94.64
Stayer Patents [+1,+5]	2,396	14.37	87.54	2,257	13.46	86.28	139	29.06	105.3
Deal Characteristics									
Relative Deal Size (%)	3,566	26.92	76.61	3,360	23.63	49.25	206	80.57	243.41
Same SIC2 (%)	5,404	51.89	49.97	5,105	51.81	49.97	299	53.18	49.98
All Cash (%)	5,404	22.69	41.88	5,105	23.11	42.16	299	15.38	36.14
All Stock (%)	5,404	16.06	36.72	5,105	15.24	35.94	299	30.1	45.95
Public Target (%)	5,404	27.26	44.53	5,105	25.33	43.49	299	60.2	49.03

Panel B: Inventor Characteristics

	All Deals			Completed			Withdrawn		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Acquirer Inventor Characteristics									
Base Overlap Ratio (%)	2,266,089	0.41	3.38	2,221,122	0.40	3.37	44,967	0.80	3.98
Patent Count [-5,-1]	2,266,550	2.94	5.27	2,221,582	2.95	5.29	44,968	2.44	3.83
Average Team Size [-5,-1]	2,266,550	3.98	2.59	2,221,582	3.99	2.60	44,968	3.41	2.24
Total # Co-Inventors [-5,-1]	2,266,550	6.37	6.72	2,221,582	6.40	6.75	44,968	4.82	4.40
Target Inventor Characteristics									
Base Overlap Ratio (%)	95,401	8.07	17.73	82,727	8.85	18.63	12,674	2.98	8.40
Patent Count [-5,-1]	95,409	2.37	3.39	82,735	2.42	3.51	12,674	2.04	2.38
Average Team Size [-5,-1]	95,409	3.72	2.53	82,735	3.81	2.59	12,674	3.14	2.00
Total # Co-Inventors [-5,-1]	95,409	5.08	4.77	82,735	5.24	4.91	12,674	4.07	3.53

Panel C: Innovation Specificity

	All Deals			Completed			Withdrawn		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Acquirer Inventors' Innovation Specificity									
Innovation Specificity Unique (%)	871,814	3.99	5.05	856,630	4.02	5.07	15,184	2.21	3.57
Innovation Specificity TF (%)	871,814	4.18	6.17	856,630	4.22	6.20	15,184	2.29	4.30
Innovation Specificity TF-IDF (%)	871,814	4.16	6.36	856,630	4.18	6.38	15,184	2.79	5.07
Target Inventor's Innovation Specificity									
Innovation Specificity Unique (%)	38,894	2.56	4.44	34,472	2.72	4.57	4,422	1.31	2.88
Innovation Specificity TF (%)	38,894	2.61	5.12	34,472	2.78	5.28	4,422	1.30	3.41
Innovation Specificity TF-IDF (%)	38,894	3.14	6.04	34,472	3.31	6.21	4,422	1.80	4.23

Table 2. Inventor Attrition Statistics

The table presents inventor attrition statistics for both completed and withdrawn deals. Panel A illustrates the distribution of attrition status for the acquirer and counterfactual acquirer inventors. Acquirer inventors are from the main sample (merger deals where both the target and the acquirer have at least 1 patent in the same period, and have participated in at least one patents with the either the target or the acquirer firm in the 5 years before the deal announcement dates). Counterfactual acquirer inventors are from the counterfactual acquirer and have participated in at least one patents with the counterfactual acquirer firm in the 5 years before the deal announcement dates. Panel B provides that of the target and counterfactual target inventors defined accordingly. The *Stayer* is defined as inventors who have filed at least 1 patent with the joint firm in the 5 years after the deal resolution date (withdrawn date for the withdrawn deals or effective date for the completed deals). The *Leaver* is defined as inventors who did not file any patents with the joint entity and have filed at least 1 patent with another firm in the 5 years after the deal resolution date. The *Stopper* is defined as inventors who did not file any patents in the 5 years after the deal resolution date.

Panel A. Acquirer Inventors

	Acquirer Inventors				Counterfactual Acquirer Inventors			
	Completed		Withdrawn		Completed		Withdrawn	
	Obs	%	Obs	%	Obs	%	Obs	%
Stayer	837,463	37.70	14,378	31.97	1,715,780	36.75	29,057	32.56
Leaver	364,872	16.42	6,965	15.49	814,999	17.46	14,596	16.36
Stopper	1,019,247	45.88	23,625	52.54	2,137,620	45.79	45,581	51.08
All	2,221,582	100.00	44,968	100.00	4,668,399	100.00	89,234	100.00

Panel B. Target Inventors

	Target Inventors				Counterfactual Target Inventors			
	Completed		Withdrawn		Completed		Withdrawn	
	Obs	%	Obs	%	Obs	%	Obs	%
Stayer	23,546	28.46	2,894	22.83	74,355	26.85	10,890	29.96
Leaver	17,980	21.73	2,552	20.14	62,418	22.54	7,339	20.19
Stopper	41,209	49.81	7,228	57.03	140,116	50.60	18,122	49.85
All	82,735	100.00	12,674	100.00	276,889	100.00	36,351	100.00

Table 3. Statistics on Post-Merger Team Composition in Completed Deals

The table presents stayer inventor post-merger team composition statistics for the completed deals. The sample includes post-merger patents participated by at least one inventor from the main sample, which include deals where both the target and the acquirer have at least 1 patent in the 5 years before the deal announcement date, and inventors who have filed at least 1 patent with either the target or the acquirer firm in the same period. Panel A is for the acquirer inventors while Panel B is for target inventors. "*Non-mix with target*" indicates cases where the acquirer inventors do not have any co-inventors on the same patent that are affiliated with the target pre-merger, while "*Mix with target*" indicates cases where at least one co-inventor are from the target side. "*Lead inventor identity*" categorizes the affiliation of the lead inventors of the patent, where "*Other*" includes pre-merger inventors whose affiliation is indecisive, or new inventors that didn't participate in any pre-merger patents. "*Majority of inventor identity*" categorizes the majority of the affiliation of all the inventors of the patent. "*Target*" includes cases where target inventors constitute high than or equal to 50% of the team, "*Acquirer*" includes cases where the acquirer inventors make up at least 50% of the team. "*Other*" captures all the remaining cases.

Panel A: Acquirer Inventors

	Non-mix with target inventors			Mix with target inventors		
Unique patent-inventor pairs	3,854,556			6,860		
% of total	99.82%			0.18%		
Unique patents	1,762,240			3,808		
% of total	99.78%			0.22%		
	Lead inventor identity					
	Acquirer	Target	Other	Acquirer	Target	Other
Unique patents	1,350,184	0	412,056	1,611	1,325	872
% of total	76.62%	0.00%	23.38%	42.31%	34.80%	22.90%
	Majority of inventor identity					
	Acquirer	Target	Other	Acquirer	Target	Other
Unique patents	1,473,369	0	288,871	962	1,118	1,728
% of total	83.61%	0.00%	16.39%	25.26%	29.36%	45.38%

Panel B: Target Inventors

	Non-mix with acquirer inventors			Mix with acquirer inventors		
Unique patent-inventor pairs	91,672			5,661		
% of total	94.18%			5.82%		
Unique patents	44,046			3,808		
% of total	92.04%			7.96%		
	Lead inventor identity					
	Target	Acquirer	Other	Target	Acquirer	Other
Unique patents	34,918	0	9,128	1,325	1,611	872
% of total	79.28%	0.00%	20.72%	34.80%	42.31%	22.90%
	Majority of inventor identity					
	Target	Acquirer	Other	Target	Acquirer	Other
Unique patents	36,783	0	7,263	1,118	962	1,728
% of total	83.51%	0.00%	16.49%	29.36%	25.26%	45.38%

Table 4. Inventor Complementarity and Inventor Attrition

The table presents the linear probability regression estimates of inventor attrition. The sample includes inventors from the main sample. Specifically, the sample only includes deals (both completed and withdrawn) where both the target and the acquirer have at least 1 patent in the five years before the deal announcement date, and the inventors are included if they file at least 1 patent with either the target or the acquirer in the same window. The regression includes inventors who are either stayers or leavers and the dependent variable *Prob(Stayer)* is a dummy variable that equals to one if the inventor is a stayer. Column (1) and (2) present the regressions for acquirer inventors while Column (3) and (4) present that for the target inventors. *High Complementarity* is a dummy variable that equals to one if the inventor whose knowledge base overlap ratio is greater than or equal to 75th percentile of the deal. For column (2) and (4), the regressions also include inverse hyperbolic transformed *patent count [-5,-1], average team size [-5,-1], and Total # Co-Inventors [-5,-1],* based on patents participated by the focal inventor. Column (3) and (6) further include inverse hyperbolic transformed *patent count [+1,+5]* based on patents participated by the focal inventor as additional control. The details of variable definitions are presented in Appendix Variable Definitions. All equations also include deal fixed effects and the standard errors are clustered at the deal level.

	Prob (Stayer)					
	Acquirer Inventors			Target Inventors		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
High Complementarity	0.028***	0.031***	0.031***	0.056***	0.054***	0.055***
	(0.005)	(0.004)	(0.004)	(0.011)	(0.011)	(0.011)
Patent Count [-5,-1]		0.050***	0.039***		0.071***	0.060***
		(0.002)	(0.002)		(0.009)	(0.009)
Average Team Size [-5,-1]		0.106***	0.129***		0.117***	0.147***
		(0.003)	(0.003)		(0.018)	(0.018)
Total # Co-Inventors [-5,-1]		-0.085***	-0.106***		-0.115***	-0.142***
		(0.003)	(0.003)		(0.014)	(0.014)
Patent Count [+1,+5]			0.041***			0.050***
			(0.001)			(0.005)
Constant	0.695***	0.614***	0.562***	0.559***	0.487***	0.425***
	(0.000)	(0.006)	(0.006)	(0.002)	(0.021)	(0.021)
Observations	1,223,055	1,223,055	1,223,055	45,880	45,880	45,880
R-squared	0.198	0.201	0.206	0.369	0.373	0.379
Y Mean	0.696	0.696	0.696	0.568	0.568	0.568
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering	Deal	Deal	Deal	Deal	Deal	Deal

Table 5. Inventor Complementarity and Innovation Specificity

The table presents the regression estimates of triple differences regression of inventor specificity. The panel includes deal-inventor-relative year observations of acquirer stayer lead inventors (Panel A) and target stayer lead inventors (Panel B) for the 5 years before the deal announcement date and the 5 years after the deal resolution date (withdrawn date for the withdrawn deals and effective date for the completed deals). The dependent variables are three different measures of inventor specificity, *Innovation Specificity Unique (%), TF (%)*, and *TF-IDF (%),* capturing the acquirer (target) inventor's use of acquirer-(target-) specific words in various ways. *Complete* is a dummy variable that equals to one if the deal is completed, and zero if withdrawn. *Post* is a dummy variable that equals to one if the observation comes from post-merger years. *High Cmpl* is a dummy variable that equals to one if the inventor's knowledge base overlap ratio with the counterparty in the acquisition is above or equal to 75th percentile of all the inventors who have filed at least 1 patent in the 5-year pre-merger window. For column (2), (4) and (6), the regressions also include inventor pre-merger time invariant control variables, inverse hyperbolic transformed *patent count [-5,-1], average team size [-5,-1],* and *Total # Co-Inventors [-5,-1],* based on patents led by the focal lead inventor with the target/acquirer firm of the deal. The details of variable definitions are presented in Appendix Variable Definitions. All equations also include deal fixed effects and the standard errors are clustered at the deal level.

Panel A. Acquirer Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	1.043***	1.043***	1.057***	1.057***	1.093***	1.093***
	(0.243)	(0.243)	(0.273)	(0.272)	(0.264)	(0.264)
Complete × Post	0.160	0.160	0.204	0.203	0.225	0.223
	(0.179)	(0.179)	(0.224)	(0.223)	(0.234)	(0.234)
Complete × High Cmpl	0.282	0.278	0.523*	0.519*	0.687**	0.682**
	(0.228)	(0.228)	(0.273)	(0.274)	(0.328)	(0.329)
Post × High Cmpl	-0.457**	-0.457**	-0.494**	-0.494**	-0.565***	-0.565***
	(0.178)	(0.177)	(0.205)	(0.205)	(0.203)	(0.203)
Post	-0.315*	-0.316*	-0.389*	-0.391*	-0.364*	-0.366*
	(0.173)	(0.173)	(0.211)	(0.211)	(0.213)	(0.213)
High Cmpl	0.365***	0.373***	0.389***	0.397***	0.665***	0.675***
	(0.132)	(0.132)	(0.126)	(0.126)	(0.145)	(0.146)
Patent Count [-5,-1]		0.004		-0.009		-0.015
		(0.042)		(0.042)		(0.041)
Average Team Size [-5,-1]		0.002		-0.017		-0.016
		(0.051)		(0.059)		(0.060)
Total # Co-Inventors [-5,-1]		-0.042		-0.024		-0.027
		(0.057)		(0.059)		(0.058)
Constant	3.196***	3.274***	3.168***	3.263***	2.727***	2.836***
	(0.168)	(0.175)	(0.221)	(0.230)	(0.270)	(0.279)
Observations	871,750	871,377	871,750	871,377	871,750	871,377
R-squared	0.357	0.357	0.290	0.290	0.259	0.259
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	3.993	3.993	4.183	4.183	4.158	4.158

Panel B. Target Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	0.745**	0.750**	0.755**	0.761**	0.981**	0.988**
	(0.328)	(0.328)	(0.344)	(0.345)	(0.451)	(0.452)
Complete × Post	-0.027	-0.032	-0.129	-0.137	-0.188	-0.197
	(0.333)	(0.332)	(0.362)	(0.361)	(0.488)	(0.487)
Complete × High Cmpl	-0.362*	-0.349	-0.339	-0.321	-0.541*	-0.523*
	(0.217)	(0.220)	(0.241)	(0.244)	(0.310)	(0.315)
Post × High Cmpl	-0.252	-0.255	-0.308	-0.312	-0.512	-0.517
	(0.201)	(0.201)	(0.251)	(0.252)	(0.347)	(0.348)
Post	-0.150	-0.149	-0.118	-0.114	-0.092	-0.088
	(0.281)	(0.279)	(0.322)	(0.320)	(0.434)	(0.432)
High Cmpl	0.295***	0.291**	0.346**	0.340**	0.617***	0.612***
	(0.111)	(0.115)	(0.155)	(0.160)	(0.213)	(0.219)
Patent Count [-5,-1]		0.063		0.091		0.087
		(0.061)		(0.098)		(0.099)
Average Team Size [-5,-1]		-0.259**		-0.317***		-0.388***
		(0.116)		(0.118)		(0.147)
Total # Co-Inventors [-5,-1]		-0.088		-0.098		-0.087
		(0.122)		(0.170)		(0.181)
Constant	2.549***	3.027***	2.604***	3.146***	3.094***	3.734***
	(0.073)	(0.295)	(0.082)	(0.240)	(0.102)	(0.294)
Observations	38,886	38,873	38,886	38,873	38,886	38,873
R-squared	0.554	0.555	0.484	0.486	0.443	0.444
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	2.562	2.563	2.614	2.615	3.142	3.143

Table 6. Innovation Specificity: Dynamics of the Effect

The table presents the dynamic regression estimates of inventor specificity. The panel includes deal-inventor-relative year observations of acquirer stayer lead inventors (Panel A) and target stayer lead inventors (Panel B) for the 5 years before the deal announcement date and the 5 years after the deal resolution date (withdrawn date for the withdrawn deals and effective date for the completed deals). The dependent variables are three different measures of inventor specificity, *Innovation Specificity Unique (%), TF (%),* and *TF-IDF (%),* capturing the acquirer (target) inventor's use of acquirer-(target-) specific words in various ways. *Complete* is a dummy variable that equals to one if the deal is completed, and zero if withdrawn. *High Cmpl* is a dummy variable that equals to one if the inventor's knowledge base overlap ratio with the counterparty in the acquisition is above or equal to 75th percentile of all the inventors who have filed at least 1 patent in the 5-year pre-merger window. The regression includes a set of year dummy variables indicating the respective relative year. The omitted Lower Degree Interactions include the single regressors (except Completed omitted due to collinearity) as well as their pairwise interactions between *Complete*, *High Comp*, and the year dummies. For column (2), (4) and (6), the regressions also include inventor pre-merger time invariant control variables, inverse hyperbolic transformed *patent count [-5,-1], average team size [-5,-1],* and *Total # Co-Inventors [-5,-1],* based on patents led by the focal lead inventor with the target/acquirer firm of the deal. The details of variable definitions are presented in Appendix Variable Definitions. All equations also include deal fixed effects and the standard errors are clustered at the deal level.

Panel A. Acquirer Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × High Cmpl × (t = T-1)	0.047	0.050	0.081	0.084	0.215	0.217
	(0.198)	(0.198)	(0.259)	(0.259)	(0.307)	(0.306)
Complete × High Cmpl × (t = T+1)	0.676***	0.683***	0.637**	0.647**	0.650**	0.659**
	(0.261)	(0.262)	(0.258)	(0.259)	(0.263)	(0.264)
Complete × High Cmpl × (t = T+2)	1.296***	1.296***	1.490***	1.489***	1.672***	1.671***
	(0.325)	(0.324)	(0.384)	(0.383)	(0.414)	(0.413)
Complete × High Cmpl × (t = T+3)	1.412***	1.408***	1.475***	1.471***	1.600***	1.594***
	(0.355)	(0.355)	(0.416)	(0.416)	(0.452)	(0.452)
Complete × High Cmpl × (t = T+4)	0.851**	0.847**	0.829**	0.830**	0.894**	0.895**
	(0.386)	(0.386)	(0.380)	(0.380)	(0.426)	(0.426)
Complete × High Cmpl × (t = T+5)	1.486***	1.484***	1.376***	1.376***	1.386***	1.385***
	(0.398)	(0.399)	(0.432)	(0.432)	(0.468)	(0.468)
Constant	3.056***	3.139***	3.033***	3.133***	2.583***	2.698***
	(0.168)	(0.174)	(0.220)	(0.228)	(0.269)	(0.277)
Observations	871,750	871,377	871,750	871,377	871,750	871,377
R-squared	0.358	0.358	0.291	0.291	0.259	0.259
Lower Degree Interactions	YES	YES	YES	YES	YES	YES
Controls	NO	YES	NO	YES	NO	YES
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	3.993	3.993	4.183	4.183	4.158	4.158

Panel B. Target Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × High Cmpl × (t = T-1)	0.129	0.141	0.141	0.159	0.139	0.158
	(0.288)	(0.285)	(0.334)	(0.332)	(0.428)	(0.426)
Complete × High Cmpl × (t = T+1)	0.266	0.271	0.137	0.145	0.175	0.184
	(0.307)	(0.305)	(0.334)	(0.333)	(0.419)	(0.416)
Complete × High Cmpl × (t = T+2)	0.947**	0.960**	0.941**	0.957**	1.301**	1.319**
	(0.412)	(0.414)	(0.431)	(0.433)	(0.581)	(0.582)
Complete × High Cmpl × (t = T+3)	1.180***	1.211***	1.314**	1.355***	1.718**	1.764**
	(0.429)	(0.433)	(0.516)	(0.520)	(0.698)	(0.701)
Complete × High Cmpl × (t = T+4)	0.538	0.529	0.586	0.578	0.652	0.642
	(0.423)	(0.416)	(0.486)	(0.483)	(0.642)	(0.638)
Complete × High Cmpl × (t = T+5)	1.248**	1.248**	1.493***	1.494***	1.807**	1.809**
	(0.536)	(0.535)	(0.556)	(0.556)	(0.748)	(0.746)
Constant	2.548***	3.030***	2.610***	3.158***	3.087***	3.734***
	(0.084)	(0.256)	(0.099)	(0.232)	(0.130)	(0.293)
Observations	38,886	38,873	38,886	38,873	38,886	38,873
R-squared	0.555	0.556	0.485	0.486	0.443	0.445
Lower Degree Interactions	YES	YES	YES	YES	YES	YES
Controls	NO	YES	NO	YES	NO	YES
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	2.562	2.563	2.614	2.615	3.142	3.143

Table 7. Innovation Specificity: Excluding Common Patent Attorneys

The table presents the regression estimates of triple differences regression of inventor specificity for separating patent attorney observations only. The panel includes deal-inventor-relative year observations as Table 5, except removing acquirer (target) inventor-years after the year the inventor starts to share a common patent attorney with the target (acquirer) pre-merger patent attorneys. The dependent variables are three different measures of inventor specificity, *Innovation Specificity Unique (%), TF (%),* and *TF-IDF (%)*, capturing the acquirer (target) inventor's use of acquirer-(target-) specific words in various ways. *Complete* is a dummy variable that equals to one if the deal is completed, and zero if withdrawn. *Post* is a dummy variable that equals to one if the observation comes from post-merger years. *High Cmpl* is a dummy variable that equals to one if the inventor's knowledge base overlap ratio with the counterparty in the acquisition is above or equal to 75th percentile of all the inventors who have filed at least 1 patent in the 5-year pre-merger window. For column (2), (4) and (6), the regressions also include inventor pre-merger time invariant control variables, inverse hyperbolic transformed *patent count [-5,-1], average team size [-5,-1],* and *Total # Co-Inventors [-5,-1],* based on patents led by the focal lead inventor with the target/acquirer firm of the deal. The details of variable definitions are presented in Appendix Variable Definitions. All equations also include deal fixed effects and the standard errors are clustered at the deal level.

Panel A: Acquirer Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	1.030***	1.030***	1.027***	1.029***	1.076***	1.078***
	(0.252)	(0.252)	(0.280)	(0.280)	(0.269)	(0.269)
Complete × Post	0.130	0.128	0.190	0.186	0.190	0.186
	(0.174)	(0.173)	(0.216)	(0.216)	(0.225)	(0.225)
Complete × High Cmpl	0.332	0.326	0.601**	0.596**	0.754**	0.747**
	(0.223)	(0.223)	(0.270)	(0.270)	(0.326)	(0.326)
Post × High Cmpl	-0.463***	-0.463***	-0.484**	-0.484**	-0.576***	-0.576***
	(0.179)	(0.179)	(0.203)	(0.203)	(0.202)	(0.202)
Post	-0.260*	-0.260*	-0.345*	-0.346*	-0.287	-0.288
	(0.157)	(0.157)	(0.193)	(0.193)	(0.195)	(0.195)
High Cmpl	0.375***	0.384***	0.396***	0.405***	0.681***	0.693***
	(0.136)	(0.136)	(0.127)	(0.127)	(0.149)	(0.150)
Patent Count [-5,-1]		-0.005		-0.014		-0.020
		(0.043)		(0.043)		(0.042)
Average Team Size [-5,-1]		0.000		-0.017		-0.011
		(0.051)		(0.060)		(0.060)
Total # Co-Inventors [-5,-1]		-0.037		-0.023		-0.028
		(0.057)		(0.060)		(0.058)
Constant	3.113***	3.198***	3.051***	3.150***	2.588***	2.699***
	(0.159)	(0.168)	(0.217)	(0.227)	(0.267)	(0.276)
Observations	813,375	813,071	813,375	813,071	813,375	813,071
R-squared	0.354	0.354	0.286	0.287	0.255	0.255
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	3.959	3.959	4.144	4.144	4.099	4.099

Panel B: Target Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	0.755**	0.759**	0.806**	0.812**	1.048**	1.054**
	(0.322)	(0.323)	(0.341)	(0.342)	(0.454)	(0.455)
Complete × Post	-0.066	-0.068	-0.198	-0.200	-0.272	-0.274
	(0.324)	(0.323)	(0.354)	(0.353)	(0.488)	(0.487)
Complete × High Cmpl	-0.354*	-0.339*	-0.335	-0.315	-0.550*	-0.528*
	(0.183)	(0.185)	(0.215)	(0.217)	(0.288)	(0.292)
Post × High Cmpl	-0.272	-0.275	-0.374	-0.378	-0.591*	-0.596*
	(0.192)	(0.192)	(0.246)	(0.246)	(0.345)	(0.345)
Post	-0.089	-0.092	-0.031	-0.033	0.024	0.021
	(0.259)	(0.258)	(0.301)	(0.300)	(0.422)	(0.420)
High Cmpl	0.313***	0.309***	0.382**	0.375**	0.665***	0.659***
	(0.108)	(0.112)	(0.150)	(0.155)	(0.211)	(0.218)
Patent Count [-5,-1]		0.062		0.098		0.097
		(0.054)		(0.102)		(0.100)
Average Team Size [-5,-1]		-0.264**		-0.309***		-0.377***
		(0.118)		(0.115)		(0.145)
Total # Co-Inventors [-5,-1]		-0.083		-0.103		-0.096
		(0.126)		(0.177)		(0.188)
Constant	2.567***	3.044***	2.593***	3.119***	3.043***	3.665***
	(0.062)	(0.292)	(0.075)	(0.231)	(0.094)	(0.286)
Observations	35,045	35,036	35,045	35,036	35,045	35,036
R-squared	0.556	0.557	0.481	0.483	0.440	0.441
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	2.607	2.608	2.642	2.642	3.141	3.142

Table 8. Placebo Test: Use of Common Words in Patents

The table presents the regression estimates of triple differences regression of inventor use of the common words. The panel includes deal-inventor-relative year observations of acquirer stayer lead inventors (Panel A) and target stayer lead inventors (Panel B) for the 5 years before the deal announcement date and the 5 years after the deal resolution date (withdrawn date for the withdrawn deals and effective date for the completed deals). The dependent variables are three different measures of inventor's use of words that are used by both the acquirer (target) and the counterfactual acquirers (counterfactual targets) patents, *Common Words Unique (%), TF (%),* and *TF-IDF (%)*. *Complete* is a dummy variable that equals to one if the deal is completed, and zero if withdrawn. *Post* is a dummy variable that equals to one if the observation comes from post-merger years. *High Cmpl* is a dummy variable that equals to one if the inventor's knowledge base overlap ratio with the counterparty in the acquisition is above or equal to 75th percentile of all the inventors who have filed at least 1 patent in the 5-year pre-merger window. For column (2), (4) and (6), the regressions also include inventor pre-merger time invariant control variables, inverse hyperbolic transformed *patent count [-5,-1]*, *average team size [-5,-1],* and *Total # Co-Inventors [-5,-1]*, based on patents led by the focal lead inventor with the target/acquirer firm of the deal. The details of variable definitions are presented in Appendix Variable Definitions. All equations also include deal fixed effects and the standard errors are clustered at the deal level.

Panel A: Acquirer Inventors

	Common Words					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	% Unique	% Unique	% TF	% TF	% TF-IDF	% TF-IDF
Complete × Post × High Cmpl	-0.010	-0.010	-0.013	-0.013	-0.011	-0.011
	(0.013)	(0.013)	(0.012)	(0.012)	(0.009)	(0.009)
Complete × Post	0.025*	0.025*	0.025*	0.025*	0.012	0.012
	(0.014)	(0.014)	(0.013)	(0.013)	(0.010)	(0.010)
Complete × High Cmpl	0.021**	0.021**	0.028**	0.028**	0.025**	0.025**
	(0.011)	(0.010)	(0.012)	(0.012)	(0.011)	(0.011)
Post × High Cmpl	0.007	0.007	0.008	0.008	-0.002	-0.002
	(0.009)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)
Post	0.002	0.001	0.004	0.004	0.019***	0.019**
	(0.011)	(0.011)	(0.010)	(0.010)	(0.007)	(0.007)
High Cmpl	0.021***	0.021***	0.023**	0.023***	0.032***	0.032***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.008)	(0.008)
Patent Count [-5,-1]		-0.002*		-0.002**		-0.002**
		(0.001)		(0.001)		(0.001)
Average Team Size [-5,-1]		-0.005***		-0.005***		-0.004***
		(0.002)		(0.002)		(0.001)
Total # Co-Inventors [-5,-1]		0.001		0.001		0.001
		(0.001)		(0.001)		(0.001)
Constant	0.234***	0.243***	0.210***	0.219***	0.139***	0.148***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
Observations	871,750	871,377	871,750	871,377	871,750	871,377
R-squared	0.783	0.783	0.729	0.729	0.716	0.716
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	0.285	0.285	0.270	0.270	0.202	0.202

Panel B: Target Inventors

	Common Words					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	% Unique	% Unique	% TF	% TF	% TF-IDF	% TF-IDF
Complete × Post × High Cmpl	-0.004	-0.004	-0.004	-0.004	-0.016	-0.016
	(0.014)	(0.014)	(0.015)	(0.015)	(0.017)	(0.016)
Complete × Post	0.012	0.012	0.015	0.015	0.020	0.020
	(0.017)	(0.017)	(0.017)	(0.017)	(0.019)	(0.019)
Complete × High Cmpl	-0.018	-0.017	-0.021	-0.021	-0.022	-0.021
	(0.025)	(0.024)	(0.029)	(0.029)	(0.033)	(0.033)
Post × High Cmpl	0.016	0.016	0.016	0.016	0.021	0.021
	(0.013)	(0.013)	(0.014)	(0.014)	(0.016)	(0.016)
Post	-0.004	-0.004	-0.006	-0.006	-0.008	-0.009
	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)	(0.018)
High Cmpl	0.026	0.025	0.033	0.032	0.039	0.039
	(0.024)	(0.024)	(0.028)	(0.028)	(0.033)	(0.033)
Patent Count [-5,-1]		0.004**		0.005**		0.004*
		(0.002)		(0.002)		(0.002)
Average Team Size [-5,-1]		0.006		0.008		0.008
		(0.006)		(0.007)		(0.007)
Total # Co-Inventors [-5,-1]		-0.007		-0.009*		-0.009*
		(0.004)		(0.005)		(0.005)
Constant	0.640***	0.639***	0.635***	0.633***	0.562***	0.560***
	(0.003)	(0.012)	(0.003)	(0.015)	(0.004)	(0.015)
Observations	38,886	38,873	38,886	38,873	38,886	38,873
R-squared	0.877	0.877	0.857	0.857	0.832	0.832
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	0.652	0.652	0.650	0.649	0.580	0.580

Table 9. Innovation Specificity: Stacked Triple-Differences Specification

The table presents the regression estimates of stacked triple differences regression of inventor specificity. The panel includes cohort-deal-inventor-relative year observations of acquirer stayer lead inventors (Panel A) and target stayer lead inventors (Panel B) for the 5 years before the deal announcement date and the 5 years after the deal resolution date (withdrawn date for the withdrawn deals and effective date for the completed deals). A cohort is defined as a completed deal and all the withdrawn deals with the same announcement year. The dependent variables are three different measures of inventor specificity, *Innovation Specificity Unique (%), TF (%), and TF-IDF (%),* capturing the acquirer (target) inventor's use of acquirer-(target-) specific words in various ways. *Complete* is a dummy variable that equals to one if the deal is completed, and zero if withdrawn. *Post* is a dummy variable that equals to one if the observation comes from post-merger years. *High Cmpl* is a dummy variable that equals to one if the inventor's knowledge base overlap ratio with the counterparty in the acquisition is above or equal to 75th percentile of all the inventors who have filed at least 1 patent in the 5-year pre-merger window. For column (2), (4) and (6), the regressions also include inventor pre-merger time invariant control variables, inverse hyperbolic transformed *patent count [-5,-1], average team size [-5,-1],* and *Total # Co-Inventors [-5,-1],* based on patents led by the focal lead inventor with the target/acquirer firm of the deal. The details of variable definitions are presented in Appendix Variable Definitions. All equations also include cohort fixed effects and the standard errors are clustered at the cohort level.

Panel A. Acquirer Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	1.134***	1.133***	1.080***	1.080***	1.112***	1.111***
	(0.169)	(0.169)	(0.181)	(0.181)	(0.173)	(0.173)
Complete × Post	0.181	0.180	0.254**	0.252**	0.287**	0.286**
	(0.111)	(0.111)	(0.128)	(0.128)	(0.137)	(0.137)
Complete × High Cmpl	0.239	0.232	0.514**	0.504**	0.675**	0.665**
	(0.188)	(0.188)	(0.244)	(0.244)	(0.296)	(0.296)
Post × High Cmpl	-0.572***	-0.572***	-0.526***	-0.526***	-0.594***	-0.594***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.036)	(0.036)
Post	-0.020	-0.017	-0.244***	-0.241***	-0.223***	-0.219***
	(0.063)	(0.063)	(0.062)	(0.062)	(0.058)	(0.058)
High Comp	0.417***	0.427***	0.400***	0.411***	0.679***	0.691***
	(0.024)	(0.025)	(0.024)	(0.024)	(0.023)	(0.024)
Patent Count [-5,-1]		0.084***		0.111***		0.138***
		(0.020)		(0.020)		(0.020)
Average Team Size [-5,-1]		0.194***		0.233***		0.281***
		(0.029)		(0.033)		(0.035)
Total # Co-Inventors [-5,-1]		-0.155***		-0.195***		-0.232***
		(0.028)		(0.030)		(0.030)
Constant	2.406***	2.256***	2.503***	2.326***	2.467***	2.239***
	(0.077)	(0.083)	(0.099)	(0.105)	(0.120)	(0.126)
Observations	1,994,368	1,993,640	1,994,368	1,993,640	1,994,368	1,993,640
R-squared	0.392	0.393	0.330	0.330	0.263	0.263
Calendar Year FE	YES	YES	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES	YES	YES
Y Mean	2.861	2.861	2.961	2.961	3.214	3.214

Panel B. Target Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	0.909***	0.916***	0.965***	0.972***	1.294***	1.303***
	(0.341)	(0.342)	(0.270)	(0.271)	(0.318)	(0.318)
Complete × Post	0.149	0.150	-0.062	-0.061	-0.129	-0.129
	(0.199)	(0.199)	(0.202)	(0.202)	(0.259)	(0.260)
Complete × High Cmpl	-0.515**	-0.506**	-0.513***	-0.507***	-0.824***	-0.824***
	(0.209)	(0.211)	(0.189)	(0.191)	(0.228)	(0.230)
Post × High Cmpl	-0.462***	-0.469***	-0.574***	-0.581***	-0.905***	-0.915***
	(0.027)	(0.027)	(0.031)	(0.032)	(0.043)	(0.043)
Post	0.066*	0.055	0.131***	0.119***	0.357***	0.341***
	(0.038)	(0.039)	(0.045)	(0.045)	(0.057)	(0.057)
High Cmpl	0.469***	0.469***	0.550***	0.553***	0.938***	0.949***
	(0.013)	(0.013)	(0.020)	(0.020)	(0.027)	(0.027)
Patent Count [-5,-1]		0.095***		0.059***		-0.005
		(0.018)		(0.021)		(0.028)
Average Team Size [-5,-1]		-0.071**		-0.101***		-0.262***
		(0.032)		(0.032)		(0.047)
Total # Co-Inventors [-5,-1]		-0.262***		-0.254***		-0.243***
		(0.035)		(0.037)		(0.049)
Constant	1.167***	1.629***	1.143***	1.695***	1.394***	2.281***
	(0.017)	(0.058)	(0.022)	(0.056)	(0.027)	(0.069)
Observations	299,534	299,521	299,534	299,521	299,534	299,521
R-squared	0.483	0.487	0.467	0.470	0.308	0.312
Calendar Year FE	YES	YES	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES	YES	YES
Y Mean	1.327	1.327	1.339	1.339	1.809	1.809

Appendix: Variable Definitions

Variable	Definitions	Data Source
Innovation Specificity Measures		
Staying Lead Inventor's Patents	It includes both pre-merger patents and post-merger patents. For pre-merger patents, it includes all the patents *led* by the staying lead inventor before deal announcement date. For post-merger patents, it includes *either* (if she is a lead inventor for at least one post-merger patents) patents led by the focal inventor, *or* (if she is not a lead inventor for any of the post-merger patents) patents participated by the focal inventor as non-leader, the lead inventor of which is not from the opposite party of the deal.	PatentsView
Innovation Specificity Unique (%)	The number of unique acquirer (target)-specific words used by a given target (acquirer) lead inventors as a percentage of total number of unique words of patents she filed within a given relative year *t,* calculated using *Staying Lead Inventor's Patents* only.	
Innovation Specificity TF (%)	The total word frequency of acquirer (target)-specific words used by a given target (acquirer) lead inventors as a percentage of total number of words of patents she filed within a given relative year *t,* calculated using *Staying Lead Inventor's Patents* only.	
Innovation Specificity TF-IDF (%)	The sum of Inverse Document Frequency scaled total word frequency of acquirer (target)-specific words used by a given target (acquirer) lead inventors as a percentage of sum of TF-IDF of patents she filed within a given relative year *t,* calculated using *Staying Lead Inventor's Patents* only.	
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 Platinum, Compustat
Same 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 Platinum, Compustat, CRSP
Toehold	The percentage of shares owned by acquirers before deal announcement date.	SDC Platinum
All Stock/Cash	Dummy variable that equals to one if the consideration description is "Cash Only/Stock Only" and zero otherwise.	SDC Platinum

Firm Characteristics		
Total Assets	Book total assets in $million.	Compustat
Avg. Patent Age	The average age of patents filed before deal announcement date, with patent application date as year 0.	PatentsView
All Patents [-5,-1]	The total number of patents filed by the firm during relative year [-5,-1].	
Stayer Patents [-5,-1]	The total number of *Staying Lead Inventor*'*s* Patents during relative year [-5,-1].	
Stayer Patents [+1,+5]	The total number of *Staying Lead Inventor's Patents* during relative year [+1,+5].	
Inventor Characteristics		
Inventor Complementarity	For target inventor, first define acquirer firm's knowledge base as the set of patents that received at least one citation from any of the acquirer's patents with application date before the deal announcement date. Similarly, define the inventor's knowledge base as the set of patents that received at least one citation from any of the inventor's patents with application date before deal announcement date. Second, define common knowledge base as the intersection between the acquirer firm knowledge base and target inventor knowledge base. Finally, compute the complementarity as the base overlap ratio by scaling the total number of patents in common knowledge base over the total number of patents in the inventor's knowledge base. Acquirer inventor complementarity is defined vice versa.	PatentsView
Patent Count [-5,-1]	Total number of patents filed by the focal inventor between relative year [-5,-1].	
Average Team Size [-5,-1]	Average total number of inventors per each patents, averaged across all patents filed by the inventor between relative year [-5,-1].	
Total # Co-inventors [-5,-1]	Total number of unique inventors of patents filed by the inventor between relative year [-5,-1].	
Inventor Attrition Status		
Stayer	Inventors who file a patent with the firms involved in the transaction in the five years after the deal resolution date (completion date for completed deals and withdrawn date for withdrawn deals).	PatentsView
Leaver	Inventors who file one with a different firm, not involved in the transaction, in the five years after deal resolution date.	
Stopper	Inventors who do not file any patent in the five years following the deal resolution date.	

Internet Appendix to

Relationship-Specific Investments and Firms' Boundaries: Evidence from Textual Analysis of Patents

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Appendix A. Additional Results and Robustness Checks

This section of the Internet Appendix provides additional results and robustness analyses referenced in the main text.

Table A.1. Sample Formation Procedure and Sample Size

The table presents the size of the sample at different stages of screenings.

	Completed	Withdrawn
M&A sample after initial screening	73,454	4,292
Patent matching [Inventor Attrition Analysis Sample]		
Target has at least 1 patent in [-5,-1] & acquirer has at least 1 patent in [-5,-1]	5,105	299
Target has at least 1 patent in [-5,-1] & acquirer has at least 1 patent in [-5,-1] & joint firm has at least 1 patent in [+1,+5]	4,848	281
Counterfactual Matching		
The firm having matched counterfactual target	4,189	223
The firm having matched counterfactual acquirer	4,709	271
Staying Leader		
The firm having at least 1 target staying leader and 1 acquirer staying leader	2,159	108
Specificity measure [Specificity Regression Sample]		
The deal having at least 1 target specificity measure	1,688	78
The deal having at least 1 acquirer specificity measure	1,955	103

Table A.2. Comparison of Completed and Withdrawn Deals

The table represents comparison between the completed and the withdrawn deals. The sample includes deals from the main sample, where both the target and the acquirer have at least 1 patent in the 5-year pre-merger period. Panel A reports the team summary statistics defined by staying lead inventor. The staying lead inventors included in the sample lead at least 1 patent both in the 5-year before and after the merger. The *Number of Teams* refers to the number of unique staying lead inventors ("the team") the acquirer or target has that satisfy the sample selection criteria. 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 reported as the median across deals. Panel B provides firm characteristics of the acquirer for completed and withdrawn deals separately. Acquirer *Sales*, *Total Assets*, and *log(R&D/Total Assets)* are calculated using the latest financial data before the deal announcement date. The t-statistics on the differences between the two groups assuming unequal variance are also reported.

Panel A: Inventor Team Statistics

	Completed		Withdrawn	
	Pre-Merger	Post-Merger	Pre-Merger	Post-Merger
Acquirer				
Number of Teams	11.00	11.00	5.00	5.00
Average Team Size	2.44	2.58	2.00	2.16
Average Number of Patents	2.44	2.34	2.11	2.06
Target				
Number of Teams	1.00	1.00	2.00	2.00
Average Team Size	2.05	2.25	1.94	2.00
Average Number of Patents	2.00	2.00	2.00	2.00

Panel B: Pre-Merger Firm Characteristics

	Completed	Withdrawn	t-stat on Difference
Sales	7,453.65	4,368.22	3.53
Total Assets	11,848.59	6,101.48	2.86
log(R&D/Total Assets)	0.22	0.26	-1.33

Table A.3. Innovation Specificity: Robustness using Alternative Aggregation Method

The table presents the regression estimates of triple differences regression of inventor specificity. The panel includes deal-inventor-relative year observations of acquirer stayer lead inventors (Panel A) and target stayer lead inventors (Panel B) for the 5 years before the deal announcement date and the 5 years after the deal resolution date (withdrawn date for the withdrawn deals and effective date for the completed deals). The dependent variables are three different measures of inventor specificity, *Innovation Specificity Unique (%)*, *TF (%)*, and *TF-IDF (%)*, capturing the acquirer (target) inventor's use of acquirer-(target-) specific words in various ways. Compared with Table 5, the measures are constructed in an alternative manner by first scaling at patent level then averaging across all patents filed by the inventor for the particular relative year (whereas in Table 5 the measure is first aggregating across patents of the same year then scaling). *Complete* is a dummy variable that equals to one if the deal is completed, and zero if withdrawn. Post is a dummy variable that equals to one if the observation comes from post-merger years. *High Cmpl* is a dummy variable that equals to one if the inventor' s knowledge base overlap ratio with the counterparty in the acquisition is above or equal to 75th percentile of all the inventors who have filed at least 1 patent in the 5-year pre-merger window. For column (2), (4) and (6), the regressions also include inventor pre-merger time invariant control variables, inverse hyperbolic transformed *patent count [-5,-1]*, *average team size [-5,-1]*, and *Total # Co-Inventors [-5,-1]*, based on patents led by the focal lead inventor with the target/acquirer firm of the deal. The details of variable definitions are presented in the Appendix. All equations also include deal fixed effects and the standard errors are clustered at the deal level.

Panel A: Acquirer Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	1.035***	1.034***	1.059***	1.059***	1.089***	1.089***
	(0.241)	(0.241)	(0.272)	(0.272)	(0.262)	(0.262)
Complete × Post	0.167	0.167	0.207	0.205	0.235	0.234
	(0.180)	(0.180)	(0.224)	(0.224)	(0.234)	(0.234)
Complete × High Cmpl	0.290	0.285	0.524*	0.519*	0.681**	0.676**
	(0.226)	(0.226)	(0.274)	(0.275)	(0.330)	(0.331)
Post × High Cmpl	-0.455***	-0.455***	-0.505**	-0.506**	-0.574***	-0.574***
	(0.176)	(0.176)	(0.204)	(0.204)	(0.201)	(0.201)
Post	-0.319*	-0.320*	-0.385*	-0.387*	-0.368*	-0.370*
	(0.173)	(0.173)	(0.211)	(0.211)	(0.213)	(0.213)
High Cmpl	0.368***	0.376***	0.402***	0.411***	0.684***	0.694***
	(0.128)	(0.128)	(0.126)	(0.126)	(0.148)	(0.148)
Patent Count [-5,-1]		0.001		-0.015		-0.016
		(0.043)		(0.042)		(0.041)
Average Team Size [-5,-1]		0.002		-0.017		-0.019
		(0.051)		(0.059)		(0.060)
Total # Co-Inventors [-5,-1]		-0.044		-0.026		-0.026
		(0.058)		(0.059)		(0.057)
Constant	3.185***	3.270***	3.147***	3.255***	2.718***	2.830***
	(0.169)	(0.176)	(0.222)	(0.231)	(0.272)	(0.279)
Observations	871,750	871,377	871,750	871,377	871,750	871,377
R-squared	0.355	0.356	0.291	0.291	0.260	0.260
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	3.989	3.989	4.174	4.174	4.159	4.159

Table B: Target Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	0.764**	0.768**	0.748**	0.754**	0.984**	0.991**
	(0.329)	(0.329)	(0.345)	(0.346)	(0.453)	(0.454)
Complete × Post	-0.031	-0.037	-0.134	-0.141	-0.184	-0.193
	(0.333)	(0.332)	(0.364)	(0.364)	(0.490)	(0.490)
Complete × High Cmpl	-0.371*	-0.359	-0.340	-0.324	-0.545*	-0.529*
	(0.218)	(0.221)	(0.240)	(0.242)	(0.307)	(0.312)
Post × High Cmpl	-0.270	-0.273	-0.300	-0.304	-0.512	-0.517
	(0.204)	(0.204)	(0.254)	(0.255)	(0.350)	(0.351)
Post	-0.160	-0.160	-0.121	-0.119	-0.104	-0.102
	(0.283)	(0.281)	(0.326)	(0.324)	(0.439)	(0.437)
High Cmpl	0.299***	0.296**	0.334**	0.330**	0.601***	0.597***
	(0.113)	(0.116)	(0.151)	(0.155)	(0.207)	(0.213)
Patent Count [-5,-1]		0.053		0.077		0.070
		(0.061)		(0.096)		(0.099)
Average Team Size [-5,-1]		-0.271**		-0.318***		-0.389***
		(0.112)		(0.117)		(0.144)
Total # Co-Inventors [-5,-1]		-0.080		-0.095		-0.082
		(0.126)		(0.173)		(0.186)
Constant	2.554***	3.053***	2.610***	3.170***	3.101***	3.764***
	(0.073)	(0.294)	(0.082)	(0.238)	(0.101)	(0.290)
Observations	38,886	38,873	38,886	38,873	38,886	38,873
R-squared	0.553	0.555	0.484	0.485	0.443	0.444
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	2.557	2.557	2.609	2.610	3.134	3.135

Table A.4. Innovation Specificity: Robustness using Inverse Hyperbolic Sine Transformation

The table presents the regression estimates of triple differences regression of inventor specificity (inverse hyperbolic sine transformed). The panel includes deal-inventor-relative year observations of acquirer stayer lead inventors (Panel A) and target stayer lead inventors (Panel B) for the 5 years before the deal announcement date and the 5 years after the deal resolution date (withdrawn date for the withdrawn deals and effective date for the completed deals). The dependent variables are three different measures of inventor specificity, *Innovation Specificity Unique (%), TF (%),* and *TF-IDF (%),* capturing the acquirer (target) inventor's use of acquirer-(target-) specific words in various ways. The measures are inverse hyperbolic transformed from the measures in Table 5. *Complete* is a dummy variable that equals to one if the deal is completed, and zero if withdrawn. Post is a dummy variable that equals to one if the observation comes from post-merger years. *High Cmpl* is a dummy variable that equals to one if the inventor's knowledge base overlap ratio with the counterparty in the acquisition is above or equal to 75th percentile of all the inventors who have filed at least 1 patent in the 5-year pre-merger window. For column (2), (4) and (6), the regressions also include inventor pre-merger time invariant control variables, inverse hyperbolic transformed *patent count [-5,-1], average team size [-5,-1],* and *Total # Co-Inventors [-5,-1],* based on patents led by the focal lead inventor with the target/acquirer firm of the deal. The details of variable definitions are presented in the Appendix. All equations also include deal fixed effects and the standard errors are clustered at the deal level.

Panel A. Acquirer Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	0.010***	0.010***	0.011***	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Complete × Post	0.002	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Complete × High Cmpl	0.003	0.003	0.005*	0.005*	0.007**	0.007**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Post × High Cmpl	-0.005**	-0.005**	-0.005**	-0.005**	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Post	-0.003*	-0.003*	-0.004*	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
High Cmpl	0.004***	0.004***	0.004***	0.004***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Patent Count [-5,-1]		0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
Average Team Size [-5,-1]		0.000		-0.000		-0.000
		(0.001)		(0.001)		(0.001)
Total # Co-Inventors [-5,-1]		-0.000		-0.000		-0.000
		(0.001)		(0.001)		(0.001)
Constant	0.032***	0.033***	0.032***	0.033***	0.027***	0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	871,750	871,377	871,750	871,377	871,750	871,377
R-squared	0.358	0.358	0.291	0.291	0.260	0.260
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	0.0398	0.0398	0.0416	0.0416	0.0414	0.0414

Panel B. Target Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	0.007**	0.007**	0.007**	0.008**	0.010**	0.010**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Complete × Post	-0.000	-0.000	-0.001	-0.001	-0.002	-0.002
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Complete × High Cmpl	-0.004*	-0.003	-0.003	-0.003	-0.005*	-0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Post × High Cmpl	-0.002	-0.003	-0.003	-0.003	-0.005	-0.005
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Post	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
High Cmpl	0.003***	0.003**	0.003**	0.003**	0.006***	0.006***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Patent Count [-5,-1]		0.001		0.001		0.001
		(0.001)		(0.001)		(0.001)
Average Team Size [-5,-1]		-0.003**		-0.003***		-0.004***
		(0.001)		(0.001)		(0.001)
Total # Co-Inventors [-5,-1]		-0.001		-0.001		-0.001
		(0.001)		(0.002)		(0.002)
Constant	0.025***	0.030***	0.026***	0.031***	0.031***	0.037***
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)
Observations	38,886	38,873	38,886	38,873	38,886	38,873
R-squared	0.554	0.556	0.485	0.486	0.444	0.445
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	0.0256	0.0256	0.0260	0.0260	0.0313	0.0313

Table A.5. Innovation Specificity: Alternative Definition of High Inventor Complementarity

The table presents the regression estimates of triple differences regression of inventor specificity, using an alternative definition of inventor High Complementarity. The panel includes deal-inventor-relative year observations of acquirer stayer lead inventors (Panel A) and target stayer lead inventors (Panel B) for the 5 years before the deal announcement date and the 5 years after the deal resolution date (withdrawn date for the withdrawn deals and effective date for the completed deals). The dependent variables are three different measures of inventor specificity, *Innovation Specificity Unique (%), TF* (%), and *TF-IDF (%),* capturing the acquirer (target) inventor's use of acquirer-(target-) specific words in various ways. *Complete* is a dummy variable that equals to one if the deal is completed, and zero if withdrawn. *Post* is a dummy variable that equals to one if the observation comes from post-merger years. *High Cmpl* is defined using similar procedures with Table 5 (a dummy variable that equals to one if the inventor's knowledge base overlap ratio with the counterparty in the acquisition is above or equal to 75th percentile) except that they are defined within the set of stayer inventors instead of all the inventors who have filed at least 1 patent in the 5-year pre-merger window. For column (2), (4) and (6), the regressions also include inventor pre-merger time invariant control variables, inverse hyperbolic transformed *patent count [-5,-1], average team size [-5,-1],* and *Total # Co-Inventors [-5,-1],* based on patents led by the focal lead inventor with the target/acquirer firm of the deal. The details of variable definitions are presented in the Appendix. All equations also include deal fixed effects and the standard errors are clustered at the deal level.

Panel A: Acquirer Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	0.805***	0.803***	0.772***	0.772***	0.701**	0.700**
	(0.246)	(0.246)	(0.287)	(0.287)	(0.294)	(0.294)
Complete × Post	0.442***	0.442***	0.529**	0.528**	0.636**	0.635**
	(0.169)	(0.169)	(0.226)	(0.226)	(0.259)	(0.259)
Complete × High Cmpl	0.109	0.106	0.350	0.347	0.445	0.442
	(0.251)	(0.251)	(0.281)	(0.281)	(0.338)	(0.338)
Post × High Cmpl	-0.383**	-0.381**	-0.411*	-0.411*	-0.410*	-0.409*
	(0.164)	(0.164)	(0.211)	(0.211)	(0.233)	(0.233)
Post	-0.426***	-0.428***	-0.511**	-0.513**	-0.542**	-0.545**
	(0.156)	(0.156)	(0.210)	(0.210)	(0.239)	(0.239)
High Cmpl	0.540***	0.547***	0.577***	0.584***	0.872***	0.882***
	(0.196)	(0.196)	(0.201)	(0.201)	(0.251)	(0.251)
Patent Count [-5,-1]		0.003		-0.010		-0.017
		(0.042)		(0.042)		(0.041)
Average Team Size [-5,-1]		0.005		-0.013		-0.010
		(0.051)		(0.059)		(0.060)
Total # Co-Inventors [-5,-1]		-0.045		-0.028		-0.032
		(0.057)		(0.059)		(0.057)
Constant	3.223***	3.303***	3.194***	3.291***	2.816***	2.927***
	(0.131)	(0.141)	(0.168)	(0.180)	(0.197)	(0.209)
Observations	871,808	871,435	871,808	871,435	871,808	871,435
R-squared	0.357	0.357	0.290	0.290	0.259	0.259
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	3.993	3.993	4.183	4.183	4.158	4.158

Panel B: Target Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	0.829***	0.839***	0.855***	0.867***	1.086***	1.100***
	(0.312)	(0.314)	(0.322)	(0.324)	(0.420)	(0.422)
Complete × Post	-0.033	-0.041	-0.142	-0.152	-0.188	-0.201
	(0.308)	(0.307)	(0.331)	(0.330)	(0.446)	(0.445)
Complete × High Cmpl	-0.356	-0.354	-0.320	-0.318	-0.534	-0.532
	(0.233)	(0.234)	(0.250)	(0.250)	(0.336)	(0.336)
Post × High Cmpl	-0.298	-0.306	-0.400	-0.410*	-0.590*	-0.602*
	(0.202)	(0.202)	(0.243)	(0.243)	(0.333)	(0.332)
Post	-0.150	-0.147	-0.097	-0.090	-0.093	-0.085
	(0.278)	(0.275)	(0.308)	(0.306)	(0.413)	(0.410)
High Cmpl	0.261*	0.265*	0.283	0.287	0.525**	0.530**
	(0.149)	(0.147)	(0.179)	(0.179)	(0.261)	(0.259)
Patent Count [-5,-1]		0.062		0.089		0.085
		(0.061)		(0.098)		(0.099)
Average Team Size [-5,-1]		-0.261**		-0.319***		-0.391***
		(0.116)		(0.117)		(0.147)
Total Team Size [-5,-1]		-0.086		-0.095		-0.083
		(0.122)		(0.170)		(0.181)
Constant	2.564***	3.045***	2.630***	3.175***	3.145***	3.788***
	(0.065)	(0.290)	(0.075)	(0.234)	(0.093)	(0.288)
Observations	38,890	38,877	38,890	38,877	38,890	38,877
R-squared	0.554	0.555	0.484	0.486	0.443	0.444
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	2.562	2.563	2.614	2.615	3.141	3.142

Table A.6. Innovation Specificity: Robustness Using Continued Leaders Only

The table presents the regression estimates of triple differences regression of inventor specificity using continued leader only. The panel includes deal-inventor-relative year observations of acquirer stayer continued leader inventors (Panel A) and target stayer continued leader inventors (Panel B) for the 5 years before the deal announcement date and the 5 years after the deal resolution date (withdrawn date for the withdrawn deals and effective date for the completed deals). Continued leader is defined as an inventor who are leaders in the 5-year pre-merger period, stays in the firm, and are leaders of at least 1 patent with the combined entity in the 5-year post-merger period. The dependent variables are three different measures of inventor specificity, *Innovation Specificity Unique (%), TF (%)*, and *TF-IDF (%),* capturing the acquirer (target) inventor's use of acquirer-(target-) specific words in various ways. *Complete* is a dummy variable that equals to one if the deal is completed, and zero if withdrawn. *Post* is a dummy variable that equals to one if the observation comes from post-merger years. *High Cmpl* is a dummy variable that equals to one if the inventor's knowledge base overlap ratio with the counterparty in the acquisition is above or equal to 75th percentile of all the inventors who have filed at least 1 patent in the 5-year pre-merger window. For column (2), (4) and (6), the regressions also include inventor pre-merger time invariant control variables, inverse hyperbolic transformed *patent count [-5,-1], average team size [-5,-1],* and *Total # Co-Inventors [-5,-1],* based on patents led by the focal lead inventor with the target/acquirer firm of the deal. The details of variable definitions are presented in the Appendix. All equations also include deal fixed effects and the standard errors are clustered at the deal level.

Panel A: Acquirer Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	1.001***	1.000***	1.070***	1.072***	1.121***	1.122***
	(0.250)	(0.250)	(0.267)	(0.266)	(0.263)	(0.263)
Complete × Post	0.209	0.208	0.209	0.208	0.229	0.227
	(0.174)	(0.174)	(0.205)	(0.205)	(0.213)	(0.213)
Complete × High Cmpl	0.335	0.333	0.524*	0.521*	0.683**	0.681**
	(0.243)	(0.242)	(0.279)	(0.279)	(0.333)	(0.332)
Post × High Cmpl	-0.436**	-0.436**	-0.498**	-0.500**	-0.579***	-0.581***
	(0.195)	(0.195)	(0.204)	(0.203)	(0.204)	(0.204)
Post	-0.373**	-0.372**	-0.431**	-0.431**	-0.409**	-0.408**
	(0.164)	(0.164)	(0.187)	(0.187)	(0.186)	(0.186)
High Cmpl	0.364**	0.370**	0.411***	0.418***	0.711***	0.720***
	(0.155)	(0.154)	(0.142)	(0.142)	(0.157)	(0.156)
Patent Count [-5,-1]		0.013		0.002		-0.004
		(0.043)		(0.043)		(0.042)
Average Team Size [-5,-1]		0.016		0.013		0.020
		(0.053)		(0.063)		(0.065)
Total # Co-Inventors [-5,-1]		-0.053		-0.042		-0.046
		(0.059)		(0.062)		(0.062)
Constant	3.161***	3.222***	3.166***	3.228***	2.714***	2.784***
	(0.171)	(0.180)	(0.220)	(0.231)	(0.270)	(0.281)
Observations	658,563	658,261	658,563	658,261	658,563	658,261
R-squared	0.361	0.361	0.295	0.295	0.264	0.264
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	3.986	3.986	4.181	4.182	4.164	4.164

Panel B: Target Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	0.862**	0.870**	0.937**	0.947**	1.268**	1.279**
	(0.354)	(0.354)	(0.386)	(0.386)	(0.505)	(0.505)
Complete × Post	-0.101	-0.111	-0.243	-0.255	-0.394	-0.408
	(0.390)	(0.389)	(0.432)	(0.431)	(0.578)	(0.577)
Complete × High Cmpl	-0.367	-0.355	-0.374	-0.357	-0.639*	-0.622*
	(0.245)	(0.251)	(0.273)	(0.281)	(0.344)	(0.353)
Post × High Cmpl	-0.357*	-0.364*	-0.489*	-0.497*	-0.799**	-0.808**
	(0.215)	(0.215)	(0.292)	(0.292)	(0.396)	(0.395)
Post	-0.109	-0.104	0.000	0.007	0.145	0.152
	(0.319)	(0.316)	(0.379)	(0.377)	(0.508)	(0.506)
High Cmpl	0.388***	0.384***	0.471***	0.464***	0.837***	0.831***
	(0.108)	(0.113)	(0.166)	(0.173)	(0.222)	(0.232)
Patent Count [-5,-1]		0.080		0.116		0.110
		(0.062)		(0.096)		(0.101)
Average Team Size [-5,-1]		-0.305*		-0.315**		-0.404**
		(0.156)		(0.138)		(0.171)
Total # Co-Inventors [-5,-1]		-0.098		-0.140		-0.126
		(0.114)		(0.165)		(0.188)
Constant	2.550***	3.080***	2.572***	3.138***	3.037***	3.727***
	(0.086)	(0.340)	(0.094)	(0.272)	(0.117)	(0.326)
Observations	30,752	30,744	30,752	30,744	30,752	30,744
R-squared	0.558	0.559	0.488	0.490	0.452	0.453
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	2.601	2.602	2.641	2.642	3.182	3.183

Table A.7. Innovation Specificity: Robustness using Clean Treatments Only

The table presents the regression estimates of triple differences regression of inventor specificity with non-overlapping treatments. The panel includes deal-inventor-relative year observations of acquirer stayer lead inventors (Panel A) and target stayer lead inventors (Panel B) for the 5 years before the deal announcement date and the 5 years after the deal resolution date (withdrawn date for the withdrawn deals and effective date for the completed deals). The sample removed completed deals that overlap with another deal in the 5-year pre- or post-merger period. The dependent variables are three different measures of inventor specificity, *Innovation Specificity Unique (%), TF (%)*, and *TF-IDF (%),* capturing the acquirer (target) inventor's use of acquirer-(target-) specific words in various ways. *Complete* is a dummy variable that equals to one if the deal is completed, and zero if withdrawn. *Post* is a dummy variable that equals to one if the observation comes from post-merger years. *High Cmpl* is a dummy variable that equals to one if the inventor's knowledge base overlap ratio with the counterparty in the acquisition is above or equal to 75th percentile of all the inventors who have filed at least 1 patent in the 5-year pre-merger window. For column (2), (4) and (6), the regressions also include inventor pre-merger time invariant control variables, inverse hyperbolic transformed *patent count [-5,-1], average team size [-5,-1],* and *Total # Co-Inventors [-5,-1],* based on patents led by the focal lead inventor with the target/acquirer firm of the deal. The details of variable definitions are presented in the Appendix. All equations also include deal fixed effects and the standard errors are clustered at the deal level.

Panel A: Acquirer Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	1.756***	1.743***	2.221***	2.209***	2.069***	2.052***
	(0.570)	(0.569)	(0.646)	(0.647)	(0.655)	(0.655)
Complete × Post	-0.306	-0.298	-0.621	-0.610	-0.397	-0.384
	(0.430)	(0.429)	(0.505)	(0.506)	(0.518)	(0.519)
Complete × High Cmpl	0.767	0.775	1.028	1.054	1.441	1.462
	(0.747)	(0.727)	(0.982)	(0.965)	(1.268)	(1.241)
Post × High Cmpl	-0.400*	-0.396*	-0.506**	-0.501**	-0.448*	-0.441*
	(0.207)	(0.206)	(0.227)	(0.225)	(0.246)	(0.245)
Post	-0.051	-0.044	-0.146	-0.141	-0.245	-0.235
	(0.194)	(0.196)	(0.221)	(0.223)	(0.247)	(0.248)
High Cmpl	0.793***	0.796***	0.982***	0.987***	1.462***	1.467***
	(0.189)	(0.190)	(0.258)	(0.258)	(0.345)	(0.345)
Patent Count [-5,-1]		0.210**		0.272**		0.339***
		(0.084)		(0.111)		(0.119)
Average Team Size [-5,-1]		0.263		0.258		0.368
		(0.206)		(0.247)		(0.274)
Total # Co-Inventors [-5,-1]		-0.239		-0.337*		-0.390*
		(0.152)		(0.193)		(0.214)
Constant	2.501***	2.187***	2.565***	2.338***	2.606***	2.195***
	(0.190)	(0.359)	(0.259)	(0.429)	(0.334)	(0.489)
Observations	22,991	22,979	22,991	22,979	22,991	22,979
R-squared	0.474	0.475	0.414	0.415	0.400	0.400
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	3.164	3.164	3.320	3.320	3.729	3.730

Panel B: Target Inventors

	Innovation Specificity					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unique (%)	Unique (%)	TF (%)	TF (%)	TF-IDF (%)	TF-IDF (%)
Complete × Post × High Cmpl	1.296**	1.293**	1.015	1.009	1.254	1.247
	(0.575)	(0.575)	(0.797)	(0.797)	(0.906)	(0.906)
Complete × Post	-0.436	-0.432	-0.209	-0.204	-0.229	-0.222
	(0.524)	(0.524)	(0.777)	(0.776)	(0.889)	(0.888)
Complete × High Cmpl	1.004	0.979	2.206	2.159	2.475	2.409
	(0.992)	(1.006)	(1.462)	(1.482)	(1.715)	(1.742)
Post × High Cmpl	-0.529***	-0.528***	-0.576**	-0.575**	-0.876**	-0.874**
	(0.200)	(0.201)	(0.261)	(0.263)	(0.353)	(0.356)
Post	0.030	0.027	0.165	0.160	0.423	0.416
	(0.192)	(0.193)	(0.271)	(0.271)	(0.348)	(0.348)
High Cmpl	0.429***	0.432***	0.476***	0.483***	0.799***	0.807***
	(0.109)	(0.108)	(0.165)	(0.163)	(0.227)	(0.226)
Patent Count [-5,-1]		-0.015		-0.072		-0.064
		(0.119)		(0.132)		(0.160)
Average Team Size [-5,-1]		-0.015		-0.114		-0.140
		(0.364)		(0.394)		(0.469)
Total # Co-Inventors [-5,-1]		-0.047		-0.001		-0.056
		(0.251)		(0.292)		(0.350)
Constant	1.527***	1.659***	1.270***	1.564***	1.425***	1.846***
	(0.194)	(0.540)	(0.272)	(0.582)	(0.332)	(0.707)
Observations	5,956	5,956	5,956	5,956	5,956	5,956
R-squared	0.567	0.567	0.552	0.552	0.443	0.444
Calendar Year FE	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Y Mean	1.886	1.886	1.931	1.931	2.395	2.395

Appendix B. Procedure for Matching M&A Deals with PatentsView Dataset

In this section we outline the procedures employed to establish the link table between M&A deals from SDC Platinum database and patent assignees from the PatentsView dataset. The name matching process consists of two primary steps. First, we perform name matching using the target name, acquirer name, and the acquirer ultimate patent name from the SDC database and match them with the assignee names from PatentsView. Second, to address cases where the combined entity undergoes name changes post-merger, we extract the name history of the involved parties in the deal, which remains publicly available post-deal, from the CRSP *dsenames* dataset and match them with the assignee names.

We begin by selecting assignees likely to be companies, excluding individuals and public sectors. The screened organization types include "Unassigned", "US Company" or "Foreign Company". Given that assignee names on each patents lack unique official identifiers for tracking entities over time, we rely on PatentsView's disambiguated *assignee ID* to compile the complete set of patents granted to each company. The PatentsView database employs a disambiguation algorithm that effectively groups similar assignee names, mitigating issues such as typos, short names or nicknames (e.g., "IBM" for "International Business Machines"), and acronyms[16]. Our name matching occurs at the *assignee ID* level, where we compare assignee names on individual patents belonging to an *assignee ID*. If one assignee name is identified as the correct match with a party in the M&A deal, we attribute all patents granted to the same *assignee ID* to the matched party. Similarly, we leverage PatentsView's disambiguated *inventor IDs* to trace the patent history of each individual inventor.

B.1: Fuzzy Name Matching for SDC Platinum-PatentsView

We perform fuzzy name matching between the target, acquirer or acquirer ultimate patent names and the assignee names using the cosine similarity score calculated through the TF-IDF method. The TF-IDF cosine similarity method compares two strings based on term overlap, assigning proper weights to each term to indicate its distinctiveness in differentiating one name from another. The weight is determined by the inverse of term's frequency across all names in the corpus, known as "Inverse Document Frequency" ("IDF"). In essence, if a term is commonly used (high document frequency, low IDF) across a broad spectrum of names (e.g., "corporation"), it

[16] Refer to https://patentsview.org/disambiguation for detail.

contributes little information for distinguishing names. In such cases, the term is associated with a lower weight to account for its low importance. Conversely, if a term is used by a small fraction of the firms (e.g., "Howitt"), it provides a distinctive feature of a string, leading to a higher weight.

We start by standardizing all names using the Stata standardization package *stnd_compname* to resolve variations in terms of plurality, abbreviations, punctuations, etc. Special characters, excluding "&" and single quotes, are removed and single-letter names are consolidated (e.g., "C K & I Industries" to "CK&I Industries"). Subsequently, each name is transformed into the TF-IDF vectors using the *sklearn TfidfVectorizer* module. For each name from the target, acquirer, and acquirer ultimate parent, we calculate its cosine similarity with all assignee names from PatentsView. The resulting similarity measure ranges between [0, 1]. Notably, an *assignee ID* may have multiple names from various patents due to the disambiguation algorithm, resulting in multiple similarity scores. In the next step, we determine the maximum similarity an assignee has with the given name from the deal.

We evaluate fuzzy name matching results through the following steps. First, for each name from the deal, we rank all the *assignee ID*s based on their maximum patent similarity to the name. As a preliminary screening, we then retain the highest-ranked *assignee ID* or the lower-ranked *assignee ID* whose maximum similarity is within 0.05 of that of the highest-ranked *assignee ID.* We exclude other lower-ranked matches since, through manual checking, they are highly unlikely to be the true match in the presence of higher ranked matches.

Second, we assess the location match between the two matched entities. For names in the deal, we extract the city, state (if in the US), and country information of the target, acquirer, and acquirer ultimate parents from SDC Platinum. Similarly, for assignees, we retrieve the city, state (if in the US), and country information from individual patents associated with the *assignee ID* in PatentsView. We categorize each match from the previous step as either "City Match", "State Match" (US only), "Country Match", and "No Location Match". In instances where *assignee ID*s have multiple locations from different patents, we categorize them based on their best location match.

Third, we perform the final screening of the fuzzy matching scores, incorporating the location matching information. We recognize that the location matching results strongly indicate the quality of the matching and therefore adopt different fuzzy name matching score cutoffs for different location matching categories. To establish these cutoffs, we begin by creating a randomly selected small sample that includes matchings with different cosine similarity scores and location matching categories. We manually verify the correctness of these matchings. For each location matching category, we then select a set of potential cutoff points incrementally ranging from 0.8 to 1.

At each cutoff point, using the manually labeled sample, we calculate the False Positive Rate (percentage of matchings with a similarity score above the cutoff point but are incorrect matches) and the False Negative Rate (percentage of matches with a similarity score below the cutoff point but are correct matches). We plot these rates in a graph (Figure B.1). The graph indicates that matches with a City Match have the highest quality, with the False Positive rate increasing slowly as the cutoff lowers from 1 to 0.8. In contrast, State, Country and No Location Match exhibit increasingly sharper jump as the cutoff moves from right to the left, suggesting the need for a higher cutoff. Based on the plot, we select 0.85 as the final cutoff for matches with City Match, 0.95 for State Match, 0.97 for Country Match, and 0.99 for No Location Match.

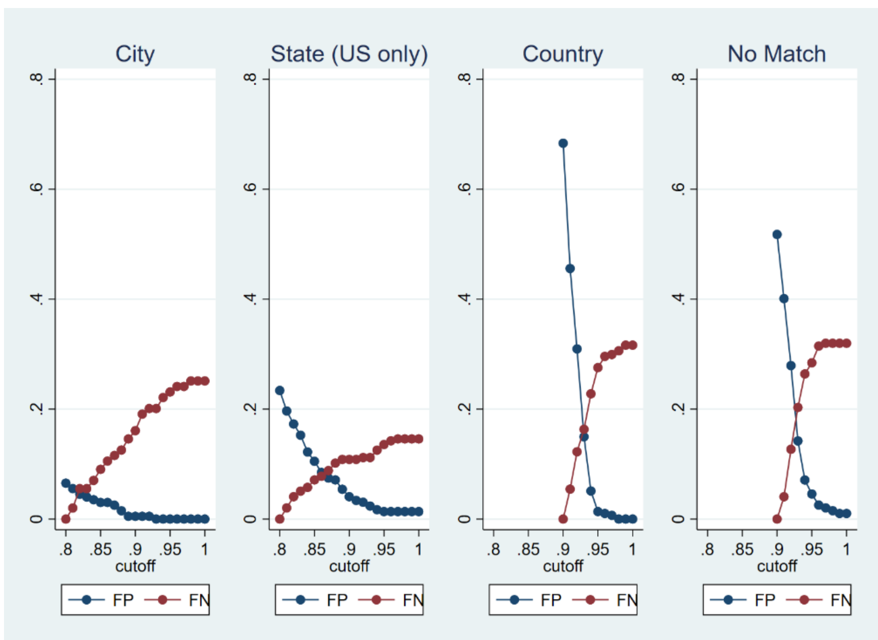

Figure B.1: False Positive and False Negative Rates for Different Cutoffs

Finally, we exclude matches related to division sales since the target name is likely include the target's selling parent name, potentially leading to a false attribution of patents filed by the target parent to the target. Specifically, we eliminate matches associated with deals where the target mid-level pubic status is "Branch" (*TARGET_PUB_MID_DESC,* indicating the refined form of ownership of the target at the time of the transaction).

B.2: Fuzzy Name Matching for CRSP Name History-PatentsView

We supplement the SDC name-assignee matching by incorporating the post-merger name-changing history of the combined entity to address concerns related to potential name changes after the merger. This supplementation is essential as drastic name changes may lead to the failure of the PatentsView disambiguation algorithm to group them with patents filed by pre-merger entities. To start, we retrieve the CUSIP identifiers of the target, acquirer and acquirer ultimate parent from SDC Platinum and obtain the corresponding PERMCO at the announcement date of the deal using the link table *dsenames* from CRSP. Subsequently, using *dsenames* dataset once again, we obtain all company names associated with the PERMCO that are effective after the deal announcement date.

We conduct a similar procedure of fuzzy name matching as outlined in Section A between the new CRSP names and the assignee names. The key distinction in this step is that for each new name, we only consider patents with the grant date after the name effective date (*NAMEDT*). We utilize the same location matching-specific cutoffs to evaluate each fuzzy matching score.

In the final step, we merge the matching pairs obtained from Section A and B. We exclude matchings in rare cases where the target and the acquirer (or the acquirer ultimate parent) are matched to the same *assignee ID.*

Appendix C. Calculation of TF-IDF Innovation Specificity Measure

We construct *tf-idf* measure by weighting the term frequency (*tf)* by inverse document frequency (*idf*), following Kelly, Papanikolaou, Seru and Taddy (2020). The *idf* weighting scheme overweigh the terms that are more unique to individual patents and underweight the terms that are more common across patents in the entire sample.

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 that contain the word, which adjusts for the fact that some words appear more frequently in general. Formally, for a given patent filed in year *t,* we define the corpus as the set of all principal claims of patents filed over five years on or before *t*. By allowing $the\ corpus$ to vary over time we adjust for the change of relevancy of terms over our long time-series sample.[17] On the other hand, by using a long enough 5-year rolling window, we mitigate any short-term fluctuations in the use of the words that add noise to the IDF weights. 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 (IDF_{wt})" is defined as the natural logarithm of the total number of documents in a given year *t*'s $corpus_t$ over the number of documents in the $corpus_t$ using a specific word *w*.

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).

[17] 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.