Human Capital Synergies in Mergers and Acquisitions*

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Abstract

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Keywords: human capital synergies, mergers and acquisitions, collaboration, knowledge spillovers, radical innovation, impactful innovation, valuable innovation

JEL classification: G34, O32, O34

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"Technology is unique in the sense that the pace of innovation is really fast, so rather than viewing M&A as a 'we have excess cash, let's buy something,' larger companies are looking at it as a tool to jump into a new market or ramp up a new technology quickly, … M&A can solve time-to-market issues and talent issues far quicker than internal activities can."

- Garrett Herbert, Managing Partner at Deloitte

1. Introduction

Observers have long argued that many mergers and acquisitions (M&As) are driven by the pursuit of technological innovation. Recent high-profile examples include IBM's purchase of the open-source software and cloud services company Red Hat, and Microsoft's acquisition of the open-source software platform GitHub and the communications application Skype. However, extant literature offers no direct evidence of how M&As help expand acquirers' innovative capabilities to produce path-breaking innovation. In this paper, we provide novel inventor- and patent-level evidence on how M&As achieve human capital synergies. By expanding the opportunity set for collaboration between acquirer and target inventors, M&As increase path-breaking innovation.

Innovation as a key driver of firm competitiveness, productivity, and firm value is well established (e.g., Pakes 1985; Romer 1990; Aghion and Howitt 1992; Hall, Jaffe, and Trajtenberg 2005). Innovation within a firm is path dependent, and firms often turn to external sources to expand their innovative capabilities – hiring, forming alliances, and making acquisitions (Cohen and Levinthal 1990; Kogut and Zander 1992; Mowery, Oxley, and Silverman 1996; Song, Almeida, and Wu 2003). However, the core technology of a firm is often tacit in nature; deeply embedded in a firm's past experience, this technology shapes its current systems, processes, routines, and people, which in turn limits opportunities for effective knowledge transfer through employee mobility or alliances (Winter 1987; Ranft and Lord 2002;

Hoetker and Agarwal 2007; Phene, Tallman, and Almeida 2012). In contrast to hiring from competitors or forming alliances, M&As are the only transaction that ensures target inventors' human capital will not be separated from the systems, processes, and routines with which it can be effectively utilized (Hart and Holmström 2010). Expanding firm boundaries via M&As thus emerges as a viable mechanism for facilitating collaboration and knowledge transfer between acquirer and target inventors, leading to more path-breaking innovation.

To examine human capital synergies in M&As, we compile a large and unique inventor- and patent-level data set over the period 1976–2019. We match patent, inventor, and assignee information in the United States Patent and Trademark Office's (USPTO) PatentsView database with patent and PERMCO (the firm identifier in the CRSP database) information in the Kogan, Papanikolaou, Seru, and Stoffman's Patent and Citation File (2017, referred to hereafter as the KPSS database). Our inventor-level data allow us to track acquirer and target inventors' career paths, which is key to determining whether postmerger collaboration has occurred. Our patent-level data allow us to examine the relation between acquirer and target inventors' collaborative efforts and their innovation outcomes.

To capture an inventor's or an inventor team's patenting performance, we introduce three new measures of path-breaking innovation to the M&A literature – radical patents based on the (*ex ante*) unprecedented combination of knowledge (e.g., Weitzman 1998; Eggers and Kaul 2018; Bernstein, Diamond, McQuade, and Pousada 2019); impactful patents based on the (*ex post*) number of citations (e.g., Balsmeier, Fleming, and Manso 2017; Eggers and Kaul 2018); and valuable patents based on the (*ex post*) movement in stock prices in the days immediately after a patent has been issued to a firm (Kogan et al. 2017).

Using a sample of 28,166 acquirer inventors and 4,257 target inventors in 942 deals announced and completed between 1981–2012 with inventor career information spanning 1976–2019, we first show that acquirer and target inventors produce a similar number of patents, although the number of patent citations acquirer inventors receive is significantly higher than those accorded to target inventors. Moreover, we show that acquirer inventors have significantly larger networks, and are significantly more specialized, than target inventors.

We then show a steep increase postmerger in the frequency of collaboration between acquirer and target inventors. In terms of economic significance, the number of collaborative projects increases by 0.580 per deal-year after deal completion, which is substantial relative to the average number of collaborative projects per deal-year at 0.015 over the five-year period before bid announcement. This finding represents one of the first pieces of evidence on how M&As achieve human capital synergies—by expanding firm boundaries, M&As enlarge the opportunity set for acquirer inventors to form collaborative teams. The very fact of a steep increase postmerger in the number of collaborative teams suggests that there had been a binding constraint for collaboration and knowledge transfer within the acquiring firm premerger.

To establish the causal effect of M&As on collaboration between acquirer and target inventors, we exploit a quasi-experiment in which the control group is a sample of failed bids due to reasons unrelated to innovation. This approach addresses the possibility that collaboration between acquirer and target inventors is driven by selection (i.e., a firm-pair is more likely to merge if their inventors need to collaborate with one another), rather than by treatment. With this approach, we can difference out any selection effects by comparing the frequency of collaboration between acquirer and target inventors in the completed deal sample pre- and postmerger with that in the withdrawn bid sample (i.e., the control group). We find that deal completion results in a significant increase in the frequency of collaboration between acquirer and target inventors. A comparison of the total effect and treatment effect using the quasi-experiment, together with univariate statistics on the frequency of collaboration over the ten-year period centered at deal completion, suggest that the treatment effect is dominant.

We next show that compared to patents by acquirer/target inventor-only teams, patents produced by collaboration between acquirer and target inventors are more likely to be radical, impactful, and valuable. In terms of economic significance, the number of radical/impactful/valuable patents by inventors on hybrid teams is 0.250/0.204/0.222 more than that by inventors not on hybrid teams. These differences are economically significant given the number of radical/impactful/valuable patents by acquirer/target inventor-only teams at 0.144/0.139/0.169 over the five-year period postmerger. Our finding thus provides novel evidence on the unique benefit of M&As in expanding acquirers' innovative capabilities: collaboration between acquirer and target inventors postmerger is associated with more path-breaking innovation than acquirer/target inventor-only teams.

We then examine what target inventor characteristics are associated with more collaboration with acquirer inventors postmerger. We find that acquirer inventors are more likely to collaborate with target inventors who share the same core expertise and are geographically proximate, are less specialized inventors, whose significant collaborators are not staying in the merged firm, are star inventors, and are inventors with large networks. To the extent that those in the latter two categories are more capable, our findings suggest that M&As allow acquirers to tap into opportunities for collaboration with target inventors who would otherwise be inaccessible or unavailable. We further show that acquirer inventors produce more path-breaking innovation via collaboration with target inventors than the reverse, highlighting the importance of human capital synergies to acquirers.

In addition to providing opportunities to collaborate with target inventors, M&As offer two other well-known benefits that help improve acquirers' innovation performance: access to target inventors' patenting output and knowledge spillovers from target firms (Holmström and Roberts 1998; Ahuja and Katila 2001). We show that collaboration between acquirer and target inventors is more important in expanding acquirers' innovative capabilities than just having target inventors working for acquirers and/or receiving knowledge spillovers. We further show that the positive association between collaboration and path-breaking innovation is unlikely due to (codified) knowledge spillovers (e.g., through reading patent filings) between the acquirer and its target firm. Instead, our results suggest that tacit knowledge transfer (e.g., through learning and mentoring) is the mechanism underlying the positive association between collaboration and path-breaking innovation.

We conclude that M&As achieve human capital synergies by expanding the opportunity set for collaboration between acquirer and target inventors, resulting in more path-breaking innovation.

Our paper differs from prior work, and thus contributes to the M&A and innovation literature, in at least three ways. First, using unique inventor- and patent-level data, our paper provides novel large-sample evidence on M&As as an effective mechanism for bringing inventors of diverse knowledge and innovation experience together under the same roof and facilitating the recombination of knowledge, resulting in more path-breaking innovation. Second, our paper highlights a number of inventor characteristics such as inventor productivity and network size that are conducive to achieving human capital synergies in M&As. Third, our paper provides suggestive evidence that the positive association between acquirer and target inventor collaboration postmerger and path-breaking innovation is more likely due to tacit knowledge transfer rather than codified knowledge spillovers. More broadly, our paper suggests that by fostering path-breaking innovation, M&As are an important means of addressing the pressing issue of the scarcity of original ideas (Bloom, Jones, Van Reenen, and Webb 2019).

Our paper is closely related to an emerging strand of the M&A literature examining the human capital factor in acquisitions. Ouimet and Zarutskie (2016), Beaumont, Hebert, and Lyonnet (2019), and Chen, Gao, and Ma (2020) show that the desire to gain human capital is a key impetus for corporate takeovers. Tate and Yang (2016) find that diversifying mergers are more likely to occur among industry pairs with high human capital transferability, and that such acquisitions result in larger labor productivity gains and fewer post-merger divestitures. Lee, Mauer, and Xu (2018) show that acquisitions are more likely, and announcement period returns and postmerger operating performance are higher, when employees of merging firms have similar job skills, as defined by the Occupational Employment Statistics (OES) of the Bureau of Labor Statistics (BLS). Ma, Ouimet, and Simintzi (2018) and Lagaras (2020) highlight the scope of post-merger labor restructuring in target firms. Seru (2014) is one of the first to present evidence on post-merger target inventor turnover and productivity. He finds that following M&As, the likelihood of target inventors leaving an acquired firm increases by around 80%, and the average number of citations per patent by target inventors drops by 70%.

Our paper is also related to the literature on post-merger restructuring and the boundaries of the firm. Maksimovic and Phillips (2001) show that firms possess different levels of ability to exploit assets, with comparative advantages in their respective main industries, and that more skilled firms are better able to improve their acquired assets. They conclude that the market for corporate assets facilitates the redeployment of assets from firms with a lower ability to exploit them to firms with a higher ability to do so. Schoar (2002) presents a more nuanced picture: Acquired plants increase productivity whereas incumbent plants suffer, leading to diversifying acquisitions associated with a net reduction in productivity. Maksimovic, Phillips, and Prabhala (2011) find that acquirers skilled in running their peripheral divisions tend to retain more acquired plants, and that retained plants increase in productivity, whereas sold plants do not. They conclude that acquirers restructure targets in ways that exploit their own comparative advantage. Shedding light on that productivity gain, Li (2013) shows that acquirers make more efficient use of capital and labor, and reallocate capital to industries with better investment opportunities.

Finally, our paper is also related to the large economics literature on knowledge spillovers and growth. Jaffe (1986) and Jaffe, Trajtenberg, and Henderson (1993) show that both technological and geographic proximity facilitate knowledge spillovers. Ahuja and Katila (2001) show that technological acquisitions expand an acquirer's knowledge base and provide scale, scope, and recombination benefits. This literature further recognizes that state-of-the-art technologies are often tacit knowledge embodied in the human capital of a firm's employees that cannot easily be transferred across firms (Winter 1987; Cohen and Levinthal 1990; Leonard-Barton 1995; Song, Almeida, and Wu 2003).

2. The Conceptual Framework

2.1. M&As, collaboration, and path-breaking innovation

There is a long-standing economics literature studying the relation between competition and innovation in the context of an agency problem (see the seminal work by Hart (1983) and

Schmidt (1997) and empirical evidence in Aghion et al. (2005)). The general conclusion is that it is complicated.

Fulghieri and Sevilir (2011) examine the effect of mergers between competing firms on employee incentives to innovate. They show that although a merger between two competing firms can increase market power, this benefit is offset by a negative effect on employee incentives to innovate, because the merger decreases competition for human capital, allowing the combined firm to extract greater rents from employees. The net effect is that mergers can be harmful for corporate innovation and new product development. Using patent-based metrics, Seru (2014) finds that conglomerate mergers stifle innovation at target firms as these firms experience high inventor turnover and low patenting productivity postmerger. Using pharmaceutical industry data, Cunningham, Ederer, and Ma (2019) show that incumbent firms may acquire innovative target firms solely to discontinue the latter's innovation projects and preempt future competition.

On the other hand, the property rights theory of the firm developed by Grossman and Hart (1986) and Hart and Moore (1990) and its extension to M&As by Rhodes-Kropf and Robinson (2008), posit that in a world with incomplete contracting, complementary assets should be placed under the control of a single firm to achieve synergies.

Fulghieri and Sevilir (2019) develop a model of human capital integration postmerger. In their model, employees in the combined firm choose between collaboration to create synergies, and competition to extract greater resources from the corporate headquarters. The authors show that incentives to collaborate are stronger in mergers between firms with greater human capital complementarity because when employees collaborate, they learn from each other and enhance their own human capital/productivity; and the effect is larger when there is more to learn from employees of the other firm. Their model provides a theoretical justification for why mergers between firms with greater human capital complementary are associated with better postmerger performance (e.g., Lee, Mauer, and Xu 2018).

In summary, although M&As may be bad for individual employees to work hard postmerger, there is a bright side: M&As bring employees of acquirers and target firms together, and give them the opportunity to exchange knowledge and collaborate through formation of teams. To the extent that M&As are used to place complementary assets, including the human capital attached to those assets, under one roof, we expect that common ownership will result in more knowledge transfers and collaboration (Holmström and Roberts 1998; Hart and Holmström 2010; Fulghieri and Sevilir 2019).[1]

Radical innovation, by definition, is a combination of knowledge from domains that might ordinarily not be connected (e.g., Weitzman 1998; Eggers and Kaul 2018; Bernstein et al. 2019). Taylor and Greve (2006) and Singh and Fleming (2010) show that teams with diverse knowledge domains are more likely to generate cutting-edge ideas and novel combinations of knowledge components. Bernstein et al. (2019) find that combining the different knowledge bases of immigrant and native inventors is especially important in producing highly valuable patents.

Postmerger, acquirer inventors can collaborate with target inventors; with each bringing a different set of knowledge domains and past experience to their collaboration, the potential for path-breaking innovation is heightened. Moreover, target inventors may be uniquely positioned to facilitate acquirer inventors in exploring novel combinations of a target firm's core technology

[1] As a result, our paper is related to Tate and Yang (2015) who examine the bright side of corporate diversification. They show that the presence of internal labor markets provides strong incentives for workers to invest in and develop skills, as well as collaborate across divisions, resulting in significant labor productivity gains.

embodied in their human capital (i.e., tacit knowledge) in addition to codified knowledge (e.g., patent filings). We thus expect that M&As will facilitate radical innovation through collaboration between acquirer and target inventors.

It is worth noting that M&As are not the only means of expanding firms' innovative capabilities; innovative firms also turn to hiring talent and forming strategic alliances to facilitate inter-firm knowledge transfer (Mowery, Oxley, and Silverman 1996; Song, Almeida, and Wu 2003; Li, Qiu, and Wang 2019). However, firms that hold state-of-the-art technology are often reluctant to allow such a transfer because the tacit nature of this knowledge is an important source of competitive advantage and firm value (Winter 1987; Kogut and Zander 1996). In contrast, M&As ensure that target inventors' human capital is not separated from the systems, processes, and routines with which it can be effectively utilized (Hart and Holmström 2010) and facilitate tacit knowledge transfer via social interactions, learning, and mentoring between acquirer and target inventors (Winter 1987; Kogut and Zander 1996; Song, Almeida, and Wu 2003).

2.2. Inventor characteristics and collaboration between acquirer and target inventors

As discussed earlier, expanding firm boundaries via M&As removes frictions to forming collaborative teams between acquirer and target inventors and facilitates tacit knowledge transfers, leading to more path-breaking innovation. We expect the likelihood of collaborating, and its benefits, to differ depending on a number of inventor characteristics.

We first introduce the concept of an inventor's core class, which is the technology class in which an inventor has been granted the highest number of patents applied for up to the year before bid announcement (i.e., year *ayr-1*). Given that collaboration is typically built on common ground (Cohen and Levinthal 1990; Kogut and Zander 1992; Ahuja and Katila 2001), we expect that *ceteris paribus*, acquirer and target inventors who share a common core technology class will be more likely to work together.

Second, geography matters. Jaffe, Trajtenberg, and Henderson (1993) study the geography of knowledge spillovers using patent citations, and find that knowledge spillovers are strongly localized. Phene, Tallman, and Almeida (2012) further show that geographic overlap between target and acquirer locations is conducive to exploratory innovation. To the extent that geographic proximity facilitates forming a social community (e.g., a group or network), learning, and mentoring, we expect that *ceteris paribus*, acquirer and target inventors in geographic proximity will be more likely to work together.

Third, the ability of an inventor to contribute to innovation in a merged firm might depend on whether her premerger team was retained. On the one hand, recent studies (e.g., Jaravel, Petkova, and Bell 2018; Bernstein et al. 2019) show that team capital is an important factor in inventor productivity. Thus, a loss of key collaborators might negatively affect an inventor's postmerger productivity and prompt her to join a new team. On the other hand, an inventor may choose to stay in a merged firm in spite of the departure of her key collaborators, a self-selection (e.g., due to her limited dependence on collaborators) that might mitigate the negative effect on her productivity, and thus limit the likelihood of her joining a new team. It is thus an empirical question whether the loss of key collaborators will negatively affect an inventor's propensity to collaborate with inventors of another firm.

Fourth, the potential of an inventor to contribute to innovation in a merged firm might depend on whether she is a star inventor. On the one hand, past productivity breeds future productivity given that knowledge creation is cumulative (see the survey by Jones, Reedy, and Weinberg 2014). On the other hand, M&As are a watershed event in the research environment of retained inventors, and especially of target inventors who might have difficulty adapting to the research culture/environment of their acquirer, leading to lower productivity postmerger (Ranft and Lord 2002). If acquiring talent is one important motive of M&As, we would expect that target star inventors would be more likely to be invited to collaborate with acquirer inventors than target average inventors.

Fifth, an inventor's network might enhance her contribution to innovation in a merged firm. Singh (2005) finds that inventor collaborative networks are important in explaining knowledge diffusion across regional or firm boundaries. Singh and Fleming (2010) show that a broader network enables greater recombinant opportunity, leading to breakthrough innovation. On the other hand, inventors with large collaborative networks are less likely to be subject to binding constraints on finding collaborators outside their home firm. It is thus an empirical question whether inventors with a broad network are more likely to collaborate postmerger.

Finally, we consider the degree of inventor specialization. Melero and Palomeras (2015) find that the presence of generalists with a broader knowledge set on a team enables a more effective recombination of knowledge. We thus expect that *ceteris paribus*, generalist inventors will be more likely to work collaboratively with inventors of another firm.

3. Sample Formation and Variable Constructions

3.1. The M&A sample, the patent sample, and the inventor sample

Our M&A sample comes from Thomson Financial's SDC Platinum Database on Mergers and Acquisitions. We start with all U.S. deals announced and completed between January 1, 1981 and December 31, 2012. We impose the following filters to obtain our final sample: 1) the deal is classified as "Acquisition of Assets (AA)", "Merger (M)," "Acquisition (A)", or

"Acquisition of Majority Interest (AM)" by the data provider; 2) both the acquirer and its target firm are U.S. public firms; 3) the acquirer holds less than 50% of the shares of the target firm before bid announcement and ends up owning 100% of the shares of the target firm through the deal; 4) the deal value is at least $1 million (in constant 2019 dollars); 5) the relative size of the deal (i.e., the ratio of transaction value over an acquirer's book value of assets) is at least 1%; and 6) both the acquirer and its target firm have at least one inventor in the year prior to bid announcement. We end up with a sample of 942 completed deals.

Our sample period starts in 1981, when data coverage on M&As started. Our M&A sample ends in 2012 for the following reason. The year 2019 was the last year in which the KPSS database has coverage; given the well-known patent approval lag between application and award, the year 2017 would be the last year in which patent-related measures do not suffer serious truncation bias. Since we require a five-year window after the year of deal completion to examine postmerger innovation outcomes, the last year for completed deals to have a full postmerger five-year window is 2012.

The PatentsView database contains application dates of granted patents and the number of citations received by these patents, as well as the patents' technology classes (using the Cooperative Patent Classification). It also has the list of assignees of a patent, which are typically firms or their subsidiaries where the research was conducted, as well as the list of inventors. Of particular importance to us, the PatentsView database provides a unique identifier for each assignee and a unique identifier for each inventor, which are required to help establish inventor-employer linkage over time in order to track inventors' career paths. The KPSS database provides the patent-PERMCO link for patents applied for between 1926 and 2019; we use this information to match patent and patent assignees to CRSP firms.

In our analysis, an inventor's place of employment is identified by the assignee of her patent. For example, an inventor who applies for one patent with firm A in 2000 and another with firm B in 2005 is assumed to be an employee of firm A in 2000 and an employee of firm B in 2005. We then assume that her job change occurs at the midpoint between the two patent application years following convention (e.g., Marx, Strumsky, and Fleming 2009; Hombert and Matray 2017). Inventors are included in the sample for their entire active career, i.e., the period between the year of their first and the year of their last patent applications. A detailed description of our matching scheme to link inventors in the PatentsView database with U.S. public firms in the CRSP database is provided in Appendix A. An acquirer (target) inventor is identified as someone whose active career spans the year before bid announcement (*ayr-1*) and whose employer at that particular point in time is the acquirer (target firm). Our final sample of inventors consists of 28,166 acquirer inventors and 4,257 target inventors who have applied for at least one patent in target classes (to be defined below) over the period *cyr+1* to *cyr+5*.

An acquirer often has multiple segments of business that might or might not overlap with the segment(s) of its target (e.g., Microsoft's acquisitions of Skype and GitHub). To examine the contribution of target inventors to the innovation performance of the acquirer relative to that of incumbent acquirer inventors in an apples-to-apples comparison, we focus on technology classes in which target inventors produce patenting output in the merged firms. Consider Microsoft's 2011 acquisition of Skype as an example; while Skype specializes in telecommunications application, Microsoft has divisions in many different areas, such as operating systems (Windows), a suite of office applications (Office), cloud computing (Azure), and gaming (Xbox), and at the time of the acquisition had a telecommunications application (MSN messenger). To examine Skype inventors' contributions to Microsoft's innovation performance, we focus on technology classes in which Skype inventors produce patents after the acquisition, which are more likely to be in telecommunications applications than in other areas such as operating systems. For this reason, for each year over the period from one year after deal completion (i.e., year *cyr+1*) to five years after (i.e., year *cyr+5*), we define target classes as the technology classes in which target inventors (either alone or on a hybrid team with acquirer inventors) apply for at least one patent in that year. The term target classes thus refer to the specific technological areas in which target inventors file patents at a merged firm following deal completion. Among patents in target classes, we identify those that involve at least one target (acquirer) inventor who works in the target firm (acquirer) in *ayr-1*. Our final sample of patents consists of 51,286 patents applied for over the period *cyr+1* to *cyr+5* and in target classes in their application year.

3.2. Key variables

To capture path-breaking innovation, we introduce three new measures to the M&A literature (see detailed definitions in Appendix B) – radical patents based on (*ex ante*) unprecedented knowledge combination (e.g., Weitzman 1998; Eggers and Kaul 2018; Bernstein et al. 2019), impactful patents based on the (*ex post*) number of citations (Phene, Tallman, and Almeida 2012; Balsmeier, Fleming, and Manso 2017; Eggers and Kaul 2018), and valuable patents based on the (*ex post*) price reaction to the news that a patent has been issued to a firm (Kogan et al. 2017). Specifically, a patent is radical if it draws on knowledge that has never or rarely been used before by inventors in the same field.[2] The measure looks at the class-to-class citation pattern of patents to determine how rare a given citation is. If patents in Class A

[2] Bhattacharya and Packalen (2020) show that the emphasis on citations in the measurement of scientific productivity has shifted scientists' behavior on the margins towards incremental discoveries and away from more innovative and riskier discoveries, which tend to gather fewer citations but lay the necessary groundwork for subsequent breakthroughs. Their findings motivate us to adopt a measure of radical patents that captures path-breaking innovation on an *ex-ante* basis and is not based on citations *ex post*.

frequently cite patents in Class B, then a new A-to-B citation would be common and expected (i.e., neither rare nor radical). If, however, hardly any patent in Class A cited a Class B patent in the last five years, then such a citation would signal an attempt at a more radical recombination. At the patent level, the measure looks at all citations a patent makes and takes the value of the most unlikely citation. We define radical patents as those in the top 5th percentile in terms of drawing on fundamentally new knowledge among granted patents in the same technology class-year (Eggers and Kaul 2018).[3] A patent is impactful if the number of citations it received (up to 2019) is in the top 5th percentile among granted patents in the same technology class-year. A patent is valuable if its change in market capitalization over the three-day period from the patent issuance day to two days thereafter (Kogan et al. 2017) is in the top 5th percentile among granted patents in the same technology class-year.

We also introduce a number of inventor-specific characteristics to shed light on cross-sectional variation in the propensity to form collaborative teams. *Same core* is an indicator variable that takes the value of one if two inventors share the same core technology class, and zero otherwise. An inventor's core class is the technology class in which she has been granted the most number of patents applied for up to the year before bid announcement (*ayr-1*). *Distance* is the natural logarithm of the number of kilometers between two inventors' locations in the PatentsView dataset. *Inventor significant co-inventor stay* is an indicator variable that takes the value of one if at least one significant co-inventor works for the merged firm over the period *cyr+1* to *cyr+5*, and zero otherwise. A significant co-inventor is a collaborator for a focal

[3] Applying textual analysis to patent filings, Bowen, Frésard, and Hoberg (2019) construct a measure of technological disruptiveness for individual patents. According to the authors, their measure captures "the extent to which it uses vocabulary that is new and is experiencing rapid growth across all patents compared to existing knowledge." A key difference between their measure and the radical innovation measure in our study is that our measure is not based on the growth rate of a particular knowledge domain, and thus is a relatively clean measure of path-breaking innovation that could occur not only in "hot" but also in "cold" technological areas.

inventor whose number of jointly developed patents with the focal inventor is more than 50% of the latter's total number of patents over the five-year period *ayr-5* to *ayr-1*. *Star inventor* is an indicator variable that takes the value of one if an inventor's number of citations (up to 2019) for granted patents applied for up to *ayr-1* is in the top 5^{th} percentile among all inventors in the PatentsView database, and zero otherwise. *Inventor network size* is the natural logarithm of one plus the number of unique inventors who have collaborative links of no more than two teams away from the focal inventor up to *ayr-1*. Thus, *Inventor network size* is a measure of the number of the co-inventors and these co-inventors' own respective co-inventors. *Inventor specialization* is the Herfindahl index based on the technology class-share of granted patents applied for by an inventor up to *ayr-1*. The bigger this value is, the more specialized the inventor is in terms of her patenting output.

3.3. Sample overview

Table 1 presents the summary statistics of sample deals and firms. Our M&A sample consists of 942 deals announced and completed over the period 1981–2012. We show that over 40% of these deals take place between firm pairs in different two-digit SIC industries. The average/median ratio of transaction value to acquirer book value of assets is 46%/23%. About a third of the deals are paid entirely in cash, and about another a third are paid entirely by stock. Overall, deals in our sample are not very different from deals in much larger samples such as Li, Qiu, and Shen (2018).

In terms of acquirer and target firms in our sample, acquirers are far larger than their target firms. Acquirers also have higher Tobin's Q, return on assets (ROA), and prior year return than their target firms.

3.4. Inventor characteristics and patenting outcome

Table 2 Panel A presents the summary statistics of inventor characteristics as of *ayr-1* for those inventors who apply for patents in target classes over the period *cyr+1* to *cyr+5*. For each year, target classes are technology classes in which at least one patent applied for in that year involves target inventors.

We show that acquirer inventors experience similar degrees of disruption to their teams as target inventors: 58% of acquirer inventors experience disruption to their collaborative teams, compared to 57% of target inventors (albeit the difference is statistically significant at the 10% level). We further show that acquirer inventors are significantly more likely to be star inventors than target inventors: 14% for the former versus 12% for the latter. The average size of a co-inventor network is 105 for acquirer inventors and 79 for target inventors. We further show that acquirer inventors are significantly more specialized than target inventors. Finally, we show that both groups of inventors have similar patenting outcomes as measured by the median number of patents, and acquirer inventors' patents generate significantly more citations than those of target inventors.

Panel B presents the summary statistics of patents in target classes produced by collaboration between acquirer and target inventors (i.e., hybrid teams) and by acquirer/target inventor-only teams over the period *cyr+1* to *cyr+5*. We show that patents produced by collaboration between acquirer and target inventors are significantly more likely to be radical than those produced by acquirer/target inventor-only teams: close to 9% of patents by the former compared to only 5% by the latter. Moreover, more than 6% of patents by hybrid teams are impactful, compared to only 5% of patents by acquirer/target inventor-only teams. Finally, we show that 8% of patents by hybrid teams are valuable, compared to about 6% of the patents by acquirer/target inventor-only teams.

In untabulated analysis, we find that the Pearson correlations between radical and impactful, between radical and valuable, and between impactful and valuable patents are 0.025, 0.012, and 0.026, respectively, suggesting that our three measures capture distinct facets of path-breaking innovation.

Next, we explore whether and how M&As help achieve human capital synergies.

4. Main Findings

4.1. M&As and collaboration between acquirer and target inventors

In this section, we investigate whether M&As facilitate collaboration between acquirer and target inventors in merged firms. To do so, we take advantage of the detailed information available on inventor teams of each patenting project, i.e., project-level collaboration between acquirer and target inventors. Our outcome variable is the frequency of collaboration as measured by the number of patents by collaborative teams of acquirer and target inventors. We compare the number of patents produced by collaboration between acquirer and target inventors premerger to postmerger. Table 3 column (1) presents the ordinary least squares (OLS) regression results.

We show a significant rise in the number of patents produced by collaboration between acquirer and target inventors postmerger, suggesting an increased frequency of collaboration after deal completion. In terms of economic significance, the number of collaborative projects increases by 0.580 per deal-year, which is substantial relative to the average number of collaborative projects per deal-year at 0.015 over the five-year period prior to bid announcement.

Figure 1 presents the frequency of collaboration between acquirer and target inventors over time for our sample deals. We show that there is indeed a steep increase postmerger in the frequency of collaboration as shown by the number of patents produced by those collaborative teams compared to the frequency premerger.

These findings represent one of the first pieces of evidence on how M&As achieve human capital synergies; by expanding firm boundaries, M&As enlarge the opportunity set for acquirer inventors to form collaborative teams. The fact of a steep increase postmerger in the number of collaborative teams suggests that there had been a binding constraint for collaboration and knowledge transfer within the acquiring firm premerger.

To disentangle selection (i.e., a firm-pair is more likely to merge if their inventors need to collaborate with each other) from the treatment effect of M&As (i.e., M&As result in more collaboration between the two firms), we exploit a quasi-experiment in which the control group is a sample of failed bids for reasons unrelated to innovation (Bena and Li 2014; Seru 2014). With this approach, we can difference out any selection concerns by comparing the frequency of collaboration between acquirer and target inventors in the completed deal sample pre- and postmerger with that in the withdrawn bid sample (i.e., the control group).

To form the control sample, we identify withdrawn bids over the period 1981–2012 by manually examining the reason for withdrawal and including only bids whose reason for withdrawal is unlikely to be related to innovation performance (i.e., difficulties in securing financing, objections by regulatory bodies, or adverse macroeconomic/market conditions). For each withdrawn bid, we then identify completed deals in our sample using the following criteria: 1) the announcement year of the completed deal is no more than ten years away from the withdrawn bid; and 2) the core area of the acquirer in the completed deal is the same as the core area of the acquirer in the withdrawn bid. For each withdrawn bid, we then pick up to five completed deals whose relative size is closest to that of the withdrawn bid. We obtain 74 completed deals matched to 19 withdrawn bids. Table 3 column (2) repeats the analysis in column (1) using only the matched completed deals to establish the total effect of M&As on hybrid team formation. We show that the coefficient on the standalone term *After* is positive and significant at the 5% level.

To disentangle the treatment and selection effects, we run the following difference-in-differences regression:

$$\#Patents\ by\ hybrid\ teams_{i,m,t} = \alpha + \beta_1 After_t + \beta_2 After_t \times Completed_{i,m} + Deal\ FE_m + e_{i,m,t}, \quad (1)$$

where the dependent variable is *#Patents by hybrid teams*. *After* is an indicator variable that takes the value of one over the period *cyr+1* to *cyr+5*, and zero otherwise. *Completed* is an indicator variable that takes the value of one for patents by hybrid teams in completed deals, and zero otherwise. Deal fixed effects are included to control for deal/firm-specific time-invariant unobservables that might drive the M&A decision and outcome variable. The sample consists of collaborative project observations associated with those completed deals/withdrawn bids over the period *ayr-5* to *ayr-1* and the period *cyr+1* to *cyr+5*. Table 3 column (3) presents the regression results.

We show that the coefficient on the interaction term *After × Completed* is positive and significant at the 5% level, suggesting a significant treatment effect from deal completion on the frequency of collaboration between acquirer and target inventors. Moreover, we show that the coefficient on the standalone term *After* is positive and significant at the 5% level, suggesting increasing collaboration over time between inventors across sample firm-pairs. More importantly, we show that the selection effect of M&As on hybrid team formation as captured by the coefficient on *After* at 0.211 is much smaller than the treatment effect as captured by the coefficient on the interaction term *After* $\times$ *Completed* at 1.695, suggesting that the treatment effect dominates, at least from the human capital synergy angle from which we view M&As.

In summary, using the quasi-experiment to separate treatment from selection, we show a significant treatment effect of deal completion on the frequency of collaboration between acquirer and target inventors.

In the next section, we examine the consequence of having more collaboration between acquirer and target inventors on acquirers' innovative capabilities.

4.2. Collaboration between acquirer and target inventors and path-breaking innovation

Jaravel, Petkova, and Bell (2018) show that the practice of forming inventor teams is growing over time, and that the majority (over 60%) of patents in the USPTO database are produced by teams of two or three inventors. The mean (median) inventor team size in our inventor sample is 3.2 (3). The mean/median share of acquirer/target inventors on hybrid teams is 0.40/0.33 (0.35/0.33), as a hybrid team could also include other inventor(s) who are not identified as acquirer/target inventor(s) as of *ayr-1*. The share of a single inventor accounts for about a fifth of our sample.

Table 4 reports our investigation of how path-breaking innovation occurs following M&As by making use of inventor team information at the patent level. Panel A presents the patent-level linear probability regression results on the relation between collaboration and path-breaking innovation controlling for deal fixed effects. The dependent variables are the indicator variables for radical/impactful/valuable patents. The baseline case is patenting output by acquirer/target inventor-only teams.

We show that compared to patents by acquirer/target inventor-only teams, patents by hybrid teams composed of acquirer and target inventors are more likely to be radical: the likelihood is higher by 2.3 percentage points. This difference is economically significant given that the share of patents by acquirer/target inventor-only teams that are radical is 5.0 percentage points, suggesting an almost 50% increase in the likelihood of a patent being radical. Moreover, we show that patents by large inventor teams are more likely to be radical and impactful but less likely to be valuable.

Panel B examines the relation between an inventor on hybrid teams and her number of path-breaking patents using inventor-level data. The dependent variables are an inventor's number of radical/impactful/valuable patents. The baseline case is the number of radical/impactful/valuable patents filed by inventors not on hybrid teams over the period *cyr+1* to *cyr+5*.

Consistent with the patent-level results in Panel A, we show that compared to inventors not on hybrid teams, inventors who collaborate on such teams produce more radical/impactful/valuable patents postmerger. In terms of economic significance, the number of radical/impactful/valuable patents by inventors on hybrid teams is 0.250/0.204/0.222 more than the corresponding numbers by inventors not on hybrid teams. These differences are economically significant given the number of radical/impactful/valuable patents by acquirer/target inventor-only teams at 0.144/0.139/0.169 over the five-year period postmerger. Our finding thus provides novel evidence on the unique benefit of M&As in expanding acquirers' innovative capabilities: collaboration between acquirer and target inventors postmerger is associated with more path-breaking innovation than acquirer/target inventor-only teams.[4]

There are two possible reasons why collaboration between acquirer and target inventors is associated with more path-breaking information. One is the direct effect of collaboration from recombination of knowledge and expertise (e.g., Taylor and Greve 2006; Singh and Fleming 2010), and the other is the indirect effect of collaboration that calls for more capable inventors to join hybrid teams, so it is individual inventors' capabilities, and not collaboration per se, that drive the result. Our subsequent analysis suggests that both effects are at play.[5]

Overall, Table 4 provides novel patent- and inventor-level evidence on how M&As achieve human capital synergies—by expanding firm boundaries, M&As enlarge the opportunity set for acquirer inventors to collaborate and facilitates knowledge transfer and recombination, which in turn result in more path-breaking innovation.[6]

We next explore which inventor characteristics are more conducive to forming collaboration between acquirer and target inventors.

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[4] One other way to expand a firm's innovative capability is to hire individual inventors from its competitors. If hiring is one important way to do so, we would expect the association between hybrid teams and path-breaking innovation will be attenuated in states in which it is easy to hire talent from competitors. Using state-level data on adoptions of the Inevitable Disclosure Doctrine (IDD) (Chen, Gao, and Ma 2020), we find that there is no significant effect of IDD on the positive association between hybrid teams (resulting from M&As) and path-breaking innovation. This finding suggests that hiring individual inventors from competitors and acquiring competitors have different implications for expanding the hiring/acquiring firm's innovative capability.

[5] In an earlier version of the paper, we attempted to differentiate between these two effects, by using data on patent-inventor pairs and adding inventor fixed effects, which effectively control for time-invariant inventor capability. However, this approach fails to account for heterogeneity in capability across collaborating inventors (relative to the focal inventor as captured by inventor fixed effects). We leave this endeavor to future research.

[6] There are other innovation-related benefits and costs that our empirical design fails to capture. First, one important dimension of knowledge transfer from target inventors to their acquiring firms is the diffusion of tacit knowledge to incumbent and newly hired inventors in the acquiring firms. Through collaborative research, social interaction, and mentoring, target inventors may impact the innovative capabilities of the acquirers more broadly than reported in this paper (via collaboration to produce patents). Second, the very acquisition itself may attract new inventors to the merged firm in order for them to collaborate with target inventors. Offsetting these benefits, the very acquisition could also prompt departure of some of acquirer inventors.

4.3. Inventor characteristics and collaboration between acquirer and target inventors

To examine what inventor characteristics are positively associated with the likelihood of collaboration between acquirer and target inventors, we form pseudo pairs. Specifically, we first identify acquirer-target inventor pairs in which these inventors have collaborated on at least one patent filed over the period *cyr+1* to *cyr+5*. For the acquirer (target) inventor in the sample pair, we then randomly pick three other acquirer (target) inventors and form pseudo pairs with the target (acquirer) inventor. The sample thus consists of the sample pair plus up to three pseudo pairs. Table 5 presents the linear probability regression results where the dependent variable is an indicator variable that takes the value of one for the sample pair, and zero for the pseudo pairs.

Panel A presents the results focusing on target inventor characteristics. Given that we control for deal fixed effects and that acquirer inventor characteristics are invariant within a deal, we do not need to control for the characteristics of acquirer inventors. In column (1), we show that a target inventor and an acquirer inventor are more likely to form a hybrid team if they share the same core area, or are geographically proximate. Our inventor-level finding that acquirer and target inventors with the same core expertise are more likely to collaborate is consistent with the firm-level evidence in Phene, Tallman, and Almeida (2012) and Bena and Li (2014), and supports the notion that common ground is necessary for collaboration and knowledge transfer (Cohen and Levinthal 1990; Kogut and Zander 1992).[7] Given that geographic proximity

[7] It is worth noting that the variable *Same core* used in our analysis only captures common ground (based on technology classes, i.e., codified knowledge) on which to build a collaborative relationship. An inventor's knowledge domains and experience, most of which is tacit in nature, equal more than the technology classes in which she produces patents. For example, acquirer and target inventors working for different firms could possess very different knowledge and innovation experience in the form of tacit knowledge, even when their expertise is categorized as in the same technology class.

facilitates forming a social community (e.g., a group or network), learning, and mentoring, we expect that postmerger collaboration will foster tacit knowledge transfer.

In columns (2) – (5), when we include one target inventor characteristic at a time, we further show that a target inventor is more likely to join a hybrid team if her significant collaborators are not staying in the merged firm, she is a star inventor, she has a larger network, and she is less specialized. To the extent that star inventors and inventors with larger networks are more capable, our findings suggest that M&As allow acquirers to tap into opportunities for collaboration with such target inventors who would otherwise be inaccessible or unavailable.

Panel B presents the results focusing on acquirer inventor characteristics. In column (1), we show that an acquirer inventor and a target inventor are more likely to form a hybrid team if they share the same core area, or are geographically proximate. In columns (2) – (5), when we include one acquirer inventor characteristic at a time, we further show that an acquirer inventor is more likely to join a hybrid team if she has a larger network, and if she is less specialized.

In summary, we conclude that acquirer inventors are more likely to collaborate with target inventors who share the same core expertise and are geographically proximate, are star inventors, are inventors with large networks, are less specialized inventors, and whose significant collaborators are not staying in the merged firm; whereas target inventors are more likely to collaborate with acquirer inventors who share the same core expertise and are geographically proximate, are inventors with large networks, and are less specialized inventors.

Next, we explore how collaboration and inventor characteristics together are associated with path-breaking innovation.

4.4. Collaboration, inventor characteristics, and path-breaking innovation

In this section, we shed light on what type of target/acquirer inventors are more productive on collaborative teams. Table 6 Panel A presents the target inventor-level OLS regression results where the dependent variable is the number of radical patents.[8]

We show that across all specifications, target inventors on hybrid teams are associated with more radical patents (except for column (3)). More importantly, we show that target star inventors on hybrid teams are associated with significantly more radical patents. The coefficient on the interaction term *Hybrid team × Star inventor* is positive and significant at the 5% level. In terms of economic significance, a target star inventor on a hybrid team is associated with 0.265 more radical patents than a target average inventor on a hybrid team, which is non-trivial given that the average number of radical patents per inventor is 0.082. This finding again highlights that M&As offer acquirer inventors collaboration opportunities they would otherwise not have.

Panel B presents the acquirer inventor-level results. We show that across the board, acquirer inventors on hybrid teams are associated with more radical patents (except for column (3)). More importantly, we show that acquirer specialist inventors on hybrid teams are associated with significantly fewer radical patents. The coefficient on the interaction term *Hybrid team × Inventor specialization* is negative and significant at the 5% level. In terms of economic significance, an increase in acquirer inventor specialization by one standard deviation (0.175) is associated with a drop of 0.126 radical patents, which is again non-trivial given that the average number of radical patents per inventor is 0.082.

Overall, Table 6 shows that target star inventors and acquirer generalist inventors tend to outperform when working collaboratively with their counterparts on a hybrid team.

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[8] Tables IA1 (IA2) in the Internet Appendix presents the results when the dependent variable is the number of impactful (valuable) patents. Our main findings remain.

In summary, we show a causal link between deal completion and collaboration between acquirer and target inventors, and that such collaboration is associated with more path-breaking innovation. Our paper thus provides new evidence on the human capital synergies in M&As.

In next section, we explore other benefits of M&As and how they interact with hybrid teams to produce path-breaking innovation.

5. Other Benefits of M&As

In addition to providing opportunities to collaborate with target inventors, M&As offer two other well-known benefits that help improve acquirers' innovation performance: access to target inventors' patenting output and knowledge spillovers from target firms (Holmström and Roberts 1998; Ahuja and Katila 2001). In this section, we explore these two benefits to shed light on the possible mechanisms underlying human capital synergies in M&As.

5.1. Acquiring target talent

The fact that M&As are immediately beneficial in that they have target inventors working for acquirers begs the question: is an acquiring firm's hiring of target inventors sufficient on its own to produce path-breaking innovation? We answer this question by first comparing acquirer and target inventors' patenting performance and then accounting for whether they are on a hybrid team or not. Table 7 presents the OLS regression results where the dependent variables are the number of radical/impactful/valuable patents. The baseline case is the number of radical/impactful/valuable patents produced by acquirer inventors postmerger.

Columns (1) – (3) present the results without considering human capital synergies, i.e., without accounting for collaboration between acquirer and target inventors. We show that compared to acquirer inventors, target inventors are associated with more radical and valuable patents. Moreover, we show that star inventors, inventors with large networks, and less specialized inventors are associated with more path-breaking innovation. To assess whether target inventors produce more path-breaking innovation on their own or in collaboration with acquirer inventors, we add the indicator variable, *On hybrid team,* and the interaction term *Target inventor × On hybrid team*. Columns (4) – (6) present the results.

We show that the coefficient on the indicator variable, *On hybrid team,* is positive and significant at the 1% level across all three specifications, suggesting that collaboration between acquirer and target inventors produces significantly more radical/impactful/valuable patents than those by acquirer/target inventor-only teams. In stark contrast to columns (1) – (3), we show that after accounting for collaboration between acquirer and target inventors, the coefficient on *Target inventor* becomes insignificant, suggesting that target inventors alone are no more productive in path-breaking innovation than their acquirer peers. This result is an important finding in the M&A literature, i.e., the benefit of M&As in expanding acquirers' innovative capabilities comes from collaboration between acquirer and target inventors rather than from hiring target inventors alone.

Finally, we show that the coefficient on the interaction term *Target inventor × On hybrid team* is negative and significant in two out of three specifications, suggesting that compared to the positive association between hybrid teams and acquirer inventors' productivity, the positive association between hybrid teams and target inventors' productivity is less pronounced in terms of the number of radical or impactful patents. In sum, the negative interaction term suggests that the benefit of collaboration in producing path-breaking innovation is not symmetric – acquirer inventors on hybrid teams experience greater increases in productivity than target inventors.[9]

Considering our results as a whole, we conclude that the benefit of M&As in expanding acquirers' innovative capabilities comes from collaboration between acquirer and target inventors within expanded firm boundaries rather than from gaining access to target talent alone. Moreover, the positive association between being on hybrid teams and path-breaking innovation is stronger for acquirer inventors than for target inventors, indicative of binding constraints on collaboration for acquirer inventors prior to deal completion.

5.2. Codified knowledge spillovers

As noted above, M&As facilitate acquirer and target inventors gaining access to each other's respective knowledge domains. Following Ahuja and Katila (2001), we measure a firm's knowledge domain as the sum of its portfolio of patents and citations made by those patents over the five-year period ending *cyr-1*. Bena and Li (2014) find that M&As are more likely to take place between firm-pairs that share common knowledge domains. Motivated by their study, we introduce three indicator variables to capture citing a common knowledge domain, citing the target's exclusive knowledge domain (i.e., nonoverlapping with that of its acquirer), and citing the acquirer's exclusive knowledge domain (i.e., nonoverlapping with that of its target firm). By construction, knowledge spillovers largely refer to codified knowledge spillovers, i.e., via patent filings and citations. Table 8 presents the linear probability regression results where the dependent variables are indicator variables for radical/impactful/valuable patents.

[9] It is worth noting that using a subsample of target star inventors and acquirer inventors, we find that compared to acquirer inventors, target star inventors are associated with more valuable patents, and that after controlling for collaboration, target star inventors alone are not significantly associated with more path-breaking innovation. Moreover, we find that target star inventors on hybrid teams are associated with a similar level of path-breaking innovation as acquirer inventors on hybrid teams.

Panel A compares patenting output by acquirer inventor-only teams and hybrid teams, focusing on the role of codified knowledge spillovers from target firms to acquirer inventors. We show that the coefficient on *Citing target's exclusive knowledge* is not significantly different from zero, suggesting no significant association between knowledge spillovers from target firms to acquirer inventors and path-breaking innovation. In contrast, we show that both *Citing acquirer's exclusive knowledge* and *Citing common knowledge* are positively and significantly associated with the likelihood of a patent being radical and impactful, suggesting that the acquirer's knowledge base drives the direction of innovation endeavor postmerger. Finally, we show that compared to acquirer inventor-only teams, hybrid teams are positively and significantly associated with the likelihood of a patent being radical and impactful.

Panel B compares patenting output by target inventor-only teams and hybrid teams, focusing on the role of codified knowledge spillovers from acquirers to target inventors. We show that the coefficient on *Citing acquirer's exclusive knowledge* is not significantly different from zero, suggesting no significant association between knowledge spillovers from acquirers to target inventors and path-breaking innovation. In contrast, we show that *Citing common knowledge* is positively and significantly associated with the likelihood of a patent being radical.

To the extent that common knowledge captures complementary assets between the acquirer and its target firm, our findings in Table 8 support the prediction of property rights theory (Grossman and Hart 1986; Hart and Moore 1990; Rhodes-Kropf and Robinson 2008) that in a world with incomplete contracting, synergies are realized when complementary assets are placed under common ownership.

In summary, we find that codified knowledge spillovers from target firms to acquirer inventors (or from acquirers to target inventors) as commonly defined do not contribute to path-breaking innovation.

5.3. Codified knowledge spillovers via collaboration

The literature on knowledge spillovers recognizes that state-of-the-art technologies are often tacit and embodied in the human capital of a firm's employees, such that they cannot easily be transferred across firms (Winter 1987; Cohen and Levinthal 1990; Leonard-Barton 1995; Song, Almeida, and Wu 2003). While collaboration facilitates both spillovers of codified knowledge and transfers of tacit knowledge, it is essential in the latter, because such transfers occur within social communities (e.g., groups or networks), and through learning and mentoring. In contrast, spillovers of codified knowledge can take place without social interaction/collaboration (e.g., via reading patent documents). By expanding firm boundaries, M&As facilitate social interactions between acquirer and target inventors and hence are likely to have a greater effect on transfers of tacit knowledge than on spillovers of codified knowledge.

As shown above, spillovers of codified knowledge from target firms to acquirer inventors (or from acquirers to target inventors) per se are not associated with path-breaking innovation. However, spillovers of codified knowledge could still be a channel through which collaboration between acquirer and target inventors is positively associated with path-breaking innovation. In order to assess the possibility that spillovers of codified knowledge are behind the positive association between hybrid teams and path-breaking innovation, we give spillovers of codified knowledge its best shot, i.e., when a patent by acquirer (target) inventors cites its target firm's (acquirer's) exclusive knowledge, and examine whether the positive association is strengthened when the patent clearly relies on the merger partner's exclusive knowledge domain. If the positive association between collaboration and path-breaking innovation is not getting stronger for such innovation, it would be safe for us to infer that spillovers of codified knowledge is not the main mechanism underlying the positive association between collaboration between acquirer and target inventors and path-breaking innovation. This analysis thus allows us to determine to what extent the positive association between collaboration and path-breaking innovation is due to collaboration facilitating spillovers of codified knowledge. Table 9 extends the analysis in Table 8 by adding an interaction term between hybrid teams and the indicator variable for spillovers of codified knowledge.

Panel A compares patenting output by acquirer inventor-only teams and hybrid teams, focusing on spillovers of codified knowledge via collaboration between acquirer and target inventors. The variables of interests are *Citing target's exclusive knowledge* and *Hybrid team* × *Citing target's exclusive knowledge.* We show that the coefficient on *Citing target's exclusive knowledge* is not statistically different from zero, and the coefficient on the interaction term is negative and significant when the dependent variable is the number of impactful patents, suggesting that codified knowledge spillovers via collaboration is negatively associated with impactful innovation.

Panel B compares patenting output by target inventor-only teams and hybrid teams, focusing on spillovers of codified knowledge via collaboration between acquirer and target inventors. The variables of interests are *Citing acquirer's exclusive knowledge* and *Hybrid team* × *Citing acquirer's exclusive knowledge.* We show that the coefficient on neither variable is statistically different from zero across all three specifications, suggesting that codified knowledge spillovers alone or via collaboration are not significantly associated with path-breaking innovation.

Overall, Tables 8 and 9 show that spillovers of codified knowledge between merger partners, either alone or via collaborative teams, are not significantly associated with path-breaking innovation. These findings thus provide suggestive evidence that it is the transfer of the other type of knowledge—tacit knowledge embodied in the human capital of inventors—via collaboration that results in path-breaking innovation. As far as we are aware, we are the first in the M&A literature to make an attempt to differentiate the roles of these two types of knowledge capital in producing path-breaking innovation.

In summary, we conclude that recombining tacit knowledge embodied in the human capital of acquirer and target inventors is likely the mechanism underlying the human capital synergies in M&As.

6. Conclusions

Using a large and unique data set tracking inventors' career paths over the period 1976–2019, we provide novel evidence on how M&As help improve acquirers' innovative capabilities to produce path-breaking innovation.

First, we show a steep increase postmerger in the frequency of collaboration between acquirer and target inventors, and that such collaboration is associated with more radical, impactful, and valuable patents than those filed by either acquirer or target inventor-only teams. We further show that acquirer inventors are more likely to collaborate with target inventors who share the same core expertise and are geographically proximate, are less specialized, whose significant collaborators do not stay in the merged firms, are star inventors, and are inventors with large networks. Finally, we show that collaboration between acquirer and target inventors is more important to improving acquirers' innovative capabilities than hiring target inventors alone and spillovers of codified knowledge.

We conclude that M&As achieve human capital synergies by expanding the opportunity set for collaboration between acquirer and target inventors, increasing path-breaking innovation.

Appendix A: Tracking an inventor's patenting career

To determine an inventor's employer(s) throughout her patenting career, we rely on inventor and assignee information in the PatentsView database (https://www.patentsview.org) and patent-PERMCO (i.e., the firm identifier in the CRSP database) link in the KPSS database. We proceed in the following steps.

Step 1
Using the PatentsView database, we first identify all inventor-year pairs in which an inventor applied for at least one patent in that year. For each inventor-year pair, we then obtain assignees associated with all of that inventor's patents. If there is only one assignee for all her patents applied for in that year, the inventor's employer for that year is unambiguously identified. If there are multiple assignees for her patents in that year, the assignee to which the inventor applied for the most number of patents in that year is identified as her employer.

Step 2
The process from Step 1 divides inventor-year pairs into two sets: those associated with a unique assignee (UA) and those associated with multiple assignees (MA, representing 13% of the sample). We determine the employer of an inventor-year pair in Set MA using the matched information in Set UA. Specifically, we match an assignee to an inventor-year pair in Set MA if the inventor has been matched to the same assignee for the year prior in Set UA. If we cannot determine an assignee for an inventor-year pair based on the matched information in Set UA, we randomly pick one of the assignees. The above process results in matched inventor-assignee-year observations for years in which an inventor applied for patents.

Step 3
We augment the inventor-assignee-year (I-A-Y) sample from Step 2 by filling gaps in which an inventor is not matched to an assignee as follows. If both I-A-Y1 and I-A-Y2 are observations in the sample and there are no other observations of inventor I between year Y1 and Y2, then we assume inventor I's employer is A during the period from Y1 to Y2. If both I-A1-Y1 and I-A2-Y2 are observations in the sample and there are no other observations of inventor I between year Y1 and Y2, then we assume inventor I's employer is A1 during the period from Y1 to Ym and A2 during the period from Ym+1 to Y2, where Ym = int (Y1 + (Y2 – Y1) / 2).

By the end of Step 3, we obtain inventor-assignee-year information on each inventor's active career that spans the year of her first patent application and the year of her last patent application in the PatentsView database.

Step 4
Using the patent-PERMCO link in the KPSS database, we further match inventor-assignee-year observations to U.S. public firms. Specifically, we first merge patent-PERMCO pairs in KPSS and patent-assignee pairs in PatentsView by patent number, and keep only those patent-PERMCO pairs in which a patent has a solo assignee. We then merge the resulting assignee-PERMCO pairs with the inventor-assignee-year sample from Step 3 by patent number and obtain the sample of inventor-PERMCO-year observations.

Step 5

The inventor-PERMCO-year sample from Step 4 can be divided into two sets: those inventor-year pairs associated with a unique public firm (UP) and those inventor-year pairs associated with multiple public firms (MP). For inventor-PERMCO-year observations in Set UP, the public firm is identified as the employer of the inventor for the year. For inventor-PERMCO-year observations in set MP, we use information on the starting and ending dates of firm names provided by CRSP to help filter out firms if the date range of the matched firm name does not cover the focal year. For those inventor-year pairs that are still associated with multiple firm names, we manually check and pick the most likely match.

By the end of Step 5, we obtain inventor-PERMCO-year information on each inventor's active career that spans the year of her first patent application and the year of her last patent application in the PatentsView database.

Appendix B: Variable definitions

All firm characteristics are measured at the fiscal year end before bid announcement. All dollar values are in 2019 dollars.

Inventor-level patenting performance measures	
#Radical patents	The number of an inventor's radical patents applied for over the period from one year after deal completion (*cyr+1*) to five years after (*cyr+5*). A patent is radical if it draws on knowledge that has never or rarely been used before by inventors in the same field (Eggers and Kaul 2018). We define radical patents as those in the top 5th percentile in terms of drawing on fundamentally new knowledge among granted patents in the same technology class-year.
#Impactful patents	The number of an inventor's impactful patents applied for over the period *cyr+1* to *cyr+5*. A patent is impactful if its number of citations (received up to 2019) is in the top 5th percentile among granted patents in the same technology class-year.
#Valuable patents	The number of an inventor's valuable patents applied for over the period *cyr+1* to *cyr+5*. A patent is valuable if its value using Kogan et al.'s (2017) measure is in the top 5th percentile among granted patents in the same technology class-year.
Inventor characteristics	
Target inventor	An indicator variable that takes the value of one if an inventor is working at the target firm in the year before bid announcement (*ayr-1*), and zero otherwise.
On hybrid team	An indictor variable that takes the value of one if an inventor is on at least one hybrid team over the period *cyr+1* to *cyr*+5, and zero otherwise.
Inventor significant co-inventor stay	An indicator variable that takes the value of one if at least one significant co-inventor works for the merged firm over the period *cyr+1* to *cyr+5*, and zero otherwise. A significant co-inventor is a collaborator to a focal inventor whose number of jointly-developed patents with the focal inventor is more than 50% of the latter's total number of patents over the period *ayr-5* to *ayr-1*.
Star inventor	An indicator variable that takes the value of one if an inventor's number of citations received (up to 2019) for granted patents applied for up to *ayr-1* is in the top 5th percentile among all inventors in the PatentsView database, and zero otherwise.
Inventor network size	The natural logarithm of one plus the number of unique inventors who have collaborative links of no more than two teams away from the focal inventor up to *ayr-1*.
Inventor specialization	The Herfindahl index based on the technology class-share of granted patents applied for by an inventor up to *ayr-1*. The bigger this value is, the more specialized the inventor is in terms of her patenting output.
#Patents	The number of granted patents applied for by an inventor up to *ayr -1*.
#Citation-weighted patents	The total number of citations received over the five-year period since the grant date of an inventor's patents applied for up to *ayr-1*.
Inventor-pair characteristics	
Same core	An indicator variable that takes the value of one if two inventors share the same core technology class, and zero otherwise. An inventor's core class is the technology class in which she has been granted the most number of patents applied for up to *ayr-1*.
Distance	The natural logarithm of the number of kilometers between two inventors' locations in the PatentsView database.
Patent characteristics	
Radical	An indicator variable that takes the value of one if a patent is radical, and zero otherwise.

Impactful	An indicator variable that takes the value of one if a patent is impactful, and zero otherwise.
Valuable	An indicator variable that takes the value of one if a patent is valuable, and zero otherwise.
Acquirer inventor-only team	An indicator variable that takes the value of one if inventors of a patent do not include any target inventor, but include at least one acquirer inventor, and zero otherwise.
Target inventor-only team	An indicator variable that takes the value of one if inventors of a patent do not include any acquirer inventor, but include at least one target inventor, and zero otherwise.
Hybrid team	An indicator variable that takes the value of one if inventors of a patent include at least one target inventor and at least one acquirer inventor, and zero otherwise.
#Inventors	The number of inventors behind a patent.
Citing target's exclusive knowledge	An indicator variable that takes the value of one if a patent cites at least one patent in the target firm's knowledge domain that is not overlapping with the acquirer's knowledge domain. Following Ahuja and Katila (2001), a firm's knowledge domain is the sum of its portfolio of patents applied for over the five-year period up to *cyr-1* and citations made by those patents.
Citing acquirer's exclusive knowledge	An indicator variable that takes the value of one if a patent cites at least one patent in the acquirer's knowledge domain that is not overlapping with the target firm's knowledge domain.
Citing common knowledge	An indicator variable that takes the value of one if a patent cites at least one patent that is in both the acquirer's and the target firm's knowledge domains.
Deal/firm characteristics	
Diversifying	An indicator variable that takes the value of one if the first two-digit SIC code of an acquirer is different from that of its target firm, and zero otherwise.
Relative size	The ratio of transaction value to an acquirer's book value of assets.
All cash	An indicator variable that takes the value of one if a deal is entirely financed by cash, and zero otherwise.
All stock	An indicator variable that takes the value of one if a deal is entirely finance by equity, and zero otherwise.
Tobin's Q	The ratio of market value of assets to book value of assets.
ROA	The ratio of operating income before depreciation to book value of assets.
Leverage	The ratio of total debt to book value of assets.
Prior year stock return	The cumulative return over the calendar year right before *ayr-1*.

References:

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, 2005. Competition and innovation: An inverted-U relationship, *Quarterly Journal of Economics* 120 (2): 701-728.

Aghion, Philippe, and Peter Howitt, 1992. A model of growth through creative destruction, *Econometrica* 60 (2): 323-351.

Ahuja, Gautam, and Riitta Katila, 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study, *Strategic Management Journal* 22 (3): 197-220.

Balsmeier, Benjamin, Lee Fleming, and Gustavo Manso, 2017. Independent boards and innovation, *Journal of Financial Economics* 123 (3): 536-557.

Beaumont, Paul, Camille Hebert, and Victor Lyonnet, 2019. Build or buy? Human capital and corporate diversification, Université Paris Dauphine working paper.

Bena, Jan, and Kai Li, 2014. Corporate innovations and mergers and acquisitions, *Journal of Finance* 69 (5): 1923-1960.

Bernstein, Shai, Rebecca Diamond, Timothy McQuade, and Beatriz Pousada, 2019. The contribution of high-skilled immigrants to innovation in the United States, Stanford University working paper.

Bhattacharya, Jay, and Mikko Packalen, 2020. Stagnation and scientific incentives, NBER Working Paper No. 26752.

Bloom, Nicholas, Charles I. Jones, John Van Reenen, and Michael Webb, 2019. Are ideas getting harder to find? Stanford University working paper.

Bowen, Donald, Laurent Frésard, and Gerard Hoberg, 2019. Technological disruptiveness and the evolution of IPOs and sell-outs, Virginia Tech working paper.

Chen, Deqiu, Huasheng Gao, and Yujing Ma, 2020. Human capital driven acquisition: Evidence from the Inevitable Disclosure Doctrine, *Management Science* forthcoming.

Cohen, Wesley M., and Daniel A. Levinthal, 1990. Absorptive capacity: A new perspective on learning and innovation, *Administrative Science Quarterly* 35 (1): 128-152.

Cunningham, Colleen, Florian Ederer, and Song Ma, 2019. Killer acquisitions, London Business School working paper.

Eggers, J. P., and Aseem Kaul, 2018. Motivation and ability? A behavioral perspective on the pursuit of radical invention in multi-technology incumbents, *Academy of Management Journal* 61 (1): 67-93.

Fulghieri, Paolo, and Merih Sevilir, 2011. Mergers, spinoffs, and employee incentives, *Review of Financial Studies* 24 (7): 2207-2241.

Fulghieri, Paolo, and Merih Sevilir, 2019. Human capital integration in mergers and acquisitions, UNC-Chapel Hill working paper.

Grossman, Sanford J., and Oliver D. Hart, 1986. The costs and benefits of ownership: A theory of vertical and lateral integration, *Journal of Political Economy* 94 (4): 691-719.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, M., 2005. Market value and patent citations, *Rand Journal of Economics* 36 (1): 16-38.

Hart, Oliver D., 1983. The market mechanism as an incentive scheme, *Bell Journal of Economics* 14 (2): 366-382.

Hart, Oliver D., and Bengt Holmström, 2010. A theory of firm scope, *Quarterly Journal of Economics* 125 (2): 483-513.

Hart, Oliver D., and John Moore, 1990. Property rights and the nature of the firm, *Journal of Political Economy* 98 (6): 1119-1158.

Hoetker, Glenn, and Rajshree Agarwal, 2007. Death hurts, but it isn't fatal: The postexit diffusion of knowledge created by innovative companies, *Academy of Management Journal* 50 (2): 446-467.

Holmström, Bengt, and John Roberts, 1998. The boundaries of the firm revisited, *Journal of Economic Perspectives* 12 (4): 73-94.

Hombert, Johan, and Adrien Matray, 2017. The real effects of lending relationships on innovative firms and inventor mobility, *Review of Financial Studies* 30 (7): 2413-2445.

Jaravel, Xavier, Neviana Petkova, and Alex Bell, 2018. Team-specific capital and innovation, *American Economic Review* 2018, 108 (4-5): 1034-1073.

Jaffe, Adam B., 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value, *American Economic Review* 76 (5): 984-1001.

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson, 1993. Geographic localization of knowledge spillovers as evidenced by patent citations, *Quarterly Journal of Economics* 108 (3): 577-598.

Jones, Benjamin, E.J. Reedy, and Bruce A. Weinberg, 2014. Age and scientific genius, NBER Working Paper No. 19866.

Kogan Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017. Technological innovation, resource allocation, and growth, *Quarterly Journal of Economics* 132 (2): 665-712.

Kogut, Bruce, and Udo Zander, 1992. Knowledge of the firm, combinative capabilities, and the replication of technology, *Organization Science* 3 (3): 383-397.

Kogut, Bruce, and Udo Zander, 1996. What firms do? Coordination, identity, and learning, *Organization Science* 7 (5): 502-518.

Lagaras, Spyridon, 2020. Corporate takeovers and labor restructuring, University of Pittsburg working paper.

Lee, Kyeong Hun, David C. Mauer, and Emma Qianying Xu, 2018. Human capital relatedness and mergers and acquisitions, *Journal of Financial Economics* 129 (1): 111-135.

Leonard-Barton, Dorothy, 1995. *Wellsprings of Knowledge: Building and Sustaining the Sources of Innovation*, Harvard Business School Press: Boston, MA.

Li, Kai, Buhui Qiu, and Rui Shen, 2018. Organization capital and mergers and acquisitions, *Journal of Financial and Quantitative Analysis* 53 (4): 1871-1909.

Li, Kai, Jiaping Qiu, and Jin Wang, 2019. Technology conglomeration, strategic alliances, and corporate innovation, *Management Science* 65 (11): 5065-5090.

Li, Xiaoyang, 2013. Productivity, restructuring, and the gains from takeovers, *Journal of Financial Economics* 109 (1): 250-271.

Ma, Wenting, Paige Ouimet, and Elena Simintzi, 2018. Mergers and acquisitions, technological change and inequality, UNC working paper.

Maksimovic, Vojislav, and Gordon Phillips, 2001. The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains? *Journal of Finance* 56 (6): 2019-2065.

Maksimovic, Vojislav, Gordon Phillips, and N. R. Prabhala, 2011. Post-merger restructuring and the boundaries of the firm, *Journal of Financial Economics* 102 (2): 317-343.

Marx, Matt, Deborah Strumsky, and Lee Fleming, 2009. Mobility, skills, and the Michigan Non-Compete experiment, *Management Science* 55 (6): 875-889.

Melero, Eduardo, and Neus Palomeras, 2015. The Renaissance Man is not dead! The role of generalists in teams of inventors, *Research Policy* 44 (1): 154–167.

Mowery, David C., Joanne E. Oxley, and Brian S. Silverman, 1996. Strategic alliances and interfirm knowledge transfer, *Strategic Management Journal* 17 (S2): 77-91.

Ouimet, Paige, and Rebecca Zarutskie, 2016. Acquiring labor, UNC working paper.

Pakes, Ariel, 1985. On patents, R & D, and the stock market rate of return, *Journal of Political Economy* 93 (2): 390-409.

Phene, Anupama, Stephen Tallman, and Paul Almeida, 2012. When do acquisitions facilitate technological exploration and exploitation? *Journal of Management* 38 (3): 753-783.

Ranft, Annette L., and Michael D. Lord, 2002. Acquiring new technologies and capabilities: A grounded model of acquisition implementation, *Organization Science* 13 (4): 420-441.

Rhodes-Kropf, Matthew, and David T. Robinson, 2008. The market for mergers and the boundaries of the firm, *Journal of Finance* 63 (3): 1170-1211.

Romer, Paul M., 1990. Endogenous technological change, *Journal of Political Economy* 98 (5): S71-S102.

Schmidt, Klaus M. 1997. Managerial incentives and product market competition, *Review of Economic Studies* 64 (2): 191-213.

Schoar, Antoinette, 2002. The effect of diversification on firm productivity, *Journal of Finance* 57 (6): 2379-2403.

Seru, Amit, 2014. Firm boundaries matter: Evidence from conglomerates and R&D activity, *Journal of Financial Economics* 111 (2): 381-405.

Singh, Jasjit, 2005. Collaborative networks as determinants of knowledge diffusion patterns, *Management Science* 51 (5): 756-770.

Singh, Jasjit, and Lee Fleming, 2010. Lone inventors as sources of breakthroughs: Myth or reality? *Management Science* 56 (1): 41-56.

Song, Jaeyong, Paul Almeida, and Geraldine Wu, 2003. Learning–by–hiring: When is mobility more likely to facilitate interfirm knowledge transfer? *Management Science* 49 (4): 351-365.

Tate, Geoffrey, and Liu Yang, 2015. The bright side of diversification: Evidence from internal labor markets, *Review of Financial Studies* 28 (8): 2203-2249.

Tate, Geoffrey, and Liu Yang, 2016. The human factor in acquisitions: Cross-industry labor mobility and corporate diversification, University of Maryland working paper.

Taylor, Alva, and Henrich R. Greve, 2006. Superman or the fantastic four? Knowledge combination and experience in innovative teams, *Academy of Management Journal* 49 (4): 723-740.

Weitzman, Martin L. 1998. Recombinant growth, *Quarterly Journal of Economics* 113 (2): 331-360.

Winter, Sidney, 1987. Knowledge and competence as strategic assets, in: David J. Teece, ed., *The Competitive Challenge—Strategies for Industrial Innovation and Renewal*, Ballinger: Cambridge, MA, 159-184.

Figure 1
Frequency of collaboration between acquirer and target inventors over time

This figure shows the total number of patents across sample deals by collaboration between acquirer and target inventors over the period *ayr-5* to *ayr-1* and the period *cyr+1* and *cyr+5*. Acquirer (target) inventors are inventors who work at the acquirer (target firm) in *ayr-1*. Our sample consists of M&A deals announced and completed over the period 1981–2012.

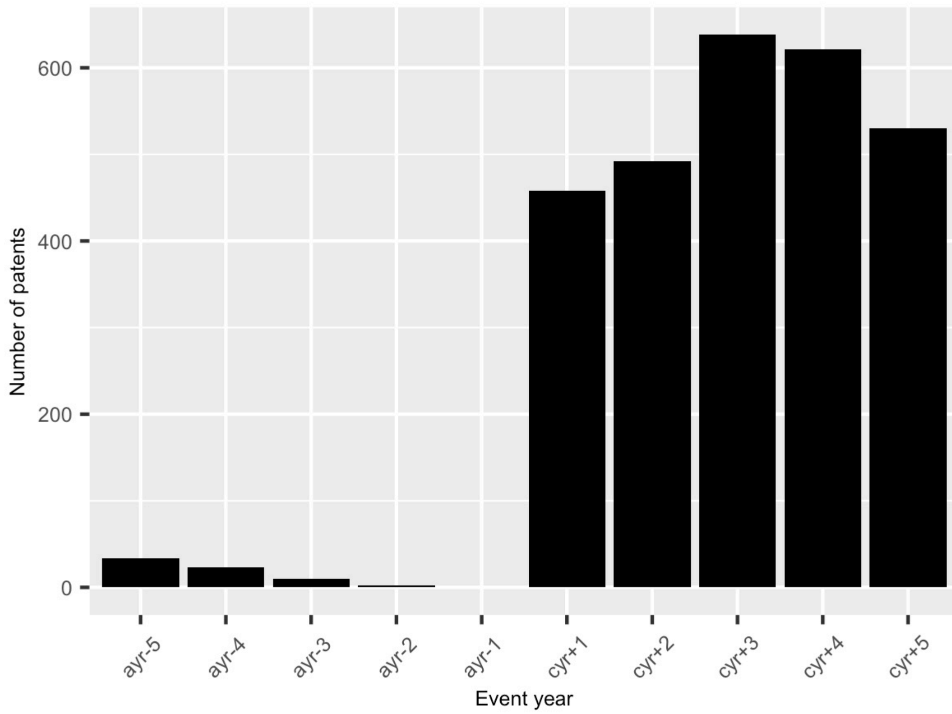

Table 1
Summary statistics of sample deals and firms

This table presents the summary statistics of M&A deal characteristics and acquirer and target firm characteristics. Our sample consists of M&A deals announced and completed over the period 1981–2012 that satisfy the following conditions: 1) the deal is classified as "Acquisition of Assets", "Merger," "Acquisition", or "Acquisition of Majority Interest" by the data provider; 2) both the acquirer and its target firm are U.S. public firms; 3) the acquirer holds less than 50% of the shares of the target firm before bid announcement and ends up owning 100% of the shares of the target firm through the deal; 4) the deal value is at least $1 million (in 2019 dollars); 5) the relative size of the deal (i.e., the ratio of transaction value over an acquirer's book value of assets) is at least 1%; and 6) both the acquirer and its target firm have at least one inventor in the year before bid announcement (*ayr-1*). All ratios are winsorized at the 1st and 99th percentiles. Detailed variable definitions are provided in Appendix B.

	Mean	*STD*	*Min*	*25th percentile*	*Median*	*75th percentile*	*Max*
Deal characteristics							
Diversifying	0.433	0.496	0.000	0.000	0.000	1.000	1.000
Relative size	0.460	1.004	0.010	0.085	0.232	0.494	15.643
All cash	0.329	0.470	0.000	0.000	0.000	1.000	1.000
All stock	0.340	0.474	0.000	0.000	0.000	1.000	1.000
Acquirer characteristics							
Sales	10,130	21,182	0.000	475	2,318	9,579	193,517
Book assets	15,777	78,970	1.224	558	2,602	10,398	2,116,445
Tobin's Q	2.597	3.310	0.354	1.323	1.868	2.844	83.692
ROA	0.118	0.204	-2.282	0.088	0.146	0.206	0.506
Leverage	0.188	0.162	0.000	0.056	0.167	0.273	0.967
Prior year stock return	0.287	0.743	-0.992	-0.063	0.179	0.455	8.301
Target characteristics							
Sales	2,480	8,038	-0.162	81	266	1,234	93,237
Book assets	4,750	45,699	1.864	95	302	1,228	1,258,274
Tobin's Q	2.244	2.166	0.498	1.175	1.614	2.428	29.103
ROA	0.033	0.305	-3.285	0.012	0.107	0.167	0.493
Leverage	0.182	0.202	0.000	0.014	0.131	0.285	1.749
Prior year stock return	0.195	1.040	-0.982	-0.264	0.018	0.385	15.688
# of deals	942						

Table 2
Summary statistics of inventors and patents after deal completion

This table presents the summary statistics of inventor and patent characteristics after deal completion. The postmerger inventor sample consists of 28,166 acquirer inventors and 4,257 target inventors who have applied for at least one patent in target classes over the period from one year after deal completion (*cyr+1*) to five years after (*cyr+5*). Acquirer (target) inventors are inventors working at the acquirer (target firm) in *ayr-1*. Target classes in year *t* are patent classes in which target inventors have applied for at least one patent. Panel A presents the summary statistics of inventor characteristics. Panel B presents the summary statistics of 51,286 patents in target classes applied for over the period *cyr+1* to *cyr+5* by acquirer and target inventors and whose assignee is the merged firm (or the target firm in cases where it remains standalone after deal completion). Detailed variable definitions are provided in Appendix B. *p*-values for testing the difference in means and medians are presented at the end of the table.

Panel A: Characteristics of inventors in *ayr-1*

	Acquirer inventors			*Target inventors*			*p-value*	
	Mean	*STD*	*Median*	*Mean*	*STD*	*Median*	*t-test*	*Wilcoxon*
Inventor significant co-inventor stay	0.584	0.493	1.000	0.569	0.495	1.000	0.064	0.063
Star inventor	0.140	0.347	0.000	0.124	0.329	0.000	0.004	0.005
Inventor network (raw)	104.772	199.806	43.000	78.529	143.515	26.000	0.000	0.000
Inventor specialization	0.535	0.174	0.599	0.504	0.183	0.486	0.000	0.000
#Patents	8.418	15.781	4.000	7.807	12.578	4.000	0.004	0.639
#Citation-weighted patents	73.532	137.533	30.000	68.000	140.670	25.000	0.005	0.000
# of observations	28,166			4,257				

Panel B: Characteristics of patents by different inventor teams after deal completion

	By hybrid teams			*By acquirer/target inventor-only teams*			*p-value*	
	Mean	*STD*	*Median*	*Mean*	*STD*	*Median*	*t-test*	*Wilcoxon*
Radical	0.087	0.281	0.000	0.050	0.219	0.000	0.000	0.087
Impactful	0.062	0.241	0.000	0.049	0.215	0.000	0.005	0.002
Valuable	0.080	0.271	0.000	0.062	0.241	0.000	0.001	0.000
# of observations	2,739			48,547				

Table 3
Increase in collaboration between acquirer and target inventors after deal completion

This table examines how the frequency of collaboration between acquirer and target inventors changes after deal completion. The sample consists of deal-year observations over the period *ayr-5* to *ayr-1* and the period *cyr+1* to *cyr+5*. The dependent variable is the number of patents in target classes applied for by hybrid teams consisting of both acquirer and target inventors. Acquirer (target) inventors are identified as inventors working at the acquirer (target firm) in *ayr-1*. *After* is an indicator variable that takes the value of one over the period *cyr+1* to *cyr+5*, and zero over the period *ayr-5* to *ayr-1*. In column (1), the sample consists of 942 completed deals announced over the period 1981−2012. Column (2) repeats and column (3) extends the analysis in column (1) using a quasi-experiment described as follows. We identify withdrawn bids over the period 1981−2012 by manually examining the reason for withdrawal and keeping bids whose reason for withdrawal is unlikely to be related to innovation performance (i.e., difficulties to secure financing, objections by regulatory bodies, or adverse macroeconomic/market conditions). For each withdrawn bid, we then try to identify completed deals in our sample using the following criteria: 1) the announcement year of the completed deal is no more than ten year away from the withdrawn bid; and 2) the core area of the acquirer in the completed deal is the same as the core area of the acquirer in the withdrawn bid. A firm's core technology class is the class with the greatest number of granted patents applied for over the five-year period ending in *ayr-1*. For each withdrawn bid, we then pick up to five matched completed deals whose relative size to acquirer book assets is closest to that of the withdrawn bid. We obtain 74 completed deals matched to 19 withdrawn bids. Column (2) repeats the analysis in column (1) using only the matched completed deals. Column (3) employs the specification in Equation (1). The sample consists of both the withdrawn bids and matched completed deals. *Completed* is an indicator variable that takes the value of one for completed deals, zero for withdrawn bids. Detailed variable definitions are provided in Appendix B. All models control for deal fixed effects. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	#Patents by hybrid teams		
	(1)	(2)	(3)
After	0.580***	1.905**	0.211**
	(0.129)	(0.779)	(0.104)
After × Completed			1.695**
			(0.785)
# of observations	9,200	740	930
Adjusted R^2	0.470	0.425	0.427

Table 4
Collaboration between acquirer and target inventors and path-breaking innovation

This table examines the relation between hybrid teams and path-breaking innovation over the period *cyr+1* to *cyr+5*. Panel A presents the linear probability regression results where the dependent variables are the indicator variables for radical, impactful, and valuable patents. The sample consists of 51,286 patents in target classes applied for by 28,166 acquirer inventors and 4,257 target inventors over the period *cyr+1* to *cyr+5*. The baseline case is the patenting output by acquirer/target inventor-only teams. All models control for deal fixed effects. Robust standard errors clustered at the deal level are reported in parentheses. Panel B presents the OLS regression results where the dependent variables are the number of radical/impactful/valuable patents. The sample consists of 28,166 acquirer inventors and 4,257 target inventors who file at least one patent in target classes over the period *cyr+1* to *cyr+5*. The baseline case is the patenting output by inventors not on hybrid teams. All models control for deal fixed effects. Robust standard errors clustered at the deal level are reported in parentheses. Detailed variable definitions are provided in Appendix B. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Collaboration between acquirer and target inventors and path-breaking innovation (patent level)

	Radical	*Impactful*	*Valuable*
	(1)	(2)	(3)
Hybrid team	0.023**	0.010	0.006
	(0.009)	(0.007)	(0.008)
#Inventors	0.009**	0.021***	-0.010**
	(0.004)	(0.004)	(0.004)
# of observations	51,286	51,286	51,286
Adjusted R^2	0.036	0.062	0.155

Panel B: Collaboration between acquirer and target inventors and path-breaking innovation (inventor level

	#Radical patents	*#Impactful patents*	*#Valuable patents*
	(1)	(2)	(3)
On hybrid team	0.250***	0.204***	0.222***
	(0.065)	(0.043)	(0.058)
# of observations	32,423	32,423	32,423
Adjusted R^2	0.055	0.057	0.211

Table 5
Inventor- and inventor-pair characteristics and collaboration between acquirer and target inventors

This table examines the relation between inventor- and inventor-pair characteristics and collaboration between acquirer and target inventors. The dependent variable is an indicator variable that takes the value of one for a sample pair, and zero for pseudo pairs. We first identify acquirer-target inventor pairs that have collaborated in at least one patent applied for over the period *cyr+1* to *cyr+5*. For the target (acquirer) inventor in each sample pair, we then randomly pick three other target (acquirer) inventors and form pseudo pairs with the acquirer (target) inventor in the sample pair. In Panel A (B), the sample consists of true pairs and pseudo pairs where acquirer (target) inventors are matched with randomly picked target (acquirer) inventors. Detailed variable definitions are provided in Appendix B. All models control for deal fixed effects. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Acquirer inventors paired with randomly picked target inventors

	1 for sample pairs, 0 for pseudo pairs				
	(1)	(2)	(3)	(4)	(5)
Same core	0.236***	0.236***	0.222***	0.207***	0.244***
	(0.036)	(0.036)	(0.030)	(0.037)	(0.038)
Distance	-0.046***	-0.047***	-0.047***	-0.045***	-0.047***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
Target inventor significant co-inventor stay		-0.053**			
		(0.024)			
Target star inventor			0.169***		
			(0.030)		
Target inventor network size				0.067***	
				(0.010)	
Target inventor specialization					-0.212**
					(0.103)
# of observations	21,344	21,344	21,344	21,344	21,344
Adjusted R^2	0.133	0.135	0.146	0.160	0.138

Panel B: Target inventors paired with randomly picked acquirer inventors

	1 for sample pairs, 0 for pseudo pairs				
	(1)	(2)	(3)	(4)	(5)
Same core	0.193***	0.193***	0.193***	0.191***	0.195***
	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)
Distance	-0.084***	-0.084***	-0.084***	-0.084***	-0.084***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Acquirer inventor significant co-inventor stay		0.008			
		(0.011)			
Acquirer star inventor			-0.012		
			(0.012)		
Acquirer inventor network size				0.011*	
				(0.006)	
Acquirer inventor specialization					-0.088**
					(0.037)
# of observations	19,283	19,283	19,283	19,283	19,283
Adjusted R^2	0.248	0.248	0.248	0.248	0.248

Table 6
Collaboration, inventor characteristics, and radical innovation

This table examines how collaboration between acquirer and target inventors and inventor characteristics together are associated with radical innovation over the period *cyr+1* to *cyr+5*. The dependent variable is the number of radical patents. In Panel A, the sample consists of 4,257 target inventors who have applied for at least one patent over the period *cyr+1* to *cyr+5*. In Panel B, the sample consists of 28,166 acquirer inventors who have applied for at least one patent over the period *cyr+1* to *cyr+5*. Detailed variable definitions are provided in Appendix B. All models control for deal fixed effects. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Collaboration, target inventor characteristics, and radical innovation

	#Radical patents			
	(1)	(2)	(3)	(4)
On hybrid team	0.181***	0.174***	0.148	0.360***
	(0.043)	(0.035)	(0.100)	(0.131)
Inventor significant co-inventor stay	-0.009			
	(0.023)			
On hybrid team × Inventor significant co-inventor stay	0.051			
	(0.062)			
Star inventor		-0.001		
		(0.072)		
On hybrid team × Star inventor		0.265**		
		(0.128)		
Inventor network size			0.033***	
			(0.013)	
On hybrid team × Inventor network size			0.013	
			(0.029)	
Inventor specialization				-0.218***
				(0.084)
On hybrid team × Inventor specialization				-0.306
				(0.212)
# of observations	4,257	4,257	4,257	4,257
Adjusted R^2	0.187	0.192	0.190	0.193

Panel B: Collaboration, acquirer inventor characteristics, and radical innovation

	#Radical patents			
	(1)	(2)	(3)	(4)
On hybrid team	0.257***	0.216***	0.086	0.664***
	(0.063)	(0.043)	(0.096)	(0.228)
Inventor significant co-inventor stay	0.002			
	(0.008)			
On hybrid team × Inventor significant co-inventor stay	0.079			
	(0.092)			
Star inventor		0.143***		
		(0.029)		
On hybrid team × Star inventor		0.533		
		(0.401)		
Inventor network size			0.025***	
			(0.004)	

On hybrid team × Inventor network size			0.052	
			(0.040)	
Inventor specialization				-0.172***
				(0.035)
On hybrid team × Inventor specialization				-0.721**
				(0.314)
# of observations	28,166	28,166	28,166	28,166
Adjusted R^2	0.044	0.057	0.049	0.050

Table 7
Collaboration, target inventors alone, and path-breaking innovation

This table compares collaboration between acquirer and target inventors and target inventors alone in producing path-breaking innovation. The sample consists of 4,257 target inventors and 28,166 acquirer inventors who have applied for at least one patent in target classes over the period *cyr+1* to *cyr+5*. The dependent variables are the number of radical/impactful/valuable patents. The baseline case is the number of radical/impactful/valuable patents by acquirer inventors alone. Detailed variable definitions are provided in Appendix B. All models control for deal fixed effects. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	#Radical patents	*#Impactful patents*	*#Valuable patents*	*#Radical patents*	*#Impactful patents*	*#Valuable patents*
	(1)	(2)	(3)	(4)	(5)	(6)
Target inventor	0.049*	-0.009	0.078***	0.020	-0.013	0.022
	(0.029)	(0.021)	(0.026)	(0.032)	(0.028)	(0.030)
On hybrid team				0.277***	0.255***	0.200***
				(0.081)	(0.060)	(0.066)
Target inventor × On hybrid team				-0.105*	-0.150**	0.006
				(0.060)	(0.059)	(0.051)
Inventor significant co-inventor stay	0.014	-0.006	-0.023**	0.018*	-0.002	-0.019*
	(0.011)	(0.009)	(0.011)	(0.011)	(0.009)	(0.010)
Star inventor	0.150***	0.222***	0.097***	0.147***	0.219***	0.095***
	(0.028)	(0.042)	(0.023)	(0.028)	(0.041)	(0.023)
Inventor network size	0.012***	0.017***	0.020***	0.009*	0.015***	0.017***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Inventor specialization	-0.155***	-0.050	-0.095**	-0.154***	-0.048	-0.094**
	(0.040)	(0.041)	(0.047)	(0.040)	(0.041)	(0.046)
# of observations	32,423	32,423	32,423	32,423	32,423	32,423
Adjusted R^2	0.055	0.064	0.210	0.065	0.070	0.217

Table 8
Codified knowledge spillovers and path-breaking innovation

This table examines the relation between codified knowledge spillovers and path-breaking innovation over the period *cyr+1* to *cyr+5*. The dependent variables are the indicator variables for radical, impactful, and valuable patents. In Panel A, the sample consists of patents applied for by either acquirer inventor-only teams or hybrid teams. In Panel B, the sample consists of patents applied for by either target inventor-only teams or hybrid teams. Detailed variable definitions are provided in Appendix B. All models control for deal fixed effects. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Codified knowledge spillovers from target firms to acquirer inventors and path-breaking innovation

	Radical	*Impactful*	*Valuable*
	(1)	(2)	(3)
Hybrid team	0.025**	0.011*	0.011
	(0.010)	(0.006)	(0.007)
Citing target's exclusive knowledge	0.016	-0.001	-0.009
	(0.017)	(0.010)	(0.012)
Citing acquirer's exclusive knowledge	0.028***	0.010**	0.002
	(0.004)	(0.004)	(0.003)
Citing common knowledge	0.068***	0.015***	0.006
	(0.009)	(0.005)	(0.010)
#Inventors	0.010**	0.022***	-0.007**
	(0.004)	(0.004)	(0.004)
# of observations	45,350	45,350	45,350
Adjusted R^2	0.041	0.069	0.145

Panel B: Codified knowledge spillovers from acquirers to target inventors and path-breaking innovation

	Radical	*Impactful*	*Valuable*
	(1)	(2)	(3)
Hybrid team	0.012	0.003	-0.002
	(0.009)	(0.002)	(0.003)
Citing target's exclusive knowledge	0.017	-0.004*	-0.008*
	(0.014)	(0.002)	(0.005)
Citing acquirer's exclusive knowledge	0.010	-0.002	-0.001
	(0.008)	(0.002)	(0.003)
Citing common knowledge	0.063***	0.001	0.0001
	(0.012)	(0.002)	(0.003)
#Inventors	0.008	-0.001	0.002
	(0.007)	(0.002)	(0.004)
# of observations	8,675	8,675	8,675
Adjusted R^2	0.092	0.056	0.026

Table 9
Codified knowledge spillovers via collaboration and path-breaking innovation

This table examines whether codified knowledge spillovers via collaboration is associated with path-breaking innovation over the period *cyr+1* to *cyr+5*. The dependent variables are the indicator variables for radical, impactful, and valuable patents. In Panel A, the sample consists of patents applied for by either acquirer inventor-only teams or hybrid teams. In Panel B, the sample consists of patents applied for by either target inventor-only teams or hybrid teams. Detailed variable definitions are provided in Appendix B. All models control for deal fixed effects. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Codified knowledge spillovers via collaboration from target firms to acquirer inventors and path-breaking innovation

	Radical	*Impactful*	*Valuable*
	(1)	(2)	(3)
Hybrid team	0.026**	0.013*	0.011
	(0.011)	(0.007)	(0.008)
Citing target's exclusive knowledge	-0.014	0.004	-0.015
	(0.015)	(0.014)	(0.014)
Hybrid team × Citing target's exclusive knowledge	0.018	-0.043*	0.012
	(0.039)	(0.023)	(0.031)
#Inventors	0.010**	0.022***	-0.007**
	(0.004)	(0.004)	(0.004)
# of observations	45,350	45,350	45,350
Adjusted R^2	0.034	0.068	0.145

Panel B: Codified knowledge spillovers via collaboration from acquirers to target inventors and path-breaking innovation

	Radical	*Impactful*	*Valuable*
	(1)	(2)	(3)
Hybrid team	0.017	0.017	-0.027**
	(0.011)	(0.011)	(0.013)
Citing acquirer's exclusive knowledge	-0.017	0.003	-0.007
	(0.016)	(0.009)	(0.010)
Hybrid team × Citing acquirer's exclusive knowledge	-0.003	0.0002	0.007
	(0.008)	(0.018)	(0.014)
#Inventors	0.010	0.006	-0.007
	(0.007)	(0.007)	(0.012)
# of observations	8,675	8,675	8,675
Adjusted R^2	0.087	0.070	0.197

Internet Appendix

Table IA1
Collaboration, inventor characteristics, and impactful innovation

This table examines how collaboration between acquirer and target inventors and inventor characteristics together are associated with impactful innovation over the period *cyr+1* to *cyr+5*. The dependent variable is the number of impactful patents. In Panel A, the sample consists of 4,257 target inventors who have applied for at least one over the period *cyr+1* to *cyr+5*. In Panel B, the sample consists of 28,166 acquirer inventors who have applied for at least one patent over the period *cyr+1* to *cyr+5*. Detailed variable definitions are provided in Appendix B. All models control for deal fixed effects. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Collaboration, target inventor characteristics, and impactful innovation

	#Impactful patents			
	(1)	(2)	(3)	(4)
On hybrid team	0.218***	0.128***	0.076	0.293***
	(0.067)	(0.026)	(0.083)	(0.091)
Inventor significant co-inventor stay	-0.008			
	(0.017)			
On hybrid team × Inventor significant co-inventor stay	-0.092			
	(0.071)			
Star inventor		0.132**		
		(0.063)		
On hybrid team × Star inventor		0.195*		
		(0.105)		
Inventor network size			0.022*	
			(0.013)	
On hybrid team × Inventor network size			0.021	
			(0.027)	
Inventor specialization				-0.156**
				(0.068)
On hybrid team × Inventor specialization				-0.269*
				(0.144)
# of observations	4,257	4,257	4,257	4,257
Adjusted R^2	0.089	0.102	0.091	0.093

Panel B: Collaboration, acquirer inventor characteristics, and impactful innovation

	#Impactful patents			
	(1)	(2)	(3)	(4)
On hybrid team	0.265***	0.218***	0.147	0.541***
	(0.073)	(0.054)	(0.097)	(0.135)
Inventor significant co-inventor stay	-0.008			
	(0.008)			
On hybrid team × Inventor significant co-inventor stay	0.035			
	(0.063)			
Star inventor		0.225***		
		(0.042)		
On hybrid team × Star inventor		0.377**		

		(0.172)		
Inventor network size			0.034***	
			(0.006)	
On hybrid team × Inventor network size			0.032	
			(0.029)	
Inventor specialization				-0.141***
				(0.044)
On hybrid team × Inventor specialization				-0.509**
				(0.198)
# of observations	28,166	28,166	28,166	28,166
Adjusted R^2	0.059	0.072	0.063	0.061

Table IA2
Collaboration, inventor characteristics, and valuable innovation

This table examines how collaboration between acquirer and target inventors and inventor characteristics together are associated with valuable innovation over the period *cyr+1* to *cyr+5*. The dependent variable is the number of valuable patents. In Panel A, the sample consists of 4,257 target inventors who have applied for at least one patent over the period *cyr+1* to *cyr+5*. In Panel B, the sample consists of 28,166 acquirer inventors who have applied for at least one patent over the period *cyr+1* to *cyr+5*. Detailed variable definitions are provided in Appendix B. All models control for deal fixed effects. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Collaboration, target inventor characteristics, and valuable innovation

	#Valuable patents			
	(1)	(2)	(3)	(4)
On hybrid team	0.301***	0.210***	-0.019	0.525***
	(0.096)	(0.062)	(0.102)	(0.136)
Inventor significant co-inventor stay	-0.095***			
	(0.030)			
On hybrid team × Inventor significant co-inventor stay	-0.039			
	(0.062)			
Star inventor		0.059		
		(0.056)		
On hybrid team × Star inventor		0.444***		
		(0.154)		
Inventor network size			0.006	
			(0.020)	
On hybrid team × Inventor network size			0.079**	
			(0.037)	
Inventor specialization				-0.096
				(0.089)
On hybrid team × Inventor specialization				-0.509**
				(0.226)
# of observations	4,257	4,257	4,257	4,257
Adjusted R^2	0.220	0.231	0.223	0.222

Panel B: Collaboration, acquirer inventor characteristics, and valuable innovation

	#Valuable patents			
	(1)	(2)	(3)	(4)
On hybrid team	0.265***	0.218***	0.147	0.541***
	(0.073)	(0.054)	(0.097)	(0.135)
Inventor significant co-inventor stay	-0.008			
	(0.008)			
On hybrid team × Inventor significant co-inventor stay	0.035			
	(0.063)			
Star inventor		0.225***		
		(0.042)		
On hybrid team × Star inventor		0.377**		
		(0.172)		

Inventor network size			0.034***	
			(0.006)	
On hybrid team × Inventor network size			0.032	
			(0.029)	
Inventor specialization				-0.141***
				(0.044)
On hybrid team × Inventor specialization				-0.509**
				(0.198)
# of observations	28,166	28,166	28,166	28,166
Adjusted R^2	0.059	0.072	0.063	0.061