Corporate Innovations and Mergers and Acquisitions[*]

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Abstract

Using a large patent-merger dataset over the period 1984-2006, we examine the motives and outcomes of acquisitions from the perspective of property rights theory of the firm. Our measures of corporate innovation capture not only quantity, quality, but also more importantly, asset complementarity that stem from technological overlaps of merger partners. We first show that more innovative companies, as measured by both patent quantity and quality, are more likely to engage in acquisition activities. Further, technological overlaps between the bidder's and the target firm's innovation activities as captured by patent cross-citations and common knowledge base have positive and significant impact on merger pairing. Finally, we show that innovation-driven acquisitions achieve better long-term new outcomes: more and significant innovation output as well as improved operating and stock market performance. Overall, our evidence provides strong support for the property rights theory of the firm.

Keywords: Asset complementarity, boundaries of the firm, mergers and acquisitions, innovation, property rights, technological overlap
JEL classification: G34, O32

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Abstract

Using a large patent-merger dataset over the period 1984-2006, we examine the motives and outcomes of acquisitions from the perspective of property rights theory of the firm. Our measures of corporate innovation capture not only quantity, quality, but also more importantly, asset complementarity that stem from technological overlaps of merger partners. We first show that more innovative companies, as measured by both patent quantity and quality, are more likely to engage in acquisition activities. Further, technological overlaps between the bidder's and the target firm's innovation activities as captured by patent cross-citations and common knowledge base have positive and significant impact on merger pairing. Finally, we show that innovation-driven acquisitions achieve better long-term new outcomes: more and significant innovation output as well as improved operating and stock market performance. Overall, our evidence provides strong support for the property rights theory of the firm.

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I. Introduction

There has been a long standing debate in the literature on why mergers occur.[1] Since mergers are corporate events where boundaries of the firm are redrawn, our paper is founded on the property rights theory of the firm (Grossman and Hart (1986), Hart and Moore (1990), and Hart (1995)). The theory argues that merger decisions are important because ownership determines residual control rights over assets when unforeseen or non-contractible contingencies force parties to negotiate how their relationship should be continued. In such circumstances, integration is seen as a way of reducing the opportunistic behavior and eliminating hold-up problems, and thus generating economic gains.

In this paper, we focus on the role asset complementarity in the space of technological innovations plays in corporate acquisitions. Our setting fits the property rights theory of the firm particularly well as the realization of technological synergies requires relationship-specific investments, while intangible assets in general and R&D investments in particular are hard to contract upon. Firms that choose to contract with each other instead of merging risk facing hold-up problems as either firm can threaten to quit the relationship and/or to search for another partner. Foreseeing such opportunistic behavior leads to *ex ante* under-investment in relationship-specific assets. Hart and Moore (1990) show that inefficiencies due to incomplete contracting are most severe when assets are highly complementary. This implies that firms with the highest degree of complementarity have the strongest incentive to merge as, for them, the opportunity cost of under-investment is the highest. In the context of technological innovations where the underlying assets are hard to contract upon by nature, asset complementarity accentuates the incentive to merge. We thus expect that the need to transact R&D-related assets may trigger mergers, and that joint ownership of such assets by one formal organization would

[1] At least three, not mutually exclusive, schools of thoughts appear to emerge. First, mergers take place because of incompetent target management and/or hubris (Jensen and Ruback (1983), and Roll (1986)). Second, mergers take place because acquirer managers take advantage of the market's overvaluation of their firms and/or there exists correlated misinformation whereby errors in valuing potential takeover synergies are correlated with overall market valuation error (Shleifer and Vishny (2003), and Rhodes-Kropf and Viswanathan (2004)). Lastly, mergers take place because of efficiency gains (Jovanovic and Rousseau (2002), and Harford (2005)).

lead to an increase in innovation activity and R&D investments post-merger. In other words, asset complementarity in the technology space could be an important motive behind corporate acquisitions. Indeed, about 60% of all corporate acquisitions in our sample are associated with firms that are involved in R&D activities, as captured by patents, shortly prior to the transaction.

The acquisition of Closure Medical Corporation by Johnson & Johnson (J&J) is illustrative of the role asset complementarity in the technology space plays in redrawing the boundaries of the firm. Closure Medical, a global leader in biomaterial-based medical devices, developed the cyanoacrylate technology that was used in J&J's products prior to the acquisition. On March 4, 2005, J&J announced the acquisition of Closure Medical stating that, "cyanoacrylate formulations offer several advantages, include
ng speed, ease-of-use and performance [and that] the capabilities and experience [J&J] expects to gain from this transaction can significantly contribute to the company's sustained success."[2] Similarly, Intel's President described the acquisition of Chips and Technologies on July 27, 1997, "Intel and Chips and Technologies already share an excellent working relationship based on our joint efforts in graphics accelerators. Intel's acquisition of Chips and Technologies will provide [Intel] with the ability to bring strong graphics solutions to the mobile market segment." The acquisition was triggered by the Chips and Technologies' industry-leading technology (HiQColor) in graphics accelerators for the mobile computers.[3]

The two examples above highlight several key features of the merger transactions that we study in this paper. First, a particular technology of the target firm appears to be very important from the acquirer's perspective, hence triggering the bid. Second, efficiency gains stemming from asset complementarities, i.e., technological overlaps, can only be realized if the assets are joined together under the acquiring firm's ownership. Therefore, integration has a positive impact on the acquirer's future performance. These features lead us to the following main

[2] See J&J's press release, "Johnson & Johnson and CLOSURE Medical Corporation Announce Acquisition Agreement" on March 4, 2005 at http://www.investor.jnj.com/textonly/releasedetail.cfm?ReleaseID=157299.
[3] See Intel's press release, "Intel to Acquire Chips and Technologies, Inc." on July 27, 1997 at http://www.intel.com/pressroom/archive/releases/1997/CN072797.HTM.

research questions: Are acquisitions driven by technologically advanced firms to further enhance their competitive edge or by technology laggards? Do merger partners possess complementary technologies? Do innovation-driven acquisitions improve firm innovativeness as well as operating and stock market performance?

To answer these questions we compile the largest patent-merger dataset ever and develop innovation measures that capture quantity, quality, and more importantly, asset complementarities that stem from technological overlaps of merger partners. Using cross-citations between the acquirers' and the target firms' patents, our new measures identify whether merger partners' innovation activities are directly related and/or whether they are originated from the same knowledge base. This allows us to examine whether and how technological complementarities affect merger motives and outcomes.

We first show that more innovative companies, as measured by both patent quantity and quality, are more likely to engage in acquisition activities. Second, technological overlaps between the bidder's and the target firm's innovation activities as captured by correlation of innovation activities and patent cross-citations have positive and significant impact on merger pairing. Finally, we show that innovation-driven acquisitions achieve better long-term real outcomes: more and significant innovation output as well as improved operating and stock market performance.

Our paper differs from prior work in the following dimensions. First, we develop new measures of technological relatedness in the merger setting and provide evidence in support of the property rights theory of the firm. Second, we identify both unilateral and bilateral technology-specific firm characteristics that trigger merger pairing and that lead to improved operating and stock market performance. Finally, we present large sample evidence on the real consequences of mergers on the acquirers' future innovation activities, using a sample that spans most industries and covers the past two decades.

Our paper adds to the large literature examining the motives and outcomes of mergers (see the survey by Andrade, Mitchell, and Stafford (2001)) and is closely related to two recent papers taking the boundaries of the firm view of mergers.

Building upon the property rights theory of the firm, Rhodes-Kropf and Robinson (2008) apply the classical search model of Diamond-Mortensen-Pissarides to explain the observed pattern of market-to-book ratios of acquirers and target firms. In their model, merger surplus is not contractible and hence can only be realized under joint ownership. The market-to-book ratios are determined by gains from merger synergies and the probability of a merger taking place, which depends on search frictions. Their model predicts that there should be more firms with complementary assets or technologies joining together—redrawing the boundaries of the firm—to gain the efficiencies associated with coordinated ownership.

Hoberg and Phillips (2010) provide direct evidence showing that product market synergies are important drivers of mergers. Using a text-based analysis of merging firms' 10-K reports to identify product market interactions among merger candidates, they show that acquirers merge with target firms that have complementary assets in order to achieve product range expansions, while, at the same time, acquirers pick target firms that are related enough so that they can manage the new assets.

Complementing the above papers, we focus on technological overlaps to directly measure synergies between the acquirer and the target firm. We show that such synergies trigger merger pairings and are important for achieving the real positive effects of mergers.

The paper proceeds as follows. We review the literature and develop our hypotheses in the next section. We describe our sample and construction of key innovation variables in Section III. We examine merger incentives and outcomes with a focus on asset complementarity in the technology space in Section IV. Additional investigations are presented in Section V, and we conclude in Section VI.

II. Literature Review and Hypothesis Development

In this section, we first review the literature on the boundaries of the firm that motivate our study. We then develop our hypotheses focusing on how *ex ante* asset complementarities (measured using acquirers' and target firms' technological overlaps) give firm incentives to merge and how mergers may realize synergies and subsequent real improvement.

II.A. Literature on the Boundaries of the Firm

The property rights approach to understanding firm boundaries, pioneered by Grossman and Hart (1986) starts by noting that asset ownership is irrelevant under complete contracting and hence it must be contractual incompleteness that prevents a party from getting the *ex post* return required to compensate for his *ex ante* investment, that leads to a theory of ownership. In Grossman and Hart (1986), integration is optimal when one firm's investment decision is particularly important relative to the other firm's, whereas non-integration is desirable when both investment decisions are "somewhat" important. The impossibility of *ex ante* negotiating over all aspects of the product to be delivered, that is, the incompleteness of the contract, leads Grossman and Hart to conclude that the distribution of property rights has efficiency consequences.

Hart and Moore (1990) develop a theory of the optimal allocation of ownership of assets and use it to understand the boundaries of the firm. They show that an agent should own an asset if his action that generates social surplus is sensitive to whether he has access to the asset or not. Similarly, an agent should own an asset if he is a crucial trading partner for others whose actions are sensitive to whether they have access to the asset and are important in the generation of the surplus. They further show that in a world of incomplete contracts, assets that are highly complementary should be owned together. This is because that the realization of synergies usually involves relationship-specific investments but these spillovers also create opportunities for rent-seeking that can be minimized by allocating decision rights over the use of assets to a single party. In contrast, assets without complementarities can be easily contained in different firms, and their coordination can be mediated through simple product market transactions. Given that mergers are costly, it follows that firms with complementary assets should be more willing to pay the costs of merging to realize the benefits associated with common ownership.

In this paper, we apply the property rights perspective of the firm with a focus on asset complementarity to gain understanding of merger motives and outcomes.

II.B. Our Hypotheses

Our starting point is that firms not active in the technology space may never be able to realize big synergistic gains from buying R&D. As such, we hypothesize that:

Hypothesis 1: Merger Occurrence: More innovative firms are more likely to engage in M&As as acquirers.

Inter-firm linkages in technological innovations can lead to merger decisions through several channels. First, the property rights theory of the firm argues that mergers help resolve hold-ups and/or increase relationship-specific investments of merger partners towards the optimal level (Grossman and Hart (1986), Hart and Moore (1990), and Hart(1995)). Given that hold-ups or relationship-specific under-investments are more likely to occur in circumstances where there are potential synergies but contracts are presumably incomplete, such as in settings involving R&D activities and intangible assets in general, changes of control rights are called for to achieve efficiency. The technological overlaps of any two firms' innovation activities would be the first step in mapping out the new firm boundaries.

Second, technological overlaps can help overcome information asymmetry in acquisitions. R&D intensive assets, by nature, are more difficult to evaluate than tangible ones. One of the concerns for any acquirer is its ability to accurately value the target firm. If the acquirer and the target firm are familiar with each other's technologies, then information asymmetry between merger partners is mitigated (Higgins and Rodriguez (2006), and Zhang (2010)).

Finally, the target firm's technology can complement the acquirer's technology or it can fill particular gaps in the acquirer's R&D portfolio so that the innovation prowess or the competitive position of the combined firm is strengthened (see the two motivating examples in the introduction, Breitzman and Thomas (2002), and Higgins and Rodriguez (2006)). As such, we expect that innovative acquirers pursue target firms with which they have innovation overlaps or target firms with similar technological competency:

Hypothesis 2: Merger Pairing: Mergers are more likely to take place between firms with overlapping innovation activities.

According to the property rights theory of the firm, integration changes incentives to invest and thus improves efficiency. In our particular setting, innovation-driven mergers have the potential to perform well if the acquirer achieves economies of scale and scope in production of innovation by buying target firms with related R&D activities. Specifically, R&D activities typically have a significant fixed cost component, mergers between firms with related R&Ds can lead to a substantial reduction in development costs by avoiding duplication and/or sharing inputs. Such economies of scale and scope are likely to be the greater the more related the merger partners' R&D activities are (Ornaghi (2009)). Furthermore, by unifying R&D activities, mergers can facilitate knowledge spillovers that increase the productivity of R&D activities of the combined firm. In contrast to pure economies of scale and scope in the production of innovation, knowledge-based spillovers imply improvement in innovation performance, irrespective of any change in R&D inputs (Kamien and Schwartz (1982), and De Bondt (1996)). As such, we hypothesize that:

Hypothesis 3: Merger Outcomes: Innovation-driven mergers generate more future innovation output, and are associated with higher stock market price reaction, and better post-merger operating and stock market performance.

In our empirical investigation, we test these hypotheses and also attempt to control for some of the alternative explanations for why and how mergers take place. In the next section we describe our data, define key innovation variables, and present summary statistics.

III. Sample Formation and Key Variable Definitions

III.A. Our Sample

To form our M&A sample, we begin with all announced and completed US M&As with announcement dates between January 1, 1984 and December 31, 2006 covered by the Mergers and Acquisitions database of the Thomson Financial's SDC Database.[4] We identify all deals where the form of deal was coded as a merger, an acquisition of majority interest, or an acquisition of assets. Then we only retain an acquisition if the acquirer owns less than 50 percent of the target firm prior to the bid, is seeking to own greater than 50 percent of the target firm, and owns greater than 90 percent of the target firm after the deal completion. We require that: 1) both the acquirer and the target firm be bigger than $1 million or that the transaction value be no less than $1 million (all in 1984 constant dollars) to get rid of many small deals; 2) neither the acquirer nor the target firm be from the financial sector (SIC 6000-6999); and 3) both the acquirer and the target firm be covered by Compustat (with information on their industry classification and sales). These filters yield 3,651 deals—the *SDC Sample*.

To examine the effect of asset complementarity in the technology space on M&A decisions, we form samples of pseudo deals using matching acquirers and matching target firms and append them to the *SDC Sample* that contains the actual acquirers and the actual target firms. Matching acquirers (target firms) are selected in the following way: 1) we consider all Compustat firms over the sample period that were never an acquirer nor a target firm in the *SDC Sample*; 2) they are from the same 2-digit SIC industry as the actual acquirer (target firm) as of the fiscal year end before the bid announcement; 3) their sales is the closest to the actual acquirer's (target firm's) sales as of the fiscal year end before the bid announcement; and 4) both the actual acquirer and its closest matching firm (both the actual acquirer-target pair and their

[4] Our sample period begins in 1984 because the information in SDC is less reliable before 1984 and ends in 2006 because the patent data ends in 2006.

respective closest matches) have available information (from Compustat and CRSP) to construct firm characteristics as defined in Appendix 1.

There are 1,859 deals in the *SDC Sample*, for which we are able to form pseudo deals by pairing the closest match of the actual acquirer with the actual target firm using the procedure described above—the *Acquirer Sample*. There are 1,478 deals in the *SDC Sample*, for which we are able to form at least one pseudo deal by pairing: 1) the actual acquirer with the closest match of the deal's actual target firm; 2) or the actual target firm with the closest match of the deal's actual acquirer; 3) or the closest match of the deal's actual acquirer with the closest match of the deal's actual target firm—the *Acquirer-Target Sample*.

We then retrieve patent related information for the actual acquirers and the actual target firms and their respective matches from the patent database compiled by combining the NBER Patent Data Project (May 2009) with the worldwide Patent Statistical Database (PATSTAT, April 2008) of the European Patent Office (EPO). The NBER project provides data about all utility patents[5] awarded by the US Patent and Trademark Office (USPTO) over the period 1976-2006. Among other variables, the NBER project contains, for each patent, a unique patent number, patent assignee names matched to firms in Compustat (a patent number-GVKEY link), and a patent's technology field defined according to the standards of the International Patent Classification (IPC) system. The original matching of patent assignees, by name, to firms in Compustat is done by Hall, Jaffe, and Trajtenberg (2001). Since then, the matching has been updated using multiple manual and computer generated matches (see Bessen (2009) for details). The PATSTAT database contains, among other information, the identification of the set of patent publications that cite a particular patent (citations received by a patent) and the identification of the set of patent publications a particular patent is citing (citations made by a patent), based on all patent documents submitted to the USPTO. The key advantage of using the NBER project

[5] According to the US Patent Law (35 U.S.C. 101) utility is a necessary requirement for patentability and is used to prevent the patenting of inoperative devices. In our analysis, we do not use plant patents, i.e., patents for new varieties of plants.

together with the PATSTAT for our analysis is that the combined database allows us to track patenting output and patent citation activity over time by technology fields as well as by firms and firm-pairs.

III.B. Our Innovation Measures

The IPC system is a hierarchical patent classification system created under the Strasbourg Agreement (1971) and updated on a regular basis by a committee of experts, consisting of representatives of the contracting states of that agreement. The structure of the IPC classification is made up of a section, class, subclass, main group, and subgroup. There are eight sections and about 600-700 classes (depending on the version) in the second-level of the IPC system. For our purpose, we use the second-level of the IPC classification as a technology field of innovation—technology class.

The technology classes differ in the nature of R&D activity and resources required to produce a patentable innovation to the extent that patents in two distinct classes may not be directly comparable. Further, there are technology class-specific time trends in the number of patents applied/awarded, i.e., technology class "business cycles," and hence patent counts from different years may not be (time) consistent measure of innovation output even within the same technology class. To adjust for differences across technology classes as well as for technology class-specific time trends, we scale the firm-level patent (citation) counts by the median patent (citation) counts taken across all firms that are active in a given technology class in a given time period. Our approach is similar to, although more parsimonious than, the fixed-effects method recommended by Hall, Jaffe, and Trajtenberg (2001). Below we introduce our innovation measures, while detailed definitions are provided in Appendix 1.

To capture the quantity of innovation, we employ *Patent Count* and *Patent Index*. The first variable is a count of the number of awarded patents to a firm (either the acquirer or the target firm) applied over the three-year period before/after an acquisition (see Figure 1 for an illustration of these time periods which we denote “BEFORE” and “AFTER”). The second variable measures the quantity of a firm’s innovation output benchmarked relative to the median quantity of innovation output in each technology class and time period where and when the firm was active in patenting.

To capture the quality of innovation, we employ *Citation Count* and *Citation Index*. The number of citations a patent receives conveys information about its importance and allows gauging the enormous heterogeneity in the quality of patents. This is because, if firms invest in further developing an innovation disclosed in a previous patent, then the resulting (citing) patents presumably signify that the cited patent is economically valuable. Further, if there are citations years after the award of the cited patent, it must be that the cited patent has indeed proven to be valuable (Hall, Jaffe, and Trajtenberg (2005)). *Citation Count* is a count of citations received by a firm’s awarded patents with award years from the three-year period before/after an acquisition (see Figure 1 for an illustration of time periods over which we measure awarded patents as well as time periods over which we measure citation counts for each patent awarded in a given year). *Citation Index* captures the quality of a firm’s patent portfolio benchmarked relative to the median quality of patenting output in each technology class and time period where and when the firm was active in patenting. Both *Patent Index* and *Citation Index* are new constructs to the literature.

An important consideration, however, is not necessarily the quantity and quality of innovation output, but the trend of these measures in the years prior to an acquisition. A declining quantity (quality) of innovation output in the years prior to an acquisition would be indicative of a company whose technological output is deteriorating. As such, we also compute changes in our measures of innovation quantity and quality between the three-year period before an acquisition and the time period prior to that (see Figure 1 for an illustration of these time periods which we denote “BEFORE” and “AGO”).

We employ three variables to capture innovation overlaps. The first variable, following Jaffe (1986), *Correlation of Innovation Activities*, measures the proximity of any two firms' innovation activities in the technology space using patent counts in different technology classes. The second variable, *Cross Citation*, measures the extent of a firm's patent portfolio being directly cited by another firm's patent portfolio. *Cross Citation* captures the immediate importance of a firm's innovation activity to that of another firm. The final variable, new to the literature, *Knowledge Base Overlap*, measures the extent to which any two firms' awarded patents cite the same set of past patents. *Knowledge Base Overlap* captures the similarity of technological foundations of any two firms' patent portfolios, specifically, whether the two firms base their innovation activities on the same underlying knowledge.

III.C. Measures of Merger Performance

We adopt a number of measures to evaluate the impact of mergers and acquisitions on innovation and firm operating and stock market performance (detailed definitions are provided in Appendix 1).

The first set of performance measures is our innovation variables defined in Section III.B, measured both in levels (as of the three-year period after the deal completion—year *cyr+1* to *cyr+3*, see Figure 1) and in changes (between the three-year period after the deal completion to the three-year period before the bid announcement—year *ayr-3* to *ayr-1*).

The second set of performance measures captures the immediate stock price reaction of the acquirer and the target firm to the bid announcement. *Acquirer CAR3*, is the acquirer's abnormal announcement-period return over days (−1, 1), where day 0 is the bid announcement date. Daily abnormal stock returns are computed using the market model and the value-weighted CRSP index. The estimation window is days (–252, –60) prior to the bid announcement date. *Target CAR3* is computed similarly. Following Bradley, Desai, and Kim (1988), we also compute the value-weighted announcement period return, *Deal CAR*3, as (*Acquirer CAR3* ×

acquirer market capitalization + *Target CAR3* × target market capitalization) / (acquirer market capitalization + target market capitalization).

Our final set of performance measures complements the immediate price reaction measures with the post-merger long-run operating and stock market performance. We use the ratio of earnings before interest, taxes, depreciation, and amortization to total assets (EBITDA/Assets) as a measure of operating performance (ROA) and control for both industry and year effects following Chen, Harford, and Li (2007). For the post-merger long-run stock market performance, we control for size, book-to-market, and pre-acquisition return following Lyon, Barber, and Tsai (1999).

III.D. Sample Overview

Table 1 presents the temporal distribution of the M&A samples that we use in our analyses. From the 1,859 actual deals in the *Acquirer Sample* (*All Deals*), there are 1,031 deals where the acquirers engaged in patenting activities over the five-year period prior to the bid announcement—*Acquirers with Patents*. From the 1,478 actual deals in the *Acquirer-Target Sample*, there are 955 deals where either the acquirers or the target firms engaged in patenting activities—*Acquirers or Targets with Patents*, and 453 deals where both the acquirers and the target firms engaged in patenting activities over the five-year period prior to the bid announcement—*Acquirers and Targets with Patents*.

We observe a trough in the early 1990s and a strong surge in the late 1990s in M&A activities, coinciding with a recession and a subsequent rising stock market and economic boom. The five samples exhibit very similar temporal trends, with M&A activities bottomed in 1992 and peaked in 1998. It is clear that deals made by innovative acquirers exhibit similar cyclicality as those made by acquirers at large.

Appendix 2 presents a detailed breakdown of sample deals by industry using 2-digit SICs. We show that deals in the *Acquirers or Targets with Patents* sample span 48 different industries. The five industries with the highest number of acquisition deals are: Chemicals and Allied Products (SIC 28, including pharmaceutical and biotech industries), Industrial and Commercial Machinery and Computer Equipment (SIC 35), Electronic and Other Electrical Equipment and Components (SIC 36), Transportation Equipment (SIC 37), and Measuring, Analyzing, and Controlling Instruments (SIC 38).[6]

Table 2 Panel A presents the descriptive statistics for the *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*.[7] Total assets are in billions of 2006 constant dollars. We show that the acquirers tend to produce more patents than their target firms as measured by both patent counts and patent indices. Further, in terms of the quality of innovation, both the acquirers' citation counts and citation indices are greater than those of their target firms. Our univariate statistics are suggestive of that the acquirers are more innovative than their target firms.

The firm characteristics show that our sample firms are large firms (in the 9th and 8th deciles of the Compustat universe over the same time period for the acquirers and the target firms in the *Acquirers or Targets with Patents* sample, respectively), and that the acquirers have higher sales growth and profitability, better operating and stock market performance, and lower B/M ratios than the target firms. Overall, our acquisition sample is similar to those used in other studies of mergers between public firms (see for example, Gaspar, Massa, and Matos (2005), and Jenter, Harford, and Li (2011)).

At the bottom of Panel A, we show that there are innovation overlaps between the acquirers and their target firms using different measures. In particular, there are 255 deals (out of 955 deals) where one or more measures of innovation overlaps are non-zero. There are more

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[6] In the technological strand of the merger literature, most prior work is limited to technology/research intensive industries that represent a narrow snapshot of the economy (see for example, Cloodt, Hagedoorn, and Van Kranenburg (2006) on four high-tech sectors, Higgins and Rodriguez (2006) and Ornaghi (2009) on the pharmaceutical industry, and Danzon, Epstein, and Nicholson (2007) on the pharmaceutical/biotechnology industry) and typically uses measures of firms' innovation output that fail to capture asset complementarity from innovation-driven acquisitions (see for example, Danzon, Epstein, and Nicholson (2007), Zhao (2009), and Zhang (2010)).
[7] The descriptive statistics for all other samples exhibit similar patterns, and are available upon request.

target firms making cites of their acquirers' patents (*Target's Cross-Cites of Acquirer*) than the other way round (*Acquirer's Cross-Cites of Target*). Naturally, the common knowledge base between the acquirers and the target firms is more important to the latter than to the former.

Table 2 Panel B presents the descriptive statistics for the sample of pseudo deals to the *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*. There are 2,567 pseudo deals to 955 actual deals.

We show that among these pseudo deals, the acquirers tend to produce more patents with higher citation counts than their target firms, but both the acquirers and the target firms are less innovative in comparison to the merger partners of the actual deals. The firm characteristics suggest that the matching firms are similar in firm size, as intended, to the actual acquirers and target firms.[8] Interestingly, the extent of innovation overlaps is minimal between the merger partners in those pseudo deals, as compared to the merger partners in the actual deals as shown in Panel A.

Table 2 Panel C presents the correlation matrix of the innovation variables for the same sample as described in Panel A. We show that there is high correlation among the two measures of patent quantity—*Patent Count* and *Patent Index*, the two measures of patent quality—*Citation Count* and *Citation Index*, and between the measures of patent quantity and quality. As a result, in our multivariate analyses later on we will include either patent quantity or quality measures but not both. There is moderate correlation among the five measures of innovation overlap between the acquirer and the target firm, and between these overlap measures and the measures of patent quantity and quality. In our multivariate analyses of merger pairing, we will include both unilateral and bilateral innovation measures.

[8] Because the firms in pseudo deals are matched to their respective actual merger partners by sales, the sales differences between the actual and matching firms are minimal, while we still see some differences in total assets. In our multivariate analyses, we include total assets as a control variable, so we effectively control for both measures of size.

IV. Main Results

In this section, we implement various multivariate analyses to test our hypotheses regarding the interaction between corporate innovations and asset complementarity in particular and acquisitions.

IV.A. Who Are the Acquirers?

Are acquisitions driven by technologically advanced firms, probably to preserve or further enhance their competitive edge, or by technology laggards? To answer this question, we run the following probit regression using cross sectional data with one observation for each actual deal and one observation for each pseudo deal:

$$Acquirer_{it} = \alpha + \beta_1 Innovation\ Measure_{it-1} + \beta_2 Acquirer\ Characteristics_{it-1} + Industry\ FE_i + Year\ FE_t + \varepsilon_{it}. \quad (1)$$

The dependent variable is, *Acquirer*$_{it}$, equal to one if the firm is the actual acquirer, and zero otherwise (i.e., if the firm is the acquirer matching firm). *Innovation Measure*$_{it-1}$ is one of the measures of innovation quantity and quality as defined in Section III.B. *Acquirer Characteristics*$_{it-1}$ are measured as of the fiscal year end before the bid announcement. Table 3 presents average marginal effects from the probit regression in Equation (1) computed across all firms in the sample.

In Panel A, we focus on the quantity of innovation measures and employ both *All Deals* and *Acquirers with Patents* of the *Acquirer Sample*. Across both samples and all specifications, we show that more innovative firms are more likely to become acquirers. In terms of the economic significance, under Column (1) specification, if the value of *Patent Count* increases by a tiny bit, the probability of a sample firm to become an acquirer increases by 2.9 percentage points, on average. As a comparison, an infinitesimal increase in prior year stock returns is associated with 4.4 percentage points increase in the likelihood of a sample firm to become an acquirer, on average. It is worth noting that the largest effect on the likelihood of a firm becoming an acquirer is its R&D expenditures, reinforcing our conjecture that innovations drive acquisitions. Similarly, under Column (3) where we employ *ΔPatent Count* between year *ayr-3* and year *ayr-1* as the key explanatory variable, if the trend of patent count increases by a tiny bit, the probability of a sample firm to become an acquirer increases by 5.4 percentage points, on average. In contrast to Zhao (2009), our results suggest that both the level of innovation quantity and its time trend play an important role in M&A decisions.[9] *ΔPatent Index* is shown to have similar effect (see Column (4)).

Using the subsample of innovative acquirers in Columns (5)-(8), we show that the effect of innovation quantity is strengthened. In terms of the economic significance, under Column (5) specification, if the value of *Patent Count* increases by a tiny bit, the probability of a sample firm to become an acquirer increases by 9.0 percentage points, on average; and under Column (7) where we employ *ΔPatent Count* as the key explanatory variable, if the trend of patent count increases by a tiny bit, the probability of a sample firm to become an acquirer increases by 7.2 percentage points, on average. Our results suggest that innovation output becomes even more important consideration in M&A decisions when the potential acquirer has been innovative prior to an acquisition bid.

There are other findings that are not directly related to innovation but are consistent with prior work in M&As (see for example, Moeller, Schlingemann, and Stulz (2004), and Gaspar, Massa, and Matos (2005)). We show that larger firms, firms with fast growth, high R&D expenditures, low B/M ratios, and high prior year stock returns are more likely to engage in M&As.

In Panel B, we focus on the quality of innovation measures and employ the same two samples as in Panel A. Across both samples, we show that innovative firms with more extensively cited patents are more likely to become acquirers. In terms of the economic

[9] It is worth noting that when we include both the level and change in patenting output variables, the coefficients on the level variables are unchanged and remain highly statistically significant while the coefficients on the change variables become only marginally significant (results available upon request).

significance, under Column (1) specification, if the value of *Citation Count* increases by a tiny bit, the probability of a sample firm to become an acquirer increases by 2.3 percentage points, on average; and under Column (5) specification where the acquirer has been innovative, if the value of *Citation Count* increases by a tiny bit, the probability of a sample firm to become an acquirer increases by 5.9 percentage points, on average. There is no significant association between the time trend in patent quality and the likelihood of a firm becoming an acquirer.

Overall, our results provide strong support for our hypothesis (**H1**) that more innovative firms are more likely to become acquirers. Our findings are consistent with the empirical investigation by Maksimovic and Phillips (2001) who show that firms divest assets/divisions that are less productive than their respective industry benchmarks while keeping the more productive assets/divisions, and that more efficient firms are more likely to be buyers for corporate assets.

IV.B. Bidder-Target Pairing

Do merger partners possess complementary technologies as predicted by the property rights theory of the firm? To address this question, we employ the *Acquirer-Target Sample* where information on the acquirers, the target firms, their respective matching firms, and importantly, the extent of acquirer-target firm pre-merger innovation overlaps, is available. Specifically, we run the following probit regression using cross sectional data with one observation for each actual deal and one observation for each pseudo deal:

$$Acquirer\text{–}Target_{ijt} = +\beta_1 Innovation\ Overlap_{ijt-1} + \beta_2 Acquirer\ Innovation\ Measure_{it-1} + \beta_3 Target\ Innovation\ Measure_{jt-1} + \beta_4 Acquirer\ Characteristics_{it-1} + \beta_5 Target\ Characteristics_{jt-1} + \beta_6 Diversifying_{ij} + \beta_7 Same\ State_{ij} + Industry\ FE_i + Year\ FE_t + \varepsilon_{ijt}. \quad (2)$$

The dependent variable is, *Acquirer-Target*$_{ijt}$, equal to one if the pair is the actual acquirer-actual target firm pair, and zero otherwise (i.e., if the pair is one of the pseudo deals defined before). *Innovation Overlap*$_{ijt-1}$ are the five different measures of innovation overlaps computed for the merger partners involved in actual deals as well as for the firm pairs in pseudo deals, and is measured prior to the bid announcement. *Acquirer (Target) Innovation Measure*$_{it-1}$ is one of the measures of innovation quantity and quality. *Acquirer (Target) Characteristics*$_{it-1}$ *Characteristics*$_{jt-1}$) are measured as of the fiscal year end before the bid announcement. *Diversifying*$_{ij}$ is an indicator variable equal to one if the acquirer and the target firm operate in the same industry, and zero otherwise. *Same State*$_{ij}$ is an indicator variable equal to one if the acquirer and the target firm are incorporated in the same state, and zero otherwise. Table 4 presents average marginal effects from the probit regression in Equation (2) computed across all firms in the sample.

In Panel A, using both samples, we show that there is a significant and positive association between *Correlation of Innovation Activities* between merger partners and the formation of a merger pair. In terms of the economic significance, under Column (1) specification, if the value of *Correlation of Innovation Activities* increases by a tiny bit, the probability of a merger pairing increases by 42 percentage points, on average. Under Column (3) specification, if the value of *Correlation of Innovation Activities* increases by a tiny bit, the probability of a merger pairing increases by 34 percentage points, on average.

Further, it is *Target's Cross-Cites of Bidder* (*Target's Knowledge Base Overlap*), not *Acquirer's Cross-Cites of Target* (*Acquirer's Knowledge Base Overlap*), that is important in the merger pairing decision. This is an important and new finding in the literature, suggesting that the selection of target firms by acquirers is made based on the target firms' proximity to their acquirers in terms of innovation, in particular, due to potential synergistic gains in the technology space and possibly also due to the reduction of information asymmetry with respect to target firms' intangible assets that are being acquired. From the perspective of boundaries of the firm and the property rights theory in particular, the technological overlaps of any two firms' innovation activities are the impetus in identifying the new firm boundaries.

Finally, we show that target firm innovativeness, measured by either patent quantity or quality, is negatively and significantly associated with the formation of a merger pair. This result is mostly driven by the fact that more innovative firms become acquirers (as shown in our Table 3), leaving the less innovative ones to become target firms almost by construction.

There are other findings that are not directly related to innovation but are consistent with prior work in M&As (see for example, Gaspar, Massa, and Matos (2005), and Harford, Jenter, and Li (2011)). We show that large firms with fast sales growth, high R&D expenditures, low B/M ratios, and high prior year stock returns are more likely to be acquirers; while firms with high R&D expenditures, and low prior year stock returns are more likely to be takeover targets.

In Panel B, we focus on changes in innovation overlaps during the period preceding the bid announcement as our key explanatory variables and employ the same two samples as in Panel A. Due to space constraints, we only report average marginal effects associated with the innovation measures. Across both samples, we show that the rising trend in the extent of overlaps between the acquirer and the target firm as captured by Δ *Target's Cross-Cites of Target* and Δ *Target's Knowledge Base Overlap*, are positively and significantly associated with the formation of a merger pair. Importantly, consistent with findings in Panel A, we show that acquirers are firms with increasing trend in patenting activities, while target firms are ones with declining trend in patenting activities. This evidence is consistent with findings in Maksimovic and Phillips (2001) that more productive firms buying less productive ones.

Our evidence in Table 4 provides strong support for our second hypothesis (**H2**) that mergers are more likely to take place between parties with complementary assets and in our particular setting, with overlapping innovation activities. Hoberg and Phillips (2010) show that mergers are more likely to take place among firms with similar products where the ability of acquirers to exploit product market synergies through asset complementarities is the greatest. We show that there are also potential synergistic gains due to innovation overlaps between merger partners. Our evidence is consistent with the property rights theory of the firm which posits that in circumstances where relationship-specific investments are required to realize synergies while contracts are incomplete, such as involving R&D investments, ownership changes to redraw the firm boundaries help materialize synergies.

Next we investigate whether and how technology-driven acquisitions impact future innovation as well as operating and stock market performance of the combined firm after merger completion.

IV.C. Post-Merger Innovation

To mitigate the potential truncation bias in our post-merger measures, all post-merger analyses are implemented on subsamples with the transaction completion date on or before December 31, 2003, which is three years before our patent data ending in 2006. Further, to clearly delineate the effect of each acquisition on innovation and firm operating and stock market performance, in cases where a sample firm makes multiple acquisitions, only those acquisitions that do not overlap are included. Specifically, we only keep bids by the same acquirer that do not overlap with any other bid made within a three-year window both before and after the sample bid. Note that we chose this three-year time frame because we measure post-merger and pre-merger innovation quantity/quality as the level of patent/citation counts in a three-year window after the deal completion and prior to the bid announcement, respectively. Similarly, we measure post-merger operating and stock market performance over the same three-year window after the deal completion. These filters yield 1,206 deals for the *Acquirer Sample*, and 991 deals for the *Acquirer-Target Sample*.

The Difference-in-Difference Approach

To examine the impact of acquisition events on post-merger firm innovation activity, we run the following difference-in-differences regression using a panel dataset where we have two time series observations, the post-merger and the pre-merger value, for each actual and pseudo deal, respectively:

$$Innovation\ Measure_{it} = \alpha + \beta_1 Acquisition_i + \beta_2 After_t + \beta_3 Acquisition_i \times After_t + \beta_4 Acquirer\ Characteristics_{it} + \beta_5 Deal\ Characteristics_i + Industry\ FE_i + Year\ FE_t + \varepsilon_{it}. \quad (3)$$

The dependent variable is one of the measures of innovation quantity and quality defined in Section III.B, which we measure over the three-year period following the deal completion (the post-merger value) and over the three-year period prior to the bid announcement (the pre-merger value). $Acquisition_i$ is an indicator variable equal to one if the firm is an actual acquirer, and zero otherwise (i.e., if the firm is the acquirer matching firm). $After_t$ is an indicator variable equal to one for the post-merger time period, and zero for the pre-merger time period. The interaction term $Acquisition_i \times After_t$ captures the post- versus pre-merger change in the dependent variable for the actual acquirer relative to the same change for the acquirer matching firm. $Acquirer\ Characteristics_{it}$ are measured as of the fiscal year end before the bid announcement. $Deal\ Characteristics_i$ are from SDC.

Panel A of Table 5 presents estimates of the panel data regression in Equation (3) using *All Deals* (Columns (1)-(4)) and *Acquirers with Patents* (Columns (5)-(8)) of the *Acquirer Sample*. We show that there is a general positive shift in patenting output, particularly in terms of innovation quality, *Citation Count* and *Citation Index*, post-merger as compared to pre-merger. Further, there is an even bigger positive post-merger versus pre-merger shift in patenting output for the actual acquirers as shown by the positive and significant coefficient on the interaction term $Acquisition_i \times After_t$. Under Column (1) specification, compared to post-merger versus pre-merger increase in *Patent Count* achieved by matching acquirers, the actual acquirers are able to improve *Patent Count* by 0.07, which is 4.5% of the standard deviation of the *Patent Count* variable used in this regression (the sample mean of *Patent Count* is 1.08, while the sample standard deviation is 1.65). Under Column (3) specification, compared to post-merger versus pre-merger increase in *Citation Count* achieved by matching acquirers, the actual acquirers are able to improve *Citation Count* by 0.25, which is 14% of the standard deviation of the *Citation Count* variable used in this regression (the sample mean of *Citation Count* is 1.08, while the sample standard deviation is 1.76). The analysis using *Acquirers with Patents* of the *Acquirer Sample* leads to similar results.

In Panel B of Table 5, Columns (1)-(4) present the analogous difference-in-differences estimates using *All Deals*, while Columns (5)-(8) present the results using *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*.[10] Again we show that there is a general positive shift in patenting output, post-merger as compared to pre-merger. Further, there is an even bigger positive post-merger versus pre-merger shift in patenting output for the actual acquirers as shown by the positive and significant coefficient on the interaction term $Acquisition_i \times After_t$. Under Column (1) specification, compared to post-merger versus pre-merger increase in *Patent Count* achieved by matching acquirers, the actual acquirers are able to improve *Patent Count* by 0.05, which is about 3% of the standard deviation of the *Patent Count* variable used in this regression. Under Column (3) specification, compared to post-merger versus pre-merger increase in *Citation Count* achieved by matching acquirers, the actual acquirers are able to improve *Citation Count* by 0.18, which is about 10% of the standard deviation of the *Citation Count* variable used in this regression. The analysis using *Acquirers or Targets with Patents* of the *Acquirer-Target Sample* leads to similar results.

<u>*The Propensity-Score Matching Approach*</u>

Estimating the causal effect of acquisitions on acquirers' post-merger performance using the difference-in-differences estimator described above may lead to biased estimates if the decision to engage in acquisitions is related to the expected improvement in future performance. For example, if acquirers foresee that their patents are expiring (or if acquirers are running out of

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[10] In Panel B of Table 5, we control for $Acquirer\ Characteristics_{it}$ as well as for $Target\ Characteristics_{jt}$, all measured as of the fiscal year end before the bid announcement.

innovation ideas) and are hence more likely to merge than firms with strong growth prospects, then the post-merger performance of the acquirers may be worse than that of the non-merging industry peers, but still better than it would have been in the absence of a merger. Failure to account for such selection effects would bias downwards the estimated effect of a merger on the change in innovation activities of the acquirers.

Our investigation of the likelihood of a merger occurrence indicates that there are indeed significant differences in observed characteristics between firms that were involved in M&As as acquirers (treatment firms) and those that were not (control firms). To alleviate the effect of this observed heterogeneity across the two groups of firms on selection into acquisitions, we use the propensity-score metric and the three-nearest neighbors matching method as implemented in STATA by Leuven and Sianesi (2003) to estimate the "average treatment effect on the treated" (ATT) by matching control firms to treatment firms based on the firms' observable pre-merger characteristics.[11] The matching approach aims to estimate the missing counterfactual of what an acquirer's performance would have been had it not made an acquisition.

Panels A and B of Table 6 presents the ATT estimates using the same sample as in Panels A and B of Table 5, respectively. In Panel A, the counterfactual for an acquirer's performance is estimated using the characteristics of its matching acquirers. In Panel B, we recognize that an acquirer's counterfactual performance might depend not only on whether it makes a particular acquisition or makes no acquisition, but also on which firm it acquires. To this end, we generalize the estimation of the counterfactual by matching on the acquirer's as well as its target firm's characteristics using the set of pseudo deals. Both panels show that there is a positive and significant improvement in all measures of innovation quantity and quality after merger completion for the actual acquirers.

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[11] Our results are robust to changes in the matching metric and also changes in the matching method. For example, all results are similar if we use the Mahalanobis-metric matching (see Rubin (1980)) and the kernel method. We assess the matching quality by checking whether the matching procedure is able to balance the distribution of the observable variables across the control and treatment groups. To this effect, we perform two-sample t-tests as suggested by Rosenbaum and Rubin (1985).

In summary, our findings that post-merger, both innovation quantity and quality increase significantly in transactions involving complementary assets are consistent with the predictions of the property rights theory of the firm: Integration changes investment incentives and leads to optimal investments.

IV.D. Merger Performance

To examine the effect of acquisitions on post-merger firm operating and stock market performance, we run the following OLS regression using cross sectional data with one observation for each actual deal:

$$\begin{aligned}
&Merger\ Performance_{it+1} = \\
&\alpha + \beta_1 Innovation\ Overlap_{ijt-1} + \beta_2 Acquirer\ Innovation\ Measure_{it-1} + \\
&\beta_3 Target\ Innovation\ Measure_{jt-1} + \beta_4 Acquirer\ Characteristics_{it-1} + \\
&\beta_5 Target\ Characteristics_{jt-1} + \beta_6 Diversifying_{ij} + \beta_7 Same\ State_{ij} + Industry\ FE_i + \\
&Year\ FE_t + \varepsilon_{it}. \qquad (4)
\end{aligned}$$

The dependent variable could be merger firms' abnormal announcement-period returns (*Acquirer CAR3*, *Target CAR3*, and *Deal CAR3*), acquirer post-merger operating (*Acquirer* Δ *ROA*) or stock market performance (*Acquirer BHAR*). To conserve space, Table 7 Panels A and B only presents the estimated coefficients in Equation (4) on the innovation measures and changes in innovation measures, respectively.

We show that there is some evidence suggesting that the acquirer's familiarity with the target's innovation activity, as captured by *Acquirer's Cross-Cites of Target*, is negatively and significantly associated with the target gain (*Target CAR3*). In addition, we also show that the importance of common knowledge base between the acquirer and the target firm to the acquirer prior to the bid (*Acquirer's Knowledge Base Overlap with Target*) measured both in levels and changes is negatively and significantly associated with *Target CAR3*. These results indicate some bargaining power on the acquirer side. More importantly, we show that *Acquirer's Knowledge*

Base Overlap with Target measured in levels is positively and significantly associated with both short-term acquirers' announcement period returns (*Bidder CAR3*) and long-term acquirers' stock market performance (*Bidder BHAR*). This evidence suggests that there are important benefits that stem from buying the target firms whose R&D activities are important to that of the acquirers'.

Finally, both more innovative acquirers and more innovative target firms are positively and significantly associated with improved post-merger performance: Four out of eight measures of the acquirers' and target firms' innovation quantity and quality are positively and significantly associated with the acquirer's post-merger operating and stock market performance (and the other four all have the right sign but not statistically significant).

Overall, the evidence in Tables 5-7 provides support for our final hypothesis (**H3**) that technology-driven acquisitions induce more future innovation and result in better operating and stock market performance—highlighting the importance of technological complementarity in *ex post* merger success. Our results are also consistent with the property rights theory of the firm that mergers, an effective way of redrawing the firm boundaries, lead to more investments in intangible assets and improvement in firm performance.

V. Additional Investigations

We conduct a battery of robustness checks on our main results. First, when forming pseudo deals to examine which firms are acquirers, instead of pairing the actual target firm with the closest match (in sales) of the deal's actual acquirer, we include up to five closest matches of the deal's actual acquirer. Using this alternative procedure, for the *Acquirer Sample* of 1,859 deals, we are able to obtain 4,331 pseudo deals, where the matching acquirers have information available to construct the full set of control variables used in Equation (1). In unreported analysis (the same as Table 3), we find that the effect of levels of innovation quantity and quality on the likelihood of a firm being an acquirer does not change, while the effect of a change in innovation quantity is weakened. In particular, the time trend in both *Patent Count* and *Patent Index* becomes only marginally significantly associated with the likelihood of a firm being an acquirer. The main results in Table 3 are further robust to: (i) expanding the set of pseudo deals by using up to ten closest matches of the deal's actual acquirer; (ii) using only the bigger/smaller matching acquirers (compared to the actual acquirer's sales) from the set of five (ten) closest matches; and (iii) using only matching acquirers with sales within 25 (50) percent range of the actual acquirer's sales.

Second, when forming pseudo deals to examine merger pairing decision, we use up to five closest matches of the deal's actual acquirer and up to five closest matches of the deal's actual target firm to form pseudo deals. For each actual acquirer-actual target pair, we create all possible actual acquirer-matching target firms pairs, matching acquirer-actual target firm pairs, and matching acquirer-matching target firm pairs. Using this alternative procedure, for the *Acquirer-Target Sample* of 1,478 deals, we are able to obtain 13,969 pseudo deals, where the matching acquirers and the matching target firms have information available to construct the full set of control variables used in Equation (2). In unreported analysis of this alternative sample, we find that the effect of innovation overlap on the likelihood of forming a merger pair is unchanged compared to the results presented in Table 4. The results reported in Table 4 are further robust to expanding the set of pseudo deals, using only the bigger/smaller matching firms, and using only matching firms with sales within a given sales range as discussed in the previous paragraph.

Third, we implement our main analysis using *Acquirers and Targets with Patents* of the *Acquirer-Target Sample* (shown in Table 1 last column) and 1,221 (when we use the closest matching firms) or 4,371 (when we use up to five closest matching firms) pseudo deals. In unreported analysis, we again find that the effect of innovation overlap on the likelihood of forming a merger pair remains the same as those presented in Table 4.

Finally, all our main results are unchanged when we use logit regression or linear probability model instead of probit regression when estimating Equations (1) and (2).

VI. Summary and Conclusion

Using a comprehensive sample of corporate acquisitions and detailed information on innovation activities of merger partners, we show that more innovative firms are more acquisitive, and that firms with complementary assets as captured by innovation overlaps are more likely to become merger partners. Finally, technology-driven acquisitions foster innovations: the extent of innovation in the acquirer and the target firm and innovation overlaps between them before the merger are positively and significantly associated with an increase in innovation activities post-merger as well as with improvement in operating and stock market performance. Overall, our findings are consistent with the property rights theory of the firm, and help uncover the underlying efficiency motives behind a particular transaction and provide a fruitful avenue for identifying whether and how value is created through acquisitions.

Appendix 1
Definition of Variables

Innovation Variables	
Patent Count	The number of awarded patents to the acquirer/target firm with application years from *ayr-3* to *ayr-1*. Year *ayr-1* is the calendar year that has the largest overlap with the fiscal year before the bid announcement, and year *ayr-3* is two years prior to *ayr-1*. When assessing the post-merger quantity of innovation, the measurement window for patent application years is from *cyr+1* to *cyr+3*. Year *cyr+1* is the calendar year that has the largest overlap with the first fiscal year after the deal completion, and year *cyr+3* is two years after *cyr+1*.
Patent Index	This measure is constructed in three steps. First, for each technology class *k* and patent application year *t*, we compute the median value of the number of awarded patents in technology class *k* with application year *t* across all firms that were awarded at least one patent in technology class *k* with application year *t*. Second, we scale the number of awarded patents to the acquirer/target firm in technology class *k* with application year *t* by the corresponding (technology class- and application year-specific) median value from the first step. Third, for the acquirer/target firm, we sum the scaled number of awarded patents from the second step across all technology classes and across application years from *ayr-3* to *ayr-1*. When assessing the post-merger quantity of innovation, the measurement window for patent application years in the third step is from *cyr+1* to *cyr+3*.
Citation Count	The number of citations received by patents awarded to the acquirer/target firm with award years from *ayr-3* to *ayr-1* within a three-year period starting from the patent award year. When assessing the post-merger quality of innovation, the measurement window for patent award years is from *cyr+1* to *cyr+3*.
Citation Index	This measure is constructed in three steps. First, for each technology class *k* and patent award year *t*, we compute the median value of the number of citations received within a three-year period starting from the patent award year across all patents awarded in technology class *k* with award year *t* that received at least one citation. Second, for each patent awarded to the acquirer/target firm in technology class *k* with award year *t*, we scale the number of citations received within a three-year period starting from the patent award year by the corresponding (technology class- and award year-specific) median value from the first step. Third, for the acquirer/target firm, we sum the scaled number of citations from the second step across all technology classes and across award years from *ayr-3* to *ayr-1*. When assessing the post-merger quality of innovation, the measurement window for patent award years in the third step is from *cyr+1* to *cyr+3*.
Correlation of Innovation Activities	The correlation coefficient is computed as $$\mathrm{Corr}_{\mathrm{acq,targ}} = \frac{\mathrm{S_{acq}S'_{targ}}}{\sqrt{\mathrm{S_{acq}S'_{acq}}}\sqrt{\mathrm{S_{targ}S'_{targ}}}},$$ where the vector $S_{acq} = (S_{acq,1}, \ldots, S_{acq,K})$ captures the scope of innovation activity for the acquirer, the vector $S_{targ} = (S_{targ,1}, \ldots, S_{targ,K})$ captures the scope of innovation activity for the target firm, and $k \in (1,K)$ is the technology class index. $S_{acq,k}$ ($S_{targ,k}$) is the ratio of the number of awarded patents to the acquirer (the target firm) in technology class *k* with application years from *ayr-3* to *ayr-1* to the total number of awarded patents to the acquirer (the target firm) in all technology classes applied over the same three-year period.
Acquirer's (Target's) Cross-Cites of Target (Acquirer)	The fraction of the acquirer's (the target firm's) awarded patents with award years from *ayr-3* to *ayr-1* that make citations of any of the target firm's (the acquirer's) awarded patents.
Acquirer's (Target's) Knowledge Base	This measure is constructed in two steps. First, we determine the set of patents that received at least one citation from any of the acquirer's patents with award years from *ayr-3* to *ayr-1* ("the acquirer's knowledge base"), the set of patents that received at least

Overlap with Target (*Acquirer*)	one citation from any of the target firm's patents awarded over the same three-year period ("the target's knowledge base"), and the intersection of these two sets as the set of patents cited by both the acquirer and the target firm ("the common knowledge base"). Second, we compute the ratio of the number of citations the acquirer's (the target firm's) patents made to the patents in "the common knowledge base" to the number of citations made to "the acquirer's knowledge base" ("the target firm's knowledge base").
Acquisition Performance	
Acquirer (*Target*) *CAR3*	The cumulative abnormal announcement period stock return over days (−1, +1), where day 0 is the date of the bid announcement (or the first trading day after the bid announcement). Daily abnormal stock returns are computed using the market model where the value-weighted CRSP index proxies the market portfolio. The estimation window is days (−252, −60) prior to the bid announcement date. The variables are winsorized at the 1% level.
Deal CAR3	The weighted average of the *Acquirer CAR3* and the *Target CAR3*, where the weights are the acquirer's (the target firm's) market capitalization from Compustat as of the fiscal year end before the bid announcement.
Acquirer Δ *ROA*	The residual from a cross-sectional regression of the acquirer's post-acquisition three-year average of industry median-adjusted ROA measured over the period from year *cyr+1* to year *cyr+3* on the analogously defined pre-acquisition variable measured over the period from year *ayr-3* to year *ayr-1*. ROA is the ratio of earnings before interest, taxes, depreciation, and amortization to total assets. (See Chen, Harford, and Li (2007) for details of this approach.) The variable is winsorized at the 1% level.
Acquirer BHAR	The 36-month buy-and-hold abnormal stock return computed using size-, book-to-market-, and prior performance-matched control firm as the benchmark. Each month, we sort the population of NYSE/NASDAQ/AMEX firms into NYSE size deciles (by market capitalization) and then further partition the bottom decile into quintiles, producing 14 total size groups. We simultaneously sort firms into NYSE book-to-market (B/M) deciles. After determining in which of the 140 (14 size × 10 B/M) groups the acquirer is at month -3 relative to the month of the bid announcement, we choose from that group the control firm that has the closest 12-month buy-and-hold stock return computed over the period from month -14 to month -3. The 36-month buy-and-hold abnormal stock return is computed over the period from month +1 to month +36 relative to the month of the bid completion as the difference between the buy-and-hold stock return of the acquirer and the contemporaneous buy-and-hold stock return of the control firm. (See Lyon, Barber, and Tsai (1999) for details of this approach.) The variable is winsorized at the 1% level.
Firm Characteristics	
Total Assets	The natural logarithm of total assets in millions of 2006 constant dollars. All firm characteristics are measured as of the fiscal year end before the bid announcement and are winsorized at the 1% level.
Sales Growth	The growth rate of sales.
ROA	The earnings before interest, taxes, depreciation, and amortization scaled by total assets.
Leverage	Total long-term debt plus debt in current liabilities scaled by total assets.
Cash	Cash and short-term investment scaled by total assets.
R&D	Research and development expenses scaled by total assets.
B/M	The book value of common equity scaled by the market value of common equity.
Stock Return	The difference between the buy-and-hold stock return from month −14 to month −3 relative to the month of the bid announcement and the analogously defined buy-and-hold stock return on the value-weighted CRSP index.
Deal Characteristics	
Relative Size	The acquisition's transaction value divided by the market capitalization of the acquirer measured as of the fiscal year end before the bid announcement.
All Cash (*Stock*)	Equal to one if only cash (equity) is used to pay for the acquisition, and zero otherwise.
Number of Acquirers	The number of entities (including the acquirer) bidding for the target firm.

Hostile	Equal to one if the target firm's management or board of directors does not recommend the transaction, and zero otherwise.
Challenged	Equal to one if a third party launches an offer for the target firm while the original bid is pending, and zero otherwise.
Tender Offer	Equal to one if a tender offer is launched for the target firm, and zero otherwise.
Diversifying	Equal to one if the acquirer and the target firm operate in different 2-digit SIC industries, and zero otherwise.
Same State	Equal to one if the acquirer and the target firm are incorporated in the same state, and zero otherwise.

Appendix 2
Corporate Acquisitions by Industry

The table reports the number of corporate acquisitions by 2-digit SIC industry. The samples are the same as in Table 1.

	Acquirer Sample		Acquirer-Target Sample		
2-digit SIC	All Deals	Acquirers with Patents	All Deals	Acquirers or Targets with Patents	Acquirers and Targets with Patents
01	2	1	2	1	0
10	5	1	7	4	1
12	3	2	2	2	1
13	70	7	55	8	1
14	1	1	0	0	0
15	7	0	4	0	0
16	3	1	2	1	0
17	5	0	4	0	0
20	35	24	35	25	8
21	3	0	3	2	0
22	10	8	7	6	2
23	23	9	14	9	3
24	7	4	5	3	1
25	17	14	12	11	4
26	10	6	11	9	4
27	36	14	26	11	0
28	128	102	109	96	66
29	5	2	6	4	1
30	22	15	16	13	8
31	2	1	1	0	0
32	10	5	8	4	2
33	30	17	22	15	10
34	33	32	21	21	12
35	190	155	147	132	82
36	147	125	118	111	72
37	48	39	36	32	19
38	156	127	116	107	66
39	34	26	24	22	9
40	10	6	9	5	0
42	15	2	13	3	0
44	2	0	1	1	0
45	17	0	18	3	0
47	4	2	3	1	1
48	63	27	60	28	9
49	61	12	68	27	3
50	37	9	29	10	3
51	29	11	35	24	7
52	3	0	3	0	0
53	28	3	20	5	0

54	15	1	15	1	0
55	4	0	3	0	0
56	14	0	6	0	0
57	4	0	4	1	0
58	20	3	19	2	0
59	37	3	29	6	0
70	9	2	5	2	0
72	10	3	8	4	1
73	297	184	224	159	53
75	5	3	2	1	0
78	13	0	9	1	0
79	23	5	16	7	2
80	57	4	41	4	0
82	7	0	4	1	0
83	2	0	1	0	0
87	28	13	19	9	2
99	3	0	1	1	0
Total	1,859	1,031	1,478	955	453

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Figure 1
Time Line Used in Construction of Key Patent and Citation Variables

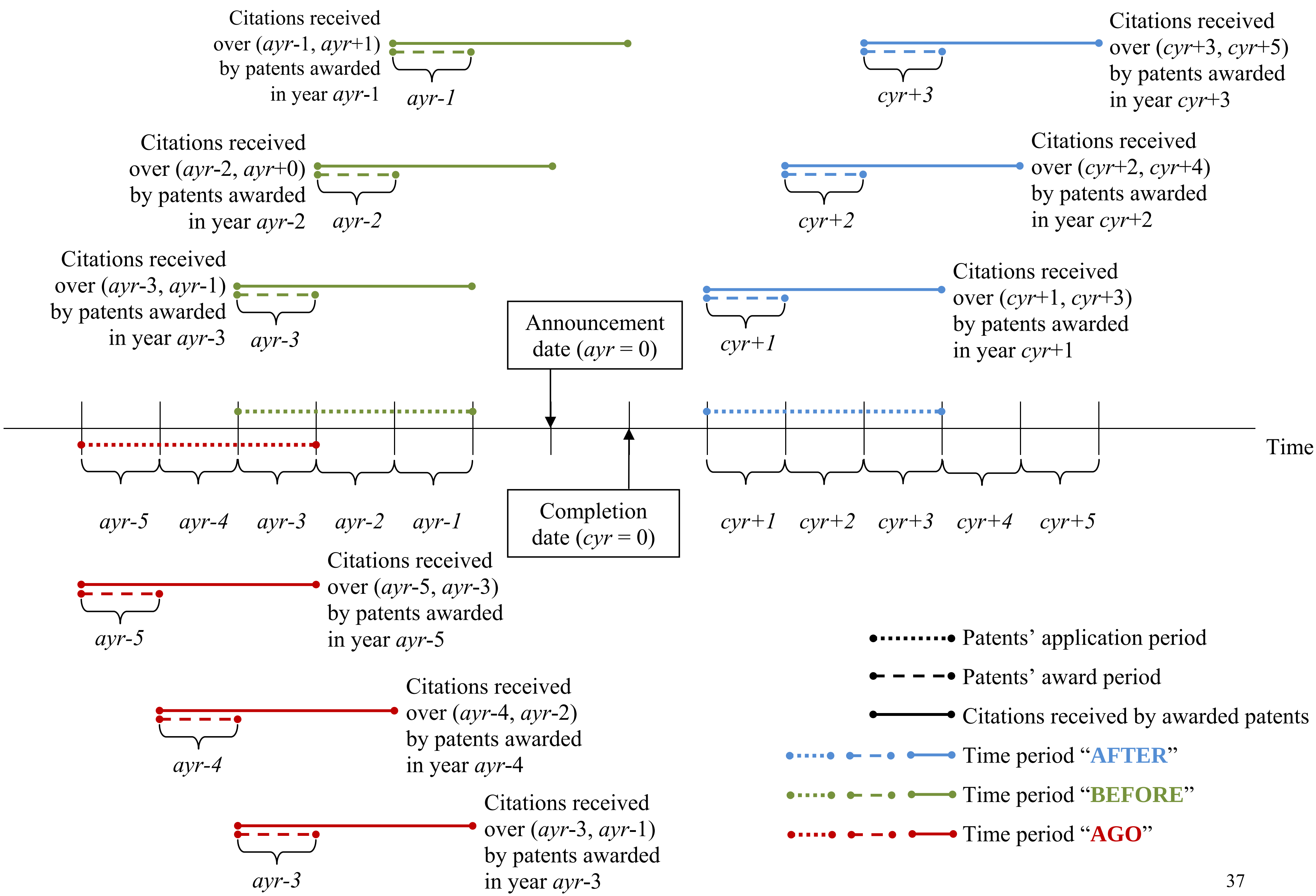

Table 1
Corporate Acquisitions over Time, 1984–2006

The table reports the number of corporate acquisitions by the year of the bid announcement. The sample consists of completed acquisitions announced during the period January 1, 1984–December 31, 2006, where the form of deal was coded as a merger, an acquisition of majority interest, or an acquisition of assets. The acquirers and target firms are listed in the SDC's Mergers and Acquisitions database. We require that the acquirer own less than 50% of the target firm prior to the bid, be seeking to own greater than 50% of the target firm, and own greater than 90% of the target firm after the deal completion. We further require that both the acquirer and the target firm be bigger than $1 million (in 1984 constant dollars) and be non-financials. A deal enters the *Acquirer Sample* if its acquirer is covered by both the Compustat and CRSP databases and has at least one 2-digit SIC industry- and size-matching (in terms of sales) acquirer as of the fiscal year end before the bid announcement (*All Deals*). A deal enters the *Acquirer-Target Sample* if both the acquirer and the target firm are covered by both the Compustat and CRSP databases and have their respective industry- and size-matching firms (*All Deals*). Deals with patents are subsamples defined as follows. For the *Acquirers with Patents* subsample, we require that the acquirer be awarded at least one patent in the period from year *ayr-5* to year *ayr-1*, where *ayr-1* is the calendar year that has the largest overlap with the fiscal year before the bid announcement, and *ayr-5* is four years prior to *ayr-1*. For the *Acquirers or Targets with Patents* (*Acquirers and Targets with Patents*) subsample, we require that either the acquirer or the target firm or both firms (both the acquirer and the target firm) be awarded at least one patent over the same five-year period.

Year	Acquirer Sample		Acquirer-Target Sample		
	All Deals	Acquirers with Patents	All Deals	Acquirers or Targets with Patents	Acquirers and Targets with Patents
1984	60	25	43	24	13
1985	52	24	45	29	10
1986	63	31	47	28	15
1987	47	28	44	29	11
1988	72	33	52	27	11
1989	40	17	32	18	7
1990	50	21	35	18	7
1991	43	22	33	21	8
1992	32	19	21	15	7
1993	41	19	30	15	9
1994	65	33	59	37	15
1995	109	56	89	51	26
1996	120	55	99	49	17
1997	143	62	113	58	28
1998	161	89	142	88	43
1999	139	90	122	90	46
2000	112	70	89	67	32
2001	109	69	91	65	36
2002	90	62	58	46	21
2003	78	53	55	42	20
2004	74	46	59	43	25
2005	86	58	63	50	25
2006	73	49	57	45	21
Total	1,859	1,031	1,478	955	453

Table 2
Summary Statistics

The table reports summary statistics of the acquirers and the target firms in the *Acquirers or Targets with Patents* subsample as defined in Table 1. Definitions of the variables are provided in Appendix 1.

Panel A: Acquirers or Targets with Patents

	Mean	S.D.	10th Percentile	Median	90th Percentile
			Acquirer		
Patent Count	65.2	272.6	0.0	5.0	116.0
Patent Index	31.5	124.6	0.0	2.5	58.3
Citation Count	124.9	649.4	0.0	4.0	143.0
Citation Index	107.0	572.9	0.0	3.5	137.0
Total Assets	3.72	8.46	0.08	1.01	8.27
Sales Growth	0.18	0.30	-0.10	0.14	0.53
ROA	0.12	0.13	-0.02	0.15	0.25
Leverage	0.18	0.16	0.00	0.16	0.42
Cash	0.20	0.20	0.01	0.12	0.53
R&D	0.06	0.08	0.00	0.03	0.17
B/M	0.46	0.33	0.14	0.38	0.89
Stock Return	0.12	0.60	-0.46	-0.01	0.78
			Target		
Patent Count	8.7	45.4	0.0	1.0	15.0
Patent Index	4.2	19.3	0.0	0.5	7.8
Citation Count	20.3	143.3	0.0	0.0	26.0
Citation Index	16.7	109.8	0.0	0.0	21.5
Total Assets	0.73	1.88	0.03	0.17	1.49
Sales Growth	0.13	0.29	-0.16	0.10	0.48
ROA	0.07	0.18	-0.16	0.12	0.23
Leverage	0.18	0.18	0.00	0.13	0.43
Cash	0.22	0.23	0.01	0.13	0.59
R&D	0.08	0.10	0.00	0.05	0.23
B/M	0.63	0.46	0.18	0.53	1.19
Stock Return	-0.05	0.64	-0.65	-0.18	0.62
			Innovation Overlaps		
Correlation of Innovation Activities	0.10	0.26	0.00	0.00	0.56
Acquirer's Cross-Cites of Target	0.01	0.04	0.00	0.00	0.00
Target's Cross-Cites of Acquirer	0.04	0.16	0.00	0.00	0.07
Acquirer's Knowledge Base Overlap	0.01	0.04	0.00	0.00	0.01
Target's Knowledge Base Overlap	0.03	0.11	0.00	0.00	0.06

Panel B: Pseudo Deals to Acquirers or Targets with Patents

The sample consists of 2,567 acquirer-target pseudo deals constructed to match the actual acquirer-target pairs presented in Panel A. Specifically, the sample contains pseudo deals formed by pairing the actual acquirer with the closest match of the deal's actual target firm, the actual target firm with the closest match of the deal's actual acquirer, and the closest match of the deal's actual acquirer with the closest match of the deal's actual target firm.

	Mean	S.D.	10th Percentile	Median	90th Percentile
			Acquirer		
Patent Count	44.3	215.4	0.0	2.0	64.0
Patent Index	21.5	99.5	0.0	1.0	37.0
Citation Count	78.9	489.8	0.0	1.0	85.0
Citation Index	66.4	424.3	0.0	1.0	78.0
Total Assets	2.93	7.53	0.07	0.69	6.32
Sales Growth	0.16	0.27	-0.06	0.12	0.47
ROA	0.12	0.13	-0.01	0.14	0.24
Leverage	0.20	0.17	0.00	0.18	0.44
Cash	0.17	0.20	0.01	0.09	0.49
R&D	0.05	0.07	0.00	0.02	0.15
B/M	0.53	0.37	0.16	0.44	1.03
Stock Return	0.05	0.58	-0.52	-0.05	0.64
			Target		
Patent Count	8.2	40.7	0.0	0.0	14.0
Patent Index	4.0	18.3	0.0	0.0	7.5
Citation Count	17.3	127.8	0.0	0.0	21.0
Citation Index	14.4	97.8	0.0	0.0	19.0
Total Assets	0.65	1.75	0.02	0.15	1.31
Sales Growth	0.13	0.30	-0.17	0.10	0.47
ROA	0.07	0.17	-0.15	0.12	0.24
Leverage	0.18	0.18	0.00	0.14	0.44
Cash	0.21	0.23	0.01	0.12	0.58
R&D	0.07	0.10	0.00	0.03	0.20
B/M	0.64	0.47	0.17	0.53	1.22
Stock Return	-0.02	0.66	-0.65	-0.16	0.67
			Innovation Overlaps		
Correlation of Innovation Activities	0.03	0.13	0.00	0.00	0.00
Acquirer's Cross-Cites of Target	0.00	0.02	0.00	0.00	0.00
Target's Cross-Cites of Acquirer	0.00	0.02	0.00	0.00	0.00
Acquirer's Knowledge Base Overlap	0.00	0.01	0.00	0.00	0.00
Target's Knowledge Base Overlap	0.00	0.03	0.00	0.00	0.00

Panel C: Correlation of Innovation Measures
The sample is the same as in Panel A.

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Acquirer Patent Count	1.00												
2	Acquirer Patent Index	0.99	1.00											
3	Acquirer Citation Count	0.92	0.92	1.00										
4	Acquirer Citation Index	0.93	0.93	1.00	1.00									
5	Target Patent Count	0.20	0.19	0.18	0.18	1.00								
6	Target Patent Index	0.18	0.18	0.16	0.16	0.99	1.00							
7	Target Citation Count	0.18	0.17	0.17	0.17	0.83	0.82	1.00						
8	Target Citation Index	0.17	0.17	0.17	0.17	0.84	0.83	1.00	1.00					
9	Correlation of Innovation Activities	0.34	0.33	0.30	0.31	0.44	0.42	0.39	0.39	1.00				
10	Acquirer’s Cross-Cites of Target	0.04	0.03	0.05	0.05	0.12	0.12	0.15	0.15	0.14	1.00			
11	Target’s Cross-Cites of Acquirer	0.18	0.18	0.19	0.19	0.14	0.12	0.19	0.19	0.20	0.08	1.00		
12	Acquirer’s Knowledge Base Overlap	0.08	0.07	0.09	0.09	0.16	0.16	0.21	0.21	0.20	0.39	0.27	1.00	
13	Target’s Knowledge Base Overlap	0.24	0.24	0.25	0.25	0.14	0.12	0.19	0.18	0.27	0.13	0.50	0.49	1.00

Table 3
Who Are the Acquirers?

The table reports average marginal effects from probit models. The dependent variable, *Acquirer*, is equal to one for the actual acquirer, and zero for the matching acquirer. Columns (1)-(4) report the results using *All Deals* of the *Acquirer Sample,* and corresponding 1,859 matching acquirers. For each acquirer, we choose the single matching acquirer to be the firm that is in the same 2-digit-SIC industry and is the closest in sales conditional on having the full set of control variables. Columns (5)-(6) report the results using *Acquirers with Patents* of the *Acquirer Sample*, and corresponding 1,031 matching acquirers. Measures of innovation and firm size are in natural logarithm. Definitions of the variables are provided in Appendix 1. All specifications include the acquirer (matching acquirer) 2-digit-SIC industry and the year of bid announcement fixed effects. Robust standard errors (clustered at the acquirer/matching acquirer level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Quantity of Innovation
The panel reports estimates from specifications that use the levels of and the changes in the acquirer's quantity of innovation measured over the three-year period prior to the bid announcement as key explanatory variables.

	All Deals				Acquirers with Patents			
	(1) Patent Count	(2) Patent Index	(3) Δ Patent Count	(4) Δ Patent Index	(5) Patent Count	(6) Patent Index	(7) Δ Patent Count	(8) Δ Patent Index
Innovation	0.029**	0.032**	0.054**	0.060**	0.090***	0.091***	0.072***	0.077***
	(0.012)	(0.014)	(0.021)	(0.027)	(0.012)	(0.014)	(0.024)	(0.030)
Total Assets	0.033***	0.034***	0.048***	0.048***	-0.005	0.002	0.062***	0.063***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.016)	(0.016)	(0.014)	(0.014)
Sales Growth	0.245***	0.246***	0.232***	0.233***	0.228***	0.234***	0.187***	0.191***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.053)	(0.053)	(0.053)	(0.053)
ROA	-0.046	-0.044	-0.042	-0.041	0.006	0.015	0.019	0.019
	(0.112)	(0.112)	(0.111)	(0.110)	(0.144)	(0.146)	(0.149)	(0.149)
Leverage	-0.024	-0.024	-0.042	-0.042	-0.080	-0.083	-0.141	-0.141
	(0.079)	(0.079)	(0.079)	(0.080)	(0.107)	(0.109)	(0.117)	(0.118)
Cash	0.177	0.182*	0.196*	0.198*	0.156	0.175	0.210	0.213
	(0.109)	(0.109)	(0.105)	(0.105)	(0.142)	(0.143)	(0.139)	(0.138)
R&D	1.013***	1.037***	1.137***	1.139***	0.690**	0.821**	1.307***	1.310***
	(0.290)	(0.289)	(0.270)	(0.269)	(0.345)	(0.347)	(0.327)	(0.326)
B/M	-0.088***	-0.087***	-0.089***	-0.089***	-0.125**	-0.124**	-0.148***	-0.148***
	(0.032)	(0.032)	(0.032)	(0.033)	(0.049)	(0.049)	(0.051)	(0.052)
Stock Return	0.044***	0.044***	0.044***	0.044***	0.004	0.004	0.006	0.005
	(0.016)	(0.016)	(0.016)	(0.016)	(0.019)	(0.019)	(0.019)	(0.019)
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	3,718	3,718	3,718	3,718	2,062	2,062	2,062	2,062
No. of Acquirers	1,859	1,859	1,859	1,859	1,031	1,031	1,031	1,031
No. of Matching Acq.	1,859	1,859	1,859	1,859	1,031	1,031	1,031	1,031

Panel B: Quality of Innovation

The panel reports estimates from specifications that use the levels of and the changes in the acquirer's quality of innovation measured over the three-year period prior to the bid announcement as key explanatory variables.

	All Deals				Acquirers with Patents			
	(1) Citation Count	(2) Citation Index	(3) Δ Citation Count	(4) Δ Citation Index	(5) Citation Count	(6) Citation Index	(7) Δ Citation Count	(8) Δ Citation Index
Innovation	0.023**	0.022*	-0.005	-0.009	0.059***	0.059***	0.015	0.011
	(0.011)	(0.012)	(0.016)	(0.016)	(0.011)	(0.011)	(0.017)	(0.018)
Total Assets	0.036***	0.037***	0.049***	0.049***	0.016	0.018	0.063***	0.063***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.015)	(0.015)	(0.014)	(0.014)
Sales Growth	0.249***	0.249***	0.241***	0.242***	0.250***	0.248***	0.208***	0.208***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.054)	(0.054)	(0.054)	(0.054)
ROA	-0.041	-0.040	-0.024	-0.024	0.018	0.018	0.039	0.040
	(0.112)	(0.112)	(0.111)	(0.111)	(0.148)	(0.148)	(0.151)	(0.151)
Leverage	-0.026	-0.027	-0.042	-0.042	-0.078	-0.082	-0.139	-0.139
	(0.079)	(0.079)	(0.080)	(0.080)	(0.110)	(0.110)	(0.118)	(0.118)
Cash	0.173	0.175	0.197*	0.197*	0.157	0.161	0.215	0.215
	(0.109)	(0.109)	(0.108)	(0.109)	(0.147)	(0.147)	(0.143)	(0.143)
R&D	1.060***	1.072***	1.219***	1.226***	0.956***	0.983***	1.382***	1.392***
	(0.294)	(0.293)	(0.270)	(0.270)	(0.361)	(0.360)	(0.329)	(0.329)
B/M	-0.087***	-0.087***	-0.089***	-0.089***	-0.126**	-0.127**	-0.147***	-0.147***
	(0.032)	(0.032)	(0.033)	(0.032)	(0.049)	(0.049)	(0.052)	(0.052)
Stock Return	0.044***	0.044***	0.045***	0.045***	0.003	0.003	0.006	0.006
	(0.016)	(0.016)	(0.017)	(0.017)	(0.019)	(0.019)	(0.020)	(0.020)
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	3,718	3,718	3,718	3,718	2,062	2,062	2,062	2,062
No. of Acquirers	1,859	1,859	1,859	1,859	1,031	1,031	1,031	1,031
No. of Matching Acq.	1,859	1,859	1,859	1,859	1,031	1,031	1,031	1,031

Table 4
Acquirer-Target Pairing

The table reports average marginal effects from probit models. The dependent variable, *Acquirer-Target*, is equal to one for the actual acquirer-actual target firm pair, and zero for one of the pseudo deals. Columns (1)-(5) report the results using *All Deals* of the *Acquirer-Target Sample*, and corresponding 3,921 matching acquirer-target pairs. For each acquirer (target firm), we choose the single matching acquirer (the single matching target firm) to be the firm that is in the same 2-digit-SIC industry and is the closest in sales conditional on having the full set of control variables. We then form pseudo deals by pairing the actual acquirer with the closest match of the deal's actual target firm, the actual target firm with the closest match of the deal's actual acquirer, and the closest match of the deal's actual acquirer with the closest match of the deal's actual target firm. Columns (6)-(10) report the results using *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*, and corresponding 2,567 matching acquirer-target pairs. Measures of innovation and firm size are in natural logarithm. Definitions of the variables are provided in Appendix 1. All specifications include the acquirer (matching acquirer) 2-digit-SIC industry and the year of bid announcement fixed effects. Robust standard errors (clustered at the acquirer/matching acquirer level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Innovation Measures in Levels

	All Deals		Acquirers or Targets with Patents	
	(1)	(2)	(3)	(4)
Correlation of Innovation Activities	0.418***	0.361***	0.336***	0.303***
	(0.068)	(0.063)	(0.065)	(0.062)
Acquirer's Cross-Cites of Target	0.350	0.335	0.374	0.356
	(0.374)	(0.379)	(0.356)	(0.359)
Target's Cross-Cites of Acquirer	1.354***	1.388***	1.286***	1.303***
	(0.246)	(0.241)	(0.229)	(0.225)
Acquirer's Knowledge Base Overlap	0.970	0.928	0.845	0.766
	(1.023)	(1.039)	(0.965)	(0.969)
Target's Knowledge Base Overlap	0.858**	0.931**	0.774**	0.826**
	(0.351)	(0.382)	(0.320)	(0.336)
Acquirer Patent Index	-0.007		0.009	
	(0.007)		(0.007)	
Target Patent Index	-0.052***		-0.035***	
	(0.010)		(0.010)	
Acquirer Citation Index		-0.007		0.004
		(0.006)		(0.006)
Target Citation Index		-0.026***		-0.014**
		(0.006)		(0.007)
Acquirer Total Assets	0.022***	0.023***	0.013	0.017**
	(0.007)	(0.006)	(0.008)	(0.008)
Acquirer Sales Growth	0.103***	0.102***	0.088***	0.088***
	(0.019)	(0.019)	(0.026)	(0.026)
Acquirer ROA	-0.092	-0.087	-0.101	-0.094
	(0.066)	(0.066)	(0.078)	(0.078)
Acquirer Leverage	-0.010	-0.012	-0.033	-0.040
	(0.047)	(0.046)	(0.060)	(0.060)
Acquirer Cash	0.100	0.106*	0.103	0.108
	(0.063)	(0.061)	(0.076)	(0.075)
Acquirer R&D	0.497***	0.499***	0.339*	0.363**
	(0.156)	(0.156)	(0.176)	(0.177)
Acquirer B/M	-0.077***	-0.077***	-0.106***	-0.106***
	(0.021)	(0.021)	(0.028)	(0.028)
Acquirer Stock Return	0.041***	0.039***	0.035***	0.034***
	(0.010)	(0.010)	(0.012)	(0.012)
Target Total Assets	0.007	0.004	0.007	0.003
	(0.005)	(0.005)	(0.006)	(0.006)
Target Sales Growth	-0.005	-0.008	-0.017	-0.019
	(0.021)	(0.022)	(0.027)	(0.027)
Target ROA	0.027	0.023	0.115**	0.110*
	(0.050)	(0.050)	(0.058)	(0.059)
Target Leverage	0.029	0.034	0.032	0.037
	(0.039)	(0.039)	(0.049)	(0.050)

Target Cash	-0.049	-0.038	-0.005	0.003
	(0.040)	(0.040)	(0.044)	(0.045)
Target R&D	0.405***	0.392***	0.501***	0.479***
	(0.102)	(0.102)	(0.111)	(0.110)
Target B/M	0.020	0.021	0.021	0.022
	(0.014)	(0.014)	(0.017)	(0.017)
Target Stock Return	-0.028***	-0.028***	-0.035***	-0.036***
	(0.010)	(0.011)	(0.013)	(0.013)
Diversifying	0.010	0.012	0.015	0.016
	(0.012)	(0.012)	(0.015)	(0.014)
Same State	0.012	0.012	0.010	0.011
	(0.015)	(0.015)	(0.018)	(0.018)
Ind. and Year FEs	Yes	Yes	Yes	Yes
No. of Observations	5,399	5,399	3,522	3,522
No. of Deals	1,478	1,478	955	955
No. of Matching Deals	3,921	3,921	2,567	2,567

Panel B: Innovation Measures in Changes

	All Deals		Acquirers or Targets with Patents	
	(1)	(2)	(3)	(4)
Δ Correlation of Innovation Activities	-0.000	-0.020	-0.002	-0.021
	(0.075)	(0.073)	(0.074)	(0.072)
Δ Acquirer's Cross-Cites of Target	0.709	0.719	0.759	0.747
	(0.456)	(0.467)	(0.465)	(0.475)
Δ Target's Cross-Cites of Acquirer	0.834***	0.811***	0.822***	0.802***
	(0.189)	(0.191)	(0.185)	(0.189)
Δ Acquirer's Knowledge Base Overlap	-0.532	-0.577	-0.469	-0.528
	(0.357)	(0.359)	(0.355)	(0.358)
Δ Target's Knowledge Base Overlap	0.669***	0.672***	0.645***	0.640***
	(0.255)	(0.257)	(0.246)	(0.248)
Δ Acquirer Patent Index	0.025*		0.034**	
	(0.015)		(0.016)	
Δ Target Patent Index	-0.038**		-0.041**	
	(0.016)		(0.017)	
Δ Acquirer Citation Index		-0.003		0.006
		(0.009)		(0.010)
Δ Target Citation Index		0.013		0.016
		(0.010)		(0.010)
Acquirer, Target Controls	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes
Ind. and Year FEs	Yes	Yes	Yes	Yes
No. of Observations	5,399	5,399	3,522	3,522
No. of Deals	1,478	1,478	955	955
No. of Matching Deals	3,921	3,921	2,567	2,567

Table 5
Post-Acquisition Innovation

The table reports estimates from OLS regressions using a panel dataset that has two time series observations, the post-acquisition and the pre-acquisition value, for each actual and matching acquirer, respectively. *Acquisition* is an indicator variable that is equal to one for actual acquirers, and zero for matching acquirers. *After* is an indicator variable that is equal to one for the post-acquisition time period, and zero for the pre-acquisition time period. When an acquirer makes multiple acquisitions, we only keep acquisitions that do not overlap with any other bid by the same acquirer in a three-year window before and after each sample acquisition is announced. For each acquirer (target firm), we choose the single matching acquirer (target firm) to be the firm that is in the same 2-digit-SIC industry and is the closest in sales conditional on having the full set of control variables. Measures of innovation and firm size are in natural logarithm. Definitions of the variables are provided in Appendix 1. All specifications include the acquirer (matching acquirer) 2-digit-SIC industry and the year of bid announcement fixed effects. Robust standard errors (clustered at the acquirer/matching acquirer level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: The Difference-in-Difference Approach

Columns (1)-(4) report regression results using *All Deals* of the *Acquirer Sample*, and corresponding matching acquirers conditional on having the full set of control variables both before and after the acquisition. Columns (5)-(8) report the results using *Acquirers with Patents* of the *Acquirer Sample*, and corresponding matching acquirers conditional on having the full set of control variables both before and after the acquisition.

	All Deals				Acquirers with Patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Patent Count	Patent Index	Citation Count	Citation Index	Patent Count	Patent Index	Citation Count	Citation Index
Acquisition	0.138*	0.118*	0.094	0.083	0.775***	0.615***	0.560***	0.527***
	(0.071)	(0.063)	(0.078)	(0.076)	(0.115)	(0.103)	(0.134)	(0.131)
After	0.003	-0.001	0.111***	0.115***	-0.006	-0.008	0.143***	0.153***
	(0.026)	(0.021)	(0.027)	(0.027)	(0.047)	(0.038)	(0.047)	(0.046)
Acquisition × After	0.074**	0.063**	0.248***	0.242***	-0.034	-0.005	0.470***	0.463***
	(0.037)	(0.030)	(0.041)	(0.040)	(0.067)	(0.055)	(0.074)	(0.072)
Total Assets	0.433***	0.378***	0.453***	0.444***	0.632***	0.566***	0.667***	0.657***
	(0.032)	(0.028)	(0.036)	(0.035)	(0.048)	(0.044)	(0.057)	(0.056)
Sales Growth	-0.034	-0.055	-0.051	-0.059	-0.144	-0.184	-0.214	-0.225
	(0.079)	(0.068)	(0.095)	(0.091)	(0.128)	(0.113)	(0.162)	(0.156)
ROA	1.008***	0.848***	0.867***	0.827***	0.820**	0.702**	0.660	0.612
	(0.259)	(0.222)	(0.294)	(0.285)	(0.363)	(0.323)	(0.420)	(0.412)
Leverage	-0.562***	-0.516***	-0.524***	-0.513***	-0.445	-0.420	-0.434	-0.427
	(0.169)	(0.145)	(0.190)	(0.186)	(0.304)	(0.267)	(0.358)	(0.351)
Cash	0.294	0.147	0.589***	0.536**	-0.022	-0.148	0.422	0.369
	(0.188)	(0.160)	(0.225)	(0.219)	(0.262)	(0.227)	(0.316)	(0.308)

R&D	5.483***	4.351***	5.825***	5.550***	6.098***	5.010***	6.294***	6.004***
	(0.622)	(0.529)	(0.724)	(0.697)	(0.674)	(0.593)	(0.854)	(0.828)
B/M	0.018	0.008	-0.013	-0.015	-0.068	-0.101	-0.168	-0.176
	(0.066)	(0.057)	(0.068)	(0.067)	(0.114)	(0.103)	(0.123)	(0.121)
Stock Return	0.071*	0.062*	0.076*	0.073*	0.105**	0.093**	0.109*	0.102*
	(0.038)	(0.032)	(0.041)	(0.040)	(0.052)	(0.045)	(0.058)	(0.057)
Relative Size	0.001	0.002	0.003	0.002	0.001	0.003	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
All Cash	0.045	0.035	0.015	0.011	0.127	0.111	0.077	0.069
	(0.066)	(0.059)	(0.069)	(0.068)	(0.095)	(0.086)	(0.103)	(0.102)
All Stock	-0.001	-0.018	-0.010	-0.015	0.170*	0.115	0.164	0.153
	(0.058)	(0.051)	(0.065)	(0.063)	(0.093)	(0.082)	(0.107)	(0.104)
Number of Acquirers	0.162	0.144	0.213	0.218	0.052	0.061	0.142	0.142
	(0.246)	(0.211)	(0.249)	(0.247)	(0.286)	(0.249)	(0.286)	(0.285)
Hostile	-0.108	-0.105	-0.038	-0.033	0.330	0.324	0.559	0.565
	(0.163)	(0.144)	(0.174)	(0.173)	(0.300)	(0.280)	(0.347)	(0.347)
Challenged	-0.151	-0.130	-0.295	-0.300	-0.229	-0.196	-0.425	-0.412
	(0.305)	(0.263)	(0.316)	(0.312)	(0.393)	(0.346)	(0.420)	(0.415)
Tender Offer	0.013	0.006	0.027	0.023	-0.062	-0.065	-0.046	-0.049
	(0.070)	(0.062)	(0.072)	(0.071)	(0.096)	(0.087)	(0.105)	(0.103)
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	4,824	4,824	4,824	4,824	2,412	2,412	2,412	2,412
No. of Acquirers	1,206	1,206	1,206	1,206	603	603	603	603
No. of Matching Acq.	1,206	1,206	1,206	1,206	603	603	603	603
Adjusted R^2	0.48	0.46	0.44	0.44	0.52	0.51	0.47	0.47

Panel B: The Difference-in-Difference Approach Controlling for Target's Characteristics

Columns (1)-(4) report regression results using *All Deals* of the *Acquirer-Target Sample*, and corresponding matching acquirer-target pairs conditional on having the full set of control variables both before and after the acquisition. Columns (5)-(8) report the results using *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*, and corresponding matching acquirer-target pairs conditional on having the full set of control variables both before and after the acquisition. We form pseudo deals by pairing the actual acquirer with the closest match of the deal's actual target firm, the actual target firm with the closest match of the deal's actual acquirer, and the closest match of the deal's actual acquirer with the closest match of the deal's actual target firm.

	All Deals				Acquirers or Targets with Patents			
	(1) Patent Count	(2) Patent Index	(3) Citation Count	(4) Citation Index	(5) Patent Count	(6) Patent Index	(7) Citation Count	(8) Citation Index
Acquisition	0.075	0.065	0.035	0.030	0.294***	0.237***	0.185**	0.173**
	(0.048)	(0.043)	(0.053)	(0.052)	(0.069)	(0.061)	(0.079)	(0.077)
After	0.017	0.010	0.179***	0.184***	-0.015	-0.014	0.265***	0.274***
	(0.022)	(0.018)	(0.025)	(0.024)	(0.034)	(0.028)	(0.038)	(0.037)
Acquisition × After	0.047*	0.040*	0.176***	0.172***	0.032	0.034	0.283***	0.278***
	(0.027)	(0.022)	(0.031)	(0.030)	(0.042)	(0.035)	(0.048)	(0.047)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	7,232	7,232	7,232	7,232	4,434	4,434	4,434	4,434
No. of Deals	991	991	991	991	600	600	600	600
No. of Matching Deals	2,625	2,625	2,625	2,625	1,617	1,617	1,617	1,617
Adjusted R^2	0.50	0.48	0.47	0.47	0.48	0.48	0.45	0.45

Table 6
Post-Acquisition Innovation: Propensity-Score Matching

The table reports the average treatment effect on the treated (ATT) of the acquisition event on the acquirer's post-acquisition innovation. When an acquirer makes multiple acquisitions, we only keep acquisitions that do not overlap with any other bid by the same acquirer in a three-year window before and after each sample acquisition is announced. Measures of innovation and firm size are in natural logarithm. Definitions of the variables are provided in Appendix 1. Standard errors are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Matching on Acquirer's Pre-Acquisition Characteristics
Columns (1)-(4) report the results using *All Deals* of the *Acquirer Sample*, and corresponding matching acquirers conditional on having the full set of control variables both before and after the acquisition. Columns (5)-(8) report the results using *Acquirers with Patents* of the *Acquirer Sample,* and corresponding matching acquirers conditional on having the full set of control variables both before and after the acquisition. Matching acquirers are determined using the propensity-score matching metric and the three-nearest neighbours matching method. We match on the acquirer's pre-acquisition firm characteristics listed in Panel A of Table 5 (not reported).

	All Deals				Acquirers with Patents			
	(1) Patent Count	(2) Patent Index	(3) Citation Count	(4) Citation Index	(5) Patent Count	(6) Patent Index	(7) Citation Count	(8) Citation Index
Acquirers	1.327	1.079	1.496	1.454	2.501	2.048	2.899	2.820
Matching Acquirers	1.012	0.798	1.092	1.072	1.720	1.375	1.870	1.835
ATT	0.315***	0.281***	0.404***	0.382***	0.780***	0.673***	1.029***	0.984***
	(0.103)	(0.088)	(0.112)	(0.110)	(0.193)	(0.167)	(0.208)	(0.206)
No. of Acquirers	1,206	1,206	1,206	1,206	603	603	603	603

Panel B: Matching on Acquirer's and Target Firm's Pre-Acquisition Characteristics

Columns (1)-(4) report the results using *All Deals* of the *Acquirer-Target Sample*, and corresponding matching acquirer-target pairs conditional on having the full set of control variables both before and after the acquisition. Columns (5)-(8) report the results using *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*, and corresponding matching acquirer-target pairs conditional on having the full set of control variables both before and after the acquisition. Matching acquirer-target pairs are determined using the propensity-score matching metric and the three-nearest neighbours matching method. We simultaneously match on the acquirer's as well as the target firm's pre-acquisition firm characteristics listed in Panel A of Table 5 (not reported).

	All Deals				Acquirers or Targets with Patents			
	(1) Patent Count	(2) Patent Index	(3) Citation Count	(4) Citation Index	(5) Patent Count	(6) Patent Index	(7) Citation Count	(8) Citation Index
Acquirers	1.409	1.151	1.582	1.539	2.255	1.849	2.579	2.510
Matching Acquirers	1.252	1.017	1.326	1.292	1.824	1.474	2.074	2.018
ATT	0.157**	0.134**	0.256***	0.247***	0.431***	0.375***	0.504***	0.492***
	(0.086)	(0.074)	(0.094)	(0.092)	(0.129)	(0.113)	(0.139)	(0.136)
No. of Deals	991	991	991	991	600	600	600	600

Table 7
Acquisition Performance

The table reports estimates from cross-sectional OLS regressions of *Acquirer/Target/Deal CAR3*, *Acquirer* Δ*ROA*, and *Acquirer BHAR* on innovation measures, the acquirer's and the target firm's pre-acquisition financial controls, and the deal characteristics listed in Panel A of Table 5 (not reported). The sample is *All Deals* of the *Acquirer-Target Sample* conditional on having the full set of dependent variables for the acquirer. When an acquirer makes multiple acquisitions, we only keep acquisitions that do not overlap with any other bid by the same acquirer in a three-year window before and after each sample acquisition is announced. Measures of innovation and firm size are in natural logarithm. Definitions of the variables are provided in Appendix 1. All specifications include the year of bid announcement fixed effects. Robust standard errors (clustered at the acquirer level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Innovation Measures in Levels

	(1) Acquirer CAR3	(2) Acquirer CAR3	(3) Target CAR3	(4) Target CAR3	(5) Deal CAR3	(6) Deal CAR3	(7) Acquirer Δ ROA	(8) Acquirer Δ ROA	(9) Acquirer BHAR	(10) Acquirer BHAR
Correlation of Innovation Activities	0.011	0.004	0.026	0.015	-0.009	-0.012	-0.027	-0.022	-0.694**	-0.597*
	(0.024)	(0.025)	(0.064)	(0.066)	(0.025)	(0.026)	(0.031)	(0.029)	(0.347)	(0.360)
Acquirer's Cross-Cites of Target	-0.003	-0.006	-0.250*	-0.260*	-0.009	-0.010	0.023	0.020	-3.120*	-2.987
	(0.068)	(0.069)	(0.144)	(0.145)	(0.071)	(0.072)	(0.092)	(0.094)	(1.848)	(1.894)
Target's Cross-Cites of Acquirer	-0.000	-0.003	0.055	0.055	0.004	0.003	-0.028	-0.031	-0.205	-0.174
	(0.038)	(0.038)	(0.096)	(0.095)	(0.039)	(0.039)	(0.052)	(0.052)	(0.528)	(0.544)
Acquirer's Knowledge Base Overlap	0.284*	0.271*	-0.552*	-0.545*	0.232	0.221	0.171	0.164	6.015**	5.950**
	(0.160)	(0.161)	(0.289)	(0.283)	(0.178)	(0.180)	(0.262)	(0.257)	(2.632)	(2.600)
Target's Knowledge Base Overlap	-0.025	-0.014	0.137	0.124	-0.014	-0.001	0.025	0.006	-0.785	-0.832
	(0.045)	(0.045)	(0.189)	(0.188)	(0.046)	(0.045)	(0.062)	(0.059)	(0.932)	(0.944)
Acquirer Patent Index	0.000		0.004		0.001		0.004*		0.057*	
	(0.002)		(0.007)		(0.002)		(0.002)		(0.034)	
Target Patent Index	-0.004		-0.010		-0.004		0.010**		0.038	
	(0.004)		(0.011)		(0.004)		(0.004)		(0.059)	
Acquirer Citation Index		-0.001		0.006		-0.001		0.003		0.033
		(0.002)		(0.006)		(0.002)		(0.002)		(0.030)
Target Citation Index		-0.000		-0.007		-0.001		0.008**		0.024
		(0.003)		(0.009)		(0.004)		(0.004)		(0.048)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.09	0.09	0.13	0.13	0.12	0.12	0.09	0.09	0.01	0.00
No. of Observations	1,013	1,013	1,012	1,012	1,012	1,012	1,013	1,013	843	843

Panel B: Innovation Measures in Changes

	(1) Acquirer CAR3	(2) Acquirer CAR3	(3) Target CAR3	(4) Target CAR3	(5) Deal CAR3	(6) Deal CAR3	(7) Acquirer Δ ROA	(8) Acquirer Δ ROA	(9) Acquirer BHAR	(10) Acquirer BHAR
Δ Correlation of Innovation Activities	0.024	0.022	0.015	0.009	0.001	0.002	0.007	0.003	0.014	0.025
	(0.025)	(0.024)	(0.074)	(0.071)	(0.025)	(0.024)	(0.027)	(0.026)	(0.309)	(0.304)
Δ Acquirer's Cross-Cites of Target	0.030	0.053	-0.017	-0.050	0.098	0.105	0.004	0.011	-1.986	-2.591
	(0.067)	(0.071)	(0.174)	(0.173)	(0.105)	(0.108)	(0.084)	(0.084)	(2.896)	(2.894)
Δ Target's Cross-Cites of Acquirer	-0.042	-0.051	-0.061	-0.052	-0.038	-0.038	0.024	0.023	0.295	0.456
	(0.043)	(0.044)	(0.099)	(0.099)	(0.042)	(0.044)	(0.047)	(0.049)	(0.748)	(0.741)
Δ Acquirer's Knowledge Base Overlap	0.027	0.022	-0.521**	-0.526**	-0.171	-0.170	0.056	0.054	1.259	1.241
	(0.151)	(0.143)	(0.250)	(0.239)	(0.111)	(0.109)	(0.116)	(0.115)	(0.881)	(0.928)
Δ Target's Knowledge Base Overlap	0.077	0.077	0.137	0.131	0.105	0.106	0.053	0.057	0.106	0.009
	(0.069)	(0.069)	(0.193)	(0.195)	(0.066)	(0.067)	(0.066)	(0.066)	(1.029)	(0.974)
Δ Acquirer Patent Index	0.009		-0.005		0.013**		0.002		0.059	
	(0.006)		(0.022)		(0.006)		(0.007)		(0.113)	
Δ Target Patent Index	-0.004		-0.010		-0.004		-0.006		-0.032	
	(0.008)		(0.018)		(0.008)		(0.010)		(0.120)	
Δ Acquirer Citation Index		-0.010**		0.016		-0.006*		-0.004		0.121
		(0.004)		(0.014)		(0.004)		(0.006)		(0.088)
Δ Target Citation Index		0.006		-0.006		0.001		-0.001		-0.061
		(0.005)		(0.015)		(0.005)		(0.006)		(0.067)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.09	0.09	0.13	0.14	0.13	0.12	0.08	0.08	0.00	0.00
No. of Observations	1,013	1,013	1,012	1,012	1,012	1,012	1,013	1,013	843	843