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 the property rights theory of the firm. Our measures of corporate innovation capture not only innovation quantity and quality, but also more importantly, asset complementarity that stem from technological overlaps between 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 technological proximity, common knowledge base, 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 impactful 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, mergers and acquisitions, innovation, boundaries of the firm, 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 the property rights theory of the firm. Our measures of corporate innovation capture not only innovation quantity and quality, but also more importantly, asset complementarity that stem from technological overlaps between 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 technological proximity, common knowledge base, 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 impactful 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 and on determinants of merger pairing decisions.[1] Harford (2005) finds that economic, regulatory, and technological shocks drive industry merger waves. This support for neoclassical explanation of aggregate merger activity suggests that neoclassical theory may also explain which firms become acquirers and targets as well as how merger pairs are formed. In particular, the transaction cost economics (Coase (1937), Williamson (1975, 1979, 1985), Klein, Crawford and Alchian (1978)) as well as the property rights theory of the firm (Grossman and Hart (1986), Hart and Moore (1990), and Hart (1995)) argue that firms merge to achieve economic gains from bilateral/multilateral relationships if these relationships and the rents they generate are not contractible.

In this paper, we examine how firms' innovation activities affect their merger activity. We ask whether the existence of synergies between firms in the space of technological innovation leads to corporate acquisitions and how characteristics of such synergies are related to who buys whom. In this context, we present direct evidence on the importance of asset complementarities for mergers and find support for the prediction of the neoclassical property rights theory of the firm that complementary assets should be owned together.

Our focus on innovation is motivated by empirical evidence, which shows that merger waves occur in response to technological progress, and the theory of the firm, which argues that contractual incompleteness is a necessary condition for economic activity to take place inside formal organizations as opposed to be run solely by market transactions. Since innovation involves investing in human capital and R&D and producing predominantly intangible assets, the

[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)).

relationships between firms that arise due to their innovative activities are presumably hard to contract upon. At the same time, such relationships arise frequently as innovativeness is the crucial contributor to future corporate profits and is pursued by many firms across a wide spectrum of industries.[2] As a result, innovation might be an economy-wide driver of corporate acquisitions. Indeed, 60% of all public-public US mergers in the 1984-2006 period are associated with firms that are involved in innovation activities, as captured by patenting, prior to the transaction.

The acquisition of Closure Medical Corporation by Johnson & Johnson (J&J) is illustrative of the role that 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, including 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."[3] 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.[4]

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[2] A large body of work in industrial organization and on the economics of innovation shows that the competitive structure of the innovation process is the most important driving force for firms' R&D investment decisions (see Tirole (1998)).

[3] 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.

[4] 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.

These examples highlight the key features of merger transactions we study. First, merger partners pursue related R&D activities prior to the acquisition. Second, a particular technology of the target firm appears to be very valuable for the acquirer, triggering the bid. This suggests that economic gains from technological complementarities can be realized only if the assets are joined under the acquiring firm's ownership. Third, the merger is expected to have a positive impact on the acquirer's future performance. To see whether these anecdotal examples, which are consistent with the property rights theory of the firm, represent a general pattern underlying merger activity, we ask the following research questions: Are acquisitions driven by technologically advanced firms or by technology laggards? Do merger partners possess complementary technologies prior to the transaction? Which characteristics of technological overlaps affect merger pairing decisions? Do innovation-driven acquisitions improve firm's innovativeness as well as operating and stock market performance?

To answer these questions we compile an economy-wide patent-merger dataset and develop measures that capture innovation quantity and quality, and more importantly, asset complementarities that stem from technological overlaps of merger partners' innovation activities. Using citations the acquirers' and the target firms' patent portfolios made to other patents, our measures identify whether merger partners' innovation activities are directly interrelated and also whether they originate from the same knowledge base. This allows us to examine 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 proximity of innovation activities, shared knowledge base, and patent cross-citations have significant impact on who buys whom decisions. Finally, we show that innovation-driven acquisitions achieve better long-term real outcomes: higher sales growth, more impactful innovation output as well as improved long-term stock market performance.

Our paper differs from prior work in the following dimensions. First, using patent and patent citations data, we develop new measures of asset complementarity 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. Our sample spans most industries and covers the past two decades.

Our paper adds to the large literature by 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 on the property rights theory of the firm, Rhodes-Kropf and Robinson (2008) use the search model of Diamond-Mortensen-Pissarides to explain the observed pattern of market-to-book ratios of acquirers and target firms. In their model, a firm's market-to-book ratio reflects expected gains from future merger synergies and hence depends on the probability with which the firm finds a merger partner as well as on the bargaining position the firm has over its merger partner. The model's equilibrium dictates positive assortative matching of firms on the market-to-book ratios which is supported by the data. We use the overlaps between firms in the space of technological innovation to directly measure potential synergies between the acquirer and the target firm. We show that such synergies drive merger pairing decisions and are important for achieving real positive effects of mergers.

Hoberg and Phillips (2010) provide direct evidence that product market synergies are important determinants of mergers. Using a text-based analysis of firms' product descriptions in the 10-K reports, they identify product market interactions among merger candidates and show that acquirers merge with target firms that have complementary assets and that such mergers achieve product range expansions. They also find that mergers between firms with similar product descriptions lead to higher operating profitability and sales growth. We analyze the role of asset complementarity in innovation and do not study how firms interact in product markets.

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 variables in Section III. We examine merger incentives and outcomes 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. We then develop our hypotheses focusing on how asset complementarities—measured using acquirers' and target firms' technological overlaps—give firms incentives to merge and how mergers may realize subsequent real improvement.

II.A. Literature on the Boundaries of the Firm

Williamson (1975, 1979, 1985) and Klein, Crawford, and Alchian (1978) observe that when parties cannot write detailed long-term contracts, they underinvest in relation-specific assets because the *ex post* quasi-rents from these investments cannot be divided up appropriately at the time of investing. Williamson (1985) places a particular weight on the role of asset specificity in the supplier-customer relationship along the supply chain and argues that vertical integration increases efficiency as it reduces underinvestment and eliminates hold-up problems.[5]

A more formal property rights theory of the firm, pioneered by Grossman and Hart (1986), also notes that asset ownership is irrelevant under complete contracting and hence it must

[5] Our empirical strategy relies on measuring asset complementarity between firm pairs as opposed to measuring asset specificity. Since asset complementarity is central to the property rights theory of the firm while asset specificity plays no role in it (see Whinston (2003) for detailed discussion), we base our hypotheses on the predictions of the property rights theory of the firm.

be contractual incompleteness that leads to setting up formal organizations and hence to understanding firm boundaries. Hart and Moore (1990) develop a theory of how ownership of assets, which confers residual rights of control over these assets, alters the efficiency of trading relationships. Decisions about asset ownership—and hence firm boundaries—are important because control gives the owner bargaining power when unforeseen or uncovered contingencies force parties to negotiate how their relationship should be continued. In their setting, a firm is a match between an agent's human capital and assets which generates social surplus, and the contractual incompleteness is with respect to the agent's *ex ante* human capital investment.

Hart and Moore (1990) show that the agent whose investment is more important for creating the surplus when working with an asset, i.e., whose investment impacts the surplus the most, should own the asset. They further show that highly complementary assets should be owned together. The latter result obtains because the realization of benefits from asset complementarities requires relationship-specific investments while, at the same time, the existence of complementarities creates opportunities for rent-seeking. Rent-seeking is minimized if control rights are allocated to a single party, which increases efficiency. In contrast, assets without complementarities should be owned by different firms without any efficiency losses.

II.B. Our Hypotheses

The starting point for our investigation in this paper is that firms with extensive innovation activities are likely to have investment opportunities with potentially significant impact on the economy. According to the property rights theory, such firms should own technology- and R&D-related assets that will allow them making these investments. Furthermore, more innovative firms are more likely owns technology- and R&D-related assets that are complementary to those of other firms. In contrast, firms not active in innovation may never be able to realize synergistic gains from buying either technology- or R&D-related assets. 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, Hart and Moore (1990) show that firms with the highest degree of complementarity have the strongest incentive to merge as, for them, the opportunity cost of not merging is the highest.[6] Moreover, if merging entails transaction cost, firms with complementary assets should be more willing to pay the costs of merging as the benefits of common ownership are bigger.

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 an 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)).

Third, Holmström and Roberts (1998) argue that information and knowledge transfers are common drivers of horizontal mergers, particularly in the areas of technology and innovation.[7] Sharing knowledge with another firm might be beneficial to both parties (and also socially efficient) due to complementarities, but it does not take place easily. This is because the buyer does not know how much to pay until the idea's value is established, which may require the seller giving away most of the idea for free in the first place. Integration would be a natural way to facilitate trade and increase efficiency in such cases.

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

[6] The search-and-matching model of Rhodes-Kropf and Robinson (2008) also suggests that asset complementarity leads to mergers.
[7] Arrow (1975) shows that information transmission between upstream and downstream firms may be facilitated by vertical integration.

competitive position of the combined firm is strengthened (see 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.

Innovation-driven mergers can result in performance improvements through three channels. First, according to the property rights theory of the firm, integration improves incentives to invest, reduces underinvestment, and enhances efficiency. If so, innovation-driven mergers should lead to greater innovation activities and investment post-merger.

Second, 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, as 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)).

Third, 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.[8] 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.

[8] 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.

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

There are 1,858 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 1,479 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 (January 2011) with the worldwide Patent Statistical Database (PATSTAT, April 2008) of the European Patent Office (EPO). The NBER project provides data about all utility patents[9] 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

[9] 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.

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 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 400 classes (depending on the version) in the second-level of the IPC system. The second-level of the IPC classification is our proxy for the technology field of innovation, technology class, which we use to construct the measures of innovation output, quality, and overlaps.

The assessment of the quantity of innovation output of a given firm using the patent count data can only be made with reference to some benchmark innovation output due to the following reasons. First, technology classes differ in the nature of R&D activity and resources required in producing a patentable innovation to the extent that patent counts in two distinct classes may not be comparable in the cross section. Second, there are technology class-specific time trends in the number of awarded patents that may not fully reflect changes in innovation output. In particular, large increases in the number of awarded patents in some classes over time might reflect the evolution of USPTO practices with respect to what is a patentable innovation, and hence patent counts from different years may not be (time) consistent measures of innovation output even within the same technology class. We address both issues by computing firms' patent counts using the scaled number of patents, where we divide the number of patents a firm received in a given technology class and year by the median number of patents received in a given technology class and year.

The assessment of the quality of innovation output of a given firm using patent citations requires dealing with two specific features of the citation count data. First, citations received by any given patent is truncated in time because we only know about the citations received so far, and hence patents of different ages are subject to various degrees of this truncation. Second, as the number of awarded patents has been rising steeply over time, the increase in the universe of citing patents mechanically increases the total number of citations made, which may mean that later citations are less significant than earlier ones. To deal with both features, we apply a variant of the "fixed-effects" method of Hall, Jaffe, and Trajtenberg (2001). Specifically, we divide each patent's citation count by the median citation count of patents in the technology class and award year to which the patent of interest belongs.[10] Below we introduce our innovation measures, while detailed definitions are provided in Appendix 1.

To capture the quantity of innovation, we employ *Citation-Weighted Patents* and *Patent Index*. The former is the sum of the citation-weighted number of awarded patents to the acquirer/target firm. The latter 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

[10] Hall, Jaffe, and Trajtenberg (2001) note that, while the fixed-effects rescaling ensures comparability, it also removes variance components of the citation data that might be real. The only way to avoid this is to impose a structure on the citation generating process, and identify real from mechanical sources of variation in the citation data using some additional assumptions. In particular, the "quasi-structural" approach developed by Hall, Jaffe, and Trajtenberg (2001) relies on stationarity, which means that citation-lag distribution is time-invariant. Stationarity is likely to be violated in our setting, as mergers between firms (especially among firms as large and highly innovative as in our sample) might affect the citation generating process in some technology classes. Indeed, since we expect that merger events do impact the innovation process, we only count citations in a "fixed window" (typically three years) starting with the patent award year. For the same reason, we also focus only on patents awarded shortly before and after each event.

where and when the firm was active in patenting. In both cases, we consider patents with an application year from the three-year period before/after an acquisition (see Figure 1 for an illustration of these time periods which we denote “BEFORE” and “AFTER”).

To capture the quality of innovation, we create *Citation Index* and *Self-Cites Ratio*. 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 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 (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). *Self-Cites Ratio* is the number of awarded patents to a firm that cite any of the firm’s earlier patents scaled by the total number of awarded patents to the firm over the same time period. Both *Patent Index* and *Citation Index* are new constructs to the literature.

An important consideration for our analysis, 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 sets of variables to capture innovation overlaps. The first set of variables includes two symmetric measures. Following Jaffe (1986), *Technological Proximity*, measures the proximity of any two firms' innovation activities in the technology space using patent counts in different technology classes. *Knowledge Base Overlap*, measures the extent to which any two firms' awarded patents cite the same set of past patents. Therefore, *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.[11] The second set of variables, new to the literature, includes two reciprocal measures. *Acquirer's/Target's Base Overlap Ratio* captures the importance of the knowledge base that is common to both firms relative to the acquirer's/target firm's entire knowledge base. The final set of variables also includes two reciprocal measures. *Acquirer's/Target's Cross-Cites Ratio* measures the extent to which the target firm's/acquirer's patent portfolio is directly cited by the acquirer's/target firm's patent portfolio. Therefore, *Cross-Cites Ratios* capture the immediate importance of a firm's innovation activity to that of another firm.

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 consists of our innovation variables defined in Section III.B. In our typical specification, we compare innovation output and quality post-merger (in the three-year period after the deal completion—year *cyr+1* to *cyr+3*, see Figure 1) relative to that of pre-merger (in the three-year period before the bid announcement—year *ayr-3* to *ayr-1*).

[11] The applicant has a legal duty to disclose any knowledge of the "prior art," but the decision regarding which patents to cite ultimately rests with the patent examiner, who is supposed to be an expert in the area and hence to be able to identify relevant prior art that the applicant misses or conceals.

The second set of performance measures captures operating performance in terms of sales growth, return on assets (ROA, i.e., the ratio of earnings before interest, taxes, depreciation, and amortization to total assets), R&D intensity (R&D, i.e., the ratio of research and development expanses to total assets), and investment activity (CAPEX, i.e., the ratio of capital expenditures to total assets).

The third set of measures focuses on stock market performance. First, we capture the acquirer's post-merger long-run stock market performance controlling control for size, book-to-market, and pre-acquisition return following Lyon, Barber, and Tsai (1999). Second, we complement the long-run performance with 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).

III.D. Sample Overview

Table 1 presents the temporal distribution of the M&A samples that we use in our analyses. From the 1,858 actual deals in the *Acquirer Sample* (*All Deals*), there are 1,009 deals where the acquirers engaged in patenting activities over the five-year period prior to the bid announcement—*Acquirers with Patents*. From the 1,479 actual deals in the *Acquirer-Target Sample*, there are 942 deals where either the acquirers or the target firms engaged in patenting activities—*Acquirers or Targets with Patents*, and 450 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 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), Measuring, Analyzing, and Controlling Instruments (SIC 38), and Business Services (SIC 73).[12]

Table 2 Panel A presents the descriptive statistics for the *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*.[13] 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 citation-weighted patents and patent indices. Further, in terms of the quality of innovation, the acquirers' citation indices as well as self-cites ratios are greater than those of their target firms. Our univariate statistics are suggestive of that the acquirers are more innovative than their target firms.

[12] 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)).

[13] The descriptive statistics for all other samples exhibit similar patterns, and are available upon request.

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 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 242 deals (out of 942 deals) where one or more measures of innovation overlaps are non-zero. The mean correlation between the acquirer's and the target firm's patent portfolios is 0.10. Naturally, the common knowledge base between the acquirers and the target firms is more important to the latter than to the former. There are more target firms making cites of their acquirers' patents (*Target's Cross-Cites Ratio*) than the other way round (*Acquirer's Cross-Cites Ratio*).

Table 2 Panel B presents the analogous descriptive statistics for the sample of pseudo deals to the *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*. There are 2,532 pseudo deals to 942 actual deals.

We show that among these pseudo deals, the acquirers tend to produce more patents with higher citation indexes than their target firms, but both the acquirers and the target firms are less innovative in comparison to their respective actual merger partners (Panel A of Table2). The reported statistics further suggest that the matching firms have similar financial characteristics (as intended) to the actual acquirers and target firms.[14] Interestingly, the extent of innovation

[14] Since 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 natural logarithm of total assets as a regressor to control for any residual variation in firm size.

overlaps is minimal between the merger partners in pseudo deals, as compared to the overlaps between 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 between the two measures of patent quantity and one measure of patent quality—*Citation-Weighted Patents, Patent Index*, and *Citation Index* (the exception is *Self-Cites Ratio*). As a result, in our multivariate analyses of selection into acquirers we include one patent quantity or quality measure at a time. There is moderate correlation among the six measures of innovation overlap between the acquirer and the target firm, and between these overlap measures and the measures of patent quantity/quality. Therefore, in our multivariate analyses of merger pairing, we use specifications with one as well as with multiple innovation measures at a time.

IV. Main Results

In this section, we implement various multivariate analyses to test our hypotheses regarding the interaction between corporate innovations 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 estimate the following probit regression using cross sectional data with one observation for each actual deal and one observation for each pseudo deal:

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

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 measured using *Citation-Weighted Patents* in levels and changes, 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 *Citation-Weighted Patents* increases by a tiny bit, the probability of a sample firm to become an acquirer increases by 2.5 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 (2) where we employ *ΔCitation-Weighted Patents* between year *ayr-3* and year *ayr-1* as the key explanatory variable, if the trend of innovation output increases by a tiny bit, the probability of a sample firm to become an acquirer increases by 4.6 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.[15]

Using the subsample of innovative acquirers in Columns (3)-(4), we show that the effect of innovation quantity is strengthened. In terms of the economic significance, under Column (3) specification, if the value of *Citation-Weighted Patents* increases by a tiny bit, the probability of a sample firm to become an acquirer increases by 8.5 percentage points, on average; and under Column (4) where we employ *ΔCitation-Weighted Patents* as the key explanatory variable, if the

[15] 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 in the internet appendix).

trend of innovation output increases by a tiny bit, the probability of a sample firm to become an acquirer increases by 6.4 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 repeat the analysis using our preferred measure of the quantity of innovation—*Patent Index,* and show that the effect of innovation quantity is strengthened.

In Panel C, we focus on the quality of innovation measure *Citation Index* and employ the same samples and specifications as in Panel A. Only among *Acquirers with Patents* of the *Acquirer Sample*, we show that innovative firms with more extensively cited patents are more likely to become acquirers. In terms of the economic significance, under Column (3) specification, if the value of *Citation Index* increases by a tiny bit, the probability of a sample firm to become an acquirer increases by 5.6 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.

Finally, in Panel D, we repeat the analysis using *Self-Cites Ratio,* and show that it has positive and significant effect on the probability of a firm to become an acquirer, especially, when measured in changes. This suggests that firms whose innovation activities are becoming increasingly self-reliant are more likely to make an acquisition.

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. Acquirer-Target Pairing

Do merger partners possess complementary technologies as predicted by the property rights theory of the firm? To answer 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 estimate the following probit regression using cross-sectional data with one observation for each actual deal and one observation for each pseudo deal:

$$Acquirer\text{–}Target_{ijt} =$$
$$+\beta_1 Innovation\ Overlaps_{ijt-1} + \beta_2 Acquirer\ Innovation\ Measures_{it-1} +$$
$$\beta_3 Target\ Innovation\ Measures_{jt-1} + \beta_4 Acquirer\ Characteristics_{it-1} +$$
$$\beta_5 Target\ Characteristics_{jt-1} + \beta_6 Diversifying_{ij} + \beta_7 Same\ State_{ij} + Industry\ FE_i +$$
$$Year\ FE_t + e_{ijt}. \tag{2}$$

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 Overlaps*$_{ijt-1}$ are the six 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 are measured prior to the bid announcement. *Acquirer Innovation Measures*$_{it-1}$ (*Target Innovation Measures*$_{jt-1}$) are the measures of innovation quantity and quality. *Acquirer Characteristics*$_{it-1}$ (*Target 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 observations in the sample.

In Panel A, using all three subsample of the *Acquirer-Target Sample*, we show that there is a significant and positive association between any of the six measures of innovation overlaps between merger partners and the formation of a merger pair. In terms of the economic significance, under Column (1) specification, if the value of *Technological Proximity* (*Knowledge Base Overlap*) increases by a tiny bit, the probability of a merger pairing increases by 37.5 (18.1) percentage points, on average.

Further, both *Acquirer's Base Overlap Ratio* (*Acquirer's Cross-Cites Ratio*) and *Target's Base Overlap Ratio* (*Target's Cross-Cites Ratio*) have an effect on the merger pairing decisions. This is an important and new finding in the literature, suggesting that the reciprocal importance of two firms' innovation activities leads to merger pairing, possibly due to potential synergistic gains in the technology space and also due to the reduction of information asymmetry with respect to the merger partners' intangible assets. 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 acquirer's (target firm's) innovativeness, measured by *Patent Index*, is positively (negatively) and significantly associated with the formation of a merger pair. This result is due 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. The interesting contrast between target innovation quantity and R&D expenditures highlights the important distinction between innovation input as measured by R&D expenditures and innovation output as measured by patenting activities.

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 three samples as in Panel A. Due to space constraints, we only report average marginal effects associated with the innovation measures. Across all samples examined, we show that the rising trend in the extent of overlaps between the acquirer and the target firm as captured by Δ *Knowledge Base Overlap,* Δ *Target's Base Overlap Ratio,* and Δ *Acquirer's/Target's Cross-Cites Ratio* is 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 output, while target firms are the ones with declining trend in patenting output. Furthermore, similarly to results in Panel D of Table 1, we again find that firms whose innovation activities are becoming increasingly self-reliant are more likely to acquire. This evidence is consistent with findings in Maksimovic and Phillips (2001) that more productive firms buying less productive ones.

In Panel C, we employ the same specifications as in Panel A with the exception that the sample of matching deals is formed only by pairing the actual acquirer with the closest match of the deal's actual target firm. These regressions ask which target firm does a predetermined acquirer select. We show that the estimated coefficients on *Acquirer's Base Overlap Ratio* and *Acquirer's Cross-Cites Ratio* are a lot bigger compared to those reported in Panel A, which suggests that the presence of innovation overlaps on the acquirer side is a very important consideration for choosing the target firm.

Finally, in Panel D, we employ the same specifications as in Panel A with the exception that the sample of matching deals is formed only by pairing the actual target firm with the closest match of the deal's actual acquirer. These regressions ask with which acquirer does a predetermined target firm merge. We show that the estimated coefficients on *Target's Base Overlap Ratio* (*Target's Cross-Cites Ratio*) are somewhat bigger (the same) compared to those in Panel A. These results suggest that it is the acquirer side of innovation overlaps that is more important for the formation of merger pairing decisions.

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 in the context of R&D, ownership changes are needed to materialize these 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-Acquisition Innovation Performance

To mitigate the potential truncation bias in our post-merger measures, all post-merger innovation performance 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, 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. Finally, for each actual deal, we require that a pseudo deal formed by pairing the closest match of the deal's actual acquirer with the closest match of the deal's actual target firm exists. Our control sample consists of these pseudo deals only. These filters yield 638 deals for *All Deals*, 351 deals for *Acquires or Targets with Patents*, and 214 deals for *Acquirers and Targets with Patents* of the *Acquirer-Target Sample*.

To examine the impact of acquisition on post-merger innovation activity, we estimate the following difference-in-differences regression using a panel dataset with time series observations running from three years prior to bid announcement (*ayr-3*) to three years after the deal completion (*cyr+3*), for each actual and pseudo deal, respectively:

$$Innovation\ Measure_{it} = \alpha + \beta_1 Actual\ Deal_i \times After_t + \beta_2 Actual\ Deal_i + \beta_3 After_t + Deal\ FE_i + Year\ FE_t + e_{it}. \tag{3}$$

The dependent variable is, in each year, the sum of the acquirer's innovation quantity/quality with that of the target firm. This way, we effectively compare the innovation performance of the actual acquirer-actual target firm pair with that of the pseudo pair. $Actual\ Deal_i$ is an indicator variable equal to one for the actual acquirer-actual target firm pair, and zero otherwise (i.e., for the pseudo pair). $After_t$ is an indicator variable equal to one for the post-merger time period (from *cyr+1* to *cyr+3*), and zero otherwise. The coefficient on the interaction term $Actual\ Deal_i \times After_t$ captures the post- versus pre-merger change in the dependent variable for the actual merger pair relative to the same change for the pseudo pair. Deal fixed effects $Deal\ FE_i$ capture unobserved heterogeneity at deal level, while year fixed effects $Year\ FE_t$ capture effects that impact all mergers in a given year.

Panel A of Table 5 presents estimates of the panel data regression in Equation (3) using *All Deals* (Columns (1)-(3)), *Acquirers or Targets with Patents* (Columns (4)-(6)), and *Acquirers and Targets with Patents* (Columns (7)-(9)) of the *Acquirer Sample*. The dependent variables are the two innovation quantity measures—*Citation-Weighted Patents,* and *Patent Index,* and one innovation quality measure—*Citation Index.* We show that the coefficients on the interaction term $Actual\ Deal_i \times After_t$ for the innovation quantity measures are negative, and for *Acquirers and Targets with Patents* of the *Acquirer Sample* significant. This means that the actual acquirer-actual target firm pair exhibits no change or a decrease in the innovation quantity post-merger relative to the benchmark change in the innovation quantity of the pseudo pair. This result is consistent with findings by Ornaghi (2009) for pharmaceutical mergers. In contrast, for *Citation Index*, we estimate positive coefficients on the interaction term, which are significant in case of specifications in Columns (3) and (6).

To understand why the results for innovation quantity and quality go in opposite direction, we re-estimate regression in Equation (3) using alternatively defined *Citation-Weighted Patents* and *Patent Index* variables. Specifically, we use patent award dates (instead of patent application dates) to assign patents to pre- and post- merger years in our panel data. The results are reported in Panel B of Table 5. With this alternative definition, we show that the coefficients on the interaction term $Actual\ Deal_i \times After_t$ are positive for the alternative innovation quantity measures and sometimes significant. This suggests that the number of patents awarded to actual acquirer-actual target firm pairs increases post-merger, while the number of application filed decreases.

In the top two graphs of Figure 2, for each of the years from *ary-3* to *cyr+3*, we plot the average values of *Patent Index* and *Citation Index* for actual merger pairs (black solid line) and pseudo pairs (gray dashed line) from *Acquirers or Targets with Patents* of the *Acquirer Sample* used in Table 5. This descriptive evidence confirms results in Panel A of Table 5 that *Patent Index* decreases for the actual merger pairs, while the *Citation Index* increases. In the bottom two graphs of Figure 2, we analogously plot *Citation-Weighted Patents* and *Patent Index*, both defined using patent award dates. We show that innovation output of actual merger pairs increases post-merger when patent awards dates are used.

In summary, innovation output decreases post-merger when we use innovation quantity measures that are based on application years. Moreover, It seems that the combined innovation output of the actual acquirer and the actual target firm is at its peak just at the time a merger takes place. This evidence complements our result in Table 4 as it further suggests that innovation activities are important not only for who buys whom, but also for deciding when a merger is launched. Our evidence in Table 5 is partially consistent with our third hypothesis (**H3**).

IV.D. Post-Acquisition Operating Performance

Table 6 presents our investigation of the effect of mergers on operating performance using the analogous differences-in-differences methodology as in Section IV.C.

We find that combined sales growth of the actual acquirer-actual target pairs increases post-merger when compared to that of the matched pseudo pairs. This result is consistent with findings in Hoberg and Phillips (2010). We also show that R&D expenditures decrease post-merger, which suggests that innovation activity indeed decreases as documented already in Table 5 using our innovation quantity measures. Finally, we find no effect of a merger on operating profitability (ROA) and on capital expenditures. Figure 3 provides description of the operating performance results.

IV.E. Stock Market Performance

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

$$\begin{aligned} &Stock\ Market\ Performance_{it+1} = \\ &\alpha + \beta_1 Innovation\ Overlaps_{ijt-1} + \beta_2 Acquirer\ Innovation\ Measures_{it-1} + \\ &\beta_3 Target\ Innovation\ Measures_{jt-1} + \beta_4 Acquirer\ Characteristics_{it-1} + \\ &\beta_5 Target\ Characteristics_{jt-1} + \beta_6 Deal\ Characteristics_{ij} + \beta_7 Diversifying_{ij} + \\ &\beta_8 Same\ State_{ij} + Industry\ FE_i + Year\ FE_t + e_{it}. \end{aligned} \tag{4}$$

The dependent variable is acquirer's post-merger long-term stock market performance (*Acquirer BHAR*) or merger firms' abnormal announcement-period returns (*Acquirer CAR3*, *Target CAR3*, and *Deal CAR3*). To conserve space, Table 7 only presents the estimated coefficients in Equation (4) on the innovation measures.

In Panel A of Table 7, we show that innovation overlap, as captured by *Knowledge Base Overlap*, is positively and significantly associated with the acquirer's long-run buy-and-hold abnormal return (*Acquirer BHAR*). Similarly, direct measures of the importance of the common knowledge base for the acquirer (*Acquirer's Base Overlap Ratio*) and the extent of cross citations (*Acquirer's Cross-Cites Ratio*) are positively and significantly associated with *Acquirer BHAR*. This provides support for our final hypothesis (**H3**) that technology-driven acquisitions result in better stock market performance.

With the exception of *Target Patent Index* that is negatively associated with *Acquirer CAR3* and *Deal CAR3*, Panels B, C, and D of Table 7 show that *Acquirer CAR3*, *Target CAR3*, and *Deal CAR3* cannot be explained using our innovation measures.

V. Additional Investigations

Corporate innovation could also exert influence on deal completion through two mechanisms. First, it is less likely to observe acquirer-target firm pairings with poor fit in innovation activities. Second, acquirer-target firm pairings with poor technological fit are less likely to consummate. So far, we have thoroughly examined the first channel. In this section, we start by investigating the role of corporate innovation in deal completion, and we then conduct various robustness checks on the impact of acquisitions on innovation.

V.A. Deal Completion

We first form an M&A sample that includes all announced US M&As with announcement dates between January 1, 1984 and December 31, 2006. After imposing the same filters as before, we end up with 1,877 deals where we have complete information on both the acquirer and the target firm, as well as on whether the deal is completed or not.[16] We expect that deals with more innovative acquirers and/or deals where there is potential for synergistic gains in terms of innovation activities are more likely to be completed. Table 8 presents average marginal effects of from the probit regression (similar to Equation (2)), where the dependent variable, *Completion*, is equal to one if the deal is completed, and zero otherwise.

In Panel A, we use the acquirer's and the target firm's innovation overlap measures, one set at a time, as the key explanatory variables. We show that across two out of three samples employed, there is a positive and significant association between *Acquirer's Cross-Cites Ratio* and the likelihood of deal completion. This suggests that pre-merger acquirers' familiarity with the target firms increases the likelihood of deal success, consistent with prior work (see for example, Higgins and Rodriguez (2006) and Zhang (2010)) as well as the property rights perspective of mergers. Further, we find that *Acquirer's Self-Cites Ratio* is positively and significantly, while *Target's Self-Cites Ratio* is negatively and significantly associated with the likelihood of deal completion. The above results add insight into our understanding of why some announced deals fail to come through. In our case, deals involving targets with very inward looking innovation output are unlikely to be completed; interestingly, deals involving acquirers with very inward looking innovation outputs are more likely to be completed.

In Panel B, we use changes in the acquirer's and the target firm's innovation overlap measures, one set at a time, as the key explanatory variables. We show that the association between the time trend in innovation overlap as measured by *Acquirer's Cross-Cites Ratio* and the likelihood of deal completion is of the same direction most of the time, and the time trend in both *Acquirer's Patent Index* and *Acquirer's Self-Cites Ratio* is positively and significantly associated with the likelihood of deal completion.

[16] This sample is different from *All Deals* in the *Acquirer-Target Sample* (1,479 deals) because we include both completed deals for which we do not require pseudo deals to exist but we require deal controls to be non-missing (1,469 deals) and not completed deals (408 deals).

Overall, our evidence strongly supports the view, that asset complementarity and innovation play an important role in every aspect of a merger transaction: in deal initiation, deal completion, and its outcomes.

V.B. Robustness Checks

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 1,858 deals, we are able to obtain 4,327 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 somewhat weakened. 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 1,479 deals, we are able to obtain 13,965 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.

We also repeat the analyses reported in Table 3 (Table 4) when we in addition control for the presence of institutional owners and the governance structure of the acquirer (both the acquirer and the target firm). Institutional ownership is measured as the fraction of equity owned by the five largest institutional investors—*Institutional Ownership*. Firms' governance is measured using *G index*. Since *G index* is available only for the biggest companies since 1990, the number of actual deals is a lot smaller 541 (188) compared to 1,858 in Table 3 (1,479 in Table 4). With these additional controls and smaller samples, the results (available in the internet appendix) are practically unchanged compared to those reported in Tables 3 and 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. We also find that acquisitions take place between acquirers and target firms when they are at the peak of their innovativeness suggesting that innovation success is important for the timing of merger activity. Finally, we find that technology-driven acquisitions are positively and significantly associated with post-acquisition sales growth and long-term stock market performance. Overall, our findings uncover the underlying efficiency motives behind particular merger transactions and provide a fruitful avenue for identifying whether and how value is created through acquisitions.

Appendix 1

Definition of Variables

Innovation Measures	
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 last 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*.
Citation Count	The number of citations received by patents awarded to the acquirer/target firm with award years from *ayr-3* to *ayr-1*. For each patent, we count citations received 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*.
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 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*.
Citation-Weighted Patents	The sum of the citation-weighted number of awarded patents to the acquirer/target firm with application years from *ayr-3* to *ayr-1*. For each patent, the weight is the number of citations received within a three-year period starting from the patent award year. When assessing the post-merger innovation, the measurement window for patent application years is from *cyr+1* to *cyr+3*.
Self-Cites Ratio	First, we compute the number of awarded patents to the acquirer/target firm with award years from *ayr-3* to *ayr-1* that cite any of the acquirer's/target firm's other awarded patents. Second, we scale the number from the first step by the total number of awarded patents to the acquirer/target firm with award years from *ayr-3* to *ayr-1*.

Technological Proximity	The correlation coefficient computed as $$\frac{S_{acq}S'_{targ}}{\sqrt{S_{acq}S'_{acq}}\sqrt{S_{targ}S'_{targ}}},$$ 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.
Knowledge Base Overlap	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 one citation from any of the target firm's patents awarded over the same three-year period ("the target firm'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 number of patents in "the common knowledge base".
Acquirer's (Target's) Base Overlap Ratio	First, we compute the number of citations any of the acquirer's (the target firm's) patents with award years from *ayr-3* to *ayr-1* made to the patents in "the common knowledge base". Second, we scale the number from the first step by the number of citations any of the acquirer's (the target firm's) patents with award years from *ayr-3* to *ayr-1* made to the patents in "the acquirer's knowledge base" ("the target firm's knowledge base").
Acquirer's (Target's) Cross-Cites Ratio	First, we compute the number of the acquirer's (the target firm's) awarded patents with award years from *ayr-3* to *ayr-1* that cite any of the target firm's (the acquirer's) awarded patents. Second, we scale the number from the first step by the number of the acquirer's (the target firm's) awarded patents with award years from *ayr-3* to *ayr-1*.
Acquisition Performance	
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.
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.

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.
CAPEX	Capital expenditures 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.
Institutional Ownership	The fraction of the acquirer's (the target firm's) equity owned by the five largest institutional investors based on the CDA/Spectrum database.
G index	An index based on the twenty-four antitakeover provisions in the RiskMetrics database. The index value increases by one for each antitakeover provision in place.
E index	An index based on the six antitakeover provisions in the RiskMetrics database: staggered board, poison pills, supermajority requirement for mergers, limits to shareholder bylaw amendments, limits to charter amendments, and golden parachutes. The index value increases by one for each antitakeover provision in place.
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.

SIC2	The Acquirer Sample		The Acquirer-Target Sample		
	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	8	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	7	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	127	98	109	95	65
29	5	2	6	4	1
30	22	15	16	13	8
31	2	1	1	0	0
32	10	4	8	4	2
33	30	17	22	15	10
34	33	32	21	21	12
35	190	154	147	132	82
36	147	121	118	108	70
37	48	39	36	32	19
38	156	125	116	106	65
39	34	25	24	21	9
40	10	6	9	5	0
42	15	2	13	3	0
44	2	0	1	1	0
45	17	0	18	2	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	1	19	1	0

59	37	2	29	6	0
70	9	2	5	2	0
72	10	0	8	2	0
73	297	182	224	156	55
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	1,858	1,009	1,479	942	450

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

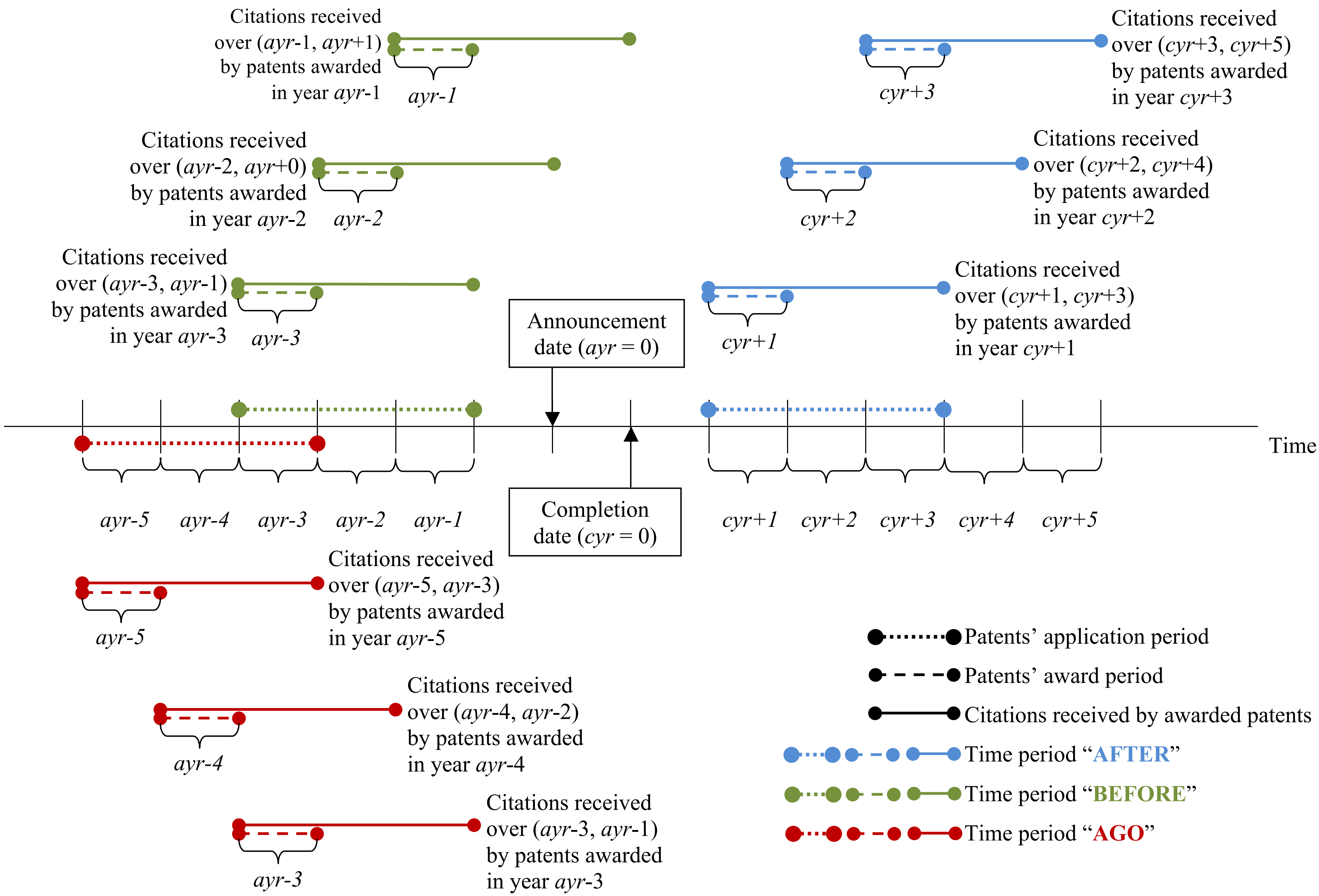

Figure 2
Post-Acquisition Innovation Performance

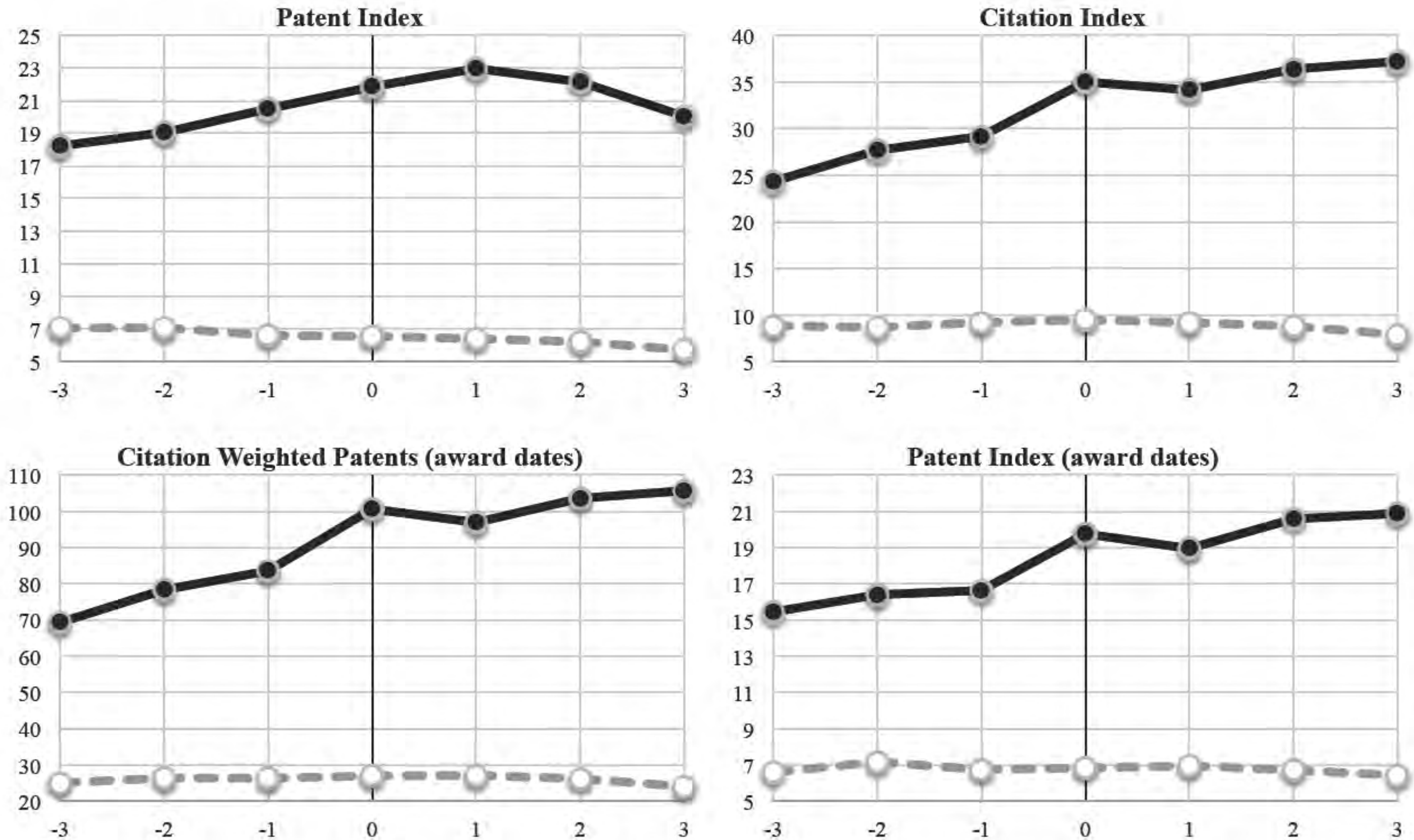

Figure 3
Post-Acquisition Operating Performance

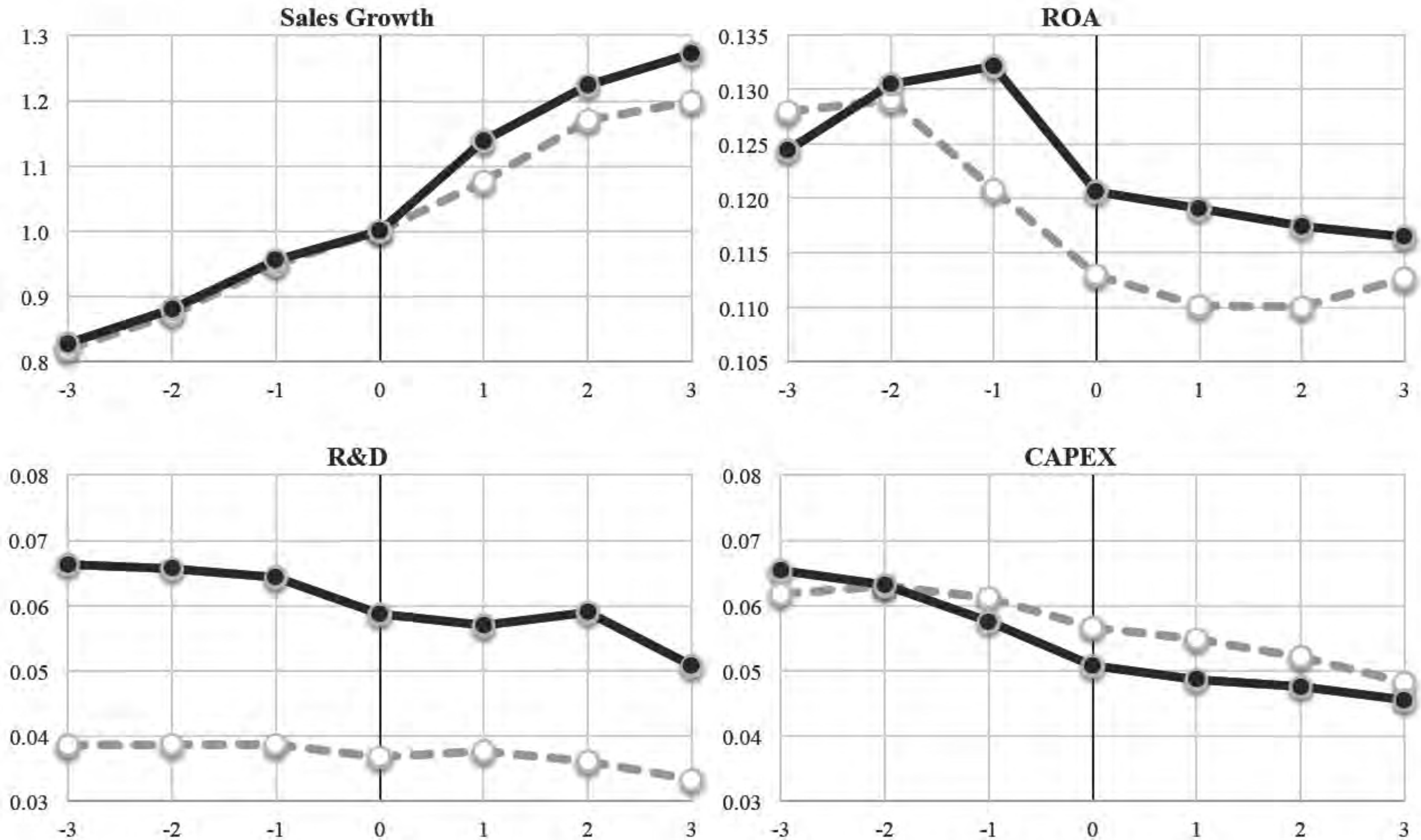

Table 1
Corporate Acquisitions over Time, 1984–2006

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	The Acquirer Sample		The 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	34	21	8
1992	32	19	21	15	7
1993	41	18	30	15	8
1994	65	28	59	35	14
1995	109	55	89	50	26
1996	120	51	99	47	16
1997	143	59	113	56	28
1998	161	87	142	86	43
1999	138	89	122	90	46
2000	112	70	89	66	32
2001	109	67	91	63	36
2002	90	62	58	45	21
2003	78	51	55	42	20
2004	74	45	59	43	25
2005	86	58	63	50	25
2006	73	49	57	45	21
Total	1,858	1,009	1,479	942	450

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		
Citation Weighted Patents	201.90	974.19	0.00	11.00	299.00
Patent Index	31.84	129.74	0.00	2.50	60.98
Citation Index	59.83	314.08	0.00	2.00	99.67
Self-Cites Ratio	0.04	0.08	0.00	0.00	0.14
Total Assets	3.80	8.64	0.09	1.02	8.25
Sales Growth	0.18	0.30	-0.10	0.13	0.54
ROA	0.12	0.13	-0.01	0.15	0.25
Leverage	0.18	0.16	0.00	0.16	0.42
Cash	0.20	0.20	0.01	0.12	0.52
R&D	0.06	0.08	0.00	0.03	0.17
B/M	0.47	0.33	0.13	0.38	0.89
Stock Return	0.13	0.61	-0.47	-0.01	0.81
			Target		
Citation Weighted Patents	25.56	150.89	0.00	1.00	41.00
Patent Index	4.23	19.39	0.00	0.50	7.83
Citation Index	11.00	69.09	0.00	0.00	15.67
Self-Cites Ratio	0.03	0.07	0.00	0.00	0.10
Total Assets	0.74	1.89	0.03	0.17	1.50
Sales Growth	0.13	0.29	-0.16	0.10	0.48
ROA	0.07	0.18	-0.15	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	1.18
Stock Return	-0.05	0.64	-0.65	-0.18	0.62
			Innovation Overlaps		
Technological Proximity	0.10	0.26	0.00	0.00	0.57
Knowledge Base Overlap	0.86	3.39	0.00	0.00	2.00
Acquirer’s Base Overlap Ratio	0.01	0.02	0.00	0.00	0.00
Target’s Base Overlap Ratio	0.02	0.08	0.00	0.00	0.05
Acquirer’s Cross-Cites Ratio	0.01	0.05	0.00	0.00	0.00
Target’s Cross-Cites Ratio	0.03	0.11	0.00	0.00	0.00

Panel B: Pseudo Deals to Acquirers or Targets with Patents

The sample consists of 2,532 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		
Citation Weighted Patents	135.38	811.57	0.00	5.00	188.50
Patent Index	23.19	124.26	0.00	1.00	33.58
Citation Index	43.68	259.82	0.00	0.50	53.75
Self-Cites Ratio	0.03	0.07	0.00	0.00	0.11
Total Assets	2.89	7.85	0.07	0.71	5.97
Sales Growth	0.16	0.28	-0.09	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	0.54	0.37	0.17	0.44	1.04
Stock Return	0.05	0.58	-0.52	-0.06	0.67
			Target		
Citation Weighted Patents	22.76	134.49	0.00	0.00	37.00
Patent Index	3.94	18.16	0.00	0.00	7.17
Citation Index	9.21	61.10	0.00	0.00	13.00
Self-Cites Ratio	0.03	0.08	0.00	0.00	0.09
Total Assets	0.66	1.77	0.02	0.15	1.31
Sales Growth	0.13	0.30	-0.16	0.10	0.47
ROA	0.07	0.17	-0.14	0.12	0.23
Leverage	0.18	0.18	0.00	0.14	0.44
Cash	0.21	0.23	0.01	0.12	0.57
R&D	0.07	0.10	0.00	0.03	0.20
B/M	0.64	0.47	0.17	0.54	1.24
Stock Return	-0.02	0.65	-0.64	-0.16	0.66
			Innovation Overlaps		
Technological Proximity	0.03	0.13	0.00	0.00	0.00
Knowledge Base Overlap	0.15	1.85	0.00	0.00	0.00
Acquirer's Base Overlap Ratio	0.00	0.01	0.00	0.00	0.00
Target's Base Overlap Ratio	0.00	0.03	0.00	0.00	0.00
Acquirer's Cross-Cites Ratio	0.00	0.02	0.00	0.00	0.00
Target's Cross-Cites Ratio	0.00	0.02	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	14
Acquirer														
Citation-Weighted Patents	1.00													
Patent Index	0.97	1.00												
Citation Index	0.90	0.93	1.00											
Self-Cites Ratio	0.47	0.51	0.52	1.00										
Target														
Citation-Weighted Patents	0.23	0.24	0.20	0.08	1.00									
Patent Index	0.18	0.21	0.17	0.09	0.94	1.00								
Citation Index	0.23	0.24	0.22	0.08	0.81	0.81	1.00							
Self-Cites Ratio	0.05	0.08	0.08	0.15	0.35	0.37	0.39	1.00						
Innovation Overlaps														
Technological Proximity	0.37	0.37	0.33	0.18	0.57	0.56	0.52	0.19	1.00					
Knowledge Base Overlap	0.44	0.45	0.48	0.17	0.43	0.39	0.55	0.15	0.46	1.00				
Acquirer's Base Overlap Ratio	0.13	0.10	0.10	0.02	0.22	0.19	0.32	0.09	0.20	0.52	1.00			
Target's Base Overlap Ratio	0.35	0.36	0.38	0.14	0.22	0.16	0.30	0.11	0.26	0.74	0.47	1.00		
Acquirer's Cross-Cites Ratio	0.04	0.03	0.05	0.02	0.11	0.09	0.12	0.08	0.13	0.20	0.36	0.20	1.00	
Target's Cross-Cites Ratio	0.28	0.29	0.30	0.19	0.20	0.15	0.22	0.10	0.20	0.48	0.26	0.50	0.10	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)-(2) report the results using *All Deals* of the *Acquirer Sample,* and corresponding 1,858 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 (3)-(4) report the results using *Acquirers with Patents* of the *Acquirer Sample*, and corresponding 1,009 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 as Measured by Citation-Weighted Patents
The panel reports estimates from specifications that use the levels of and the changes in the acquirer's *Citation-Weighted Patents* measured over the three-year period prior to the bid announcement as key explanatory variables.

	All Deals		Acquirers with Patents	
	(1)	(2)	(3)	(4)
	Citation Weighted Patents	Δ Citation Weighted Patents	Citation Weighted Patents	Δ Citation Weighted Patents
Innovation	0.025***	0.046***	0.085***	0.064***
	(0.010)	(0.014)	(0.009)	(0.016)
Total Assets	0.033***	0.049***	-0.010	0.064***
	(0.011)	(0.010)	(0.016)	(0.014)
Sales Growth	0.245***	0.234***	0.208***	0.180***
	(0.037)	(0.036)	(0.054)	(0.054)
ROA	-0.051	-0.044	0.005	0.041
	(0.112)	(0.111)	(0.142)	(0.147)
Leverage	-0.024	-0.042	-0.091	-0.160
	(0.079)	(0.079)	(0.108)	(0.119)
Cash	0.173	0.198*	0.119	0.204
	(0.109)	(0.105)	(0.141)	(0.140)
R&D	0.966***	1.117***	0.587*	1.368***
	(0.290)	(0.272)	(0.343)	(0.336)
B/M	-0.088***	-0.090***	-0.109**	-0.138***
	(0.032)	(0.032)	(0.049)	(0.052)
Stock Return	0.044***	0.045***	0.002	0.005
	(0.016)	(0.016)	(0.018)	(0.019)
Ind. and Year FEs	Yes	Yes	Yes	Yes
No. of Observations	3,716	3,716	2,018	2,018
No. of Actual Acq.	1,858	1,858	1,009	1,009
No. of Matching Acq.	1,858	1,858	1,009	1,009

Panel B: Quantity of Innovation as Measured by Patent Index

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

	All Deals		Acquirers with Patents	
	(1)	(2)	(3)	(4)
	Patent Index	Δ Patent Index	Patent Index	Δ Patent Index
Innovation	0.030**	0.081***	0.093***	0.104***
	(0.014)	(0.027)	(0.014)	(0.030)
Total Assets	0.035***	0.048***	0.002	0.063***
	(0.011)	(0.010)	(0.017)	(0.014)
Sales Growth	0.248***	0.232***	0.233***	0.181***
	(0.036)	(0.036)	(0.055)	(0.055)
ROA	-0.044	-0.047	0.029	0.034
	(0.112)	(0.111)	(0.145)	(0.146)
Leverage	-0.026	-0.043	-0.107	-0.161
	(0.079)	(0.080)	(0.110)	(0.119)
Cash	0.183*	0.197*	0.166	0.203
	(0.109)	(0.104)	(0.144)	(0.137)
R&D	1.025***	1.096***	0.866**	1.331***
	(0.290)	(0.269)	(0.352)	(0.330)
B/M	-0.087***	-0.089***	-0.110**	-0.135**
	(0.032)	(0.033)	(0.050)	(0.052)
Stock Return	0.044***	0.044***	0.002	0.003
	(0.016)	(0.016)	(0.019)	(0.019)
Ind. and Year FEs	Yes	Yes	Yes	Yes
No. of Observations	3,716	3,716	2,018	2,018
No. of Actual Acq.	1,858	1,858	1,009	1,009
No. of Matching Acq.	1,858	1,858	1,009	1,009

Panel C: Quality of Innovation as Measured by Citation Index

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

	All Deals		Acquirers with Patents	
	(1)	(2)	(3)	(4)
	Citation Index	Δ Citation Index	Citation Index	Δ Citation Index
Innovation	0.019	-0.006	0.056***	0.015
	(0.013)	(0.019)	(0.013)	(0.021)
Total Assets	0.039***	0.049***	0.023	0.064***
	(0.011)	(0.010)	(0.015)	(0.015)
Sales Growth	0.250***	0.243***	0.245***	0.206***
	(0.037)	(0.037)	(0.056)	(0.056)
ROA	-0.036	-0.027	0.044	0.056
	(0.113)	(0.112)	(0.147)	(0.148)
Leverage	-0.032	-0.043	-0.117	-0.162
	(0.079)	(0.080)	(0.114)	(0.120)
Cash	0.181*	0.197*	0.159	0.207
	(0.108)	(0.109)	(0.148)	(0.145)
R&D	1.085***	1.200***	1.098***	1.431***
	(0.292)	(0.270)	(0.365)	(0.333)
B/M	-0.087***	-0.089***	-0.116**	-0.135**
	(0.032)	(0.033)	(0.051)	(0.053)
Stock Return	0.044***	0.045***	0.002	0.004
	(0.016)	(0.017)	(0.020)	(0.020)
Ind. and Year FEs	Yes	Yes	Yes	Yes
No. of Observations	3,716	3,716	2,018	2,018
No. of Actual Acq.	1,858	1,858	1,009	1,009
No. of Matching Acq.	1,858	1,858	1,009	1,009

Panel D: Quality of Innovation as Measured by Self-Cites Ratio
The panel reports estimates from specifications that use the levels of and the changes in the acquirer's *Self-Cites Ratio* measured over the three-year period prior to the bid announcement as key explanatory variables.

	All Deals		Acquirers with Patents	
	(1)	(2)	(3)	(4)
	Self-Cites Ratio	Δ Self-Cites Ratio	Self-Cites Ratio	Δ Self-Cites Ratio
Innovation	0.268	0.460**	1.035***	0.655**
	(0.261)	(0.196)	(0.305)	(0.255)
Total Assets	0.047***	0.049***	0.057***	0.065***
	(0.010)	(0.010)	(0.014)	(0.014)
Sales Growth	0.245***	0.243***	0.221***	0.209***
	(0.037)	(0.037)	(0.055)	(0.056)
ROA	-0.029	-0.029	0.059	0.058
	(0.112)	(0.112)	(0.146)	(0.149)
Leverage	-0.040	-0.044	-0.157	-0.168
	(0.079)	(0.080)	(0.117)	(0.120)
Cash	0.197*	0.194*	0.214	0.207
	(0.109)	(0.108)	(0.145)	(0.146)
R&D	1.172***	1.177***	1.408***	1.447***
	(0.276)	(0.275)	(0.339)	(0.343)
B/M	-0.088***	-0.087***	-0.120**	-0.132**
	(0.033)	(0.033)	(0.051)	(0.052)
Stock Return	0.045***	0.045***	0.006	0.004
	(0.016)	(0.016)	(0.020)	(0.020)
Ind. and Year FEs	Yes	Yes	Yes	Yes
No. of Observations	3,716	3,716	2,018	2,018
No. of Actual Acq.	1,858	1,858	1,009	1,009
No. of Matching Acq.	1,858	1,858	1,009	1,009

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)-(3) report the results using *All Deals* of the *Acquirer-Target Sample*, and corresponding 3,922 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 (4)-(6) report the results using *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*, and corresponding 2,532 matching acquirer-target pairs. Columns (7)-(9) report the results using *Acquirers and Targets with Patents* of the *Acquirer-Target Sample*, and corresponding 1,212 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			Acquirers and Targets with Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Technological Proximity	0.375***			0.310***			0.378***		
	(0.069)			(0.068)			(0.069)		
Knowledge Base Overlap	0.181***			0.161***			0.151***		
	(0.028)			(0.027)			(0.027)		
Acquirer's Base Overlap Ratio		2.045*			1.911*			2.421*	
		(1.079)			(1.029)			(1.448)	
Target's Base Overlap Ratio		1.788***			1.602***			1.384***	
		(0.617)			(0.552)			(0.515)	
Acquirer's Cross-Cites Ratio			1.157**			1.109**			1.659***
			(0.466)			(0.438)			(0.637)
Target's Cross-Cites Ratio			1.555***			1.399***			1.240***
			(0.319)			(0.291)			(0.254)
Acquirer Patent Index	-0.010	-0.001	0.003	0.006	0.014*	0.018**	0.028***	0.040***	0.046***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.009)	(0.009)	(0.009)
Target Patent Index	-0.056***	-0.025***	-0.025***	-0.039***	-0.012	-0.012	-0.010	0.027**	0.025**
	(0.011)	(0.009)	(0.009)	(0.011)	(0.010)	(0.010)	(0.013)	(0.011)	(0.011)
Acquirer Self-Cites Ratio	0.113	0.086	-0.010	0.174	0.163	0.074	0.089	0.099	-0.071
	(0.132)	(0.136)	(0.140)	(0.134)	(0.140)	(0.145)	(0.173)	(0.187)	(0.193)
Target Self-Cites Ratio	0.081	0.020	0.005	0.179	0.126	0.112	0.267*	0.215	0.187
	(0.124)	(0.127)	(0.129)	(0.126)	(0.130)	(0.132)	(0.140)	(0.150)	(0.154)
Acquirer Total Assets	0.023***	0.023***	0.022***	0.014*	0.015*	0.014	-0.014	-0.012	-0.014
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)
Acquirer Sales Growth	0.112***	0.111***	0.111***	0.103***	0.100***	0.100***	0.111***	0.110***	0.107***
	(0.020)	(0.020)	(0.020)	(0.027)	(0.027)	(0.026)	(0.034)	(0.035)	(0.035)
Acquirer ROA	-0.090	-0.084	-0.095	-0.094	-0.085	-0.096	0.043	0.053	0.052
	(0.068)	(0.067)	(0.067)	(0.081)	(0.079)	(0.079)	(0.110)	(0.107)	(0.105)
Acquirer Leverage	-0.018	-0.014	-0.016	-0.048	-0.049	-0.054	-0.148*	-0.137*	-0.127
	(0.048)	(0.048)	(0.048)	(0.062)	(0.062)	(0.062)	(0.082)	(0.082)	(0.082)
Acquirer Cash	0.086	0.105*	0.108*	0.078	0.102	0.105	0.088	0.128	0.138
	(0.064)	(0.063)	(0.064)	(0.077)	(0.076)	(0.078)	(0.087)	(0.089)	(0.092)
Acquirer R&D	0.540***	0.523***	0.527***	0.420**	0.412**	0.408**	0.103	0.112	0.095
	(0.157)	(0.156)	(0.157)	(0.178)	(0.177)	(0.178)	(0.203)	(0.208)	(0.211)
Acquirer B/M	-0.078***	-0.081***	-0.086***	-0.104***	-0.107***	-0.113***	-0.061	-0.071*	-0.086**
	(0.021)	(0.021)	(0.021)	(0.029)	(0.029)	(0.029)	(0.040)	(0.042)	(0.042)

Acquirer Stock Return	0.038***	0.038***	0.040***	0.031**	0.030**	0.032**	0.012	0.004	0.007
	(0.010)	(0.010)	(0.010)	(0.013)	(0.012)	(0.013)	(0.015)	(0.014)	(0.015)
Target Total Assets	0.005	0.007	0.008*	0.005	0.008	0.009	-0.005	0.001	0.003
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.009)	(0.009)	(0.009)
Target Sales Growth	-0.000	-0.001	-0.002	-0.015	-0.017	-0.018	0.012	0.012	0.010
	(0.021)	(0.022)	(0.022)	(0.027)	(0.027)	(0.027)	(0.037)	(0.038)	(0.037)
Target ROA	0.025	0.035	0.024	0.114*	0.132**	0.118**	0.021	0.055	0.033
	(0.049)	(0.050)	(0.050)	(0.058)	(0.059)	(0.059)	(0.071)	(0.072)	(0.074)
Target Leverage	0.025	0.029	0.033	0.022	0.026	0.032	0.028	0.045	0.054
	(0.039)	(0.040)	(0.040)	(0.050)	(0.051)	(0.051)	(0.071)	(0.075)	(0.075)
Target Cash	-0.050	-0.034	-0.026	-0.011	0.008	0.017	0.004	0.037	0.056
	(0.040)	(0.040)	(0.040)	(0.045)	(0.046)	(0.045)	(0.059)	(0.061)	(0.060)
Target R&D	0.417***	0.426***	0.436***	0.523***	0.549***	0.553***	0.489***	0.571***	0.567***
	(0.101)	(0.102)	(0.102)	(0.112)	(0.113)	(0.113)	(0.148)	(0.150)	(0.152)
Target B/M	0.023	0.024*	0.021	0.023	0.025	0.020	0.003	0.006	-0.004
	(0.014)	(0.014)	(0.014)	(0.018)	(0.018)	(0.018)	(0.024)	(0.024)	(0.025)
Target Stock Return	-0.031***	-0.030***	-0.029***	-0.039***	-0.037***	-0.036***	-0.047***	-0.040**	-0.039**
	(0.011)	(0.010)	(0.010)	(0.013)	(0.013)	(0.013)	(0.018)	(0.018)	(0.018)
Diversifying	0.009	0.006	0.005	0.014	0.012	0.011	0.011	0.002	0.000
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.015)	(0.019)	(0.019)	(0.019)
Same State	0.011	0.011	0.015	0.008	0.010	0.015	0.010	0.011	0.018
	(0.015)	(0.015)	(0.015)	(0.019)	(0.019)	(0.019)	(0.026)	(0.025)	(0.025)
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	5,401	5,401	5,401	3,474	3,474	3,474	1,662	1,662	1,662
No. of Actual Deals	1,479	1,479	1,479	942	942	942	450	450	450
No. of Matching Deals	3,922	3,922	3,922	2,532	2,532	2,532	1,212	1,212	1,212

Panel B: Innovation Measures in Changes

	All Deals			Acquirers or Targets with Patents			Acquirers and Targets with Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Technological Proximity	0.011			0.008			0.020		
	(0.075)			(0.074)			(0.081)		
Δ Knowledge Base Overlap	0.187***			0.184***			0.210***		
	(0.037)			(0.036)			(0.038)		
Δ Acquirer's Base Overlap Ratio		1.222			1.396			1.577*	
		(0.903)			(0.875)			(0.898)	
Δ Target's Base Overlap Ratio		0.730**			0.689**			0.687**	
		(0.351)			(0.337)			(0.339)	
Δ Acquirer's Cross-Cites Ratio			0.939**			1.003**			1.202*
			(0.438)			(0.455)			(0.672)
Δ Target's Cross-Cites Ratio			1.219***			1.214***			1.235***
			(0.252)			(0.247)			(0.250)
Δ Acquirer Patent Index	0.034**	0.034**	0.033**	0.045***	0.044***	0.044***	0.046**	0.045**	0.044**
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.018)	(0.018)	(0.018)
Δ Target Patent Index	-0.044***	-0.044***	-0.048***	-0.046***	-0.046***	-0.051***	-0.056***	-0.054**	-0.061***
	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.022)	(0.021)	(0.021)
Δ Acquirer Self-Cites Ratio	0.317***	0.316***	0.308***	0.346***	0.344***	0.334***	0.155	0.143	0.109
	(0.109)	(0.110)	(0.109)	(0.113)	(0.114)	(0.114)	(0.197)	(0.202)	(0.200)
Δ Target Self-Cites Ratio	-0.010	-0.004	-0.021	0.033	0.041	0.021	0.110	0.122	0.089
	(0.130)	(0.131)	(0.130)	(0.137)	(0.139)	(0.137)	(0.175)	(0.179)	(0.174)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	5,401	5,401	5,401	3,474	3,474	3,474	1,662	1,662	1,662
No. of Actual Deals	1,479	1,479	1,479	942	942	942	450	450	450
No. of Matching Deals	3,922	3,922	3,922	2,532	2,532	2,532	1,212	1,212	1,212

Panel C: Acquirer is Predetermined

The sample of matching deals is formed only by pairing the actual acquirer with the closest match of the deal's actual target firm.

	All Deals			Acquirers or Targets with Patents			Acquirers and Targets with Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Technological Proximity	0.503***			0.442***			0.404***		
	(0.086)			(0.085)			(0.091)		
Knowledge Base Overlap	0.240***			0.227***			0.211***		
	(0.036)			(0.034)			(0.032)		
Acquirer's Base Overlap Ratio		10.464**			9.440**			6.980**	
		(4.113)			(3.753)			(3.047)	
Target's Base Overlap Ratio		1.318**			1.253**			1.228**	
		(0.672)			(0.631)			(0.594)	
Acquirer's Cross-Cites Ratio			12.025**			11.056**			9.114**
			(5.332)			(4.902)			(3.930)
Target's Cross-Cites Ratio			1.492***			1.396***			1.317***
			(0.457)			(0.426)			(0.394)
Acquirer Patent Index	-0.024***	-0.010***	-0.007**	-0.023***	-0.010***	-0.007*	-0.039***	-0.024***	-0.018**
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.008)
Target Patent Index	-0.071***	-0.033**	-0.029**	-0.056***	-0.018	-0.015	0.005	0.053***	0.053***
	(0.016)	(0.014)	(0.014)	(0.017)	(0.015)	(0.015)	(0.021)	(0.019)	(0.018)
Acquirer Self-Cites Ratio	0.041	0.035	-0.116	-0.003	0.025	-0.115	0.062	0.196	-0.063
	(0.066)	(0.059)	(0.074)	(0.071)	(0.067)	(0.083)	(0.152)	(0.155)	(0.169)
Target Self-Cites Ratio	0.105	0.039	-0.035	0.310	0.246	0.163	0.389	0.277	0.183
	(0.199)	(0.206)	(0.207)	(0.209)	(0.216)	(0.215)	(0.243)	(0.259)	(0.258)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	2,786	2,786	2,786	1,796	1,796	1,796	862	862	862
No. of Actual Deals	1,393	1,393	1,393	898	898	898	431	431	431
No. of Matching Deals	1,393	1,393	1,393	898	898	898	431	431	431

Panel D: Target Firm is Predetermined

The sample of matching deals is formed only by pairing the actual target firm with the closest match of the deal's actual acquirer.

	All Deals			Acquirers or Targets with Patents			Acquirers and Targets with Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Technological Proximity	0.325***			0.256**			0.384***		
	(0.109)			(0.103)			(0.105)		
Knowledge Base Overlap	0.140***			0.115**			0.118***		
	(0.048)			(0.047)			(0.045)		
Acquirer's Base Overlap Ratio		-0.042			0.028			0.540	
		(0.916)			(0.923)			(1.250)	
Target's Base Overlap Ratio		2.773***			2.370***			2.168***	
		(0.709)			(0.651)			(0.609)	
Acquirer's Cross-Cites Ratio			0.628			0.586			0.903
			(0.397)			(0.381)			(0.578)
Target's Cross-Cites Ratio			1.557***			1.301***			1.155***
			(0.431)			(0.384)			(0.345)
Acquirer Patent Index	0.002	0.008	0.014	0.028*	0.033**	0.039***	0.072***	0.085***	0.093***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)
Target Patent Index	-0.052***	-0.025*	-0.029**	-0.036**	-0.013	-0.017	-0.046**	-0.011	-0.017
	(0.016)	(0.014)	(0.014)	(0.018)	(0.015)	(0.016)	(0.023)	(0.020)	(0.021)
Acquirer Self-Cites Ratio	0.152	0.104	0.035	0.284	0.245	0.186	0.194	0.098	-0.026
	(0.257)	(0.261)	(0.262)	(0.272)	(0.276)	(0.278)	(0.316)	(0.336)	(0.349)
Target Self-Cites Ratio	0.057	-0.010	0.022	0.067	0.019	0.055	-0.027	-0.010	0.024
	(0.193)	(0.194)	(0.196)	(0.192)	(0.193)	(0.195)	(0.201)	(0.209)	(0.216)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	2,668	2,668	2,668	1,706	1,706	1,706	812	812	812
No. of Actual Deals	1,334	1,334	1,334	853	853	853	406	406	406
No. of Matching Deals	1,334	1,334	1,334	853	853	853	406	406	406

Table 5
Post-Acquisition Innovation Performance

The table reports estimates from OLS regressions using a panel dataset that has observations running from three years prior to bid announcement (*ayr-3*) to three years after the deal completion (*cyr+3*), for each actual and pseudo deal, respectively. The dependent variable is, in each year, the sum of the acquirer's innovation quantity/quality with that of the target firm. *Actual Deal$_i$* is an indicator variable equal to one for the actual acquirer-actual target firm pair, and zero otherwise. *After$_t$* is an indicator variable equal to one for the post-merger time period (from *cyr+1* to *cyr+3*), and zero otherwise. 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 actual deal, we create a single pseudo deal formed by pairing the closest match of the deal's actual acquirer with the closest match of the deal's actual target firm. The closest matching acquirer (target firm) is the firm that is in the same 2-digit-SIC industry and is the closest in sales. Measures of innovation are in natural logarithm. Definitions of the variables are provided in Appendix 1. All specifications include the deal fixed effects and the year 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 Quantity and Quality
Columns (1)-(3), (4)-(6), and (7)-(9) report regression results using *All Deals*, *Acquirers or Targets with Patents*, and *Acquirers and Targets with Patents*, respectively, of the *Acquirer-Target Sample* and corresponding pseudo acquirer-target pairs.

	All Deals			Acquirers or Targets with Patents			Acquirers and Targets with Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Citation Weighted Patents	Patent Index	Citation Index	Citation Weighted Patents	Patent Index	Citation Index	Citation Weighted Patents	Patent Index	Citation Index
Actual Deal × After	-0.050	-0.026	0.077**	-0.089	-0.043	0.135**	-0.235**	-0.141**	0.064
	(0.045)	(0.030)	(0.034)	(0.067)	(0.047)	(0.055)	(0.091)	(0.066)	(0.073)
Actual Deal	0.403***	0.268***	0.282***	0.949***	0.627***	0.622***	1.229***	0.837***	0.917***
	(0.061)	(0.043)	(0.049)	(0.095)	(0.069)	(0.079)	(0.122)	(0.091)	(0.104)
After	0.005	-0.001	-0.063**	0.032	0.010	-0.121**	0.082	0.026	-0.107
	(0.035)	(0.022)	(0.029)	(0.052)	(0.034)	(0.047)	(0.070)	(0.047)	(0.066)
Deal and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	9,340	9,340	9,340	5,121	5,121	5,121	3,131	3,131	3,131
No. of Actual Deals	638	638	638	351	351	351	214	214	214
No. of Matching Deals	638	638	638	351	351	351	214	214	214
Adjusted R^2	0.65	0.68	0.63	0.61	0.65	0.58	0.61	0.64	0.59

Panel B: Innovation Quantity Measured using Patent Award Dates
Columns (1)-(2), (3)-(4), and (5)-(6) report regression results using *All Deals*, *Acquirers or Targets with Patents*, and *Acquirers and Targets with Patents*, respectively, of the *Acquirer-Target Sample* and corresponding pseudo acquirer-target pairs.

	All Deals		Acquirers or Targets with Patents		Acquirers and Targets with Patents	
	(1)	(2)	(3)	(4)	(5)	(6)
	Citation Weighted Patents	Patent Index	Citation Weighted Patents	Patent Index	Citation Weighted Patents	Patent Index
Actual Deal × After	0.081*	0.043	0.158**	0.111**	0.041	0.069
	(0.042)	(0.029)	(0.066)	(0.046)	(0.084)	(0.063)
Actual Deal	0.333***	0.226***	0.798***	0.524***	1.151***	0.751***
	(0.058)	(0.042)	(0.091)	(0.068)	(0.118)	(0.089)
After	-0.078**	-0.038*	-0.166***	-0.099***	-0.128*	-0.089*
	(0.036)	(0.022)	(0.057)	(0.035)	(0.077)	(0.052)
Deal and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	9,340	9,340	5,121	5,121	3,131	3,131
No. of Actual Deals	638	638	351	351	214	214
No. of Matching Deals	638	638	351	351	214	214
Adjusted R^2	0.66	0.69	0.60	0.64	0.61	0.64

Table 6
Post-Acquisition Operating Performance

The table reports estimates from OLS regressions using a panel dataset that has observations running from three years prior to bid announcement (*ayr-3*) to three years after the deal completion (*cyr+3*), for each actual and pseudo deal, respectively. The dependent variable is, in each year, the combined performance of the acquirer-target firm pair. *Actual Deal*$_i$ is an indicator variable equal to one for the actual acquirer-actual target firm pair, and zero otherwise. *After*$_t$ is an indicator variable equal to one for the post-merger time period (from *cyr+1* to *cyr+3*), and zero otherwise. 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 actual deal, we create a single pseudo deal formed by pairing the closest match of the deal's actual acquirer with the closest match of the deal's actual target firm. The closest matching acquirer (target firm) is the firm that is in the same 2-digit-SIC industry and is the closest in sales. Columns (1)-(4), (5)-(8), and (9)-(12) report regression results using *All Deals*, *Acquirers or Targets with Patents*, and *Acquirers and Targets with Patents*, respectively, of the *Acquirer-Target Sample* and corresponding pseudo acquirer-target pairs. Definitions of the variables are provided in Appendix 1. All specifications include the deal fixed effects and the year 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.

	All Deals				Acquirers or Targets with Patents				Acquirers and Targets with Patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Sales Growth	ROA	R&D	CAPEX	Sales Growth	ROA	R&D	CAPEX	Sales Growth	ROA	R&D	CAPEX
Actual Deal × After	0.034**	0.004	-0.004***	-0.003	0.030*	0.001	-0.006***	-0.003	0.023	0.007	-0.009***	-0.002
	(0.015)	(0.005)	(0.002)	(0.002)	(0.017)	(0.006)	(0.002)	(0.002)	(0.022)	(0.008)	(0.003)	(0.002)
Actual Deal	0.023***	-0.001	0.016***	-0.002	0.029***	0.005	0.025***	-0.002	0.031**	-0.000	0.028***	-0.007***
	(0.009)	(0.003)	(0.002)	(0.002)	(0.011)	(0.005)	(0.003)	(0.002)	(0.014)	(0.006)	(0.004)	(0.002)
After	0.061***	-0.007**	0.004***	0.001	0.069***	-0.001	0.005***	0.003	0.084***	-0.004	0.006**	0.005**
	(0.013)	(0.004)	(0.001)	(0.002)	(0.017)	(0.005)	(0.002)	(0.002)	(0.021)	(0.007)	(0.003)	(0.002)
Deal and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	8,762	10,155	10,229	10,153	4,842	5,616	5,656	5,615	2,991	3,467	3,493	3,467
No. of Actual Deals	699	699	699	699	388	388	388	388	239	239	239	239
No. of Matching Deals	699	699	699	699	388	388	388	388	239	239	239	239
Adjusted R^2	0.10	0.48	0.55	0.49	0.10	0.51	0.55	0.41	0.09	0.52	0.54	0.37

Table 7
Acquisition Performance

The table reports estimates from cross-sectional OLS regressions of *Acquirer BHAR* and *Acquirer/Target/Deal CAR3* on innovation measures, the acquirer's and the target firm's pre-acquisition financial controls, and the deal characteristics listed in Appendix 1 (not reported). 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 acquirer 2-digit-SIC industry and 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: Acquirer's Long-Term Abnormal Stock Market Performance

Columns (1)-(3) report regression results using *All Deals* of the *Acquirer-Target Sample.* Columns (4)-(6) report the results using *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*. Columns (7)-(9) report the results using *Acquirers and Targets with Patents* of the *Acquirer-Target Sample*.

	All Deals			Acquirers or Targets with Patents			Acquirers and Targets with Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Acquirer BHAR	Acquirer BHAR	Acquirer BHAR	Acquirer BHAR	Acquirer BHAR	Acquirer BHAR	Acquirer BHAR	Acquirer BHAR	Acquirer BHAR
Technological Proximity	-0.018			-0.006			-0.001		
	(0.029)			(0.030)			(0.031)		
Knowledge Base Overlap	0.015**			0.017**			0.018**		
	(0.008)			(0.008)			(0.008)		
Acquirer's Base Overlap Ratio		0.606**			0.689**			0.579	
		(0.250)			(0.279)			(0.381)	
Target's Base Overlap Ratio		-0.008			-0.018			-0.013	
		(0.062)			(0.067)			(0.088)	
Acquirer's Cross-Cites Ratio			0.164*			0.190*			0.240**
			(0.085)			(0.102)			(0.112)
Target's Cross-Cites Ratio			-0.044			-0.040			-0.033
			(0.052)			(0.052)			(0.045)
Acquirer Patent Index	0.004	0.004	0.005**	-0.000	0.001	0.002	0.002	0.004	0.006
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.007)
Target Patent Index	0.004	0.003	0.005	0.002	0.003	0.006	-0.000	0.002	0.004
	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)
Acquirer Self-Cites Ratio	0.039	0.035	0.033	0.004	0.001	0.000	-0.115	-0.119	-0.122
	(0.041)	(0.042)	(0.041)	(0.046)	(0.048)	(0.046)	(0.083)	(0.085)	(0.081)
Target Self-Cites Ratio	0.079	0.075	0.073	0.053	0.045	0.043	-0.007	-0.010	-0.012
	(0.055)	(0.055)	(0.054)	(0.059)	(0.060)	(0.059)	(0.075)	(0.073)	(0.070)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	1,013	1,013	1,013	505	505	505	305	305	305
Adjusted R^2	0.00	0.19	0.19	0.19	0.20	0.19	0.19	0.20	0.19

Panel B: Technological Proximity and Knowledge Base Overlap

The dependent variable is *Acquirer/Target/Deal CAR3*. Columns (1)-(3) report regression results using *All Deals* of the *Acquirer-Target Sample.* Columns (4)-(6) report the results using *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*. Columns (7)-(9) report the results using *Acquirers and Targets with Patents* of the *Acquirer-Target Sample*.

	All Deals			Acquirers or Targets with Patents			Acquirers and Targets with Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Acquirer CAR3	Target CAR3	Deal CAR3	Acquirer CAR3	Target CAR3	Deal CAR3	Acquirer CAR3	Target CAR3	Deal CAR3
Technological Proximity	0.025	0.048	0.005	0.033	0.096	0.016	0.017	0.027	-0.001
	(0.026)	(0.074)	(0.028)	(0.027)	(0.082)	(0.029)	(0.029)	(0.085)	(0.029)
Knowledge Base Overlap	-0.004	-0.011	-0.001	0.002	-0.007	0.003	0.008	-0.025	0.004
	(0.007)	(0.024)	(0.007)	(0.007)	(0.026)	(0.008)	(0.008)	(0.026)	(0.008)
Acquirer Patent Index	0.001	0.006	0.001	0.004	0.010	0.005	0.001	-0.003	0.000
	(0.002)	(0.008)	(0.003)	(0.003)	(0.011)	(0.003)	(0.006)	(0.015)	(0.005)
Target Patent Index	-0.005	-0.018	-0.008*	-0.011**	-0.026	-0.011*	-0.017***	-0.025	-0.018**
	(0.004)	(0.013)	(0.005)	(0.005)	(0.018)	(0.006)	(0.006)	(0.025)	(0.008)
Acquirer Self-Cites Ratio	-0.038	-0.181	-0.084	-0.029	-0.119	-0.064	-0.204*	0.099	-0.143
	(0.048)	(0.133)	(0.051)	(0.056)	(0.145)	(0.056)	(0.117)	(0.268)	(0.123)
Target Self-Cites Ratio	0.018	0.064	0.035	0.018	-0.021	0.025	0.071	-0.040	0.077
	(0.049)	(0.155)	(0.059)	(0.056)	(0.169)	(0.059)	(0.064)	(0.208)	(0.066)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	1,013	1,012	1,012	506	505	505	305	305	305
Adjusted R^2	0.07	0.13	0.10	0.14	0.16	0.09	0.08	0.18	0.06

Panel C: Acquirer's/Target's Base Overlap Ratios

The dependent variable is *Acquirer/Target/Deal CAR3*. Columns (1)-(3) report regression results using *All Deals* of the *Acquirer-Target Sample.* Columns (4)-(6) report the results using *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*. Columns (7)-(9) report the results using *Acquirers and Targets with Patents* of the *Acquirer-Target Sample*.

	All Deals			Acquirers or Targets with Patents			Acquirers and Targets with Patents		
	(1) Acquirer CAR3	(2) Target CAR3	(3) Deal CAR3	(4) Acquirer CAR3	(5) Target CAR3	(6) Deal CAR3	(7) Acquirer CAR3	(8) Target CAR3	(9) Deal CAR3
Acquirer's Base Overlap Ratio	0.329	-0.590	0.355	0.320	-0.453	0.395	0.514**	-0.115	0.507**
	(0.261)	(0.411)	(0.250)	(0.208)	(0.449)	(0.241)	(0.250)	(0.524)	(0.243)
Target's Base Overlap Ratio	-0.046	0.134	-0.037	0.008	0.173	0.005	-0.034	-0.137	-0.057
	(0.065)	(0.255)	(0.064)	(0.068)	(0.243)	(0.066)	(0.082)	(0.218)	(0.067)
Acquirer Patent Index	0.001	0.006	0.001	0.004	0.009	0.005	0.003	-0.003	0.001
	(0.002)	(0.008)	(0.003)	(0.003)	(0.011)	(0.004)	(0.005)	(0.015)	(0.005)
Target Patent Index	-0.004	-0.014	-0.009**	-0.008*	-0.017	-0.010**	-0.015***	-0.027	-0.018***
	(0.004)	(0.012)	(0.004)	(0.004)	(0.016)	(0.005)	(0.005)	(0.022)	(0.007)
Acquirer Self-Cites Ratio	-0.036	-0.172	-0.083	-0.027	-0.110	-0.063	-0.208*	0.093	-0.149
	(0.048)	(0.133)	(0.052)	(0.056)	(0.143)	(0.057)	(0.118)	(0.266)	(0.125)
Target Self-Cites Ratio	0.013	0.062	0.033	0.012	-0.029	0.020	0.064	-0.045	0.073
	(0.050)	(0.154)	(0.059)	(0.057)	(0.169)	(0.060)	(0.064)	(0.206)	(0.067)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	1,013	1,012	1,012	506	505	505	305	305	305
Adjusted R^2	0.08	0.14	0.11	0.14	0.15	0.10	0.10	0.18	0.09

Panel D: Acquirer's/Target's Cross-Cites Ratios

The dependent variable is *Acquirer/Target/Deal CAR3*. Columns (1)-(3) report regression results using *All Deals* of the *Acquirer-Target Sample.* Columns (4)-(6) report the results using *Acquirers or Targets with Patents* of the *Acquirer-Target Sample*. Columns (7)-(9) report the results using *Acquirers and Targets with Patents* of the *Acquirer-Target Sample*.

	All Deals			Acquirers or Targets with Patents			Acquirers and Targets with Patents		
	(1) Acquirer CAR3	(2) Target CAR3	(3) Deal CAR3	(4) Acquirer CAR3	(5) Target CAR3	(6) Deal CAR3	(7) Acquirer CAR3	(8) Target CAR3	(9) Deal CAR3
Acquirer's Cross-Cites Ratio	-0.035	-0.016	-0.007	0.033	0.087	0.065	0.026	0.286	0.130
	(0.075)	(0.180)	(0.065)	(0.070)	(0.199)	(0.067)	(0.125)	(0.255)	(0.103)
Target's Cross-Cites Ratio	-0.004	0.087	0.001	0.001	0.062	0.004	-0.005	-0.052	-0.017
	(0.037)	(0.160)	(0.040)	(0.047)	(0.177)	(0.049)	(0.048)	(0.159)	(0.043)
Acquirer Patent Index	0.001	0.006	0.001	0.004	0.011	0.006	0.003	-0.004	0.002
	(0.002)	(0.008)	(0.002)	(0.003)	(0.011)	(0.004)	(0.005)	(0.015)	(0.005)
Target Patent Index	-0.003	-0.016	-0.008*	-0.007	-0.019	-0.009*	-0.014**	-0.026	-0.016**
	(0.004)	(0.012)	(0.004)	(0.004)	(0.016)	(0.005)	(0.005)	(0.023)	(0.007)
Acquirer Self-Cites Ratio	-0.035	-0.182	-0.083	-0.029	-0.122	-0.065	-0.203*	0.092	-0.147
	(0.048)	(0.129)	(0.051)	(0.056)	(0.141)	(0.057)	(0.120)	(0.265)	(0.126)
Target Self-Cites Ratio	0.016	0.063	0.035	0.013	-0.030	0.021	0.070	-0.063	0.073
	(0.050)	(0.153)	(0.060)	(0.057)	(0.168)	(0.060)	(0.065)	(0.206)	(0.067)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	1,013	1,012	1,012	506	505	505	305	305	305
Adjusted R^2	0.07	0.13	0.10	0.13	0.15	0.09	0.07	0.18	0.07

Table 8
Deal Completion

The table reports average marginal effects from probit models. The dependent variable, *Completion*, is equal to one for completed acquisitions, and zero for withdrawn acquisitions. *All Deals* consists of 1,469 acquirer-target pairs from completed acquisitions and 408 acquirer-target pairs from withdrawn acquisitions announced during the period January 1, 1984–December 31, 2006 conditional on having the full set of control variables. *Acquirers or Targets with Patents* consists of 927 acquirer-target pairs from completed acquisitions and 232 acquirer-target pairs from withdrawn acquisitions, where either the actual acquirer or the actual target firm or both firms were awarded at least one patent in the five-year period prior to the bid announcement conditional on having the full set of control variables. *Acquirers and Targets with Patents* consists of 431 acquirer-target pairs from completed acquisitions and 105 acquirer-target pairs from withdrawn acquisitions, where both the actual acquirer and the actual target firm were awarded at least one patent in the five-year period prior to the bid announcement 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 2-digit-SIC industry and 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

The panel reports estimates from specifications that use the measures of the overlap between the acquirer's and the target firm's innovation prior to the bid announcement as key explanatory variables.

	All Deals			Acquirers or Targets with Patents			Acquirers and Targets with Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Technological Proximity	-0.063			-0.088			-0.087		
	(0.085)			(0.081)			(0.085)		
Knowledge Base Overlap	0.018			0.013			0.023		
	(0.026)			(0.025)			(0.025)		
Acquirer's Base Overlap Ratio		0.742			0.623			0.670	
		(0.734)			(0.647)			(0.650)	
Target's Base Overlap Ratio		-0.139			-0.125			-0.152	
		(0.259)			(0.235)			(0.267)	
Acquirer's Cross-Cites Ratio			0.823*			0.743*			0.780
			(0.441)			(0.428)			(0.480)
Target's Cross-Cites Ratio			-0.254			-0.223			-0.168
			(0.157)			(0.147)			(0.152)
Acquirer Patent Index	-0.014	-0.013	-0.013	-0.007	-0.008	-0.008	-0.002	0.001	-0.001
	(0.010)	(0.009)	(0.009)	(0.011)	(0.010)	(0.010)	(0.017)	(0.016)	(0.016)
Target Patent Index	0.008	0.003	0.005	0.015	0.006	0.008	-0.008	-0.016	-0.015
	(0.015)	(0.014)	(0.013)	(0.015)	(0.014)	(0.014)	(0.021)	(0.020)	(0.020)
Acquirer Self-Cites Ratio	0.291	0.283	0.298	0.283	0.279	0.295	0.711**	0.706**	0.734**
	(0.225)	(0.224)	(0.227)	(0.216)	(0.216)	(0.220)	(0.341)	(0.342)	(0.346)
Target Self-Cites Ratio	-0.323**	-0.312*	-0.330**	-0.305**	-0.290*	-0.306**	-0.311	-0.297	-0.325*
	(0.164)	(0.164)	(0.163)	(0.150)	(0.150)	(0.149)	(0.197)	(0.193)	(0.194)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	1,877	1,877	1,877	1,159	1,159	1,159	536	536	536
No. of Completed Deals	1,469	1,469	1,469	927	927	927	431	431	431
No. of Withdrawn Deals	408	408	408	232	232	232	105	105	105

Panel B: Innovation Measures in Changes

The panel reports estimates from specifications that use the changes in innovation overlaps between the acquirer and the target firm prior the bid announcement as key explanatory variables.

	All Deals			Acquirers or Targets with Patents			Acquirers and Targets with Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Technological Proximity	-0.051			-0.047			-0.050		
	(0.072)			(0.069)			(0.072)		
Δ Knowledge Base Overlap	0.022			0.026			0.024		
	(0.045)			(0.042)			(0.039)		
Δ Acquirer's Base Overlap Ratio		-0.013			0.065			0.209	
		(0.766)			(0.687)			(0.677)	
Δ Target's Base Overlap Ratio		-0.172			-0.120			-0.237	
		(0.310)			(0.279)			(0.246)	
Δ Acquirer's Cross-Cites Ratio			0.694			0.805*			1.173**
			(0.482)			(0.462)			(0.528)
Δ Target's Cross-Cites Ratio			0.132			0.200			0.190
			(0.235)			(0.227)			(0.212)
Δ Acquirer Patent Index	0.040*	0.039*	0.039*	0.040*	0.038*	0.040*	0.040	0.036	0.040
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.026)	(0.025)	(0.025)
Δ Target Patent Index	-0.022	-0.024	-0.029	-0.009	-0.011	-0.017	-0.012	-0.014	-0.025
	(0.027)	(0.026)	(0.027)	(0.025)	(0.025)	(0.025)	(0.033)	(0.032)	(0.032)
Δ Acquirer Self-Cites Ratio	0.942***	0.960***	0.948***	0.809***	0.826***	0.812***	0.885*	0.893*	0.798*
	(0.296)	(0.297)	(0.300)	(0.270)	(0.272)	(0.275)	(0.486)	(0.489)	(0.485)
Δ Target Self-Cites Ratio	-0.270	-0.268	-0.268	-0.275	-0.273	-0.272	-0.051	-0.050	-0.033
	(0.211)	(0.211)	(0.212)	(0.189)	(0.189)	(0.190)	(0.208)	(0.208)	(0.210)
Acquirer, Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	1,877	1,877	1,877	1,159	1,159	1,159	536	536	536
No. of Completed Deals	1,469	1,469	1,469	927	927	927	431	431	431
No. of Withdrawn Deals	408	408	408	232	232	232	105	105	105