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Does Access to Patent Information Help Technological Acquisitions? Evidence from Patent Library Openings

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ABSTRACT

Technology acquirers face significant information asymmetry when identifying appropriate acquisition targets. We exploit plausibly exogenous variation in the costs of gathering technological information as the result of patent library openings. We find that, after local patent libraries open, firms become more active in technological acquisitions, acquirers prefer targets that are geographically or technologically close to a lesser extent, completion rates for technology M&A increase, and performance improves. Post-merger

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innovation output is enhanced through more collaboration between inventors of acquirers and their targets. Overall, our study sheds new light on the importance of information-gathering costs in corporate takeovers and on the search for human capital synergies.

JEL codes: G34, O3, O34, O38

Keywords: mergers and acquisitions; patent and trademark depository library; patent information; information-gathering costs

1. Introduction

The acquisition of innovation motivates many merger and acquisition (M&A) transactions (Bena and Li [2014], Frésard, Hoberg, and Phillips [2020]). Such acquisition enables firms to obtain external technologies, to complement internal R&D projects, and to speed up innovation processes (Higgins and Rodriguez [2006], Phillips and Zhdanov [2013]).[1] Nevertheless, due to information asymmetry, identifying appropriate targets and evaluating potential gains in synergy remain significant challenges for technology acquirers, particularly in acquisitions involving technologies outside their core areas of expertise (Bena and Li [2014], Seru [2014]).[2] Information frictions can ultimately divert acquirers away from identifying the best matches and can unravel promising deals (Moeller, Schlingemann, and Stulz [2005, 2007], McNichols and Stubben [2015], Moeller, Schlingemann, and Stulz [2005]).

In this study, we investigate the effects of information frictions on takeover activities and performance by exploiting plausibly exogenous variation in the access to patent information, which is caused by the openings of the Patent and Trademark Depository Library (PTDL) of the United States

[1] Although firms can acquire patents and technologies via licensing, there are several advantages associated with technological M&As. First, M&As allow acquirers to gain access to target firms' R&D pipelines in addition to existing patents (e.g., Beneish et al. [2022]); this helps acquirers replenish their research pipelines (e.g., Higgins and Rodriguez [2006]), which are particularly valuable to firms that have experienced declines in internal R&D productivity. Second, technological M&As make it easier for acquirers to reach the human capital pools of target firms (e.g., Chen, Gao, and Ma [2021]), which is a key driver of innovation. Third, M&As allow acquirers to gain tacit knowledge that is embedded in human capital, which complements the codified technical information disclosed in patent documents.

[2] Notably, information asymmetries between acquirers and targets raise significant concerns about adverse selection and inefficient transactions (Bhattacharya and Ritter [1983], Povel and Singh [2006]). This is because target firms are typically more informed about their own and their competitors' technologies, whereas acquirers often have difficulty distinguishing the real values of assets that are to be acquired (Rhodes-Kropf and Robinson [2008], Officer, Poulsen, and Stegemoller [2009]). However, there are several reasons why targets may be unable to help mitigate information asymmetries; these include the costs of revealing proprietary information (Frésard, Hoberg, and Phillips [2020]) and strategic motives (e.g., requesting a higher bid).

Patent and Trademark Office (USPTO).[3] Given the information-sensitive nature of target selection, we posit that the opening of a patent library enhances local acquirers' awareness and ability to access the technological information of potential targets nationwide, thereby facilitating acquirers' assessments of the integration value of the targets' intellectual properties (Landsman, Liss, and Sievers [2021], Beneish et al. [2022]).[4] This in turn promotes technological acquisition activities among local firms.

To test the conjecture, we employ a sample of publicly traded innovative firms during 1985–1999, and find a significant increase (about 6.4%) in acquisition activities by these firms after a patent library has opened in the county in which the acquiring firm is located. This is consistent with the notion that patent library openings reduce firms' costs of accessing patent documents, hence mitigating information frictions. We perform falsification tests and a battery of robustness checks by using alternative variable definitions, alternative model specifications to address the potential bias in log-linear transformations (e.g., Poisson regressions), alternative samples, and alternative difference-in-differences (DiD) estimates. Our main result remains.

We next examine how the openings of patent libraries alter the pairing choice between acquirers and targets. M&As often create synergies and value by combining complementary resources, such as patents, human capital, and tangible assets. Information frictions in M&As force acquirers to select geographically and technologically proximate targets because the information costs of assessing such targets are lower (Petersen and Rajan [2002], Bena and Li [2014], Kantor and Whalley [2019]). Such pairing tendencies constrain acquirers' searches and prevent them from finding the first best choice of targets, leading to economic losses for both acquirers and targets. Access to patent libraries allows acquirers to broaden their search for potential targets without being limited to candidates that are geographically or technologically close to them. We find that acquirers' reliance on geographical and technological proximity in technological acquisition is attenuated following the opening of a local patent library.

Moreover, we explore how opening patent libraries affects the completion rate and performance of M&A deals. As discussed above, better matches between acquirers and targets result in better technological complementarities and in greater synergies, thereby creating greater economic

[3] We use the terms "USPTO Patent and Trademark Depository Library," "PTDL," "patent library," and "patent depository library" interchangeably. We discuss more institutional details about the USPTO's PTDL program in section 2.

[4] To provide a more concrete sense of the patent information used by acquirers searching for targets for technological complementarity and business synergy, we present an anecdote in appendix A. Prior to acquiring Tandem Computers in 1997, Compaq discussed its technological challenge regarding computer systems with respect to client-server architecture, whereas Tandem had a patent approved in 1994 for improvements to client-server communicating processes in a distributed computer system.

value. In addition, a reduction in information asymmetry mitigates adverse selection, helping the successful completion of technological acquisitions. We find that the odds of deal completion rise by 39.2% after patent libraries open. We also find that the opening of a patent library is associated with a 1.4% higher seven-day cumulative abnormal return (CAR) around acquisition announcements and a 10.6% larger post-merger five-year buy-and-hold return of combined firms, suggesting that acquirers' pre-merger access to patent information leads to value-enhancing M&A transactions. Furthermore, we show that M&A deals completed by acquirers with access to local patent libraries are associated with a greater extent of collaboration between acquiring and target inventors after the merger, thereby enhancing firm innovation output. This evidence supports the efficiency-gain explanation but is inconsistent with the view of Cunningham, Ederer and Ma [2021] that acquiring innovation is solely for preempting future competition.

Finally, through textual analysis, we find that, following patent library openings, there is a significant increase in the overlap between acquirers' technological keywords in their SEC filings and the keywords in patent abstracts belonging to firms that they later acquire. This evidence sheds light on how the disclosed patent information facilitates M&A deals via enhancing technological complementarity between acquirers and targets.

Our paper contributes to a number of strands of existing literature. First, we add to the research examining the effect of information friction on corporate decisions. Prior literature shows that reducing information friction (e.g., providing information proximity) leads to better corporate outcomes (e.g., Jansen [2020], Baik, Berfeld and Verdi [2023], Ortiz et al. [2023]). Our paper extends this strand of literature to the takeover market with a focus on technological M&As. We show that when technological information becomes more accessible, firms adapt to more active M&A activities with better economic outcomes, as measured by a higher deal-completion rate, better post-merger stock and accounting performance, and greater innovation output. Our study thus shares a similar spirit with the literature on the impact of increased accessibility of existing information due to travel frictions on plant-level investment (Giroud [2013]), VCs' monitoring of portfolio firms (Bernstein, Giroud, and Townsend [2016]), knowledge spillovers (Bahar et al. [2023]), and analyst information production (Chen et al. [2022]).

Second, by documenting the importance of proximity to patent information pertaining to technological M&As, we add to the prior literature on a variety of factors driving technology firms' acquisition decisions, such as creating synergistic gains (Hoberg and Phillips [2010], Bena and Li [2014]), obtaining external technologies (Higgins and Rodriguez [2006], Phillips and Zhdanov [2013]), maintaining a competitive edge in the technological space (Cunningham, Ederer, and Ma [2021]), gaining human capital (Chen, Gao, and Ma [2021], Dey and White [2021]), and exploiting work-in-progress intellectual properties (Landsman, Liss, and Sievers

[2021], Beneish et al. [2022]). Our study indicates that scientific knowledge in patent documents is important for the success of technological acquisitions.

Third, we contribute to the literature on the interplay of disclosures and corporate activities. Our study is broadly related to the literature on how innovation disclosure can benefit the disclosing firms and the overall market (Merkley [2014], Dyer et al. [2023]), at the cost of facilitating rivals' exploitation of proprietary information (Kim and Valentine [2021], Kankanhalli, Kwan and Merkley [2022]). We also recognize the rich literature on how conventional disclosure mechanisms can shape innovation incentives (Zhong [2018]) and innovation outcomes (Kim and Valentine [2023], Tseng and Zhong [2024]). Instead of studying the decision and effect of self-disclosure corporate information as in prior literature, we focus on the effect of acquirers' increased access to technology information that has already been disclosed. We shed new light on how the reduction of information-gathering costs affects the intensity and quality of M&A transactions, which typically suffer from adverse selection concerns caused by information asymmetry.

The rest of the paper is organized as follows. Section 2 describes the background of the PTDL system. We discuss data and sample construction in section 3 and report the empirical results in section 4. Section 5 concludes.

2. *The Patent and Trademark Depository Library System*

Prior to 1870, patent documents in the United States were located only at the USPTO in Washington, DC. To publicly disseminate patent information to enhance information diffusion, in the early 1870s the USPTO started distributing copies of patent documents across the United States by establishing a nationwide PTDL system. The PTDL offers public access to all resources necessary to conduct a full search of patents and trademarks, increasing the awareness of the use of intellectual property systems. A total of 10 patent depository libraries were first established during 1870–1879 and included the New York State Library, the Boston Public Library, the Detroit Public Library, and the St. Louis Public Library. By the end of 1975, 20 libraries had been opened, mainly in the New England area and east of the Mississippi (see appendix B for a list of patent libraries with their opening years).

As demand for access to patent documents has increased since 1975, the USPTO has aggressively expanded the PTDL program to increase the number of patent libraries by at least three per year and to ensure that there is at least one patent library in each state. Since 1975, any existing library facilities that satisfy a set of requirements can apply to become a patent library. The requirements include: (1) having the physical capacity to store and make available all U.S. utility patents issued in the past 20 years prior to the library opening; (2) facilitating free public access to all depository materials; (3) protecting the integrity of the U.S. patent

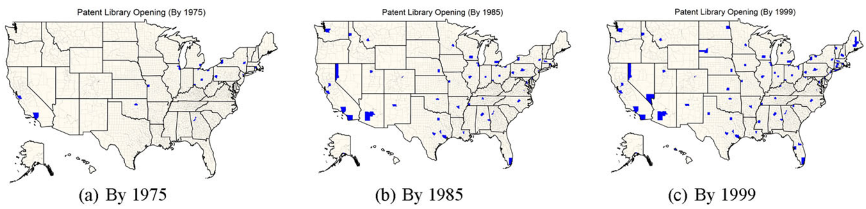

Fig. 1.—Visual Map of Patent Libraries in the United States. This figure provides visual maps of counties with patent libraries in the United States over time. The figure consists of three snapshots of the year 1975, 1985, and 1999, where the blue-colored areas denote the counties with patent libraries.

collection and thereby guaranteeing the public availability of information on individual patents; (4) sending staff members to the annual PTDL training seminar in Washington, DC, to ensure sufficient training so that they can assist the public in the efficient use of the patent collection and associated tools. In figure 1, we provide maps of patent library locations in the United States over time. The figure consists of snapshots of patent library locations in the years 1975, 1985, and 1999; blue-colored areas denote counties where patent libraries were opened.

Furman, Nagler, and Watzinger [2021] argue that a library's decision to join the patent library system is initiated by the library itself rather than solicited by the USPTO. Although reasons for joining may reflect local demand for patent information, other factors driving the decision to become a PTDL are more idiosyncratic and less predictable. These reasons include the perceived attractiveness of annual patent librarian training in Washington, DC, and the professional and personal benefits of joining the PTDL librarian community.[5] In addition, the introduction of microfilm in the 1970s minimized the requirement of library capacity as a concern and more libraries were eligible to join the patent library system. Therefore, openings of patent libraries were unlikely to be correlated with local economic conditions, M&A activities, or innovation activities. For example, in 1989 and 1991 patent libraries opened in Honolulu, Hawaii, and Big Rapids, Michigan, respectively, several years before one opened in San Francisco, California, a more populated and more technology-demanding city, in 1994.

To formally check whether the opening of a local patent library is indeed unrelated to local economic characteristics, we follow the method in Acharya, Baghai, and Subramanian [2014] to estimate a Cox proportional hazard model, which examines whether any county-level characteristics could predict the opening of a patent library in that county. Detailed description of the model and the results of hazard ratios are reported in

[5] Both the professional training lessons and personal reflections are well-publicized in the Patent and Trademark Resource Center Association newsletters. The newsletter highlighted that "the real benefits of the event were the opportunity for attendees to network with and learn from other inventors." See http://ptrca.org/newsletters.

online appendix table IA1. A hazard ratio greater than one indicates that an increase in the explanatory variable leads to a faster opening of a patent library in a county. As shown in columns (1) and (2), the results are qualitatively similar both with and without the presence of a patent library in the same state (*Same State Pat Library*). The coefficient estimates on *Income Per Capita*, Δ *Unemployment Rate (%)*, Δ *# of Establishments (%)* are all statistically insignificant, suggesting that county-level economic conditions cannot predict the timing of patent library openings. Most importantly, the coefficient estimates on *Ln(1+# of Patents)*, *Ln(1+# of M&A Deals as Acquirers)* and *Ln(1+# of M&A Deals as Targets)* are all statistically insignificant, implying no evidence of reverse causality, that is, there is no indication of local demand drives the opening of patent libraries. As expected, the coefficient estimate on *Same State Pat Library* is significantly less than one, suggesting a lower chance of having a patent library in a county when there is already a patent library in that state. Overall, county-level economic conditions, M&A activities, and innovation activities are unable to determine the opening of a local patent library.

3. Data and Sample Construction

Our M&A data are obtained from the Thomson Financial Securities Data Company (SDC). We start our sample of M&A deals with 1985 when SDC began providing high-quality M&A data. We end our sample with 1999 for two reasons. First, we want to focus our analysis on the period before the Internet boom, as Furman, Nagler, and Watzinger [2021] have shown that the effect of patent libraries on local innovation has diminished during the Internet age. Second, to alleviate concerns that our results may be driven by the American Inventor Protection Act (AIPA), which took effect in November 2000, we avoid including in our sample period those years that could be affected by the AIPA.[6]

In accordance with prior literature, we apply the following filters as we build our sample of M&A deals. We start with deals in SDC completed from 1985 to 1999 that are coded as mergers, as acquisitions of majority interest, or as acquisitions of assets. We also require the acquirers to own less than 50% of the target prior to the bid, to seek to own at least 50%, and to finally own at least 90% of the target after deal completion. Following the convention in prior literature (Nguyen and Phan [2017], Bereskin et al. [2018], and Bonaime, Gulen, and Ion [2018]) and to eliminate the many small

[6] One of the significant changes brought about by the AIPA, among many others, is that it requires patent applications filed at the USPTO on or after November 29, 2000, to be published by the USPTO within 18 months of the first filing, regardless of whether the application is eventually granted. Prior to the passage of the AIPA, patent documents became publicly available after they were granted. Before the AIPA, the average time from a patent's filing date to its grant date was approximately 36 months before the AIPA (Kim and Valentine [2021]). Effectively, the AIPA has accelerated the overall patent disclosure process.

TABLE 1
M&A Deals Distribution

Year	(1) Number of M&A Deal All Public Acquirers	(2) Number of M&A Deal Public Innovative Acquirers and Innovative Targets
1985	136	57
1986	117	53
1987	115	55
1988	156	80
1989	272	111
1990	257	105
1991	294	105
1992	396	131
1993	609	180
1994	705	210
1995	850	259
1996	1,017	338
1997	1,324	362
1998	1,327	417
1999	1,169	450
Total	8,744	2,913

This table reports the number of completed mergers and acquisition deals by year during 1985–1999. In column (1), we include all deals with acquirers being publicly traded firms. In column (2), we restrict to deals with publicly traded and innovative acquirers (firms that have been awarded at least one patent during the past five years) and targets from innovative industries (three-digit SIC coded industries where at least one firm was awarded a patent in the past five years).

and economically insignificant deals in the sample (Bena and Li [2014]), we further restrict the sample to deals with transaction values of at least $1M and to those where acquirers have at least $1M of total assets.[7] Finally, we require acquirers to be publicly traded nonfinancial firms whose accounting and stock return information are available from the Compustat and CRSP databases, respectively. Applying these filters results in a total of 8,744 M&A deals. Table 1, column (1), depicts the distribution by year of our sample deals from 1985 to 1999.

Arguably, the expansion of patent libraries serves as a shock to the cost of gathering patent information only for local innovative firms possessing knowledge and skills for evaluating technology information in patent documents that is adequate to identify appropriate targets. To ensure the sample is relevant to our analysis of technological acquisitions, we follow Bena and Li [2014] and restrict the sample to acquirers that are innovative (i.e., firms that were granted at least one patent in the previous five years). We also focus on innovative targets because patent libraries are by definition irrelevant to noninnovative target firms with no patent. Because about 77% of the M&A deals in our sample involve private targets, restricting the sample to public innovative targets therefore results in a much smaller

[7] The results are robust as we restrict the sample to deals with at least $5M or $10M in transaction value.

sample, which could possibly undermine true technological acquisitions. To circumvent this issue, we focus on target firms from an innovative industry—those three-digit SIC-coded industries in which at least one firm has been awarded a patent in the past five years.[8] We obtain patent data from the USPTO PatentsView, and firm identifiers that each patent belongs to from Noah Stoffman's Web site (https://www.stoffprof.com/). Restricting the sample to innovative acquirers and targets from innovative industries yields a total of 2,913 M&A deals. Table 1, column (2), shows the distribution of the sample by year.

We obtain the lists of patent depository libraries from Furman, Nagler and Watzinger [2021], Jenda [2005], and Martens [2023], which include the name, location (i.e., state, county, city), and opening date of each patent library. Appendix B provides a list of 84 patent library openings from 1870 to 1999. During our sample period of 1985–1999, libraries in 32 counties joined the patent library system; this represents the wave of expansions in the USPTO patent library system.

We supplement a host of firm-level and county-level data for acquirers from a variety of sources. Firms' financial accounting information is from Compustat, and stock returns are from CRSP.[9] County-level population data and personal income data are obtained from the National Cancer Institute and the Bureau of Economic Analysis, respectively.

Our baseline sample consists of all publicly traded innovative firms in Compustat from 1985 to 1999. Because we focus on technology acquisitions, we limit the sample to innovative firms that were granted at least one patent in the previous five years. We report summary statistics of the key variables of our sample in table 2. About 14.7% of firms engaged in M&A deals as acquirers in a year; this is comparable to the number reported in the previous literature, such as 14% of "unconditional probability of announcing a merger" in Bonaime, Gulen, and Ion [2018]. On average, a firm completes approximately 0.2 deals as an acquirer in a year. About 43.4% of our sample firms are located in counties with patent libraries. An average firm in our sample has $1.3 billion in assets and has been public for about 20 years. The mean values of R&D expenses over assets (7.4%), return on assets (6.5%), leverage (21.1%), cash-to-asset ratio (17.1%), market-to-book

[8] Saidi and Žaldokas [2020] argue that using industry-level patents to proxy for innovativeness can capture both the firms that filed patents in past years and the firms that did not file patents but that might do so later (suggestive of the firms' true innovation capability and potential).

[9] To merge the SDC data with that of Compustat and CRSP, we first use the mapping file in Ewens, Peters, and Wang [2024] to match each SDC deal number with acquirer (or target) GVKEY. For the rest that could not be found in the mapping file of Ewens et al. [2024], we follow Malmendier, Moretti, and Peters [2018] to link CUSIP in SDC with NCUSIP in CRSP to assign acquirer (or target) PERMCO for each SDC deal. We then obtain the acquirer (or target) GVKEY based on its PERMCO. Finally, to ensure the quality of our matching, we manually verify each matched record by cross-checking the names of acquirers (or targets) from SDC and their names in Compustat and CRSP.

TABLE 2
Summary Statistics

	N	Mean	Median	SD
Acquirer	15,718	0.147	0.000	0.354
# of M&A Deals	15,718	0.185	0.000	0.515
Pat Library	15,718	0.434	0.000	0.496
Ln(Age)	15,718	2.728	2.708	0.747
Ln(Total Asset)	15,718	4.888	4.661	2.098
RD/Asset	15,718	0.074	0.031	0.119
ROA	15,718	0.065	0.121	0.218
Leverage	15,718	0.211	0.186	0.184
Cash/Asset	15,718	0.171	0.080	0.210
Market-to-Book	15,718	2.835	1.801	4.456
Sales Growth Rate	15,718	0.225	0.088	0.737
NWC/Asset	15,718	0.233	0.227	0.203
Return	15,718	0.008	0.047	0.501
Ln(Population)	15,718	0.122	0.083	0.127
Income Per Capita	15,718	26.024	24.605	8.454

This table presents the summary statistics of the sample that consists of all publicly traded and innovative firms during 1985–1999. Innovative firms are defined as being awarded at least one patent during the past five years. We also require the firms to have nonmissing accounting and stock return information from Compustat and CRSP, respectively. We define a dummy variable, *Acquirer*, that takes the value of 1 if the firm acquired at least one innovative target in a given year, and 0 otherwise. Innovative targets are those from a three-digit SIC coded industry where at least one firm was awarded a patent in the past five years. *# of M&A Deals* is the number of innovative target acquisitions completed by a firm in a given year. *Pat Library* takes the value of 1 if the firm is headquartered in a county where a patent library opens, and 0 otherwise. Definitions of other variables are in appendix C.

ratio (2.8), and sales growth rate (22.5%) are all comparable to those reported in the prior literature (e.g., Nguyen and Phan [2017]).

4. *Empirical Results*

In this section, we discuss the results for each of the empirical tests. We start by investigating the effect of patent library openings on local firms' acquisition activities. We use the baseline sample, which is followed by the parallel pre-trend condition test, falsification tests to address the concern that our results might be driven by unobserved variables that are contemporaneously correlated with the timing of patent library openings, and a battery of additional robustness checks. We also examine an alternative interpretation of our findings that the access to patent libraries may help local firms to strategically develop innovation projects that would appeal to acquirers, hence increasing their likelihood of being acquired. We then examine how the openings of patent libraries affect the pairing choices between acquirers and targets. After that, we assess the effect of patent library openings on deal-completion rates, acquisition announcement returns, and post-merger performance. Finally, we investigate the post-acquisition cross-citations by terminated bidders to explore the underlying mechanism and further strengthen the argument that the main results are driven by reduced gathering costs of patent information for local acquiring firms.

4.1 PATENT LIBRARY OPENINGS AND LOCAL FIRM ACQUISITIVENESS

4.1.1. Baseline Results. We use a DiD approach to investigate the effect of the openings of patent libraries on firms' acquisition activities across different geographical locations. While the exclusion rights associated with patents are national in scope, the openings of local patent libraries yield regional variation in the awareness and acquisition costs of technological information.[10] Specifically, we estimate the following OLS regression model:

$$\begin{aligned} Ln(1{+}\#\,of\ M\&A\,Deals)_{i,t} &= \beta_0 + \beta_1 Pat\ Library_{c,t-1} + \gamma_1 X_{i,t-1} \\ &\quad + \gamma_2 W_{c,t-1} + \mu_i + \mu_t + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where i represents the firm, c represents the county where firm i's headquarters is located, and t represents the year. The dependent variable is the natural logarithm of one plus *# of M&A Deals*, which is the number of acquisitions of innovative targets (hereafter, innovative target acquisitions) completed by a firm in a given year (based on the M&A announcement year); we set the value of *# of M&A Deals* to 0 if there are no acquisitions of innovative targets in a year. All the right-hand side variables are lagged by one year. The key independent variable, *Pat Library*, equals 1 for firms that are headquartered in counties where there is a patent library in a given year, and 0 for those headquartered in counties without any patent libraries in a year.[11,12] We follow the existing literature to include an extensive list of firm-level ($X_{i,t-1}$) and county-level ($W_{c,t-1}$) control variables. Firm-level variables include the natural logarithm of firm age (*Ln(Age)*), the natural log-

[10] A key premise is that patent information is largely utilized by local inventors, analysts, investors, and lawyers, for economic, legal, product, and market research (Brown and Arshem [1993]). Surveys of patent depository library users show that the median users of PTDLs travel between 11 and 20 miles (U.S. Patent and Trademark Office [1999]), and roughly 70% of the users travel less than 20 miles (U.S. Patent and Trademark Office [2003]). Similarly, Furman et al. [2021] and Martens [2023] find evidence that PTDL openings enhance local innovation and local retail investors' trading, respectively, suggesting that patent information disseminated via PTDLs is localized. Therefore, as some firms experience a shock to the cost of gathering patent information due to the opening of a patent library in the local area, we assume that firms located in the areas without any patent libraries serve as a reasonable counterfactual of the treated group.

[11] As noted in Heider and Ljungqvist [2015], using the headquarters location directly from Compustat (which keeps only the most recent location) will mislabel 10% of firm-years' historical headquarters locations. We identify the historical headquarters locations of public acquirers by web-scraping their 10K and 10Q reports. When a firm-year's location information is missing, we use the available location information in the adjacent year to fill in those missing values.

[12] The underlying assumption is that firms' headquarters represent the area in which information-acquisition activity occurs, which may not be true for larger public firms with more geographically diverse economic activities. In untabulated results, we find that the treatment effect of patent library is positive and significant, both in firms that are more geographically concentrated and those that are less so; however, the effect is stronger in firms with greater geographic concentration, implying that our results are sharper/stronger among firms that have a "singular area" of economic/information.

arithm of total assets (*Ln(Total Asset)*), research and development expenses scaled by total assets (*RD/Assets*), total debts to total assets (*Leverage*), cash and cash equivalents scaled by total assets (*Cash/Assets*), growth opportunity (*Market-to-Book* ratio), *Sales Growth Rate*, noncash net working capital scaled by total assets (*NWC/Assets*), and stock returns in the past 12 months (*Return*). County-level variables include the natural logarithm of the total population in a county (*Ln(Population)*) and personal income per capita in a county (*Income Per Capita*). Detailed variable definitions are summarized in appendix C. We also include firm (μ_i) and year fixed effects (μ_t) to control for the time-invariant firm characteristics and time-varying macroeconomic shocks. We cluster standard errors at the county level.

We report the regression results estimating equation (1) in table 3. In column (1), in which we control for a vector of firm-level characteristics and firm and year fixed effects, the coefficient estimate on *Pat Library* is positive and significant at the 1% level. As we further add county-level control variables in column (2), the coefficient estimate on *Pat Library* continues to be positive and significant at the 1% level with a very similar magnitude. The results suggest that firms located in counties with patent libraries complete more acquisitions involving innovative targets than firms located in counties without patent libraries. The effect is economically sizable. Based on the coefficient estimate in column (1), patent library openings are associated with a 6.4% increase in M&A activities relative to the M&A level prior to the opening.[13] Further, we follow Bonetti, Duro, and Ormazabal [2020] and estimate the impact of patent library openings on the dollar value of M&A deals and report the results in online appendix table IA2, panel A. We find that, for an average firm-year, the dollar value of takeovers increases by 38.0% following the opening of a patent library. Given that the mean dollar value of M&A activities in our baseline sample is $34.36M, such an increase corresponds to an increase of $13.06M (= 34.36 × 38.0%) in M&A transaction values.

The coefficient estimates on the control variables exhibit signs consistent with the current literature. For example, firms with a higher leverage ratio tend to be less active in acquisitions (e.g., Uysal [2011]). Cash-rich firms are more likely to acquire targets than are cash-constrained firms (e.g., Harford [1999]). Following the time of high valuations (higher stock returns or high market-to-book ratio), firms are more active in acquiring others (e.g., Harford [2005]).

4.1.2. Dynamic Analysis. To validate the parallel trend assumption of the DiD approach, we estimate a dynamic model by including a set of dummy variables that represent each year before and after the year the patent library opened. The dynamic analysis allows us to examine whether our results are driven by reverse causality, that is, whether local economic

[13] Note that our dependent variable is log-transformed and the independent variable is a dummy variable. Hence, the economic magnitude is computed as $\exp(0.062) - 1 = 6.4\%$.

TABLE 3
Patent Library Openings and Local M&A Activities: Baseline Models

	(1)	(2)
	Dept Var = *Ln(1+# of M&A Deals)*	
Pat Library	0.062***	0.062***
	(2.980)	(2.770)
Ln(Age)	−0.024	−0.024
	(−1.058)	(−1.052)
Ln(Total Asset)	0.008	0.008
	(0.833)	(0.836)
RD/Asset	−0.070	−0.070
	(−1.230)	(−1.229)
ROA	−0.005	−0.005
	(−0.164)	(−0.164)
Leverage	−0.172***	−0.172***
	(−6.283)	(−6.272)
Cash/Asset	0.169***	0.169***
	(7.973)	(7.979)
Market-to-Book	0.002**	0.002**
	(2.469)	(2.457)
Sales Growth Rate	−0.003	−0.003
	(−1.016)	(−1.014)
NWC/Asset	−0.008	−0.007
	(−0.406)	(−0.401)
Return	0.018***	0.018***
	(4.054)	(4.055)
Ln(Population)		−0.003
		(−0.028)
Income Per Capita		0.000
		(0.124)
Constant	0.126*	0.120
	(1.771)	(1.352)
Fixed effects	Firm + Year	Firm + Year
Model	OLS	OLS
N	15,262	15,262
Adj. R^2	0.239	0.238

This table presents the results on the effect of patent library opening on local firms' M&A activities. Our sample consists of all publicly traded and innovative firms during 1985-1999. Innovative firms are defined as being awarded at least one patent during the past five years. The dependent variable, *Ln(1+# of M&A Deals)*, is the natural logarithm of one plus the number of innovative target acquisitions completed by a firm in a given year. Innovative targets are those from a three-digit SIC coded industry where at least one firm was awarded a patent during the past five years. The independent variable *Pat Library* takes the value of 1 if the firm is headquartered in a county where a patent library opens, and 0 otherwise. Definitions of other variables are in appendix C. The unit of analysis is at firm-year level. We include firm and year fixed effects in all regressions. *t*-Statistics based on robust standard errors clustered at county-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

conditions and acquisition activities increase the demand for patent libraries, which leads to patent library openings in the county. Specifically, we follow Bertrand and Mullainathan [2003] and Cornaggia et al. [2015] and construct six time-indicator variables representing the years before and after the patent library opened: *Pat Library(≤–3)* equals 1 if the sample year is three years or more prior to the year the patent library opened, and 0 otherwise; *Pat Library(-k)* ($k = 1{,}2$) equals 1 if the sample year is k year(s) prior to the year the patent library opened, and 0 otherwise; *Pat Library(+k)* ($k = 1{,}2$) equals 1 if the sample year is k year(s) following the year the patent library opened, and 0 otherwise; *Pat Library(≥+3)* equals 1 if the sample year is three years or more following the year the patent library opened, and 0 otherwise. Below is the dynamic regression model:

$$\begin{aligned} Ln(1{+}\#of\ M\&A\ Deals)_{i,t} = {} & \beta_0 + \beta_1 Pat\ Library(\leq -3)_c \\ & + \beta_2 Pat\ Library(-2)_c + \beta_3 Pat\ Library(-1)_c \\ & + \beta_4 Pat\ Library(+1)_c + \beta_5 Pat\ Library(+2)_c \\ & + \beta_6 Pat\ Library(\geq +3)_c \\ & + \gamma_1 X_{i,t-1} + \gamma_2 W_{c,t-1} + \mu_i + \mu_t + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

To avoid multicollinearity, we set the year of library openings as the base year, which is reflected in the intercept. If reverse causality exists, we expect to observe significant coefficient estimates on *Pat Library(≤-3), Pat Library(–2)*, or *Pat Library(–1)*. Results of the dynamic model are reported in table 4. In both columns (1) and (2), none of the coefficient estimates on the aforementioned dummy variables are statistically significant, satisfying the parallel trend assumption of the DiD approach: hence there is no evidence of reverse causality. In contrast, the coefficient estimates on *Pat Library(+2)* and *Pat Library (≥+3)* are positive and significant at the 5% or 1% level, suggesting that patent library openings spur local technological acquisitions as early as two years after a patent library opens.

To visualize the parallel trends, we plot the coefficient estimates obtained from the dynamic model in figure 2. The X-axis represents the years relative to the library opening year. The Y-axis represents the coefficient estimates on the time-indicator variables surrounding patent library opening (β_1–β_6). Vertical bars represent 90% confidence intervals. Figure 2 shows that the coefficient estimates for the pre-event years are virtually indifferent from zero, hence validating the parallel trends assumption. However, acquisition activities rise significantly starting in the second year following the opening of a patent library.

The dynamic model indicates that the effect is most significant in Year +2 and Year +3 after a patent library opens; this is consistent with the pattern in Furman, Nagler and Watzinger [2021] that the effect of patent library opening on innovation takes place in Year +1, becomes statistically insignificant in Year +2, and is significant in Year +3 to Year +5. To further capture the delayed effect, we examine how patent libraries affect technological M&A activities in the subsequent three years. We construct an alternative dependent variable, *Ln(1+Total # of M&A Deals, t+1 to t+3)*, which is the natural logarithm of one plus the number of innovative target acquisitions completed by a firm in the next three years. Online appendix table IA2, panel B, reports the regression results, confirming a positive effect of patent library openings on local firms' technological acquisition activities in subsequent years. Consistent with the results from the dynamic model,

TABLE 4
Patent Library Openings and Local M&A Activities: Dynamic Models

	(1)	(2)
	Dept Var = Ln(1+# of M&A Deals)	
Pat Library(≤−3)	0.029	0.031
	(1.198)	(1.229)
Pat Library(−2)	0.028	0.030
	(0.584)	(0.611)
Pat Library(−1)	0.017	0.019
	(0.521)	(0.569)
Pat Library(+1)	0.053	0.055
	(1.406)	(1.440)
Pat Library(+2)	0.077**	0.080**
	(2.014)	(2.028)
Pat Library(≥+3)	0.080***	0.084***
	(2.783)	(2.593)
Constant	0.121*	0.118
	(1.709)	(1.340)
Acquirer firm control	Y	Y
Acquirer county control	N	Y
Fixed effects	Firm + Year	Firm + Year
Model	OLS	OLS
N	15,262	15,262
Adj. R^2	0.238	0.238

This table presents the results of the dynamic effect of patent library opening on local firms' M&A activities. Our sample consists of all publicly traded and innovative Compustat firms during 1985–1999. Innovative firms are defined as being awarded at least one patent during the past five years. The dependent variable, *Ln(1+# of M&A Deals)*, is the natural logarithm of one plus the number of innovative target acquisitions completed by a firm in a given year. Innovative targets are those from a three-digit SIC coded industry where at least one firm was awarded a patent during the past five years. Independent variables include: *Pat Library(≤−3)* that is an indicator variable for sample years that occur 3 years or more prior to the year of patent library opening; *Pat Library(-k)* ($k = 1,2$) are indicator variables for the sample year that is k year prior to the year of patent library opening; *Pat Library(+k)* ($k = 1,2$) are indicator variables for the sample year that is k years following the year of patent library opening; *Pat Library(≥ +3)* is an indicator variable for sample years that are 3 years or more following the year of patent library opening. We include the same set of control variables as those in table 3, but do not report them for brevity. Definitions of other variables are in appendix C. We include firm and year fixed effects in all regressions. t-Statistics based on robust standard errors clustered at county-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

the openings of patent libraries increase local technological M&A activities by 11%−12% in the subsequent three years.

4.1.3. Falsification Tests. We undertake falsification tests to address a variety of concerns regarding our baseline findings. First, a concern arises that our results could be driven by unobserved variables that happen to be correlated with the timing of patent library openings. The staggered feature of opening patent libraries in different counties mitigates this concern to some extent because there is a small chance that other unobservable variables with similar effects move in the same geographical and temporal fashion as the opening of patent libraries; nevertheless, we conduct a formal falsification test to rule out this possibility. Following Cornaggia et al. [2015], Bradley, Kim, and Tian [2017], and Tian and Xu [2022], we first obtain

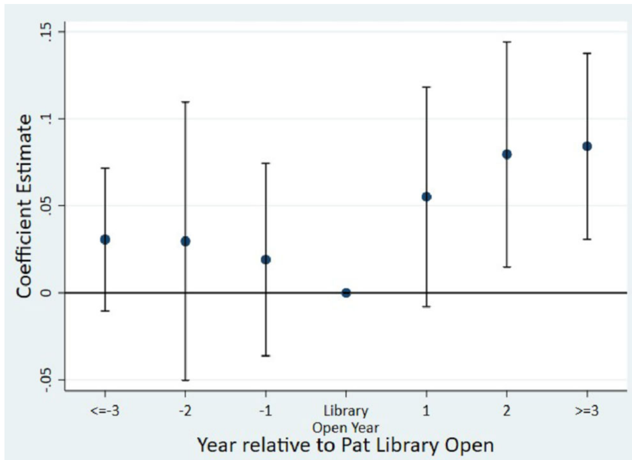

FIG. 2.—Pre-Trends in Local M&A Activities. Figure 2 plots the coefficient estimates on the time dummy variables of the dynamic regressions that estimate the effect of patent library opening on local M&A activities. The dependent variable, *Ln(1+# of M&A Deals)*, is the natural logarithm of one plus the number of innovative target acquisitions completed by a firm in a given year. Innovative targets are those from a three-digit SIC coded industry where at least one firm was awarded a patent during the past five years. Independent variables include *Pat Library*(≤ -3) that is an indicator variable for sample years that occur 3 years or more prior to the year of patent library opening; *Pat Library(-k)* ($k = 1,2$) are indicator variables for the sample year that is k year prior to the year of patent library opening; *Pat Library(+k)* ($k = 1{,}2$) are indicator variables for the sample year that is k years following the year of patent library opening; *Pat Library*($\geq +3$) is an indicator variable for sample years that are 3 years or more following the year of patent library opening. The X-axis represents the years relative to the year of patent library opening, while the Y-axis represents the coefficient estimates on the time dummy variables. Vertical bars represent 90% confidence intervals.

the empirical distribution of the dates when patent libraries were opened. Then, we randomly assign the opening dates across counties based on the empirical distribution, and re-estimate equation (1). We repeat the random assignments 1,000 times and re-estimate the regression model in each iteration. This yields 1,000 samples with pseudo patent library opening dates and therefore 1,000 DiD estimates. We plot in figure 3 the histogram of the coefficient estimates and *t*-statistics of *Pat Library* for the 1,000 iterations based on regressions in table 3, column (2). The X-axis shows the bins of the coefficient estimates in panel A and the bins of the *t*-statistics in panel B using a bin width of 30; the Y-axis represents the frequency corresponding to each bin. The vertical dashed line in panels A and B represents the DiD coefficient estimates and *t*-statistics reported in table 3, column (2), which are 0.062 and 2.77, respectively. Clearly, the vertical dashed lines lie in the top 3% and 2% of the placebo distribution, confirming that our results are unlikely to be driven by unobserved shocks contemporaneous to the openings of patent libraries.

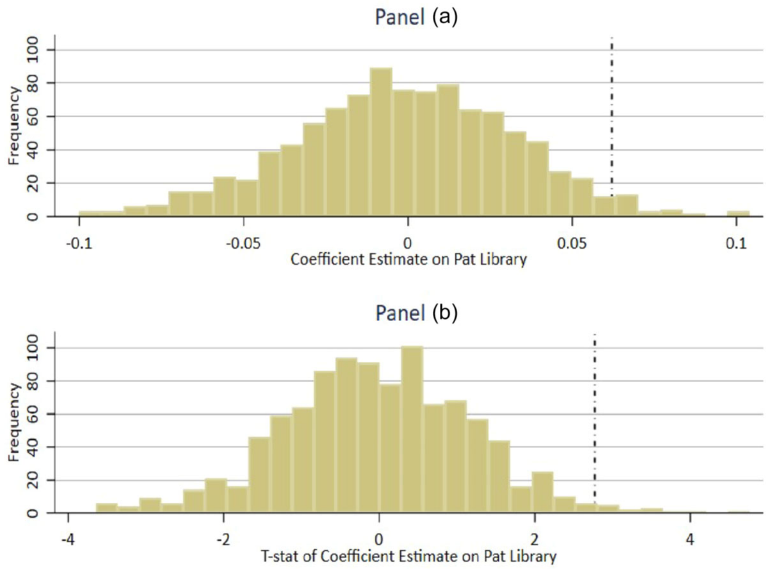

FIG. 3.—Falsification Tests. We first obtain the empirical distribution of patent library opening dates. Then, we randomly assign patent library opening dates across counties based on the empirical distribution, and re-estimate equation (1). We repeat the random assignments 1,000 times and re-estimate the regression model as table 3, column (2) in each iteration. This yields 1,000 samples with pseudo patent library opening dates and therefore 1,000 staggered DiD estimates. Panels A and B of this figure plot the histogram of the coefficient estimates and *t*-statistics of *Pat Library* for the 1,000 iterations, respectively. The X-axis shows the bins of the coefficient estimates in panel A and the bins of the *t*-statistics in panel B using a bin width of 30. The Y-axis represents the frequency corresponding to each bin. The vertical dashed line in panels A and B represents the coefficient estimates and *t*-statistics reported in table 3, column (2), which are 0.062 and 2.77, respectively.

The second falsification test we undertake is to examine the post-Internet boom period. We provide detailed discussions on this falsification test in the online appendix and tabulate the results in table IA3. We find that patent libraries have had little effect on local firms' M&A activities in more recent years, given the improved dissemination technology of patent information via the Internet (e.g., through Google Patents). Third, to validate whether our findings pertain to technological M&As, we examine (1) whether patent library openings have any effect on M&A activities of noninnovative acquiring firms, and (2) the effect of patent libraries on the extent of acquisitions involving noninnovative targets. We provide more detailed discussions in the online appendix and tabulate the results in table IA4, which confirms that the patent library openings are only relevant to acquisitions that involve innovative acquirers and innovative targets.

4.1.4. Robustness Checks. To ensure the robustness of our results, we conduct a battery of additional tests. First, we estimate alternative regression models to address potential biases in estimating log-linear regressions, including Poisson regression following the suggestions by Cohn, Liu and Wardlaw [2022] and Chen and Roth [2024]; these include the Negative Binomial regression, OLS regressions without taking log transformations, and Logit regressions (online appendix table IA5, panel A). Second, we use alternative fixed effects (online appendix table IA5, panel B) and cluster standard errors at different levels (online appendix table IA5, panel C). Third, we exclude the firms located in counties where university patent libraries reside (online appendix table IA6, panel A), the firms headquartered in Washington, DC, (online appendix table IA6, panel B), and the firms headquartered in counties where patent libraries were established before 1985 (online appendix table IA6, panel C). Fourth, we follow the suggestions of Baker, Larcker, and Wang [2022] to deal with the concern that staggered DiD regressions are susceptible to biases resulting from treatment effect heterogeneity (online appendix table IA7). Fifth, we construct a continuous distance variable that measures the distance in miles between the county where a firm is headquartered and the closest treated county where a library has been opened (online appendix table IA8). Our main result holds in all these robustness tests.

4.1.5. Patent Library Openings and Local Firms' Takeover Exposure: An Alternative Argument. We argue that patent libraries openings enhance awareness and reduce acquisition costs of technological information nationwide; this allows local firms to grow and expand their innovation pipelines as they are able to identify better targets with greater technology synergies. This, in turn, increases local patenting and enhances technology spillover across regions, as documented in Furman, Nagler, and Watzinger [2021]. To some extent, our study complements Furman, Nagler, and Watzinger [2021] by providing an alternative channel—acquisition—for the documented effect of patent libraries on local innovation. Although patent libraries can help acquirers identify potential targets, access to patent libraries could also help a local firm strategically develop innovation that would appeal to acquirers, thereby increasing the firm's likelihood of being acquired.

To explore this possibility, we investigate how the openings of patent libraries affect local firms' takeover exposure. As most targets are private firms for which financial data are unavailable, we conduct this test using county-year observations. As many U.S. counties are in rural areas with few business activities, we limit our sample to the county-year observations for counties in which at least one public firm is headquartered. We estimate the following regression in which the unit of observation is county-year.

$$Ln(1{+}\#of\ Targets)_{c,t} = \beta_0 + \beta_1 Pat\ Library_{c,t-1} + \gamma_1 W_{c,t-1} + \mu_c + \mu_t + \varepsilon_{c,t}. \quad (3)$$

We control for every county-year's natural logarithm of total population (*Ln(Population)*), *Income Per Capita*, *Unemployment Rate (%)*, the total number of establishments in thousands (*# of Establishments*), and the total number of patents (*# of Patents*). Regression results are reported in online appendix table IA9. As patent information is relevant only to technological innovation, we count acquisitions involving both innovative targets and innovative acquirers in column (1), where the dependent variable is the total number of innovative target firms acquired by publicly traded innovative firms. We find an insignificant coefficient estimate on *Pat Library*. In column (2), we count the total number of target firms (innovative and noninnovative) acquired by publicly traded innovative firms as the dependent variable. The coefficient estimate on *Pat Library* remains insignificant. We next expand M&A deals to those involving all types of acquirers (innovative and noninnovative). In columns (3) and (4), we count the total number of innovative target firms and all target firms, respectively, that are acquired by all acquirers. Again, we find little effect of patent library openings on the extent to which target firms are acquired, regardless of whether target firms are innovative or noninnovative. Overall, we do not observe any evidence supporting the conjecture that patent libraries help local firms to strategically develop innovative projects, which would increase their takeover exposure and likelihood of being acquired.

4.2 PATENT LIBRARY OPENINGS AND ACQUIRER–TARGET PAIRINGS

In the absence of information frictions, acquiring firms can consider all possible targets with various resource complementarities and synergy gains and can opt for the first, best choice that creates the largest synergy gain. Nevertheless, information frictions in M&As force acquirers to select geographically proximate targets, as acquirers can easily access soft information about such targets through site visits or interactions with targets' managers and inventors in social, civic, and business meetings (Petersen and Rajan [2002], Kantor and Whalley [2019]). By the same token, acquirers are more likely to approach technologically proximate targets, as technology proximity reduces information friction between acquirers and targets (Bena and Li [2014]). Such pairing tendencies constrain acquirers' searches and prevent them from finding the first-best choice of targets, leading to economic losses for both acquirers and targets. In this section, we investigate how the openings of patent libraries affect the pairing of acquirers and targets with respect to geographical and technological distance.

4.2.1. Matched Sample for Analyzing Acquirer–Target Pairing. To gain insights on how the openings of patent libraries affect the matching of acquirer and target in technological M&A deals, we follow Bena and Li [2014] and Bereskin et al. [2018] and identify the counterfactuals (control firms) for each acquirer based on various matching approaches. We start with the sample of 2,913 M&A deals that involve public innovative acquirers and targets from innovative industries during the sample period and use two approaches to form "pseudo" acquirer–target pairs. In the first approach, we construct a matched sample based on industry and size. For each acquirer in a deal, we select up to five public innovative firms based first on industry by using the narrowest SIC code that provides at least five candidate firms, and then based on the closest size (total assets) in the year before the deal announcement.[14] We also require the control firms to have been neither acquirers nor targets in the three years immediately prior to the year of deal announcements. As a result, for every actual acquirer–target pair in a deal, we form up to five "pseudo" pairs by pairing the matched control acquirers with the actual target. Matching based on both industry and size provides a pool of potential acquirers and takes into consideration the M&A clustering in time as well as in industry. In the second approach, we build a matched sample based on industry, size, and market-to-book ratio. We add market-to-book as an additional matching variable because it is widely accepted as a proxy for growth opportunities, overvaluation, and asset complementarity (Rhodes-Kropf and Robinson [2008], Shleifer and Vishny [2003]), all of which are important drivers of M&A activities. Following prior studies, we find up to five public innovative firms based on industry by using the narrowest SIC code that provides at least five candidate firms, then by finding the closest propensity score estimated using size and market-to-book ratio. We again require matched firms to be neither acquirers nor targets during the three years prior to the year of the deal announcement.

4.2.2. Geographical Proximity and Acquisitions. Prior literature has shown that geographical distance aggravates information frictions, leading acquirers to focus on local deals to avoid costly information gathering (e.g., Uysal, Kedia and Panchapagesan [2008], Erel, Liao, and Weisbach [2012]). Therefore, acquirers tend to take over geographically proximate targets (e.g., Kang and Kim [2008], McCarthy and Aalbers [2016]). We argue, however, that the openings of patent libraries can make it easier for local acquirers to gather technological information about potential targets that are even geographically distant; this, in turn, reduces the marginal cost of the information search associated with distant targets and ultimately encourages local firms to expand their search of distant targets. As a result, we propose that the positive relation between acquisitions and geographical proximity between acquirers and targets is weakened after the opening of patent libraries.

For this purpose, we compute the geographical distance (in miles) between each actual acquirer–target pair alongside each pseudo acquirer–target pair.[15] Following Bereskin et al. [2018], we estimate the following

[14] Specifically, we first search for matching acquirers based on four-digit SIC code. If there are fewer than five industry peers to the actual acquirer within the four-digit SIC industry group, we then try the three-digit SIC industry group. If there are fewer than five industry peers to the actual acquirer or target firm, we next search for matching peers based on the two-digit SIC code. In our sample, 54%, 23%, and 23% of the control acquirers were found based on four-digit, three-digit, and two-digit SIC code industry group, respectively.

[15] To compute geographical distance, we use the historical headquarters locations of public acquirers. For target firms, we use their zip code from SDC, if available; if the zip code is missing, we use that of the capital city of the state where the target is located.

conditional logic model to gauge the likelihood of the actual M&A deal occurring.

$$\begin{aligned} Actual\ M\&A\ Deal_{i,t} = & f(\beta_0 + \beta_1 Geo\ Prox_{i,j,t-1} \times Pat\ Library_{c,t-1} \\ & + \beta_2 Geo\ Prox_{i,j,t-1} + \beta_3 Pat\ Library_{c,t-1} \\ & + \gamma_1 X_{i,t-1} + \gamma_2 W_{c,t-1} + \mu_d + \varepsilon_{i,t}), \end{aligned} \tag{4}$$

where i and j index the acquirer and the target, respectively. The dependent variable, *Actual M&A Deal* is a binary variable that takes the value of 1 for the actual acquirer–target pair, and 0 for a pseudo pair. *Geo Prox* is the reciprocal of the logarithm of the distance (in miles) between the actual (or pseudo) acquirer and the target. We include the same list of acquirers ($X_{i,t-1}$) and county characteristics ($W_{c,t-1}$) as in table 3; following Bena and Li [2014] and Bereskin et al. [2018], for the controls variables, we do not include the variables used for matching (i.e., we exclude total assets in the industry- and size-matched sample and exclude total assets and market-to-book ratio in the industry, size, and market-to-book matched sample). Following Bena and Li [2014], we include deal fixed effects (μ_d) and cluster standard errors at the deal level.

The regression results are reported in table 5. We use the matched sample based on industry and size in column (1), and the matched sample based on industry, size, and market-to-book in column (2). Consistent with the prior results, the coefficient estimates on *Pat Library* are positive and significant at the 1% level in both columns, suggesting that patent library openings are positively related to the likelihood of M&A pairing. The coefficient estimates on *Geo Prox* are positive and significant at the 1% level in both columns, suggesting that M&A deals are more likely to take place between acquirers and targets that are geographically closer to each other. This observation is consistent with the current literature, which finds information search costs to be lower between geographically proximate acquirers and targets, thus facilitating the acquisition of nearby targets.

Regarding *Geo Prox* × *Pat Library*, our variable of interest, the coefficient estimates are negative and significant at the 1% level in both columns, suggesting that the positive relation between geographical proximity and the likelihood of technological M&A is attenuated after the openings of patent libraries due to the reduced cost of gathering technology information about targets. Post library openings, the association between geographical proximity and the likelihood of M&A pairing is captured by the sum of coefficients on *Geo Prox* and *Geo Prox* × *Pat Library*, which remains statistically significant as indicated by the F-test. It suggests that, after a local patent library opens, acquirers continue to prefer to acquire geographically proximate targets, though to a lesser extent. The effect is economically sizable: taking column (1) as an example, the marginal effect of geographical prox-

TABLE 5

Patent Library Openings and Acquirer–Target Pairings: The Effect of Geographical Proximity

	(1)	(2)
	Dept Var = *Actual M&A Deal*	
Geo Prox × *Pat Library* (β_1)	-3.785^{***}	-3.567^{***}
	(−4.023)	(−4.017)
Geo Prox (β_2)	5.476^{***}	5.185^{***}
	(10.815)	(10.726)
Pat Library (β_3)	1.031^{***}	0.992^{***}
	(5.765)	(5.840)
Matching covariates	Industry + Size	Industry + Size + M/B
Acquirer firm control	Y	Y
Acquirer county control	Y	Y
Fixed effects	Deal	Deal
Model	Clogit	Clogit
F–test on $\beta_1 + \beta_2 = 0$	$\chi^2 = 4.516$	$\chi^2 = 4.620$
	(p–value = 0.034)	(p–value = 0.032)
N	13,481	13,481
Pseudo R^2	0.134	0.127

This table presents the results of the effect of patent library opening on the pairing choices of acquirers and targets in terms of geographical proximity. For every actual M&A deal completed by a public innovative acquirer, we form "pseudo" pairs of acquirer–target by identifying up to five "pseudo acquirers" for each actual acquirer. We limit the sample to all deals completed by public innovative acquirers and innovative targets. Innovative acquirers are those being awarded at least one patent during the past five years; innovative targets are those from a three-digit SIC coded industry where at least one firm was awarded a patent during the past five years. In column (1), we select pseudo acquires that have the closest size to and from the same industry as the actual acquirer. In column (2), we select pseudo acquires that are from the same industry and have the closest propensity score estimated using size and market-to-book ratio to the actual acquirer. The dependent variable, *Actual M&A Deal* takes the value of 1 for the actual acquirer–target pair, and 0 for the pseudo pairs. The independent variable *Pat Library* takes the value of 1 if the firm is headquartered in a county where a patent library opens, and 0 otherwise. *Geo Prox* is the reciprocal of the logarithm of the distance between the actual (or pseudo) acquirer and the target. We include the same set of control variables as in table 3 except for the variables that are used as the matching covariates (i.e., exclude total assets in column (1) and exclude total assets and market-to-book ratio column (2)). Definitions of other variables are in appendix C. The unit of analysis is at deal-level. Following Bena and Li [2014], we include deal fixed effects and t-statistics based on robust standard errors clustered at deal-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

imity on actual M&A pairing declines by 74.2% following the openings of local patent libraries.[16]

4.2.3. Technological Proximity and Acquisitions. Similar to the idea of geographical proximity, technological proximity can also serve as a catalyst to reduce information searching costs. Following Jaffe [1986], we construct a

[16] We set all the continuous variables to their mean values and estimate the likelihood of an actual M&A taking place. Without patent library (*Pat Library* = 0), the likelihood of an actual M&A is 81.5% when *Geo Prox* is at its median value; the likelihood of an actual M&A increases to 91.3% when *Geo Prox* is one standard deviation above the median. This indicates an increase in likelihood of 12.0% (= 91.3%/81.5% – 1). Similarly, with patent library (*Pat Library* = 1), the likelihood of an actual M&A increases by 3.1% (= 90.3%/87.6% – 1) as the acquirer–target pair is geographically closer by one standard deviation. Altogether, this is a 74.2% reduction (= 3.1%/12.0% – 1) in the marginal effect of geographical proximity.

measure of technological proximity of acquirer or pseudo acquirer i and target j as follows:

$$Tech\ Proximity_{i,j,t} = \frac{X_{i,t}X'_{j,t}}{\sqrt{(X_{i,t}X'_{i,t})}\sqrt{(X_{j,t}X'_{j,t})}}, \tag{5}$$

where $X_{i,t} = (X_{i1,t}, X_{i2,t}, \ldots, \ldots, X_{iK,t})$ is a vector that denotes acquirer i's proportion of patent applications in technological class $k = 1, 2, \ldots$, K, over the past five years. The term $X_{j,t}$ is defined similarly for target j. In essence, the technological proximity measure is a cosine similarity of the patent portfolio of an acquirer and that of a target, which ranges between zero to one. A larger value indicates a higher degree of technological overlap between the acquirer and the target. As there are targets in innovative industries that never file patents, we follow the approach of Gompers [1995] and Liu and Tian [2022], using industry-level innovativeness to proxy for target firms' innovativeness. Specifically, for every acquirer–target pair, we first compute technology proximity based on the patent portfolios of an acquirer and on each USPTO firm in the same three-digit SIC-coded industry as its target firm. We then take an average of these technology proximity values; this average serves as a proxy for the technological proximity of the acquirer and its target.

We re-estimate equation (4) after replacing geographical proximity with technological proximity and report the results in table 6. Technologically proximate acquirers and targets are more likely to pair up in acquisitions, as indicated by the positive and significant coefficient estimates on *Tech Prox*. More importantly, we find significantly negative coefficient estimates on the interaction term *Tech Prox* × *Pat Library* in both columns, suggesting that the effect of technological proximity becomes weaker after a local patent library opens. The moderating effect of patent library openings on technological proximity is economically sizable: a patent library opening causes the positive effect of technological proximity on M&A pairing to decline by 40%.[17]

Taken together, the analyses of the pairing choices of acquirers and targets lend support to the notion that the openings of patent libraries allow local acquirers to gather technology information of potential targets at lower costs, hence broadening their search to more geographically and technologically distant targets.

[17] Following the same calculation as in table 5, we set all continuous variables to their average values and estimate the likelihood of an actual M&A taking place. Without patent library (*Pat Library* = 0), the likelihood of an actual M&A increases by 9.9% (= 82.5%/75.1% – 1) as the acquirer–target pair is technologically closer by one standard deviation. With patent library (*Pat Library* = 1), the likelihood of an actual M&A increases by 5.9% (= 86.7%/81.9% – 1) as the acquirer–target pair is technologically closer. Altogether, this represents a 40% reduction (= 5.9%/9.9% – 1) in the marginal effect of technological proximity.

TABLE 6

Patent Library Openings and Acquirer–Target Pairings: The Effect of Technological Proximity

	(1)	(2)
	Dept Var = Actual M&A Deal	
Tech Prox × Pat Library (β_1)	-0.483^{*}	-0.506^{*}
	(-1.723)	(-1.808)
Tech Prox (β_2)	2.708^{***}	2.641^{***}
	(11.742)	(11.626)
Pat Library (β_3)	0.450^{***}	0.450^{***}
	(6.325)	(6.347)
Matching covariates	Industry + Size	Industry + Size + M/B
Acquirer firm control	Y	Y
Acquirer county control	Y	Y
Fixed effects	Deal	Deal
Model	Clogit	Clogit
F-test on $\beta_1 + \beta_2 = 0$	$\chi^2 = 79.805$	$\chi^2 = 74.202$
	(p-value = 0.000)	(p-value = 0.000)
N	13,481	13,481
Pseudo R^2	0.123	0.116

This table presents the results of the effect of patent library opening on the pairing choices of acquirers and targets in terms of technological proximity. For every actual M&A deal completed by a public innovative acquirer and an innovative target, we form "pseudo" pairs of acquirer–target by identifying up to five "pseudo acquirers" for each actual acquirer. We limit the sample to all deals completed by public innovative acquirers and innovative targets so that we can measure technological proximity between the acquirer and target. Innovative acquirers are those being awarded at least one patent during the past five years; innovative targets are those from a three-digit SIC coded industry where at least one firm was awarded a patent during the past five years. In column (1), we select pseudo acquirers that have the closest size to and from the same industry as the actual acquirer. In column (2), we select pseudo acquirers that are from the same industry and have the closest propensity score estimated using size and market-to-book ratio to the actual acquirer. The dependent variable, *Actual M&A Deal* takes the value of 1 for the actual acquirer target pair, and 0 for the pseudo-pairs. The independent variable *Pat Library* takes the value of 1 if the firm is headquartered in a county where a patent library opens, and 0 otherwise. *Tech Prox* is the cosine similarly of an acquirer and a target's patent portfolio, which is computed based on the patent applications over the past five years. We include the same set of control variables as in table 3 except for the variables that are used as the matching covariates (i.e., exclude total assets in column (1) and exclude total assets and market-to-book ratio in column (2)). We do not report the control variables for brevity. Definitions of other variables are in appendix C. The unit of analysis is at deal-level. Following Bena and Li [2014], we include deal fixed effects and t-statistics based on robust standard errors clustered at deal-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3 PATENT LIBRARY OPENINGS, DEAL COMPLETION, AND ANNOUNCEMENT RETURNS

In this section, we examine how the openings of patent libraries affect the likelihood of successful completion of M&A deals as well as the quality of deals as reflected in acquirers' announcement returns. All analyses in this section are at the deal level.

4.3.1. Likelihood of Deal Completion. M&A deals that are announced do not always reach completion. Savor and Lu [2009] argue that a variety of reasons (such as disagreement between the acquirer and the target on deal valuation) can lead to deal terminations. If the cost of gathering technology information is reduced by access to patent libraries—allowing acquirers to better identify innovative targets—the deal should be more likely to be completed successfully. To investigate this conjecture, we stack the completed deals with the terminated deals during our sample period. Our sample contains 439 deals coded as "withdrawn" in SDC. To address the concern that some completed deals could have been erroneously defined, we search news articles in LexisNexis about each of the 439 deals to verify whether they were indeed terminated. We are able to confirm that 334 of these deals were terminated: 86 deals were actually completed but had been erroneously classified as withdrawn in SDC. For the other 19 deals, an initially withdrawn bid, which was followed by submission of a new bid from the same bidder, was coded as a new deal in SDC.

We stack the 334 genuinely terminated deals with 3,195 completed deals and follow the prior literature to estimate the logit regression to assess the odds of a successfully completed deal:[18]

$$\begin{aligned} \textit{Completed Deal}_d = f\,(&\beta_0 + \beta_1 \textit{Pat Library}_{c,t-1} + \gamma_1 X_{i,t-1} + \gamma_2 W_{c,t-1} \\ &+ \gamma_3 Z_d + \mu_m + \mu_t + \varepsilon_d). \end{aligned} \tag{6}$$

The dependent variable *Completed Deal* is a binary variable that takes the value of 1 if the deal is completed, and 0 otherwise. Following Bereskin et al. [2018], we add deal-level control variables (Z_d), including an indicator for an all-cash deal (*All Cash Dummy*), an indicator for whether the acquirer is from a high-tech industry (*High Tech Dummy*), an indicator for whether the acquirer and the target are from different two-digit SIC code industries (*Diversify Dummy*), an indicator for hostile takeover (*Hostile Dummy*), and an indicator for deals that are challenged by a competing offer (*Challenge Dummy*). We also control for acquirer characteristics ($X_{i,t\text{-}1}$), including acquirer's *Ln(Total Asset)*, *Market-to-Book* ratio, *Return*, *Sales Growth Rate*, *Leverage*, *ROA*, *Cash/Asset, RD/Asset*, and M&A deal value relative to acquirers' market value of equity (*Relative Size*). Finally, we control for whether the target is publicly traded (*Public Target Dummy*), and for county-level characteristics ($W_{c,t\text{-}1}$). We also include industry (μ_m) and year fixed effects (μ_t).[19] Regression results are reported in table 7.

Pat Library is significantly positively related to the likelihood of deal completion as shown in both columns. We compute an odds ratio to assess the economic magnitude. Based on the estimates in column (2), the odds of deal completion are 39.2% higher for acquirers located in counties with patent libraries than for acquirers located in counties without a patent library. The results indicate that, following the openings of local patent libraries, acquirers are better at finding appropriate innovative targets and

[18] We did not add the 86 deals to the sample of completed deals because SDC does not include their post-merger ownership information. We require the acquirers to own at least 90% of their target firms after the deal completion. Nevertheless, the results in table 7 are very similar *to what would be the results if we had included* the 86 deals in our sample.

[19] We include industry rather than firm fixed effects, as the sample for deal-level analysis is not a panel data. As few firms engage in multiple M&A deals over the sample period, adding firm fixed effects will lead to a large number of deals dropping out of the sample.

TABLE 7

Patent Library Opens and the Likelihood of Deal Completion

	(1)	(2)
	Dept Var = Completed Deal	
Pat Library	0.333**	0.331*
	(2.132)	(1.891)
Ln(Total Asset)	0.142***	0.147***
	(2.748)	(2.792)
Market-to-Book	0.009	0.009
	(0.406)	(0.452)
Return	−0.118	−0.111
	(−0.595)	(−0.551)
Sales Growth Rate	0.301*	0.296*
	(1.937)	(1.934)
Leverage	−1.153***	−1.148***
	(−2.608)	(−2.589)
ROA	1.025*	1.013*
	(1.836)	(1.816)
Cash/Asset	0.085	0.102
	(0.182)	(0.216)
RD/Asset	3.646***	3.714***
	(2.918)	(2.930)
Relative Size	−0.187**	−0.181**
	(−2.176)	(−2.063)
All Cash Dummy	0.738***	0.745***
	(4.384)	(4.373)
High Tech Dummy	0.142	0.135
	(0.497)	(0.477)
Diversify Dummy	−0.110	−0.105
	(−0.805)	(−0.772)
Hostile Dummy	−1.822***	−1.827***
	(−5.213)	(−5.255)
Challenge Dummy	−1.883***	−1.888***
	(−7.159)	(−7.171)
Public Target Dummy	−1.032***	−1.035***
	(−6.518)	(−6.452)
Ln(Population)		0.024
		(0.053)
Income Per Capita		−0.008
		(−1.064)
Constant	0.399	0.468
	(0.523)	(0.603)
Fixed effects	Industry + Year	Industry + Year
Model	Logit	Logit
N	3,087	3,087
Pseudo R^2	0.246	0.247

The table presents the effect of patent library opening on the likelihood of deal completion. The sample consists of all completed and terminated deals by public innovative acquirers that attempted to acquire innovative targets. Terminated deals refer to transactions that are genuinely terminated, as verified by news articles from LexisNexis. Innovative acquirers are those being awarded at least one patent during the past five years; innovative targets are those from a three−digit SIC coded industry where at least one firm was awarded a patent during the past five years. Definitions of variables are in appendix C. The unit of analysis is at deal-level. We include industry (defined based on three-digit SIC code) and year fixed effects in all regressions. *t*-Statistics based on robust standard errors clustered at county-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

face less severe adverse selection problems, all of which lead to a higher likelihood of successful deal completion.

4.3.2. Announcement Returns. To assess whether the acquisition activities that occur after a patent library opens enhance shareholder value, we examine market reactions to M&A announcements. Following the extant literature (e.g., Bonaime, Gulen and Ion [2018]), we compute CARs for acquirers and targets during a seven-day window around acquisition announcements (*CARs [–3,+3]*) using a market adjusted model with the CRSP value-weighted index as the market. We estimate the following OLS model:

$$CARs\,[-3,+3]_d = \beta_0 + \beta_1 Pat\ Library_{c,t-1} + \gamma_1 X_{i,t-1} + \gamma_2 W_{i,t-1} + \gamma_3 Z_d + \mu_m + \mu_t + \varepsilon_d, \quad (7)$$

If patent libraries enable local firms to access patent documents nationwide, thereby broadening their searches for targets, then acquirers could identify better targets, which would create greater synergies and post-merger economic value, than could acquirers without access to patent information. Our results are consistent with this conjecture. As shown in column (1) of table 8, *Pat Library* is positively associated with the acquirers' seven-day abnormal announcement returns, suggesting that the M&A deals completed by acquirers close to a patent library generate a higher market value for the acquirers' shareholders, compared to the deals completed by acquirers without local access to patent documents. The economic magnitude is sizable. Summary statistics in online appendix table IA10 show that the median market value of the acquirers in this sample is \$617M. Our estimate suggests that the seven-day CAR of acquirers is 1.3% higher after the opening of a local patent library; this is equivalent to an increase of \$8M (= \$617M × 1.3%) in market value.

We next examine the market reactions to M&A announcements of target firms. On one hand, patent libraries assist acquirers in their search for better targets, resulting in value-enhancing transactions that might also benefit targets through deal negotiation between the acquirers and targets. On the other hand, patent libraries reduce the information gap between acquirers and targets; this reduces targets' information advantage, hence possibly weakening their bargaining power in M&A deals. Therefore, the impact of patent libraries on targets' stock returns is unclear ex ante and remains an empirical question. The regression results are reported in column (2) of table 8. As we are limited to publicly traded targets, the sample is significantly reduced. The coefficient estimate on *Pat Library* is positive yet statistically insignificant, implying that library openings in acquirers' counties do not affect the stock market reactions of target firms. Nevertheless, the insignificant coefficient on *Pat Library* could be due to the much smaller sample of public targets, which may lack the statistical power to find significant results.

Finally, we examine the combined stock returns of both acquirers and targets. Following the extant literature (e.g., Bereskin et al. [2018], Chen, Gao

TABLE 8

Patent Library Openings, Stock Returns, and Long-term Performance

	(1) *Acquirer CARs [–3,+3]*	(2) *Target CARs [–3,+3]*	(3) *Combined CARs [–3,+3]*	(4) *Acquirer BHAR (5y)*	(5) *AcqIndAdj ROA (5y)*
Pat Library	0.013**	0.019	0.014*	0.106**	0.023*
	(2.050)	(1.058)	(1.751)	(2.113)	(1.804)
Acquirer firm control	Y		Y	Y	Y
Acquirer county control	Y		Y	Y	Y
Deal control	Y	Y	Y	Y	Y
Target firm control		Y	Y		
Acquirer industry fixed effects	Y		Y	Y	Y
Target industry fixed effects		Y	Y		
Year fixed effects	Y	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS	OLS
N	2,798	745	700	2,798	2,169
Adj. R^2	0.064	0.189	0.010	0.365	0.152

The table presents the results of the effect of patent library opening on cumulative abnormal returns around acquisition announcements and post-merger long-term returns. The sample consists of completed innovative target acquisition deals by all public innovative acquirers. In columns (1) and (2), the dependent variable is *Acquirer CARs [–3,+3]* and *Target CARs [–3,+3]*, respectively, which is the seven-day cumulative abnormal return surrounding the announcement day for acquirers and public traded targets, computed using a market adjusted model with the CRSP value-weighted index as the market. In column (3), the dependent variable is *Combined CARs [–3,+3]*, which is the weighted average of the seven-day cumulative abnormal announcement return of both acquirer and target, with the weights being the market values of the acquirer and the target a week before the announcement date. In column (4), the dependent variable is *Acquirer BHAR (5y)*, which is acquirers' post-acquisition 5-year buy-and-hold returns net of the CRSP value-weighted index return in the 5-year window. In column (5), the dependent variable is *AcqIndAdj ROA (5y)*, which is acquirers' post-acquisition 5-year return on assets (ROA) net of the median ROA of all the firms in the same three-digit SIC coded industry in the same year. *Pat Library* takes the value of 1 if the firm is headquartered in a county where a patent library opens, and 0 otherwise in the year prior to the M&A announcement year. Firm controls include *Ln(Total Asset)*, *Market-to-Book*, *Return*, *Sales Growth Rate*, *Leverage*, *ROA*, *Cash/Asset*, *RD/Asset*, *Ln(Age)*, and county controls include *Ln(Population)* and *Income Per Capita*. The deal controls include *Relative Size, All Cash Dummy, High Tech Dummy, Diversify Dummy, Hostile Dummy, Challenge Dummy, Public Target Dummy*. Definitions of other variables are in appendix C. *t*-Statistics based on robust standard errors clustered at county-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

and Ma [2021]), we compute a weighted average of seven-day CARs of both the acquirer and the target (*Combined CARs [–3,+3]*) around acquisition announcements with the weights being the market values of the acquirer and the target one week before the announcement date. We then estimate equation (7) using *Combined CARs [–3,+3]* as the dependent variable. Following Chen, Gao and Ma [2021], we control for acquirers' firm and county characteristics, deal-level characteristics, acquirers' industry and year fixed effects, target firms' characteristics, and target industry fixed effects. As shown in column (3) of table 8, *Pat Library* is significantly positively associated with *Combined CARs [–3,+3]* with a coefficient estimate of 0.014.[20]

[20] Furman et al. [2021] document a surge in local innovation activities after the opening of a patent library. One concern is that the higher *CAR*s could manifest as enhanced local

The economic value is sizable, that is, based on a weighted average of the market value of the acquirer and the target, it is equivalent to an increase in the market value of \$166M (= 11,883M × 1.4%) generated from the M&A deals that are completed by acquirers with a local patent library.

4.4 PATENT LIBRARY OPENINGS AND POST-M&A PERFORMANCE

The results of the combined abnormal return (*Combined CAR[–3,+3]*) shed some light on the expected ex ante synergy created as a result of acquirers' access to patent libraries. To gain insight into the ex post value of synergy, we conduct three additional tests. First, we examine acquirers' post-merger long-term stock returns. We follow the prior literature and construct *Acquirer BHAR (5y)* as acquirers' post-acquisition five-year buy-and-hold returns net of the CRSP value-weighted market return. We re-estimate equation (7) using *Acquirer BHAR (5y)* as the dependent variable and report the results in column (4) of table 8. The coefficient estimate on *Pat Library* is positive and significant at the 5% level, suggesting that acquirers with local access to patent libraries experience a higher post-merger, long-term stock return compared to that of acquirers without access to local patent libraries. Second, we examine acquirers' post-merger long-term operating performance. Following Bereskin et al. [2018], we construct industry-adjusted return on assets (ROA), *AcqIndAdj ROA (5y)* which is acquirers' post-acquisition five-year ROA net of the median ROA of all the firms in the same three-digit SIC-coded industry. Re-estimating equation (7) using *AcqIndAdj ROA (5y)* as the dependent variable, we find that acquirers' long-term operating performance improves among acquirers with local access to patent libraries, as shown in column (5) of table 8.

Finally, we investigate the innovation activities of post-merger combined firms. As we focus on technological acquisitions, we expect synergy creation to be reflected in innovation output as measured by patenting. Following Bena and Li [2014] and Chen, Gao and Ma [2021], we construct a panel sample that consists of completed innovative target acquisition deals by public innovative acquirers; these deals span the period from five years before the year in which each deal is announced to five years after the deal is completed. We then estimate the following OLS model:

$$\begin{aligned} \textit{Innovation Activities}_{i,t} = \beta_0 + \beta_1 \textit{Treat}_i \times \textit{Post}_{i,t} + \beta_2 \textit{Post}_{i,t} + \gamma_1 X_{i,t} \\ + \gamma_2 W_{c,t} + \mu_t + \mu_d + \varepsilon_{i,t}. \end{aligned} \tag{8}$$

We employ two dependent variables to proxy for innovation activities: "*Combined # of Patents*" and "*Combined # of Citation Weighted Patents.*" We compute "*Combined # of Patents*" and "*Combined # of Citation Weighted Patents*" as the sum of the total number of patents and citation-weighted patents,

innovation activities, which, in turn, lead to higher potential synergies between acquirers and targets. To address this concern, in an untabulated result, we control for aggregate innovation activities (total number of patents and total number of citations) in the county where the acquirer is located. The results remain robust.

respectively, from acquirers and targets in a year during the pre-acquisition period, or from the post-merger combined firms in a year during the post-acquisition period. We follow the method in Kogan et al. [2017] to compute citation-weighted patents, in which the weight of each patent is its number of forward citations scaled by the average number of forward citations received by all patents granted in the year. *Treat* takes the value of 1 if the acquirer is headquartered in a county with a patent library during the deal-announcement year, and 0 otherwise. *Post* takes the value of 1 in years post the deal completion, and 0 otherwise. As with our baseline test, we include acquirers' firm and county characteristics.[21] We also include deal and year fixed effects in the model.[22] Regression results are reported in table 9.

The interaction term *Treat* × *Post* captures the differences in the changes of innovation output before and after the mergers between deals completed by acquirers with local access to patent libraries (treated) and deals completed by acquirers without local access (control) in the deal announcement year. The coefficient estimates are positive and significant at the 5% or 1% level in all columns of table 9, suggesting that both patent counts and citation-weighted patent counts are higher in post-merger firms when an acquirer has access to local patent libraries at the time the merger occurs. This evidence is inconsistent with the view in Cunningham, Ederer, and Ma [2021] that acquiring innovation is solely for preempting future competition. Instead, our result is consistent with the higher abnormal announcement return result documented earlier, suggesting that improved innovation productivity is a plausible source of synergy gains or efficiency gains.

4.5 HUMAN CAPITAL SYNERGIES

In this section, we explore a potential mechanism—human capital synergies—through which acquirers' access to patent information boosts post-merger innovation activities. Chen, Gao, and Ma [2021] show that the desire to obtain human capital is an important driver of corporate acquisitions. Li and Wang [2023] document the collaboration between acquirer and target inventors, post-M&A, as generating patents that are more path-breaking, impactful, and valuable compared to patents by teams of acquirer-only or target-only inventors. If synergy value between acquirers and targets improves, and if post-merger innovation productivity increases as the result of greater human capital synergies between inventors from ac-

[21] For robustness, we replace acquirer characteristics with combined firm characteristics. In the pre-acquisition period, combined firm controls are the weighted average of firm controls, with the weights being the market values of the acquirer and the target in a year. In the post-acquisition period, we control for the characteristics of the post-merger combined firm.

[22] For every deal, one firm will either be "*Treat* = 1" or "*Treat* = 0" throughout the entire sample, depending on whether it is headquartered in the county where a patent library was opened in the year of deal announcement. Therefore, as we include deal fixed effects, the "*Treat*" standalone variable will be absorbed.

TABLE 9
Patent Library Openings and Post-Merger Innovation Activities

	(1)	(2)	(3)	(4)
	Ln(1+ Combined # of Patents)		*Ln(1+ Combined # of Citation Weighted Patents)*	
Treat × Post	0.242***	0.104**	0.254***	0.104**
	(4.873)	(2.334)	(4.379)	(1.972)
Post	−0.609***	−0.444***	−0.684***	−0.511***
	(−10.037)	(−8.583)	(−9.689)	(−8.222)
Acquirer firm control	Y		Y	
Combined firm control		Y		Y
Acquirer county control	Y	Y	Y	Y
Deal fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS
N	7,356	7,356	7,356	7,356
Adj. R^2	0.851	0.882	0.839	0.867

The table presents the results on post-acquisition innovation performance. The sample consists of completed innovative target acquisition deals by public innovative acquirers, spanning from five years before each deal announcement year to five years after the deal completion. The dependent variable is the natural logarithm of one plus "*Combined # of Patents*" in columns (1) and (2), and the natural logarithm of one plus "*Combined # of Citation Weighted Patents*" in columns (3) and (4), respectively. In the pre-acquisition period, "*Combined # of Patents*" is the sum of the total number of patents from acquirers and targets, and in the post-acquisition period, it is the total number of patents from the post-merger combined firms. In the pre-acquisition period, "*Combined # of Citation Weighted Patents*" is the sum of the citation-weighted patents from acquirers and targets, and in the post-acquisition period, it is the citation-weighted patents from the post-merger combined firms. The weight of each patent is its number of forward citations received scaled by the average number of forward citations received by all patents that were granted in the same year. *Treat* takes the value of 1 if the firm is headquartered in a county where a patent library opens by the year prior to the deal announcement, and 0 otherwise. *Post* takes the value of 1 in years post the deal completion, and 0 otherwise. Firm controls include *Ln(Total Asset)*, *Asset Tangibility*, *Sales Growth Rate*, *Leverage*, *RD/Asset*, *ROA*, *Tobin's Q*, and *Return*, and county controls include *Ln(Population)* and *Income Per Capita*. In the pre-acquisition period, combined firm controls are the weighted average of firm controls, with the weights being the market values of the acquirer and the target in a year, and in the post-acquisition period, it is the firm controls of the post-merger combined firm. Definitions of other variables are in appendix C. *t*-Statistics based on robust standard errors are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

quirers and targets, we expect greater collaboration between the inventors of acquirers and their targets.

For this purpose, we examine the percentage of "co-invented patents," patents co-invented by inventors from the acquirer and the target. Co-invented patents are those developed by a team that includes both acquirer and target inventors, who are identified based on their past patenting activities. In particular, acquirer (target) inventors are those who work at the acquiring (target) firm in the year prior to the deal announcement.[23]

[23] We identify the firms where inventors work based on the inventor's patenting history. For example, if an inventor applied for patents in 1990 and in 1995, both with firm *i*, we infer that the inventor worked for firm *i* from 1990 to 1995. However, if an inventor applied for a patent in 1990 with firm *i* and applied for another patent in 1995 with a different firm *j*, we follow Li and Wang [2023] and assume that the inventor changed jobs at the midpoint between the two patent application years, that is, they worked for firm *i* in 1990, 1991, and 1992 but worked for firm *j* in 1993, 1994, and 1995.

TABLE 10

Patent Library Openings and Post-Merger Co-Invention Between Target and Acquirer Inventors

	(1)	(2)	(3)	(4)
	%Co-invented Pat		*%Co-invented Cite*	
Pat Library	0.028*	0.039*	0.027*	0.039*
	(1.931)	(1.875)	(1.828)	(1.849)
Acquirer firm control	Y	Y	Y	Y
Acquirer county control	Y	Y	Y	Y
Deal control	Y	Y	Y	Y
Target firm control		Y		Y
Acquirer industry fixed effects	Y	Y	Y	Y
Target industry fixed effects		Y		Y
Year fixed effects	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS
N	761	569	761	569
Adj. R^2	0.069	0.070	0.064	0.067

The table presents the results on post-acquisition co-invention between target and acquirer inventors. The sample consists of completed deals by innovative public acquirers and innovative public targets. In columns (1) and (2), the dependent variable is "*%Co-invented Pat*," which is the number of co-invented patents filed by post-merger combined firm within 5 years after the deal completion, scaled by the total number of patents during the same period. In columns (3) and (4), the dependent variable is "*%Co-invented Cite*," which is number of citations received by co-invented patents filed by post-merger combined firm within 5 years after the deal completion, scaled by the total number of citations received by all patents. Co-invented patents are those developed by a team of both acquirer and target inventors, who are identified based on their past patenting history. Acquirer (target) inventors are those who work at the acquirer (target) firm in the year prior to the deal announcement. *Pat Library* takes the value of 1 if the firm is headquartered in a county where a patent library opens in the year prior to the M&A announcement year, and 0 otherwise. Firm controls include *Ln(Total Asset)*, *Asset Tangibility*, *Sales Growth Rate*, *Leverage*, *RD/Asset*, *ROA*, *Tobin's Q*, and *Return*, and county controls include *Ln(Population)* and *Income Per Capita*. The deal controls include *Relative Size, All Cash Dummy*, *High Tech Dummy*, *Diversify Dummy*, *Hostile Dummy*, *Challenge Dummy*, *Public Target Dummy*. Definitions of other variables are in appendix C. *t*-Statistics based on robust standard errors clustered at county-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Following the method in Chen, Gao, and Ma [2021], for every completed deal, we define *%Co-invented Pat* (or *%Co-invented Cite*) by counting the total number of co-invented patents (or citations received by co-invented patents) filed by the combined firm post-merger within five years of the deal's completion, scaled by the total number of patents (or citations of those patents) filed by the combined firm post-merger during the same period. We then run the regression following equation (7) in which we use *%Co-invented Pat* and *%Co-invented Cite* as the dependent variables. We control for acquirers' firm- and county-level characteristics, deal-level characteristics, year fixed effects, and acquirer industry fixed effects. For robustness, we add target firm characteristics and target industry fixed effects. Results are reported in table 10.

Pat Library is positive and significantly related to both *%Co-invented Pat* and *%Co-invented Cite*, suggesting a greater extent of post-merger collaboration between acquirer and target inventors in deals where acquirers have pre-merger access to a local patent library, compared to deals where acquirers do not have access. The results indicate that increased access to patent information enhances M&A value creation by pairing acquirers and targets with greater human capital synergies, thereby yielding a greater extent of inter-firm collaboration, which, in turn, enhances the long-term value of innovation (Li and Wang [2023]).

4.6 THE UNDERLYING INFORMATION MECHANISM

Welch et al. [2020] summarize the M&A process as consisting of six stages: deal initiation, target selection, bidding and negotiation, valuation and financing, deal announcement, and closure. The majority of deals are initiated by acquirers (Aktas et al. [2016], Masulis and Simsir [2018]) who are typically subject to severe information asymmetry. In the context of target selection in technological M&As, an acquirer would select a target to exploit existing knowledge developed by others to maximize complementarity in innovation pipelines. In doing so, an acquirer must first be aware of the existence of complementary innovation, then obtain information about complementary innovation from public disclosures and other sources, and finally assess the implications of such innovation to its own technologies. The costs in each step are referred to as awareness costs, acquisition costs, and integration costs, respectively (Blankespoor et al. [2019], Blankespoor, deHaan, and Marinovic [2020]).

We argue that the benefits of easier access to patent information via patent libraries are primarily relevant during the period when acquirers are trying to identify potential targets. In particular, this benefit reduces acquiring firms' awareness costs and acquisition costs in obtaining patent information during the firms' target search and selection processes. We next perform two additional tests to further support the above argument and better understand the underlying information mechanism. First, we investigate what information in patents is used by acquirers searching for targets for the purposes of technological complementarity and business synergy. Second, we examine how the openings of patent libraries enhance bidders' awareness and knowledge of targets' technology in failed mergers.

4.6.1. Acquirers' Use of Targets' Patent Information Prior to M&A Deals. We propose that easier access to patent information facilitates acquirers' identification of targets that offer the best technological complementarities and hence business synergies. If this is the case, we expect that the opening of a patent library increases the extent of technological complementarities between an acquirer and its target, that is, a better match is possible between what the acquirer seeks for versus what the target's technology offers. Motivated by the anecdote of the merger of Compaq and Tandem Computers presented in appendix A, we proxy technological complementarity using the extent to which technological keywords in a target's patent abstract coincide with the keywords in the acquirer's SEC filings before the mergers occur.

Specifically, we start with the actual M&A deals in our sample. We first identify all historical patents of the public targets in the sample deals based on the firm identifiers provided on Noah Stoffman's Web site. Second, we obtain keywords from the abstract of each patent using the data compiled by Arts, Cassiman, and Gomez [2018], who process the raw USPTO patent files and extract a list of keywords from each patent's abstract that capture its technological knowledge.[24] Third, for every acquirer in our sample deals, we download from EDGAR all the SEC filings one year before the M&A announcement date. Through textual analysis of an acquirer's SEC filings, we count the occurrences of unique keywords from its target's patent abstracts. For example, if a target's patent has ten keywords, and the acquirer mentioned each keyword five times in the SEC filings, in total the occurrences of the keywords $= 5 \times 10$ or 50 times. We define *Patent_KeyWords_Mentioned* as the ratio of the total occurrences of all unique keywords from its target's patent abstracts found in an acquirer's SEC filings, to the total number of words in these SEC filings, prior to the M&A deal.[25] Our final sample consists of 349 deals in which we can identify targets' patents and obtain acquirers' SEC filings.

We conduct a regression analysis similar to that in table 10. The results are reported in table 11, where the dependent variable is *Patent_KeyWords_Mentioned*, and the key independent variable is *Pat Library*. As shown in column (1), we find that the overlap between acquirers' technological keywords in their SEC filings and the keywords in patent abstracts belonging to firms that they later acquire increases significantly following patent library openings. The results are robust as we restrict SEC filings to 10Ks, 10Qs, and 8Ks in column (2), or to 10Ks and 10Qs in column (3). Overall, the analysis sheds light on how the disclosed patent information facilitates M&A deals.

4.6.2. Post-Acquisition Cross-Citations by Terminated Bidders. As the information role of patent libraries occurs in the pre-deal period of M&A, patent library openings are able to enhance bidders' awareness and knowledge of targets' technology even if the deal fails to go through. Bidders, even if their acquisitions are terminated, conduct full research of potential targets in the same way as bidders who complete deals. Examining a sample of terminated deals and analyzing the technology information spillovers from targets to bidders surrounding those deals allow us to pinpoint directly the effect of patent library openings on information-gathering costs for local acquiring firms. If the deal termination is due to reasons other than technology complementarities (e.g., disagreement in pricing and payment methods, incompatible firm culture, etc.), we expect an increase in knowledge spillover from targets to terminated bidders after the acquisition attempt, as technology complementarities between the bidder and the

[24] The data are available at https://dataverse.harvard.edu/file.xhtml?persistentId=doi:10.7910/DVN/JO2DQZ/ZC2OGJ&version=1.0

[25] Since *Patent_KeyWords_Mentioned* is a very small number with a median of 0.00014, for the purpose of exposition, we scale it by multiplying by 10,000 to avoid extremely large coefficient estimates.

TABLE 11

Coincidence Between Acquirers' Technological Keywords from SEC Filings and the Keywords in Targets' Patent Abstracts

	(1)	(2)	(3)
		Patent_KeyWords_Mentioned	
Dependent Variable based on:	All SEC Filings	10Ks, 10Qs, & 8Ks	10Ks & 10Qs
Pat Library	0.199**	0.186*	0.225**
	(2.107)	(1.708)	(2.297)
Acquirer firm controls	Y	Y	Y
Acquirer county controls	Y	Y	Y
Deal controls	Y	Y	Y
Acquirer industry fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Model	OLS	OLS	OLS
N	349	332	315
Adj. R^2	0.150	0.193	0.176

This table presents the results on the effect of patent library opening to the coincidence between acquirers' technological keywords from SEC filings and those in patent abstracts belonging to firms that they later acquire. The sample consists of M&A deals in which we can identify targets' patents and obtain acquirers' SEC filings. The dependent variable is *Patent_KeyWords_Mentioned*, which is the ratio of the total occurrences of all unique keywords from its target's patent abstracts found in an acquirer's SEC filings, to the total number of words in these SEC filings, prior to the M&A deal. We scale it by multiplying 10,000 because it is a very small number. In column (1), we construct the variable *Patent_KeyWords_Mentioned* using all SEC filings. In columns (2)-(3), *Patent_KeyWords_Mentioned* is computed based on 10Ks/10Qs/8Ks and 10Ks/10Qs, respectively. *Pat Library* is an indicator variable that takes the value of 1 if the firm is headquartered in a county where a patent library opens in the year before the M&A announcement year, and 0 otherwise. Firm controls include *Ln(Total Asset)*, *Asset Tangibility*, *Sales Growth Rate*, *Leverage*, *RD/Asset*, *ROA*, *Tobin's Q*, and *Return*, and county controls include *Ln(Population)* and *Income Per Capita*. The deal controls include *Relative Size, All Cash Dummy, High Tech Dummy, Diversify Dummy, Hostile Dummy, Challenge Dummy, Public Target Dummy*. Definitions of other variables are in appendix C. *t*-Statistics based on robust standard errors clustered at county-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

target have been identified and known to the bidder.[26] Specifically, if patent library openings enhance bidders' awareness of targets' technology, we expect the terminated bidders to be more likely to cite patents from the targets for which they conducted full research and submitted takeover bids, even though the deals were not completed.

We start with 334 terminated deals whose targets are in innovative industries. Studying knowledge spillovers requires that targets have patents; 79 terminated bids satisfy the requirement. For every terminated deal, we identify "pseudo" bidders as a control group by following the same matching techniques as those in tables 5 and 6. We select pseudo bidders that are from the same industry and have the closest firm size as the terminated

[26] These analyses cannot be conducted for completed acquisitions because the bidder and the target firm become one entity after the deal is completed and researchers cannot distinguish whether a patent is generated by the pre-merger bidder or the pre-merger target. Even if one could distinguish who generated the patent, cross-citations tell us little about the effect of patent library openings because technology information can be freely transferred within the combined firm.

bidder. Alternatively, we select pseudo bidders that are from the same industry and have the closest propensity score estimated using firm size and market-to-book ratio as the terminated bidder. The pseudo bidders serve as a counterfactual because they are similar to the terminated bidders, but they are unaffected by the openings of patent libraries because they have not initiated the bidding or undertaken target searches. We build a sample that spans the period beginning five years before the deal-announcement year and ending five years after the deal is terminated for both terminated bidders and their matched pseudo bidders.

To assess potential knowledge acquisitions during bidders' searches of targets, we compute the extent to which target patents are cited by bidders. Specifically, we calculate *%Acquirer's Patents Citing Target Patents*, which is the number of bidders' patents that cite at least one patent filed by the targets in the past, scaled by the total number of patents filed by the bidders in a year. We estimate a triple DiD model in which the dependent variable is *%Acquirer's Patents Citing Target Patents* and independent variables are the DiD estimate, *Treat* × *Post*, and a triple interaction term, *Terminated Acquirer* × *Treat* × *Post*. *Treat* takes the value of 1 if the bidder or pseudo bidder is headquartered in a county where a patent library had been opened by the year prior to the deal announcement, and 0 otherwise. *Post* takes the value of 1 in years after the deal is terminated, and 0 otherwise. *Terminated Acquirer* is a dummy that takes the value of 1 for the acquirer–target pair in terminated bids and 0 for matched pseudo bidders. The triple interaction term captures the difference in the treatment effect of patent library between terminated bidders and the control group. We add many firm-level control variables, including *Ln(Total Asset)*, *Asset Tangibility*, *Sales Growth Rate*, *Leverage*, *RD/Asset*, *ROA*, *Tobin's Q*, and *Return*, and county-level controls, *Ln(Population)* and *Income Per Capita*. As the level of innovation activities of both bidders and targets affects the extent of cross-citations, we also include *# of Patents Applied by Acquirer* and *# of Patents Applied by Target* as additional control variables.

Regression results are presented in table 12 in which pseudo bidders are selected based on industry and size matching in column (1) and selected based on industry and size and market-to-book matching in column (2). The DiD estimate *Treat* × *Post* is not statistically significant in either column, suggesting that patent library openings are not associated with any significant post-acquisition change in cross-citations of target patents by pseudo bidders in the control group. However, the coefficient estimates on *Terminated Acquirer* × *Treat* × *Post* are positive and significant at the 5% level in both columns. This suggests that local patent library openings drive a significant increase in post-acquisition knowledge spillovers from the target to the bidder, as a result of the bidder's search of the target's technological information during the bidding process, even though the deals are eventually terminated. The finding highlights the underlying mechanism through which patent library openings spur acquisitions activities: they facilitate bidders' searches of targets' technology information.

TABLE 12

Post-Acquisition Citation of Target Patents by Terminated Acquirers

	(1)	(2)
	%Acquirer's Patents Citing Target Patents	
Terminated Acquirer × *Treat* × *Post*	0.033**	0.033**
	(2.129)	(2.212)
Terminated Acquirer × *Treat*	0.014	0.011
	(1.559)	(1.300)
Terminated Acquirer × *Post*	0.003	0.002
	(0.517)	(0.404)
Treat × *Post*	−0.002	−0.002
	(−0.395)	(−0.443)
Treat	−0.004	−0.003
	(−1.155)	(−0.868)
Post	−0.003	−0.004
	(−0.514)	(−0.854)
Terminated Acquirer	0.003	0.004
	(0.586)	(0.995)
Number of patents applied by acquirer	Y	Y
Number of patents applied by targets	Y	Y
Acquirer firm control	Y	Y
Acquirer county control	Y	Y
Deal fixed effects	Y	Y
Year fixed effects	Y	Y
Model	OLS	OLS
Matching covariates	Industry + Size	Industry + Size + M/B
N	2,338	2,339
Adj. R^2	0.131	0.149

The table presents the results of the effect of patent library opening on the percentage of acquirers' patents citing target patents for terminated deals. Terminated deals refer to transactions that are genuinely terminated, as verified by news articles from LexisNexis. The sample consists of acquisition deals by public innovative acquirers and targets that were terminated. For every terminated deal, we identify "pseudo" acquirers as a control group following the same matching techniques as that in tables 5 and 6. In column (1), we select pseudo acquirers that are from the same industry and have the closest size as the acquirer of the terminated deal. In column (2), we select pseudoacquirers that are from the same industry and have the closest propensity score estimated using size and market-to-book ratio as the acquirer of the terminated deal. The sample spans from five years before deal announcement year to five years after the deal was terminated for both acquirers of terminated deals and their matched pseudo acquirers. The dependent variable is *%Acquirer's Patents Citing Target Patents*, which is the number of acquirers' or pseudo acquirers' patents that cited at least one patent filed by the targets in the past, scaled by the total number of patents filed by the acquirers in a year. *Terminated Acquirer* is a dummy that takes the value of 1 for the acquirer–target pair in terminated bids, and 0 for the pseudo acquirers. *Treat* takes the value of 1 if the acquirer or pseudo acquirer is headquartered in a county where a patent library opens by the year prior to the deal announcement, and 0 otherwise. *Post* takes the value of 1 in years after the deal was terminated and 0 otherwise. Firm controls include *Ln(Total Asset)*, *Asset Tangibility*, *Sales Growth Rate*, *Leverage*, *RD/Asset*, *ROA*, *Tobin's Q*, and *Return*, and county controls include *Ln(Population)* and *Income Per Capita*. Definitions of other variables are in appendix C. *t*-Statistics based on robust standard errors are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

5. *Conclusion*

In this paper, we have examined how information costs affect technological acquisitions. Exploiting plausibly exogenous variation in technology information-gathering costs generated by the openings of patent libraries, we find that firms become more active in technological acquisitions.

Reduced information costs appear to facilitate the pairing choice of acquirers and targets. Although acquirers exhibit a strong preference for geographically or technologically proximate targets, such preference is significantly attenuated after local patent library openings, highlighting that patent library openings broaden acquirers' search for more geographically and technologically distant targets.

Further analysis reveals that patent library openings enhance the economic value of M&A transactions. After a local patent library opens, deal-completion rates rise and acquirers earn higher abnormal announcement returns and long-term buy-and-hold stock returns. Acquirers' access to patent libraries leads to greater post-merger innovation output through facilitating more collaboration between inventors of both parties. These findings suggest that reduced information costs lead to better matches between acquirers and targets in terms of better technological complementarity and greater human capital synergy. Overall, our study provides evidence of the effect of information costs on the decisions, choices, and economic value of technological acquisitions. Our findings shed new light on the importance of information search costs in corporate takeovers and the search for human capital synergies.

APPENDIX A: COMPAQ ACQUIRED TANDEM COMPUTERS IN 1997: AN EXAMPLE OF TECHNOLOGICAL INFORMATION USED BY ACQUIRERS IN SEARCHING FOR TARGETS

To provide a more concrete sense of what information in patents is used as acquirers search for targets for technological complementarity and business synergy, we examine to what extent key technological information in an acquirer's SEC filings coincides with the keywords in its target firm's patent abstract before the mergers. For example, Compaq acquired Tandem Computers in 1997. Prior to the acquisition, Compaq discussed its technological challenge in computer system in its August 1996 10Q filing, *"the company is moving many of its systems from a legacy environment of the proprietary system to client-server architecture.... . the Company could experience disruptions in the operations of its business, which could have an adverse financial impact.*" See Compaq's complete 10Q discussion below.

Compaq's discussion in August 1996 10Q filing:

> Reengineering Implementation. The Company continues to expand its manufacturing capacity as well as reengineer its internal processes to support continued growth. During 1996 the Company continues to focus on making its business processes more efficient in order to increase customer satisfaction, improve productivity, and lower costs. In the event of a delay in reengineering implementation, there could be an adverse impact on inventory, cash, and related profitability. As the Company has grown it has outstripped the ability of certain of its systems to support continued expansion. In connection with its reengineering efforts the Company is moving many of its systems from a legacy environment of proprietary systems to client-server architectures. Should the Company's transition to new systems not occur in a smooth and orderly manner, the Company could experience disruptions in the operations of its business, which could have an adverse financial impact.

Meanwhile, Tandem Computers had a patent (#5307490) approved on April 26, 1994, which focuses on improving the client-server model communicating processes in a distributed computer system. See below for the Tandem Computers' patent (#5307490). Apparently, "client-server" is the key information in Tandem's patent that could be used by Compaq in searching for appropriate targets to acquire the technologies that could improve its client-server architecture in computer system.[27]

US005307490A

United States Patent [19] **Davidson et al.**

[11] **Patent Number: 5,307,490**

[45] **Date of Patent: Apr. 26, 1994**

[54] **METHOD AND SYSTEM FOR IMPLEMENTING REMOTE PROCEDURE CALLS IN A DISTRIBUTED COMPUTER SYSTEM**

[75] Inventors: **Thomas J. Davidson; Michael T. Kelley**, both of Austin, Tex.

[73] Assignee: **Tandem Computers, Inc.**, Cupertino, Calif.

[21] Appl. No.: **938,102**

[22] Filed: **Aug. 28, 1992**

[51] **Int. Cl.**[5] **G06F 13/00**

[52] **U.S. Cl.** **395/650**; 364/DIG. 1; 364/280.6; 364/230.3; 364/281.3

[58] **Field of Search** .... 364/DIG. 1 MS File, 364/DIG. 2 MS File; 395/650, 600, 725

[56] **References Cited**

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5,187,790	2/1993	East et al.	364/DIG. 1

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Attorney, Agent, or Firm—Skjerven, Morrill, MacPherson, Franklin & Friel

[57] **ABSTRACT**

A system and a method for implementing remote procedure calls in a distributed computer system provide a base object class from which all distributed objects can be derived. A program extracting all classes derived from the base class provides an inheritance tree to allow down casting from a root class to a base class and to allow passing high level data structure between participants of a remote procedure call. An Unix script provides stub routines for implementing a client-server model communicating processes.

20 Claims, 17 Drawing Sheets

Microfiche Appendix Included
(247 Microfiche, 4 Pages)

[27] In the S-4 filing following the announcement of acquiring Tandem, Compaq pointed out that the target firm "provides its customers with reliable, scalable, fault-tolerant enterprise computer systems and client/server solutions."

APPENDIX B: LIST OF PATENT DEPOSITORY LIBRARIES

State	City	County	Year of Open	Library Name
MA	Boston	Suffolk County	1870	Boston Public Library
NY	New York City	New York County	1870	New York Public Library
NY	Albany	Albany County	1870	New York State Library Cultural Education Center
OH	Columbus	Franklin County	1870	Science and Engineering Library. Ohio State University
MO	St. Louis	St. Louis City	1870	St. Louis Public Library
CA	Log Angeles	Los Angeles County	1870	Los Angeles Public Library
NY	Buffalo	Erie County	1871	Buffalo and Erie County Public Library
OH	Cincinnati	Hamilton County	1871	The Public Library of Cincinnati and Hamilton County
MI	Detroit	Wayne County	1871	Great Lakes Patent and Trademark Center. Detroit Public Library
IL	Chicago	Cook County	1876	Chicago Public Library
NJ	Newark	Essex County	1880	Newark Public Library
OH	Cleveland	Cuyahoga County	1890	Cleveland Public Library
RI	Providence	Providence County	1901	Providence Public Library
PA	Pittsburgh	Allegheny County	1902	The Carnegie Library of Pittsburgh
OH	Toledo	Lucas County	1934	Toledo/Lucas County Public Library
GA	Atlanta	Fulton County	1946	Library and Information Center. Georgia Institute of Technology
MO	Kansas City	Jackson County	1946	Linda Hall Library
WI	Milwaukee	Milwaukee County	1949	Milwaukee Public Library
OK	Stillwater	Payne County	1956	Patent and Trademark Library. Oklahoma State University
CA	Sunnyvale	Santa Clara County	1963	Sunnyvale Center for Innovation, Invention & Ideas, Sunnyvale Public Library
WI	Madison	Dane County	1976	Kurt F. Wendt Library. University of Wisconsin-Madison
TX	Houston	Harris County	1977	Fondren Library. Rice University
AL	Birmingham	Jefferson County	1977	Birmingham Public Library
WA	Seattle	King County	1977	Engineering Library. University of Washington

State	City	County	Year of Open	Library Name
NC	Raleigh	Wake County	1977	D.H. Hill Library. North Carolina State University
CO	Denver	Denver County	1977	Denver Public Library
TX	Dallas	Dallas County	1977	Dallas Public Library
NE	Lincoln	Lancaster County	1978	Engineering Library. University of Nebraska, Lincoln
TN	Memphis	Shelby County	1979	Memphis Public Library
CA	Sacramento	Sacramento County	1979	California State Library
PA	University Park	Centre County	1979	Schreyer Business Library. Paterno Library. Pennsylvania State Library
MN	Minneapolis	Hennepin County	1980	Minneapolis Public Library
DE	Newark	New Castle County	1980	University of Delaware Library
AZ	Tempe	Maricopa County	1981	The State of Arizona Research Library
LA	Baton Rouge	East Baton Rouge Parish	1981	Troy H. Middleton Library. Louisiana State University
NV	Reno	Washoe County	1983	University Library. University of Nevada-Reno
TX	Austin	Travis County	1983	McKinney Engineering Library. The University of Texas at Austin
IN	Indianapolis	Marion County	1983	Indianapolis-Marion County Public Library
AL	Auburn	Lee County	1983	Ralph Brown Draughon Library. Auburn University
ID	Moscow	Latah County	1983	University of Idaho Library
NM	Albuquerque	Bernalillo County	1983	Centennial Science and Engineering Library. The University of New Mexico
MI	Ann Arbor	Washtenaw County	1983	Media Union Library. The University of Michigan
TX	College Station	Brazos County	1983	Sterling C. Evans Library. Texas A&M University
IL	Springfield	Sangamon County	1984	Illinois State Library
MD	College Park	Prince George's County	1984	Engineering and Physical Sciences Library. University of Maryland
CA	San Diego	San Diego County	1984	San Diego Public Library
MT	Butte	Silver Bow County	1984	Montana Tech Library of the University of Montana
UT	Salt Lake City	Salt Lake County	1984	Marriott Library. University of Utah

State	City	County	Year of Open	Library Name
FL	Miami	Miami-Dade County	1984	Miami-Dade Public Library System
FL	Fort Lauderdale	Broward County	1984	Broward County Main Library
MA	Amherst	Hampshire County	1984	Physical Sciences and Engineering Library. University of Massachusetts
AK	Anchorage	Anchorage Municipality	1984	Z. J. Loussac Public Library. Anchorage Municipal Libraries
AR	Little Rock	Pulaski County	1985	Arkansas State Library
TN	Nashville	Davidson County	1985	Stevenson Science and Engineering Library. Vanderbilt
VA	Richmond	Richmond City	1985	James Branch Cabell Library. Virginia Commonwealth University
PA	Philadelphia	Philadelphia County	1986	The Free Library of Philadelphia
DC	Washington	District of Columbia	1986	Founders Library. Howard University
KY	Louisville	Jefferson County	1988	Louisville Free Public Library
IA	Des Moines	Polk County	1988	State Library of Iowa
FL	Orlando	Orange County	1988	University of Central Florida Libraries
NJ	Piscataway	Middlesex County	1989	Library of Science and Medicine. Rutgers University
HI	Honolulu	Honolulu County	1989	Hawaii State Library
ND	Grand Forks	Grand Forks County	1990	Chester Fritz Library. University of North Dakota
FL	Tampa	Hillsborough County	1990	Patent Library. Tampa Campus Library. University of South Florida
MS	Jackson	Hinds County	1990	Mississippi Library Commission
KS	Wichita	Sedgwick County	1991	Ablah Library. Wichita State University
IN	West Lafayette	Tippecanoe County	1991	Siegesmund Engineering Library. Purdue University
MI	Big Rapids	Mecosta County	1991	Abigail S. Timme Library. Ferris State Library
WV	Morgantown	Monongalia County	1991	Evansdale Library. West Virginia University
SC	Clemson	Pickens County	1992	R. M. Cooper Library. Clemson University

State	City	County	Year of Open	Library Name
ME	Orono	Penobscot County	1993	Raymond H. Fogler Library. University of Maine
CA	San Francisco	San Francisco County	1994	San Francisco Public Library
SD	Rapid City	Pennington County	1994	Devereaux Library. South Dakota School of Mines and Technology
PR	Mayaguez	Mayaguez Minicipio	1995	General Library. University of Puerto Rico-Mayaguez
OR	Portland	Multnomah County	1995	Paul L. Boley Law Library. Lewis & Clark Law School
OH	Akron	Summit County	1995	Akron-Summit County Public Library
TX	Lubbock	Lubbock County	1995	Texas Tech University Library
NH	Concord	Merrimack County	1996	New Hampshire State Library
VT	Burlington	Chittenden County	1996	Bailey/Howe Library
CT	Hartford	Hartford County	1997	Hartford Public Library
CT	New Haven	New Haven County	1997	New Haven Free Public Library
NY	Stony Brook	Suffolk County	1997	Engineering Library. Melville Library SUNY at Stony Brook
NV	Las Vegas	Clark County	1999	Las Vegas Clark County Library District
NY	Rochester	Monroe County	1999	Central Library of Rochester and Monroe County

APPENDIX C: VARIABLE DEFINITIONS

Variable	Definition
Firm Characteristics	
Pat Library	An indicator that takes the value of 1 if the firm is headquartered in a county where there is a patent library in a given year, and 0 for those headquartered in counties without any patent libraries in a year
Age	The number of years that a firm appears in Compustat.
Total Asset	The book value of assets.
RD/Asset	The ratio of R&D expenditure to the book value of total assets.
ROA	Return on assets, measured as OIBDP divided by the book value of assets.

Variable	Definition
Leverage	The ratio of the book value of short-term and long-term debt to the book value of assets.
Cash/Asset	The ratio of cash and cash equivalents to the book value of total assets.
Market to Book	The ratio of the market value of assets to the book value of assets.
Sales Growth Rate	Percentage change in sales.
NWC/Asset	The ratio of noncash net working capital to the book value of assets.
Return	The buy-and-hold 12-month stock return in the past 12 months.
Deal Characteristics	
Actual M&A Deal	An indicator that that takes the value of 1 for the actual acquirer–target pair, and 0 for the pseudo pairs.
Completed Deal	An indicator that takes the value of 1 if the deal is completed, and 0 otherwise.
Combined # of Patents	The sum of the total number of patents from acquirers and targets in a year during the pre-acquisition period, or from the post-merger combined firms in a year during the post-acquisition period.
Combined # of Citation Weighted Patents	The sum of the total number of citation weighted patents from acquirers and targets in a year during the pre-acquisition period, or from the post-merger combined firms in a year during the post-acquisition period.
%Co-invented Pat	Total number of co-invented patents filed by post-merger combined firm within 5 years after the deal completion, scaled by the total number of patents filed by post-merger combined firm during the same period.
%Co-invented Cite	Total number of citations received by co-invented patents filed by post-merger combined firm within 5 years after the deal completion, scaled by the total number citations received from those patents filed by post-merger combined firm during the same period.
Patent_KeyWords_Mentioned	The ratio of the total occurrences of all unique keywords from its target's patent abstracts found in an acquirer's SEC filings, to the total number of words in these SEC filings, prior to the M&A deal.
%Acquirer's Patents Citing Target Patents	The number of bidders' patents that cite at least one patent filed by the targets in the past, scaled by the total number of patents filed by the bidders in a year.
Treat	An indicator that takes the value of 1 if the acquirer is headquartered in a county with a patent library in the deal announcement year, and 0 otherwise.
Post	An indicator that takes the value of 1 in years post the deal completion, and 0 otherwise.

Variable	Definition
Relative Size	The ratio of M&A deal value to an acquirer's market value of equity.
All Cash Dummy	An indicator that equals 1 if the deal is financed by cash only, and 0 otherwise.
High Tech Dummy	An indicator that equals 1 if an acquirer's four-digit SIC code is equal to 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3671, 3672, 3674, 3675, 3677, 3678, 3679, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7371–7375, 7378, or 7379, and 0 otherwise.
Diversify Dummy	An indicator that equals 1 if the acquirer and target belong to different two-digit SIC code industries, and 0 otherwise.
Hostile Dummy	An indicator that equals 1 if the M&A deal is a hostile takeover, and 0 otherwise.
Challenge Dummy	An indicator that equals 1 if the acquirer's offer is challenged by a competing offer, and 0 otherwise.
Public Target Dummy	An indicator that equals 1 for a publicly listed target, and 0 otherwise.
Geo Prox	The reciprocal of the logarithm of the distance (in miles) between the actual (or pseudo) acquirer and the target.
Tech Prox	The technological proximity that is a cosine similarity of an acquirer and a target's patent portfolio.
Terminated Acquirer	An indicator that takes the value of 1 for the acquirer–target pair in terminated bids and 0 for matched pseudo bidders.
County Characteristics	
Population	Total population in one county.
Income Per Capita	The personal income per capita in 1,000 dollars in one county.

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