Does Access to Patent Information Help Technological Acquisitions?

Abstract

Technology acquirers face significant information asymmetry when identifying appropriate acquisition targets. Employing plausibly exogenous variation in technological information gathering costs caused by staggered openings of patent libraries, we find that firms become more active in technological acquisitions following local patent library openings. In addition, acquirers prefer targets that are geographically close or are similar in technological space to a lesser extent, technology M&A completion rates increase, acquirers' abnormal announcement returns are higher, and long-term stock returns of combined firms are better. Acquirers' access to patent libraries also leads to greater post-merger innovation output through fostering more collaboration between acquirers' and targets' inventors. Overall, our study sheds new light on the importance of information gathering costs in corporate takeovers and the search for human capital synergies.

JEL Classification: G34, O3, O34, O38

Keywords: Mergers and Acquisitions; Patent and Trademark Depository Library; Patent Information; Information Gathering Costs

1. Introduction

Many merger and acquisition (M&A) transactions are motivated by acquiring innovation (Holmstrom and Roberts, 1998). They offer firms opportunities to obtain external technologies, complement internal R&D projects, and speed up innovation processes (Higgins and Rodriguez, 2006; Phillips and Zhdanov, 2013). Nevertheless, identifying appropriate targets and evaluating potential synergy gains remain significant challenges for technology acquirers, particularly for acquisitions involving technologies that are outside the acquirer's core areas of expertise (Rhodes-Kropf and Robinson, 2008; Bena and Li, 2014; Seru, 2014). Notably, information asymmetries between acquirers and targets raise significant concerns about adverse selection and inefficient transactions (Bhattacharya and Ritter, 1983; Povel and Singh, 2006), because target firms are typically more informed about their own and their competitors' technologies, whereas acquirers often have difficulties distinguishing real values of assets that are to be acquired (Rhodes-Kropf and Robinson, 2008; Officer, Poulsen, and Stegemoller, 2009).[1] As a result, such information asymmetry can ultimately divert acquirers from identifying the best matches and unravel promising deals (Moeller, Schlingemann, and Stulz, 2005, 2007).

In this study, we investigate the effects of information frictions on takeover activities and performance by exploiting plausibly exogenous variation in information gathering costs caused by staggered openings of the United States Patent and Trademark Office (USPTO)'s Patent and Trademark Depository Library (PTDL, hereafter) system.[2] Recent literature shows that there are significant costs associated with searching, gathering, and analyzing public disclosures (Blankespoor, deHaan, and Marinovic, 2020). In order to exploit existing knowledge developed by others, a firm firstly, needs to be aware of the existence of the knowledge, next to obtain the knowledge from public disclosures and sources, and finally to assess the implications of the knowledge to its own technologies. The costs in each step are referred to as awareness costs, acquisition costs, and integration costs, respectively. We argue that the opening of a patent library in a county reduces the "awareness cost" and "acquisition cost" of patent information for local acquiring firms, which, in turn, enhances their awareness and ability of accessing the

[1] There are several reasons that targets may not be able to help mitigate information asymmetries, such as proprietary costs of revealing proprietary information (Frésard, Hoberg, and Phillips, 2020) or strategic motives (e.g., requesting a higher bid). Bhattacharya and Ritter's (1983) model indicates that firms could compromise their innovation abilities if they disclose details of their R&D projects to capital markets to raise financing.

[2] We will call USPTO Patent and Trademark Depository Library, PTDL, patent library, patent depository libraries interchangeably.

technological information disclosed in patent documents of potential targets nationwide, thereby facilitating their assessments of the integration value of their targets' intellectual properties (Chen, Gao, and Ma, 2020; Dey and White, 2021). 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. Therefore, we propose that the openings of local patent libraries mitigate adverse selection by alleviating information frictions between acquirers and targets, which, in turn, boosts acquisition activities and improves the optimal pairing between acquirers and targets, deal completion rates, and post-merger performance (we discuss more institutional details on the USPTO's PTDL program in section 2).

Our study uses the staggered openings of PTDLs across various locations in the U.S. as a source of variation in the availability of patent information. A key premise is the patent information is largely utilized by *local* inventors, analysts, investors, and lawyers, for economic, legal, product, and market research (Brown and Arshem, 1993). A 1997 survey of patent depository library users shows that the median users of PTDLs travel between 11 and 20 miles, and 38% of the users travel fewer than ten miles (Patent and Office, 1999). Similarly, the 1999 survey reports roughly 70% of the users travel less than 20 miles (Patent and Office, 2003). Furman et al. (2021) and Martens (2021) also 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 treatment shock to the cost of collecting patent information due to the opening of a patent library in the local area, we can assume that firms located in counties without any patent libraries serve as a counterfactual of the treated group.

We then investigate the effects of patent library openings on acquisition activities with a difference-in-differences (DiD) approach. Using a sample of public innovative firms during 1985-1999, we define treated firms as those headquartered in counties where a patent library opens, whereas control firms are those headquartered in counties without any patent libraries. We find a significant increase (about 6.2%) in acquisition activities after a patent library opens in local counties, consistent with the notion that patent library openings reduce the costs of accessing patent documents, hence mitigating information frictions. We perform a battery of robustness tests and the baseline result remains.

We next examine how the openings of patent libraries alter the pairing choice between acquirers and targets. M&As often create synergy and value by combining complementary resources, such as patents, human capital, and tangible assets. Prior research has shown that dissimilar or distant resource and knowledge are naturally complementary (Makri, Hitt, and Lane, 2010). In the absence of the aforesaid information frictions, acquiring firms are able to consider all possible targets with various resource complementarities and synergy gains, opting for the first best choice that creates the largest synergy gains. Nevertheless, information frictions in M&As force acquirers to select targets that are geographically proximate, since acquirers can easily access such targets' soft information through site visits or interactions with target 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 frictions between acquirers and targets (Bena and Li, 2014). Nevertheless, such pairing tendencies constraint acquirers' search and prevent them from finding the first best choice of targets, leading to economic losses for both acquirers and targets.

The openings of patent libraries reduce local acquirers' gathering costs of technology information about potential targets, hence alleviating information asymmetry and lowering the costs of evaluating targets that are geographically distant or technologically dissimilar. As a result, patent library openings allow acquirers to broaden their search of potential targets. We thus conjecture that the reliance on geographic or technologic proximity in technological acquisition is attenuated following a patent library opening. Our results support the conjecture. We find that M&A deals are more likely to take place between geographically (or technologically) proximate acquirers and targets. However, this effect is largely weakened after the opening of a patent library in the acquirer's headquarters county. Put differently, acquirers continue to demonstrate a preference for geographically (or technologically) proximate targets, but to a lesser extent following the opening of a local patent library.

Finally, we explore a "bottom line" question by examining the effect of patent library openings on the completion rate and performance of M&A deals. Based on our discussions above, reduced costs of evaluating technology information of potential targets allow acquirers to broaden their search without limiting to the candidates that are geographically or technologically close to them. This observation, in turn, results in better matches between acquirers and targets, such as better technology complementarities and greater synergies, hence creating greater economic value. In addition, reduced information asymmetry mitigates adverse selection, helping successful completion of technological acquisitions. Taken together, we propose that patent library openings lead to a higher deal completion rate and a higher acquirer announcement return. Consistent with our conjectures, we find that the odds of deal completion rise by 26.1% after patent library openings. We also find that patent library opening is associated with a 1.4% higher 7-day cumulative abnormal return (CARs) around acquisition announcements and a 10.6% larger post-merger 5-year buy-and-hold return of combined firms, suggesting that acquirers' pre-merger access to patent information leads to value-enhancing M&A transactions. We finally show that M&A deals completed by acquirers with access to local patent libraries are associated with a greater extent of collaboration between acquirer and target inventors after the merger, hence spurring firm innovation output.

Our paper contributes to three strands of the existing literature. First, we add to research on the effect of information frictions on M&As (Rhodes-Kropf and Robinson, 2008; Wang, 2018). Differing from the prior literature that focuses on the costs and benefits of information disclosure by acquirers (Bonetti et al., 2020) or by targets (Officer et al., 2009; Martin and Shalev, 2017; Chen, 2019; Chondrakis et al., 2021), we study the effect of acquirers' increased access to technology information through the USPTO patent documents. This new angle allows us to explore how the reduction of technology information gathering costs, as opposite to self-disclosure, alters M&A transaction activities and performance, which typically suffer from adverse selection concerns caused by information asymmetry.

Second, prior literature has documented a variety of factors that drive 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 (Levine, 2017; Cunningham, Ederer, and Ma, 2021), gaining human capital (Chen et al., 2021; Dey and White, 2021), and exploiting work-in-progress intellectual properties (Beneish et al., 2021; Landsman, Liss, and Sievers, 2021). Our paper highlights the importance of scientific knowledge itself in the success of technological acquisitions.

Lastly, we extend the literature on the effect of geographical proximity on economic decisions. Economic agents often exhibit preference for geographic proximity (or "home bias"), such as investors' investment decisions (Hong, Kubik, and Stein, 2008), analyst coverage (Malloy, 2005), bank loans (Berger et al., 2005), corporate payout (John, Knyazeva, and Knyazeva, 2011), and venture capital investment (Lerner, 1995; Tian, 2011). In the market for takeovers, approaching local targets can reduce bidders' information asymmetry while increase soft information exchange and improve post-acquisition monitoring (Kang and Kim, 2008; Uysal, Kedia, and Panchapagesan, 2008). McCarthy and Aalbers (2016) find post-acquisition innovation performance is better when the technology acquirer and target are located closer to each other. Our study sheds new light on the fundamental frictions underlying the preference for geographical proximity—information cost—and contributes to the literature by showing that reduced costs of acquiring scientific information help fuel knowledge diffusions across geographic locations, yield greater human capital synergies, and improve economic value of acquisitions.

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

2. Institutional Background of the Patent and Trademark Depository Library System

Prior to 1870, patent documents in the U.S. were only located at the USPTO in Washington, D.C. For the sake of public dissemination to enhance information diffusions, USPTO started, in the early 1870s, to distribute copies of patent documents across the U.S. by establishing a nationwide Patent and Trademark Depository Library (PTDL) system. The PTDL offers public access to all resources necessary to conduct a full search of patents and trademarks, and meanwhile, increases the awareness of the use of intellectual property systems. A total of 11 patent depository libraries were first established in the 1870s.[3] By the end of 1975, there had been 20 libraries opened, mainly in the New England area and East of the Mississippi (see Appendix A).

As demand for access to patent documents has increased since 1975, the USPTO has aggressively expanded the PTDL program with a goal of increasing the number of patent libraries by at least three per year and ensuring that there is at least one patent library in each

[3] They include the New York State Library, the Boston Public Library, the Public Library of Cincinnati and Hamilton County, the Science and Engineering Library at Ohio State University, the Detroit Public Library, the Los Angeles Public Library, the New York Public Library, and the St. Louis Public Library.

state.[4] Since then, 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 collection and hence guaranteeing the public availability of the individual patent information; (4) having staffs receiving sufficient training so that they can assist the public in the efficient use of the patent collection and the associated tools.[5] Appendix A presents a list of patent libraries with their opening year.

Furman et al. (2021) argue that the decision to join the patent library system is initiated by the library itself rather than solicited by the USPTO. Although there could be reasons reflecting the local demand for patent information, at the minimum, there are factors that are more idiosyncratic and less predictable driving the decision to become a PTDL, such as the perceived attractiveness of annual patent librarian training in Washington D.C. and the professional and personal benefits of joining the PTDL librarian community.[6] In addition, the introduction of microfilm in the 1970s makes library capacity requirement less of a concern, making more libraries eligible to join the patent library system. Therefore, the openings of patent libraries were unlikely to be correlated with local economic conditions, M&A activities, and innovation activities. For example, patent libraries opened in Honolulu, HI and Big Rapids, MI in 1989 and 1991, respectively, a couple of years before they opened in San Francisco, CA, which is a more populated and more technology-demanding city, in 1994.

To check whether local patent library opening is indeed unrelated to local economic characteristics, we follow the method in Acharya, Baghai, and Subramanian (2014) by estimating a Cox proportional hazard model, which examines whether any county-level characteristics could predict the opening of a patent library in a county. We start with a sample of county-year observations during 1985-1999 up to the year when a patent library opens in the county.[7] The dependent variable (or the "failure event") equals one if a patent library opens in a

[4] The latter goal was accomplished in 1997.

[5] Each patent library must send a representative to the annual PTDL Training Seminar in Washington DC to ensure sufficient training.

[6] 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.

[7] We start our sample of M&A deals in 1985 since SDC began to provide high quality M&A data in that year. As a result, we restrict the sample for this test to post-1985. There are 32 patent libraries opened during 1985-1999. The

county-year and zero otherwise. Similar to Guernsey, John, and Litov (2020) and Green and Shenoy (2022), we include a set of county demographic and economic variables as the potential determinants that might predict local patent library openings. Specifically, we include the natural logarithm of county population (*Ln(Population)*), the personal income per capita in 1,000 dollars in a county (*Income Per Capita*), percent change in unemployment rate (Δ *Unemployment Rate (%)*), and the percent change in the number of business establishments (Δ *# of Establishments (%)*).[8] Since our empirical strategy in the main test relies on the assumption that the openings of patent libraries are exogenous with respect to local innovation activities, we investigate whether there is a reverse causality, i.e., whether local demand for technological information (proxied by local innovation activities) predicts patent library openings. As a result, we include the natural logarithm of one plus the total number of patents generated by public firms located in a county-year (*Ln(1+# of Patents)*). To examine whether past M&A activities can predict patent library openings, we count the number of firms being acquirers (or targets) in M&A deals in a county-year and add *Ln(1+# of M&A Deals as Acquirers)* and *Ln(1+# of M&A Deals as Targets)* as predictors in the model, respectively. Lastly, given that the USPTO aims for at least one patent library in each state as they expand the PTDL program, the chance of having a local patent library is expected to be lower in states with existing patent libraries. We thus create a binary variable, *Same State Pat Library* that takes the value of one if there has already been a patent library opened in the state where the county is located and zero otherwise. Following Guernsey, John, and Litov (2020), we include year dummies in the Cox proportional hazard model.

The results of hazard ratios are reported in Table A1 in the Appendix. A hazard ratio of greater than one indicates that an increase in the explanatory variable leads to a faster opening of patent libraries in a county. The results are qualitatively similar with and without *Same State Pat Library* in columns (1) and (2). In both regressions, local population is a significant determinant of patent library openings. The coefficient estimates on *Income Per Capita*, Δ *Unemployment Rate (%)*, Δ *# of Establishments (%)* are all statistically insignificant, suggesting that the 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

patent library in Mayaguez Minicipio, PR is not in the sample because of missing county characteristics. The patent library in Washington, DC is not included because of the missing establishment data from CBP. In the end, we have 30 patent library opening events ("failure events") in the hazard model.

[8] County-level population data, personal income data, and the number of business establishments data are from The National Cancer Institute, The Bureau of Economic Analysis, and County Business Patterns (CBP), respectively.

Ln(1+# of M&A Deals as Targets) are all statistically insignificant, implying no evidence of reverse causality, i.e., local demand drives the opening of patent libraries. As expected, the coefficient estimate on *Same State Pat Library* is significantly smaller than one, suggesting a lower chance of having a patent library in the county where there has already been a patent library in the state. Overall, county-level economic conditions, M&A activities, and innovation activities are unable to determine the local patent library openings.

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 in 1985 because SDC begins to provide high quality M&A data since then. We end our sample in 1999 for two reasons. First, we want to focus on the analysis prior to the internet boom, as Furman et al. (2021) show that the effect of patent libraries on local innovation diminishes during the internet age. Second, we intend to avoid overlapping our sample period with the American Inventor Protection Act (AIPA) that becomes effective in November 2000, alleviating the concerns that our results might be driven by the AIPA.[9]

Following the prior literature, we apply the following filters as we build our sample of M&A deals. We start with completed deals in SDC during 1985 to 1999 that are coded as a merger, or an acquisition of majority interest, or an acquisition of assets. We also require the acquirers to own less than 50% of the target prior to the bid, seek to own at least 50% and finally own at least 90% of the target after deal completion.[10] We further restrict the sample to deals with at least $1 million in transaction value and the acquirers having at least $1 million of total assets. Finally, we require that acquirers are publicly traded non-financial firms whose accounting and stock return information are available from the Compustat and CRSP databases. 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 between 1985 and 1999.

[Insert Table 1 about Here]

[9] One of the significant changes 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 after the first filing, regardless of whether the application is eventually granted. Prior to the passage of the AIPA, patent documents become publicly available after they are granted. The average time from a patent's filing date to its grant date is approximately 36 months prior to the AIPA. Effectively, the AIPA accelerates the overall patent disclosure process.
[10] About 98% of acquirers in our sample have zero ownership in the target prior to the bid.

The expansion of patent libraries serves as a shock to the cost of gathering patent information, arguably, only to local innovative firms that have the adequate knowledge and skills to evaluate technology information in patent documents to identify appropriate targets. To ensure the sample is relevant to our analysis on technological acquisitions, we follow Bena and Li (2014) and restrict the sample to the acquirers that are innovative (i.e., firms that have been granted at least one patent during the past five years before the deal). We also focus on innovative targets since patent libraries are by definition not relevant to non-innovative target firms that have no patent. One issue is that about 77% of the M&A deals in our sample involve private targets. Restricting to public innovative targets therefore leads to a much smaller sample that possibly undermines the 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 is awarded a patent in the past five years.[11] We obtain patent data from USPTO PatentsView, and firm identifiers that every patent belongs to from Noah Stoffman's website (http://kelly.iu.edu/nstoffma/). Restricting to innovative acquirers and targets from innovative industries yields a total of 2,913 M&A deals. Table 1 column (2) shows the distribution by year of the sample.

We obtain the lists of patent depository libraries from Jenda (2005), Martens (2021), and Furman et al. (2021), which include name, location (i.e., state, county, city), and the opening date of each patent library. Appendix A provides a list of 84 patent library openings between 1870 and 1999. There are 32 counties that join the patent library system during our sample period of 1985-1999, which represents the wave of USPTO patent library system expansions.

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.[12] County-level population data and personal income data are obtained from the National Cancer Institute and The Bureau of Economic Analysis, respectively.

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

[12] To merge the SDC data with that of Compustat and CRSP, we first use the mapping file in Ewens, Peters, and Wang (2021) 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. (2021), 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 verified each matched record by cross-checking the names of acquirers (or targets) from SDC and their names in Compustat and CRSP.

Our baseline sample consists of all publicly traded innovative firms in Compustat from 1985 to 1999. We limit the sample to only innovative firms that have been granted at least one patent in the previous five years, since we focus on technology acquisitions. We measure acquisition activities in each firm-year observation based on the aforesaid 2,913 M&A deals. We report summary statistics of the key variables of our sample in Table 2. About 14.7% firms are engaged in M&A deals as acquirers in a year, comparable to the number reported in the previous literature.[13] 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 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).

[Insert Table 2 about Here]

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 using the baseline sample. 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 opening on deal completion rates, acquisition announcement returns, and post-merger performance. Finally, we investigate the post-acquisition cross-citations by withdrawn 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 staggered openings of patent libraries across different geographic locations on firms' acquisition activities. In our analysis, treated firms are those that are headquartered in counties where a patent library opens, whereas control

[13] For example, Bonaime, Gulen, and Ion (2018) reported 14% of "unconditional probability of announcing a merger".

firms are those headquartered in counties without any patent libraries.[14] Specifically, we estimate the following OLS regression model:

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

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).[15] All the right-hand-side variables are lagged by one year. The key independent variable, *Pat Library*, takes the value of one if the firm is headquartered in a county where a patent library is opened, and zero otherwise.[16] 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 logarithm of total assets (*Ln(Total Assets)*), 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*, non-cash working capital scaled by total assets (*Net Working Capital*), 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 B. We also include firm (μ_i) and year-fixed (μ_t) effects 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

[14] For instance, the opening a PTDL in Philadelphia will provide an easier access of all USPTO patent documents for inventors and investors in Philadelphia rather than those in areas hundreds of miles away from Philadelphia.
[15] We set the value of *# of M&A Deals* to zero if there are no acquisitions of innovative targets in a year.
[16] As noted in Heider and Ljungqvist (2015), using the headquarters location directly from Compustat (which keeps only the most recently location) will mislabel 10% of firm-years' historical headquarters locations. For public acquirers, we use the historical headquarters locations by web scrapping their 10-K and 10-Q reports. Whenever a firm-year's location information is missing, we use the available location information in the adjacent year to fill in those missing values.

firms located in counties with patent libraries opened complete more acquisitions involving innovative targets than firms located in counties without patent libraries. The effect is also economically sizeable. On average, the openings of patent libraries spur local technological M&A activities by 6.2% in the subsequent year.

[Insert Table 3 about Here]

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 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 prior to and post of the patent library opening year. The dynamic analysis allows us to examine whether our results are driven by reverse causality, i.e., local economic 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 three years before and after the patent library opening: *Pat Library(≤-3)* equals one if the sample year is three years or more prior to the patent library opening year and zero otherwise; *Pat Library(-k)* (k=1,2) equals one if the sample year is k year(s) prior to the patent library opening year and zero otherwise; *Pat Library(+k)* (k=1,2) equals one if the sample year is k year(s) following the of patent library opening year and zero otherwise; *Pat Library(≥+3)* equals one if the sample year is 3 years or more following the patent library opening year and otherwise. Below is the dynamic regression model:

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

To avoid multicollinearity, we set the year of library openings as the base year, which is reflected in the intercept. If there exits reverse causality, 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, suggesting the satisfaction of the parallel trend assumption of the DiD approach and hence 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, indicating that patent library openings spur local technological acquisitions, as early as two years after patent library openings.

[Insert Table 4 about Here]

To visualize the parallel trends, we plot the coefficient estimates obtained from the dynamic model in Figure 1. 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 1 shows that the coefficient estimates for the pre-event years are virtually indifferent from zero, hence validating the parallel trends assumption. However, acquisition activities significantly rise starting in the second year following patent library openings.

[Insert Figure 1 about Here]

The dynamic model indicates that the effect is most significant in two and three years after patent library opens. To capture the delayed effect, we examine how patent library affects technological M&A activities in the subsequent three years by constructing an alternative dependent variable, *Ln(1+# 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. Appendix Table A2 reports the regression results, confirming a positive effect of patent library openings on local firms' technological acquisition activities in the subsequent years. Consistent with the results from the dynamic model, the openings of patent libraries increase local technological M&A activities by 11%-12% in the subsequent three years.

4.1.3. Falsification Tests

A concern arises that our results could be driven by unobserved variables that happen to be correlated with the timing of patent library openings. While the staggered feature of patent library openings in different counties mitigate this concern to some extent since there is a small chance that other unobservable variables with similar effects move in the same geographic and temporal fashion as the opening of patent libraries, we conduct a formal falsification test to rule out this possibility.

Following Cornaggia et al. (2015) and Bradley, Kim, and Tian (2017), we first obtain the empirical distribution of patent library opening dates. 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 2 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, and 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 driven by unobserved shocks contemporaneous to the openings of patent libraries.

[Insert Figure 2 about Here]

4.1.4. Robustness Checks

To ensure the robustness of our results, we conduct a battery of additional tests. First, since the dependent variable is a count number, we estimate various regression models for count data, and report the results in Appendix Table A3 Panel A. Cohn, Liu, and Wardlaw (2022) demonstrate that the common practice of adding a constant to the outcome variable and then estimating log-linear regressions might produce estimates with the wrong sign. To address this concern, we follow Cohn et al. (2022) and estimate a fixed-effects Poisson model in which the dependent variable is *# of M&A Deals*. Results are reported in column (1). We control for the same sets of firm-level and county-level variables, as well as firm and year fixed effects. The coefficient estimate on *Pat Library* remains positive and significant. In column (2), we run a Negative Binomial regression in which the dependent variable is *# of M&A Deals* and find qualitatively similar results. In column (3), we estimate an OLS regression with *# of M&A Deals* being the dependent variable and find robust results. In column (4), we run a logit regression to model the likelihood of a public innovative firm completing at least one innovative target acquisition in a year.[17,18] We find that the opening of a patent library significantly increases the likelihood of local firms' technological acquisitions by 10.8%.[19]

Second, Harford (2005) documents acquisitions come in waves in different industries across different time periods. We thus use industry and year fixed effects to control for merger waves. As shown in Appendix Table A3 Panel B, our results remain robust in both columns (1) and (2) in which we add industry fixed effects based on three-digit SIC or the Fama-French 48 industry classifications, respectively. The results remain robust to the use of two-digit or four-digit SIC industry classifications, the Fama-French 12 or 30 industry classifications, or industry-times-year fixed effect that captures the time-varying unobservable factors within the industry (untabulated and available upon request). Third, to account for time varying local unobservable factors, we add state×year fixed effects in column (3), and in column (4) we control county and year fixed effects. Our results are robust to these alternative specifications.

Fourth, to assess whether our results are sensitive to the clustering methods of standard errors, we repeat our baseline estimations and cluster standard error at the firm- or industry-level, or double cluster standard errors at both county- and year-level. As shown in Appendix Table A3 Panel C, we continue to find a significant increase in firms' acquisition activities following the openings of patent libraries in their headquarters counties.

Fifth, among the 69 patent libraries in our sample, 29 of them are university libraries. Universities are often hubs of innovation, which in turn boosts innovation activities in the local firms. This likely causes a spurious correlation between the opening of patent libraries and technological acquisition activities. To address this concern, we exclude, from our sample, all the firms located in the counties where university patent libraries reside and rerun the baseline model in Equation (1). Results are presented in Appendix Table A4. The openings of non-university patent libraries continue to increase local firms' technological acquisition activities, suggesting that our results are not driven by the spurious correlation between universities and local innovation activities.

[17] Note that the sample size of the non-linear models becomes much smaller compared to that of the OLS regression. This is because with firm fixed effects, logit regression drops firms that remained being an acquirer or a non-acquirer for the entire sample period; Poisson regressions and Negative Binomial regressions drop firms that remained being a non-acquirer throughout the entire sample period.

[18] The results are qualitatively the same if we estimate Probit regressions.

[19] Using the estimated results where all county-level variables are added and setting all the continuous variables to their average values, we find that the likelihood of being an acquirer increase from 22.8% to 33.6%. That is a 10.8-percent-point increase in acquisition probability (33.6% - 22.8%).

Finally, Baker et al. (2022) point out that staggered DiD regressions are susceptible to biases resulted from treatment effect heterogeneity. To address this concern, we follow their recommendation and perform two diagnostic tests in Appendix Table A5: 1) we conduct a stacked regression and obtain qualitatively similar result as the baseline result; 2) we estimate the interaction weighted (IW) estimator and constructs pointwise confidence interval for the estimation of dynamic treatment effects, a method that is initially proposed by Sun and Abraham (2021) in the presence of treatment effects heterogeneous across cohorts, and obtain similar results.

4.2. Patent Library Openings and Acquirer-Target Pairings

In the absence of aforesaid information frictions, acquiring firms are better able to consider all available targets with various resource complementarity and synergy, and opt for the first best choice. Nevertheless, information frictions in M&A force acquirers to select targets that are geographically proximate or in similar technology space in order to lower the costs of information gathering and avoid adverse selection. 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 between 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. In particular, 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 on industry — where we use the narrowest SIC code that provides at least five candidate firms, and then based on the closest size (total assets) in the year prior to the deal announcement.[20, 21] We also require the control firms to be neither an acquirer nor a

[20] 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 (target firm), we next search for matching

target in the past three years 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 taking into consideration of 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 since it is widely accepted as a proxy for growth opportunities, overvaluation, and asset complementarity (Shleifer and Vishny, 2003; Rhodes-Kropf and Robinson, 2008), all of which are important drivers of M&A activities. Following prior studies, we find up to five public innovative firms based on industry — where we use the narrowest SIC code that provides at least five candidate firms, then by the closest propensity score estimated using size and market-to-book ratio. We again require matched firms to be neither an acquirer nor a target during the three years prior to the year of the deal announcement.

4.2.2. Geographic Proximity and Acquisitions

Prior literature has shown that geographical distance aggravates information frictions, hence leading acquirers to focus on local deals to avoid costly information gathering (e.g., Uysal et al., 2008; Erel, Liao, and Weisbach, 2012). Therefore, acquirers tend to take over geographic proximate targets (e.g., Kang and Kim, 2008; McCarthy and Aalbers, 2016). We argue that, however, the openings of patent libraries can facilitate local acquirers to collect technological information of potential targets that are even geographically distant, which, in turn, reduces the marginal cost of 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 geographic proximity between acquirers and targets is weakened after the openings of patent libraries.

For this purpose, we compute the geographic distance (in miles) between each actual acquirer-target pair alongside each pseudo acquirer-target pair.[22] Following Bereskin et al. (2018), we estimate the following conditional logic model to gauge the likelihood of the actual M&A deal occurring.

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peers based on two-digit SIC code. In our sample, 54%, 23%, and 23% of the control acquirers are found based on four-digit, three-digit, and two-digit SIC code industry group, respectively.

[21] Our results remain if we use market capitalization proxy for firm size.

[22] To compute geographic distance, we use public acquirers' historical headquarters locations. For target firms, we use their zip code from SDC, or, if missing, the zip code of the capital city of the state where the target is located.

$$Actual\ M\&A\ Deal_{i,t} = f(\beta_0 + \beta_1 Geo\ Prox_{i,j,t-1} \times Pat\ Library_{c,t-1} + \beta_2 Geo\ Prox_{i,j,t-1} + \beta_3 Pat\ Library_{c,t-1} + \gamma_1 X_{i,t-1} + \gamma_2 W_{c,t-1} + \mu_d + \varepsilon_{i,t}), \quad (3)$$

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 one for the actual acquirer-target pair, and zero for the pseudo pairs. *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 acquirer ($X_{i,t-1}$) and county characteristics ($W_{c,t-1}$) as in Table 3.[23] Following Bena and Li (2014), we include deal fixed effect (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 is 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 that information search costs are lower between geographically proximate acquirers and targets, which facilitate acquisition of nearby targets.

Regarding our variable of interest, the coefficient estimate on the interaction term *Geo Prox×Pat Library* is negative and significant at the 1% level in both columns, suggesting that the positive relation between geographical proximity and the likelihood of technological M&As is attenuated after the openings of patent libraries due to 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 remain statistically significant indicated by the F-test. It suggests that acquirers continue to prefer to acquire geographically proximate targets, though to a less extent after their local patent library opens. The effect is economically sizable: take column (1) as an

[23] Following Bena and Li (2014) and Bereskin et al. (2018), for the controls variables, we do not include the variables that are used for matching (i.e., exclude total asset in the industry and size matched sample and exclude total asset, market-to-book ratio in the industry, size, and market-to-book matched sample).

example, the marginal effect of geographical proximity on actual M&A pairing declines by 74.2% following the openings of local patent libraries.[24]

[Insert Table 5 about Here]

4.2.3. Technological Proximity and Acquisitions

Similar to the idea of geographic proximity, technological proximity can serve as a catalyst to reduce information searching costs as well. Following Jaffe (1986), we construct a measure of technological proximity of acquirer or pseudo-acquirer *i* and target *j* as follows:

$$Tech\ Proximity_{i,j,t} = \frac{X_{i,t}\, X'_{j,t}}{\sqrt{(X_{i,t}\, X'_{i,t})}\sqrt{(X_{j,t}\, X'_{j,t})}}, \tag{4}$$

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, …, K, over the past five years. $X_{j,t}$ is defined similarly for target *j*. In essence, the technological proximity measure is a cosine similarity of an acquirer and a target's patent portfolio, which ranges between zero to one. A larger value indicates a higher degree of technological overlap between the acquirer and the target. Since there are targets in an innovative industry that never file patent, we follow the approach of Gompers (1995) and Liu and Tian (2021), 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 each of the USPTO firms in the same three-digit SIC coded industry as its target firm. We then take an average of these technology proximity values, which serves as a proxy for the technological proximity of the acquirer and its target.

We re-estimate Equation (3) 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, 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

[24] We set all the continuous variables to their mean values and estimate the likelihood of actual M&A taking place. Without patent library (*Pat Library*=0), the likelihood of actual M&A is 81.5% when *Geo Prox* is at its median value; the likelihood of actual M&A increases to 91.3% when *Geo Prox* is one standard deviation above the median. That indicates an increase of the likelihood by 12.0% (=91.3%/81.5%-1). Similarly, with patent library (*Pat Library*=1), the likelihood of 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.

effect of patent library openings on technological proximity is economically sizeable: a patent library opening causes the positive effect of technological proximity on M&A pairing decline by 40%.[25]

[Insert Table 6 about Here]

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

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 these 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) argues that a variety of reasons (such as disagreement between the acquirer and the target on deal valuation) could lead to deals withdrawn. If access to patent libraries reduces technology information gathering costs, which allow acquirers to better identify innovative targets, it should make the deal more likely to be successfully completed. To investigate this conjecture, we stack the completed deals with the withdrawn deals during our sample period.[26] Our sample includes a total of 3,195 completed deals and 439 withdrawn deals, and the latter accounting for 12.08% of the total.[27]

Following the prior literature, we estimate the following logit regression to assess the odds of successfully completed deals:

$$Completed\ Deal_d = f(\beta_0 + \beta_1 Pat\ Library_{c,t-1} + \gamma_1 X_{i,t-1} + \gamma_2 W_{c,t-1}$$

[25] 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 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 actual M&A increases by 5.9% (=86.7%/81.9%-1) as the acquirer-target pair is technologically closer. Altogether, this is a 40% reduction (=5.9%/9.9%-1) in the marginal effect of technological proximity.

[26] We apply the same screening criteria to the withdrawn deals as those for the completed deals.

[27] This is consistent with Officer (2003) who reports that 10%-15% M&A deals fail or are withdrawn during 1988-2000.

$$+ \gamma_3 Z_d + \mu_m + \mu_t + \varepsilon_d) \,. \quad (5)$$

The dependent variable *Completed Deal* is a binary variable that takes the value of one if the deal is completed, and zero otherwise. Following Bereskin et al. (2018), we add deal-level control variables (Z_d), including an indicator for 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 ($X_{i,t-1}$), 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 in relative to acquirers' market value of equity (*Relative Size*). Finally, we control for whether the target is publicly traded (*Public Target Dummy*), and county-level characteristics ($W_{c,t-1}$). We also include industry (μ_m) and year fixed (μ_t) effects.[28] Regression results are reported in Table 7.

Pat Library is significantly positively related to the likelihood of deal completion 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 26.1% 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 face less severe adverse selection problems, all of which leads to a higher likelihood of successful deal completion.

[Insert Table 7 about Here]

4.3.2. Announcement Returns

To assess whether the acquisition activities following patent library openings are value enhancing for shareholders, we examine market reactions to M&A announcements. Following the extant literature (e.g., Bonaime et al., 2018), we compute cumulative abnormal returns (CARs) for acquirers and targets during a 7-day window around acquisition announcements (*CARs [-3,+3]*) using a market adjusted model with the CRSP value-weighted index as the market.[29] We estimate the following OLS model:

[28] We include industry rather than firm fixed effects, since 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 effect will lead to a large number of deals dropping out of the sample.
[29] Our results hold using an alternative estimation model (e.g., market model used in Bereskin et al. (2018)).

$$CARs\ [-3,+3]_d = \beta_0 + \beta_1 Pat\ Library_{c,t-1} + \gamma_1 X_{i,t-1} + \gamma_2 W_{i,t-1} + \gamma_3 Z_d + \mu_m + \mu_t + \varepsilon_d\ , \tag{6}$$

If patent libraries enable local firms to access patent documents nationwide, which broadens their searches for targets, acquirers could identify better targets that create greater synergies and post-merger economic value, compared to the acquirers who do not have access to patent information. Our results are consistent with the conjecture. As shown in column (1) of Table 8, *Pat Library* is positively associated with the acquirers' 7-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 who do not have local access to patent documents. The economic magnitude is sizable: our estimate suggests that the 7-day CAR of acquirers is 1.3% higher after the local patent library opens, which is equivalent to an increase of $87M (=$6,721M*1.3%) in market value.

[Insert Table 8 about Here]

We next examine the market reactions to M&A announcements of target firms. On the one hand, patent libraries assist acquirers to 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 the acquirers and the targets, causing targets to have less information advantage (hence possibly weaker bargaining power) in M&A deals. Therefore, the impact of patent library on targets' stock returns is unclear ex ante and remains an empirical question. The regression results are reported in column (2) of Table 8. Since 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 opening in acquirers' counties does 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, hence lacking 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 et al., 2021), we compute a weighted average of 7-day cumulative abnormal returns 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

(6) using *Combined CARs [-3,+3]* as the dependent variable. Following Chen et al. (2021), we control for acquirers' firm- and county-characteristics, deal-level characteristics, acquirers' industry and year fixed effects, and target firm characteristics and target industry fixed effects. As shown in column (3) of Table 8. *Pat Library* is positively associated with *Combined CARs [-3,+3]* with a coefficient estimate of 0.014. The economic value is sizable, i.e., 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 combined abnormal return (*Combined CAR[-3,+3]*) results shed some light on the ex-ante expected synergy creation resulted from acquirers' access to patent libraries. To gain insights on the ex-post value of synergy, we conduct two 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 5-year buy-and-hold returns net of the CRSP value-weighted market return. We re-estimate Equation (6) 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 acquirers that do not have access to local patent libraries.

Second, we investigate the innovation activities of post-merger combined firms. Since we focus on technological acquisitions, synergy creation is expected to be reflected in innovation output measured by patenting. Following Bena and Li (2014) and Chen et al. (2021), we construct a panel sample that 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. We then estimate the following OLS model:

$$Innovation\ Activities_{i,t} = \beta_0 + \beta_1 Treat_i \times Post_{i,t} + \beta_2 Post_{i,t} + \gamma_1 X_{i,t} + \gamma_2 W_{c,t} + \mu_t + \mu_d + \varepsilon_{i,t}\ . \qquad (7)$$

We employ two dependent variables to proxy for innovation activities — the natural logarithm of one plus "*Combined # of Patents*" and the natural logarithm of one plus "*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, 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 one if the acquirer is headquartered in a county with a patent library in the deal announcement year, and zero otherwise. *Post* takes the value of one in years post the deal completion, and zero otherwise. As with our baseline test, we include acquires' firm- and county- characteristics.[30] We also include deal- and year-fixed effects in the model.[31] 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 treated deals completed by acquirers that have local access to patent libraries versus those without. 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 acquirers have access to local patent libraries. The result is consistent with the higher abnormal announcement return result documented earlier, suggesting that improved innovation productivity is a plausible source of synergy gains.[32]

[Insert Table 9 about Here]

4.5. Human Capital Synergies

In this section, we explore a potential mechanism through which acquirers' access to patent information boosts post-merger innovation activities—human capital synergies. Chen et al. (2021) show that desires to obtain human capital is an important driver of corporate acquisitions. Li and Wang (2021) document that post-M&A, collaboration between acquirer and target inventors generates patents that are more path-breaking, impactful, and valuable, compared to

[30] For robustness, we replace acquirers' characteristics by 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, and in the post-acquisition period, it is the firm controls of the post-merger combined firm.

[31] 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 with a patent library opened in the year of deal announcement. Therefore, as we include deal fixed effects, the "*Treat*" standalone variable will be absorbed.

[32] Note that the coefficient estimates on *Post* are negative and statistically significant. This observation is consistent with the evidence in Bena and Li (2014) and Seru (2014) that acquirers, on average, experience a decrease in innovation after the acquisition.

patents by acquirer or target inventor-only teams. If improved synergy value between acquirers and targets as well as increased post-merger innovation productivity are resulted from greater human capital synergies between inventors from acquirers and targets, we expect a greater collaboration between acquirer and target inventors.

For this purpose, we examine the percentage of patents co-invented by inventors from the acquirer and the target (called 'co-invented patent'). Following the method in Chen et al. (2021), for every completed deal, we define *%Co-invented Pat* (or *%Co-invented Cite*) by counting its total number of co-invented patents (or 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 patents (or citations received from those patents) filed by post-merger combined firm during the same period. Co-invented patents are those developed by a team including 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 acquirer (target) firm in the year prior to the deal announcement.[33] We then run the regression following Equation (6), 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 treated deals in which acquirers have pre-merger access to a local patent library, compared to those in control deals in which acquirers do not have access. The results indicate that increased access to patent information enhances M&A value creation through pairing acquirers and targets with greater human capital synergies, hence yielding a greater extent of inter-firm collaboration, which, in turn, enhances the long-term value of innovation (Li and Wang, 2021).

[Insert Table 10 about Here]

[33] We identify the firm that an inventor works for based on her/his patenting history. For example, if an inventor applied for a patent in 1990 and another patent in 1995 with firm *i*, we infer that the inventor worked for firm *i* during 1990 to 1995. However, if an inventor applied for a patent in 1990 with firm *i* and applied another patent in 1995 with a different firm *j*, we follow Li and Wang (2021) and assume the inventor changed jobs at the midpoint between the two patent application years, i.e., she/he worked for firm *i* in 1990, 1991, and 1992 but worked for firm *j* in 1993, 1994, and 1995.

4.6. Post-acquisition Cross-citations by Withdrawn Bidders

To ensure the effect of patent libraries on local M&A activities is a result of reduced gathering costs of patent information for local acquiring firms, we examine the behavior of bidders of withdrawn deals. Withdrawn bidders conduct full research of potential targets just like bidders that complete the deals. Looking at a sample of failed deals and examining cross-citations by withdrawn bidders allow us to directly pinpoint the effect of patent library openings on "awareness cost" through analyzing the technology information spillovers from targets to bidders surrounding the mergers. These analyses cannot be conducted in completed acquisitions because the bidder and the target firm become one entity after the deal completion and researchers cannot distinguish whether a patent is generated by the pre-merger bidder or the pre-merger target. Even one can distinguish who generates 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. As a result, examining cross-citations by withdrawn bidders in a failed M&A deal allows us to pin down the reduced information cost mechanism.

Specifically, we examine whether local library openings affect knowledge spillovers from targets to withdrawn bidders after the acquisition attempt. If patent library openings enhance bidders' awareness of targets' technology, we expect the withdrawn 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 are not completed.

We start with 374 failed deals whose targets are in innovative industries. Studying knowledge spillovers requires the targets to have patents, which results in 98 withdrawn bids that satisfy the requirement. For every withdrawn deal, we identify "pseudo" bidders as a control group 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 withdrawn 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 withdrawn bidder. The pseudo-bidders serve as a counterfactual since they are similar to the withdrawn bidders, while they are not affected by the openings of patent libraries because they have not initiated the bidding and undertaken target search. We build a sample spanning five years before the deal announcement year to five years after the deal is withdrawn for both withdrawn bidders and their matched pseudo bidders.

To assess potential knowledge acquisitions during bidders' search 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, *Withdrawn Acquirer*×*Treat*×*Post*. *Treat* takes the value of one if the bidder or pseudo bidder is headquartered in a county where a patent library opens by the year prior to the deal announcement and zero otherwise. *Post* takes the value of one in years after the deal is withdrawn and zero otherwise. *Withdrawn Acquirer* is a dummy that takes the value of one for the acquirer-target pair in withdrawn bids and zero for matched pseudo bidders. The triple interaction term captures the difference in the treatment effect of patent library between withdrawn bidders and the control group. We include many firm-level control variables, such as *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*. Since the level of innovation activities of both bidders and targets affect 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 11 in which pseudo bidders are selected based on industry and size matching in column (1) and selected based on industry and size and M/B matching in column (2). The coefficient estimate on 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 estimate on *Withdrawn Acquirer*×*Treat*×*Post* is positive and significant at the 5% level in both columns, suggesting 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 technological information of the target during the bidding process, even though that the deals are not completed eventually. The finding highlights the underlying mechanism through which patent library openings spur acquisitions activities— they facilitate bidders in the search of targets' technology information.

[Insert Table 11 about Here]

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 staggered 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. While 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 local patent libraries open, 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 fostering more collaboration between acquirers' and targets' inventors. These findings indicate that reduced information costs lead to better matches between acquirers and targets in terms of better technology complementarity and greater human capital synergy. Finally, studying a sample of withdrawn bidders pinpoints the underlying information mechanism— reduced awareness costs. Despite of failed M&A deals, withdrawn bidders with an access to patent library are more likely to cite targets' patents after the deal is withdrawn, compared to those without an access to patent libraries. Overall, our study provides evidence on 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.

References

Acharya, V.V., Baghai, R.P. and Subramanian, K.V., 2014. Wrongful discharge laws and innovation. The Review of Financial Studies 27, 301-346.

Baker, A.C., Larcker, D.F. and Wang, C.C., 2022. How much should we trust staggered difference-in-differences estimates?. Journal of Financial Economics 144, 370-395.

Bena, J. and Li, K., 2014. Corporate innovations and mergers and acquisitions. The Journal of Finance 69, 1923-1960.

Beneish, M.D., Harvey, C.R., Tseng, A. and Vorst, P., 2021. Unpatented innovation and merger synergies. Review of Accounting Studies, forthcoming.

Bereskin, F., Byun, S.K., Officer, M.S. and Oh, J.M., 2018. The effect of cultural similarity on mergers and acquisitions: Evidence from corporate social responsibility. Journal of Financial and Quantitative Analysis 53, 1995-2039.

Berger, A.N., Miller, N.H., Petersen, M.A., Rajan, R.G. and Stein, J.C., 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. Journal of Financial Economics 76, 237-269.

Bertrand, M. and Mullainathan, S., 2003. Enjoying the quiet life? Corporate governance and managerial preferences. Journal of Political Economy 111, 1043-1075.

Bhattacharya, S. and Ritter, J.R., 1983. Innovation and communication: Signaling with partial disclosure. The Review of Economic Studies 50, 331-346.

Blankespoor, E., deHaan, E. and Marinovic, I., 2020. Disclosure processing costs, investors' information choice, and equity market outcomes: A review. Journal of Accounting and Economics 70, 101344.

Bonaime, A., Gulen, H. and Ion, M., 2018. Does policy uncertainty affect mergers and acquisitions?. Journal of Financial Economics 129, 531-558.

Bonetti, P., Duro, M. and Ormazabal, G., 2020. Disclosure regulation and corporate acquisitions. Journal of Accounting Research 58, 55-103.

Bradley, D., Kim, I., and Tian, X., 2017. Do unions affect innovation? Management Science 63, 2251-2271.

Brown, W.H. and Arshem, J.A., 1993. Survey of patent and trademark depository libraries 1991/1992. US Patent and Trademark Office Report.

Chen, C.W., 2019. The disciplinary role of financial statements: Evidence from mergers and acquisitions of privately held targets. Journal of Accounting Research 57, 391-430.

Chen, D., Gao, H. and Ma, Y., 2021. Human capital-driven acquisition: evidence from the inevitable disclosure doctrine. Management Science 67, 4643-4664.

Chondrakis, G., Serrano, C.J. and Ziedonis, R.H., 2021. Information disclosure and the market for acquiring technology companies. Strategic Management Journal 42, 1024-1053.

Cohn, J., Liu, Z. and Wardlaw, M., 2022. Regression with skewed, non-negative outcome variables in finance. Working Paper.

Cornaggia, J., Mao, Y., Tian, X. and Wolfe, B., 2015. Does banking competition affect innovation?. Journal of Financial Economics 115, 189-209.

Cunningham, C., Ederer, F. and Ma, S., 2021. Killer acquisitions. Journal of Political Economy 129, 649-702.

Dey, A. and White, J.T., 2021. Labor mobility and antitakeover provisions. Journal of Accounting and Economics71, 101388.

Erel, I., Liao, R.C. and Weisbach, M.S., 2012. Determinants of cross-border mergers and acquisitions. The Journal of Finance 67, 1045-1082.

Ewens, M., Peters, R.H. and Wang, S., 2021. Measuring intangible capital with market prices. Working Paper.
Frésard, L., Hoberg, G. and Phillips, G.M., 2020. Innovation activities and integration through vertical acquisitions. The Review of Financial Studies 33, 2937-2976.
Furman, J.L., Nagler, M. and Watzinger, M., 2021. Disclosure and subsequent innovation: Evidence from the patent depository library program. American Economic Journal: Economic Policy 13, 239-70.
Gompers, P.A., 1995. Optimal investment, monitoring, and the staging of venture capital. The Journal of Finance 50, 1461-1489.
Greene, D. and Shenoy, J., 2022. How do anti-discrimination laws affect firm performance and financial policies? Evidence from the post-World War II period. Management Science 68, 3813-3833.
Guernsey, S.B., John, K. and Litov, L.P., 2020. Actively keeping secrets from creditors: Evidence from the Uniform Trade Secrets Act. Journal of Financial and Quantitative Analysis, forthcoming.
Harford, J., 1999. Corporate cash reserves and acquisitions. The Journal of Finance 54, 1969-1997.
Harford, J., 2005. What drives merger waves?. Journal of Financial Economics 77, 529-560.
Heider, F. and Ljungqvist, A., 2015. As certain as debt and taxes: Estimating the tax sensitivity of leverage from state tax changes. Journal of Financial Economics 118, 684-712.
Higgins, M.J. and Rodriguez, D., 2006. The outsourcing of R&D through acquisitions in the pharmaceutical industry. Journal of Financial Economics 80, 351-383.
Hoberg, G. and Phillips, G., 2010. Product market synergies and competition in mergers and acquisitions: A text-based analysis. The Review of Financial Studies 23, 3773-3811.
Holmstrom, B. and Roberts, J., 1998. The boundaries of the firm revisited. Journal of Economic Perspectives 12, 73-94.
Hong, H., Kubik, J.D. and Stein, J.C., 2008. The only game in town: Stock-price consequences of local bias. Journal of Financial Economics 90, 20-37.
Jaffe, A. B., 1986, Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value, American Economic Review 76, 984–1001.
Jenda, C.A., 2005. Patent and trademark depository libraries and the United States Patent and Trademark Office: A model for information dissemination. Resource Sharing & Information Networks 18, 183-201.
John, K., Knyazeva, A. and Knyazeva, D., 2011. Does geography matter? Firm location and corporate payout policy. Journal of Financial Economics 101, 533-551.
Kang, J.K. and Kim, J.M., 2008. The geography of block acquisitions. The Journal of Finance 63, 2817-2858.
Kantor, S. and Whalley, A., 2019. Research proximity and productivity: long-term evidence from agriculture. Journal of Political Economy 127, 819-854.
Kogan, L., Papanikolaou, D., Seru, A. and Stoffman, N., 2017. Technological innovation, resource allocation, and growth. The Quarterly Journal of Economics 132, 665-712.
Landsman, W.R., Liss, A. and Sievers, S., 2021. The pricing of acquired intangibles. Working Paper.
Lerner, J., 1995. Venture capital and the oversight of private firms. Journal of Finance 50, 301-318.
Levine, O., 2017. Acquiring growth. Journal of Financial Economics 126, 300-319.

Li, K. and Wang, J., 2021. Inter-firm inventor collaboration and path-breaking innovation: Evidence from Inventor Teams Post-merger. Journal of Financial and Quantitative Analysis, forthcoming.

Liu, B. and Tian, X., 2021. Do venture capital investors learn from public markets?. Management Science, forthcoming.

Makri, M., Hitt, M.A. and Lane, P.J., 2010. Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. Strategic Management Journal 31, 602-628.

Malloy, C.J., 2005. The geography of equity analysis. The Journal of Finance 60, 719-755.

Malmendier, U., Moretti, E. and Peters, F.S., 2018. Winning by losing: Evidence on the long-run effects of mergers. The Review of Financial Studies 31, 3212-3264.

Martens, T., 2021. The disclosure function of the US Patent system: Evidence from the PTDL program and extreme snowfall. Review of Accounting Studies, forthcoming.

Martin, X. and Shalev, R., 2017. Target firm-specific information and acquisition efficiency. Management Science 63, 672-690.

McCarthy, K.J. and Aalbers, H.L., 2016. Technological acquisitions: The impact of geography on post-acquisition innovative performance. Research Policy 45, 1818-1832.

Moeller, S.B., Schlingemann, F.P. and Stulz, R.M., 2005. Wealth destruction on a massive scale? A study of acquiring-firm returns in the recent merger wave. The Journal of Finance 60, 757-782.

Moeller, S.B., Schlingemann, F.P. and Stulz, R.M., 2007. How do diversity of opinion and information asymmetry affect acquirer returns?. The Review of Financial Studies 20, 2047-2078.

Nguyen, N.H. and Phan, H.V., 2017. Policy uncertainty and mergers and acquisitions. Journal of Financial and Quantitative Analysis 52, 613-644.

Officer, M.S., 2003. Termination fees in mergers and acquisitions. Journal of Financial Economics 69, 431-467.

Officer, M.S., Poulsen, A.B. and Stegemoller, M., 2009. Target-firm information asymmetry and acquirer returns. Review of Finance 13, 467-493.

Patent, U. S. and Office, T., 1999. Survey of Patent and Trademark Depository Libraries: 1997 Customer Satisfaction Survey. No. Bd. 21 in Survey of Patent and Trademark Depository Libraries: 1997 Customer Satisfaction Survey, U.S. Patent and Trademark Office.

Patent, U. S. and Office, T., 2003. Patent and Trademark Depository Library Program 2002 customer satisfaction survey. U.S. Patent and Trademark Office.

Petersen, M.A. and Rajan, R.G., 2002. Does distance still matter? The information revolution in small business lending. The Journal of Finance 57, 2533-2570.

Phillips, G.M. and Zhdanov, A., 2013. R&D and the incentives from merger and acquisition activity. The Review of Financial Studies 26, 34-78.

Povel, P. and Singh, R., 2006. Takeover contests with asymmetric bidders. The Review of Financial Studies 19, 1399-1431.

Rhodes‐Kropf, M. and Robinson, D.T., 2008. The market for mergers and the boundaries of the firm. The Journal of Finance 63, 1169-1211.

Saidi, F. and Žaldokas, A., 2021. How does firms' innovation disclosure affect their banking relationships?. Management Science 67, 742-768.

Savor, P.G. and Lu, Q., 2009. Do stock mergers create value for acquirers?. The Journal of Finance 64, 1061-1097.

Seru, A., 2014. Firm boundaries matter: Evidence from conglomerates and R&D activity. Journal of Financial Economics 111, 381-405.
Shleifer, A. and Vishny, R.W., 2003. Stock market driven acquisitions. Journal of Financial Economics 70, 295-311.
Sun, L. and Abraham, S., 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics 225, 175-199.
Tian, X., 2011.The causes and consequences of venture capital stage financing. Journal of Financial Economics 101, 132-159.
Uysal, V.B., 2011. Deviation from the target capital structure and acquisition choices. Journal of Financial Economics 102, 602-620.
Uysal, V.B., Kedia, S. and Panchapagesan, V., 2008. Geography and acquirer returns. Journal of Financial Intermediation 17, 256-275.
Wang, W., 2018. Bid anticipation, information revelation, and merger gains. Journal of Financial Economics 128, 320-343.

Figure 1. Pre-Trends in Local M&A Activities

Figure 1 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(≥+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.

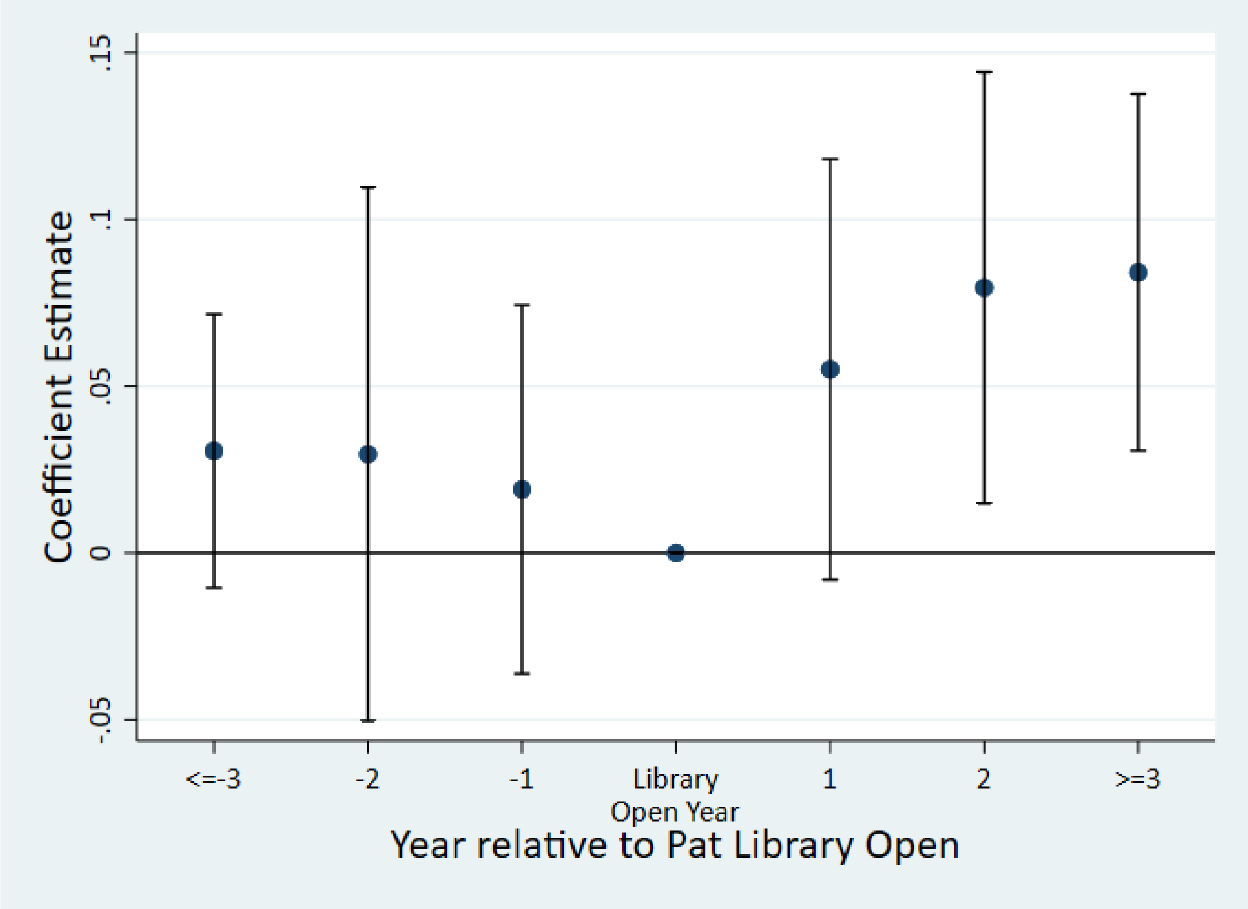

Figure 2. Falsification Tests

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.

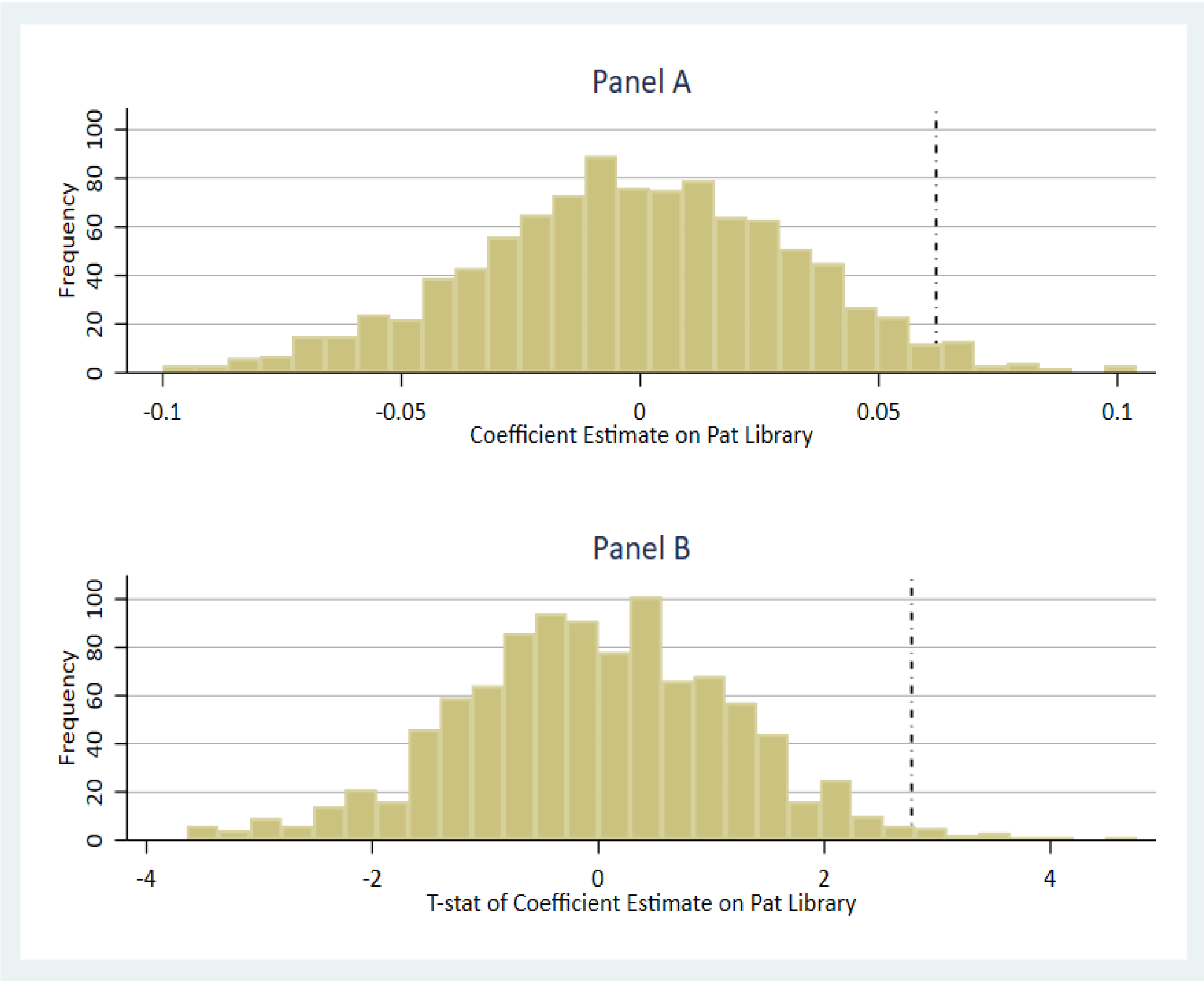

Table 1. M&A Deals Distribution

This table reports the number of completed mergers and acquisition deals by the year during 1985-1999. In column (1), we include all deals with acquirers being publicly traded Compustat firms. In column (2), we restrict to deals with publicly traded and innovative Compustat 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 year).

	(1)	(2)
Year	# of M&A Deal All Public Acquirers	# 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

Table 2. Summary Statistics

This table presents the summary statistics of the sample that consists of all publicly traded and innovative Compustat firms in 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 non-missing accounting and stock return information from Compustat and CRSP, respectively. We define a dummy variable, *Acquirer*, that takes the value of one if the firm acquired at least one innovative target in a given year, and zero 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 one if the firm is headquartered in a county where a patent library opens, and zero otherwise. Definitions of other variables are in Appendix B.

	N	Mean	Median	Std. Dev.
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
Net Working Capital	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

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

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 Compustat firms in 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 one if the firm is headquartered in a county where a patent library opens, and zero otherwise. Definitions of other variables are in Appendix B. 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% level, respectively.

	(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)
Net Working Capital	-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-sq	0.239	0.238

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

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 in 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 B. 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% level, respectively.

	(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	Yes	Yes
Acquirer County Control	No	Yes
Fixed Effects	Firm + Year	Firm + Year
Model	OLS	OLS
N	15,262	15,262
adj. R-sq	0.238	0.238

Table 5. Patent Library Openings and Acquirer-Target Pairings: The Effect of Geographical Proximity

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 one for the actual acquirer-target pair, and zero for the pseudo-pairs. The independent variable *Pat Library* takes the value of one if the firm is headquartered in a county where a patent library opens, and zero 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 B. 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% level, respectively.

	(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	Yes	Yes
Acquirer County Control	Yes	Yes
Fixed Effects	Deal	Deal
Model	Clogit	Clogit
F-test on $\beta_1 + \beta_2 = 0$	χ^2=4.516	χ^2= 4.620
	(p-value=0.034)	(p-value=0.032)
N	13,481	13,481
Pseudo. R-sq	0.134	0.127

Table 6. Patent Library Openings and Acquirer-Target Pairings: The Effect of Technological Proximity

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-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 one for the actual acquirer-target pair, and zero for the pseudo-pairs. The independent variable *Pat Library* takes the value of one if the firm is headquartered in a county where a patent library opens, and zero 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 B. 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% level, respectively.

	(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	Yes	Yes
Acquirer County Control	Yes	Yes
Fixed Effects	Deal	Deal
Model	Clogit	Clogit
F-test on $\beta_1 + \beta_2 = 0$	χ^2= 79.805	χ^2= 74.202
	(p-value=0.000)	(p-value=0.000)
N	13,481	13,481
Pseudo. R-sq	0.123	0.116

Table 7. Patent Library Opens and the Likelihood of Deal Completion

The table presents the effect of patent library opening on the likelihood of deal completion. The sample consists of all completed and withdrawn deals by public innovative acquirers that attempted to acquire 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. The dependent variable *Completed Deal* takes the value of one if the deal is completed, and zero otherwise. The independent variable *Pat Library* takes the value of one if the firm is headquartered in a county where a patent library opens, and zero otherwise. Definitions of other variables are in Appendix B. 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% level, respectively.

	(1)	(2)
	Dept Var = Completed Deal	
Pat Library	0.201*	0.232*
	(1.681)	(1.820)
Ln(Total Asset)	0.142***	0.149***
	(3.368)	(3.485)
Market-to-Book	0.010	0.012
	(0.612)	(0.737)
Return	-0.076	-0.068
	(-0.494)	(-0.434)
Sales Growth Rate	0.191**	0.187**
	(2.006)	(2.037)
Leverage	-0.588	-0.570
	(-1.494)	(-1.443)
ROA	0.768	0.736
	(1.415)	(1.377)
Cash/Asset	0.374	0.396
	(0.955)	(1.012)
RD/Asset	1.528*	1.575*
	(1.683)	(1.727)
Relative Size	-0.155**	-0.147**
	(-2.148)	(-1.982)
All Cash Dummy	0.487***	0.497***
	(2.988)	(2.993)
High Tech Dummy	0.187	0.172
	(0.838)	(0.790)
Diversify Dummy	-0.082	-0.075
	(-0.633)	(-0.579)
Hostile Dummy	-1.666***	-1.678***
	(-5.394)	(-5.511)
Challenge Dummy	-1.774***	-1.786***
	(-7.217)	(-7.223)
Public Target Dummy	-0.562***	-0.564***
	(-3.601)	(-3.587)
Ln(Population)		-0.237
		(-0.650)
Income Per Capita		-0.013*
		(-1.849)
Constant	-1.464	-1.444
	(-1.076)	(-1.072)
Fixed Effects	Industry + Year	Industry + Year
Model	Logit	Logit
N	3,333	3,333
Pseudo R-sq	0.173	0.174

Table 8. Patent Library Openings and Stock Returns

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 7-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 7-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. *Pat Library* takes the value of one if the firm is headquartered in a county where a patent library opens, and zero 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*, *RD/Asset*, *ROA*, *Cash/Asset*, and *Ln(Age)*, and county controls include *Ln(Population)* and *Income Per Capita*. The deal controls include *All Cash Dummy*, *High Tech Dummy*, *Diversify Dummy*, *Hostile Dummy*, *Challenge Dummy*, *Public Target Dummy*. Definitions of other variables are in Appendix B. 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% level, respectively.

	(1) *Acquirer* *CARs [-3,+3]*	(2) *Target* *CARs [-3,+3]*	(3) *Combined* *CARs [-3,+3]*	(4) *Acquirer* *BHAR [5y]*
Pat Library	0.013**	0.019	0.014*	0.106**
	(2.050)	(1.058)	(1.751)	(2.113)
Acquirer Firm Control	Yes		Yes	Yes
Acquirer County Control	Yes		Yes	Yes
Deal Control	Yes	Yes	Yes	Yes
Target Firm Control		Yes	Yes	
Acquirer Industry Fixed Effects	Yes		Yes	Yes
Target Industry Fixed Effects		Yes	Yes	
Year Fixed Effects	Yes	Yes	Yes	Yes
Model	OLS	OLS	OLS	OLS
N	2,798	745	700	2,798
adj. R-sq	0.064	0.189	0.010	0.365

Table 9. Patent Library Openings and Post-Merger Innovation Activities

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 one if the firm is headquartered in a county where a patent library opens by the year prior to the deal announcement, and zero otherwise. *Post* takes the value of one in years post the deal completion, and zero 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 B. 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% level, respectively.

	(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	Yes		Yes	
Combined Firm Control		Yes		Yes
Acquirer County Control	Yes	Yes	Yes	Yes
Deal Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Model	OLS	OLS	OLS	OLS
N	7,356	7,356	7,356	7,356
adj. R-sq	0.851	0.882	0.839	0.867

Table 10. Patent Library Openings and Post-Merger Co-invention Between Target and Acquirer Inventors

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 column (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 one if the firm is headquartered in a county where a patent library opens in the year prior to the M&A announcement year, and zero 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 *All Cash Dummy*, *High Tech Dummy, Diversify Dummy*, *Hostile Dummy*, *Challenge Dummy, Public Target Dummy.* Definitions of other variables are in Appendix B. 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% level, respectively.

	(1)	(2)	(3)	(4)
	%Co-invented Pat		*%Co-invented Cite*	
Pat Library	0.028*	0.034*	0.027*	0.033*
	(1.931)	(1.737)	(1.828)	(1.699)
Acquirer Firm Control	Yes	Yes	Yes	Yes
Acquirer County Control	Yes	Yes	Yes	Yes
Deal Control	Yes	Yes	Yes	Yes
Target Firm Control		Yes		Yes
Acquirer Industry Fixed Effects	Yes	Yes	Yes	Yes
Target Industry Fixed Effects		Yes		Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Model	OLS	OLS	OLS	OLS
N	761	569	761	569
adj. R-sq	0.069	0.020	0.064	0.019

Table 11. Post-acquisition Citation of Target Patents by Withdrawn Acquirers

The table presents the results of the effect of patent library opening on the percentage of withdrawn acquirers' patents citing target patents. The sample consists of acquisition deals by public innovative acquirers and targets that were withdraw. For every withdrawn deal, we identify "pseudo" acquirers as a control group following the same matching techniques as that in Tables 5 and 6. In columns (1), we select pseudo-acquirers that are from the same industry and have the closest size as the withdrawn acquirer. In columns (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 as the withdrawn acquirer. The sample spans from five years before deal announcement year to five years after the deal was withdrawn for both withdrawn acquirers 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. *Withdrawn Acquirer* is a dummy that takes the value of one for the acquirer-target pair in withdrawn bids, and zero for the pseudo acquirers. *Treat* takes the value of one 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 zero otherwise. *Post* takes the value of one in years after the deal was withdrawn and zero 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 A. 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% level, respectively.

	%Acquirer's Patents Citing Target Patents	
	(1)	(2)
Withdrawn Acquirer×Treat×Post	0.030**	0.030**
	(2.059)	(2.132)
Withdrawn Acquirer×Treat	0.013	0.011
	(1.517)	(1.272)
Withdrawn Acquirer×Post	0.004	0.003
	(0.677)	(0.581)
Treat×Post	-0.001	-0.001
	(-0.295)	(-0.296)
Treat	-0.007**	-0.006*
	(-2.116)	(-1.781)
Post	-0.003	-0.004
	(-0.479)	(-0.817)
Withdrawn Acquirer	0.003	0.004
	(0.624)	(1.031)
# of Patents Applied by Acquirer	Yes	Yes
# of Patents Applied by Targets	Yes	Yes
Acquirer Firm Control	Yes	Yes
Acquirer County Control	Yes	Yes
Deal Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Model	OLS	OLS
Matching Covariates	Industry + Size	Industry + Size + M/B
N	2,426	2,423
adj. R-sq	0.134	0.152

Appendix A. 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
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
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
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 B. Variable Definitions

Variable	Definition
Firm Characteristics	
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.
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.
Net Working Capital	The ratio of non-cash working capital to the book value of assets.
Return	The buy-and-hold 12-month stock return in the past 12 months.
Deal Characteristics	
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 4-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 2-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.
County Characteristics	
Population	Total population in one county.
Income Per Capita	The personal income per capita in 1,000 dollars in one county.

Appendix Table A1. Determinants of Patent Library Openings

The table reports the hazard ratios from Cox proportional hazard models to examine the determinants of patent library openings. The sample consists of county-year observations during 1985-1999 up to the year when a patent library opens. The dependent variable (or the "failure event") equals to one if a patent library opens in a given county-year. Explanatory variables (all lagged by one year) include the natural logarithm of total population in a county-year (*Ln(Population)*), percentage change in unemployment rate (Δ *Unemployment Rate (%)*), percentage change in the number of establishments (Δ *# of Establishments (%)*), the natural logarithm of one plus total number of patents by public firms located in a given county-year (*Ln(1+# of Patents)*), the natural logarithm of total number of firms located in a county-year being acquirers in M&A deals (*Ln(1+# of M&A Deals as Acquirers)*), the natural logarithm of total number of firms located in a county-year being targets in M&A deals (*Ln(1+# of M&A Deals as Targets)*). In column (2), we include an additional binary variable that takes the value of one if a patent library has already opened in the state where the county is located (*Same State Pat Library*). We include 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% level, respectively.

	(1)	(2)
Ln(Population)	4.061***	8.170***
	(7.747)	(8.444)
Income Per Capita	0.947	0.833
	(-0.942)	(-0.879)
Δ *Unemployment Rate (%)*	1.069	1.077
	(0.966)	(0.771)
Δ *# of Establishments (%)*	1.004	1.000
	(0.242)	(0.016)
Ln(1+# of Patents)	1.157	1.243
	(0.770)	(0.829)
Ln(1+# of M&A Deals as Acquirers)	0.682	0.867
	(-0.820)	(-0.360)
Ln(1+# of M&A Deals as Targets)	1.410	0.887
	(0.629)	(-0.222)
Same State Pat Library		0.015***
		(-4.696)
Year FE	Yes	Yes
N	45,639	45,639
Pseudo. R-sq	0.217	0.372
# Unique Counties	3,081	3,081
# of Pat Library Opened	30	30

Appendix Table A2. Cumulative Number of M&A Activities

This table presents the results on the effect of patent library opening on local firms' total M&A activities in the next three years using a sample where we exclude firms located in counties with patent library opened before 1985. The dependent variable, *Ln(1+# of M&A Deals, t+1 to t+3)*, is the natural logarithm of one plus the number of innovative target acquisitions completed by a firm in the next three 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 one if the firm is headquartered in a county where a patent library opens, and zero otherwise. We include the same set of control variables as those in Table 3, but do not report them for brevity. We use the same sample as in Table 3Definitions of other variables are in Appendix B. We include firm and year fixed effects in all regressions. The unit of analysis is at firm-year level. 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% level, respectively.

	(1)	(2)
	Dept Var=Ln(1+Total # of M&A Deals, t+1 to t+3)	
Pat Library	0.110***	0.116***
	(3.378)	(3.097)
Acquirer Firm Control	Yes	Yes
Acquirer County Control		Yes
Model	OLS	OLS
Fixed Effects	Firm + Year	Firm + Year
N	15,262	15,262
adj. R-sq	0.472	0.472

Appendix Table A3. Patent Library Openings and Local M&A Activities: Alternative Model Specifications

This table represents alternative model specifications to our baseline results. Our sample consists of all publicly traded and innovative Compustat firms in 1985-1999. The independent variable *Pat Library* takes the value of one if the firm is headquartered in a county where a patent library is opened, and zero otherwise. 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 B. In Panel A, we estimate Poisson, Negative Binomial, and OLS regression in columns (1), (2), and (3), respectively, where the dependent variable is *# of M&A Deals*, which is innovative target acquisitions completed by a firm in a given year. In column (4), we run a Logit regression where the dependent variable is a dummy variable, *Acquirer Dummy*, takes the value of one if the firm acquired at least one innovative target in a given year, and zero otherwise. We include firm and year fixed effects in all regressions, and cluster standard errors at the county-level in Panel A. Dependent variable in Panels B and C is, *Ln(1+# of M&A Deals)*. In Panel B, we include industry (either defined based on three-digit SIC industry classifications or Fama-French 48 industry classifications) and year fixed effects, firm and state×year fixed effects, firm, county, and year fixed effects in columns (1), (2), (3), and (4), respectively. Standard errors are clustered at the county-level. In Panel C, we cluster standard errors at the firm level and at the industry (three-digit SIC code) level in columns (1) and (2), respectively; In column (3), we double-cluster standard errors at the county and year level. We include firm and year fixed effects in all regressions in Panel C. In all panels, innovative targets are those from a three-digit SIC coded industry where at least one firm was awarded a patent in a given year. In all panels, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Alternative Regression Models

	(1)	(2)	(3)	(4)
		Dept Var = # of M&A Deals		*Dept Var = Acquirer Dummy*
Pat Library	0.541***	0.541***	0.116***	0.741***
	(3.861)	(3.199)	(3.148)	(3.093)
Acquirer Firm Control	Yes	Yes	Yes	Yes
Acquirer County Control	Yes	Yes	Yes	Yes
Model	Poisson	Negative Binomial	OLS	Logit
Fixed Effects	Firm + Year	Firm + Year	Firm + Year	Firm + Year
N	7,969	7,969	15,262	7,830

Panel B: Alternative Fixed Effects

	(1)	(2)	(3)	(4)
	Dept Var = Ln(1+# of M&A Deals)			
Pat Library	0.012**	0.013**	0.067***	0.047**
	(1.906)	(1.966)	(3.106)	(2.211)
Acquirer Firm Control	Yes	Yes	Yes	Yes
Acquirer County Control	Yes	Yes	Yes	Yes
Model	OLS	OLS	OLS	OLS
Fixed Effects	Industry (SIC3) + Year	Industry (FF48) + Year	Firm + State×Year	Firm + County + Year
N	15,643	15,616	15,188	15,250
adj. R-sq	0.134	0.109	0.239	0.225

Panel C: Alternative Clustering of Standard Errors

	(1)	(2)	(3)
	Dept Var = Ln(1+# of M&A Deals)		
Pat Library	0.062**	0.062**	0.062***
	(2.445)	(2.184)	(4.757)
Acquirer Firm Control	Yes	Yes	Yes
Acquirer County Control	Yes	Yes	Yes
Model	OLS	OLS	OLS
Fixed Effects	Firm + Year	Firm + Year	Firm + Year
Cluster	Firm	Industry (SIC3)	County + Year
N	15,262	15,262	15,262
adj. R-sq	0.238	0.238	0.238

Appendix Table A4. Exclude Firms Located in Counties with University Patent Libraries

This table presents the results on the effect of patent library opening on local firms' M&A activities using an alternative sample, where we exclude firms located in the counties where university patent libraries reside. 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 one if the firm is headquartered in a county where a patent library opens, and zero otherwise. 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 B. We include firm and year fixed effects in all regressions. The unit of analysis is at firm-year level. 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% level, respectively.

	(1)	(2)
	Dept Var = Ln(1+# of M&A Deals)	
Pat Library	0.066**	0.070**
	(2.348)	(2.221)
Acquirer Firm Control	Yes	Yes
Acquirer County Control	No	Yes
Model	OLS	OLS
Fixed Effects	Firm + Year	Firm + Year
N	13,853	13,853
adj. R-sq	0.243	0.243

Appendix Table A5. Alternative DiD Estimates

This table presents the alternative DiD estimates results on the effect of patent library opening on local firms' 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. In column (1), we conduct a stacked regression. In particular, we first identify each library opening event (at t=0) and the treated counties as well as the firms located in those counties; next, we choose five years before to five years after the opening event as the event time window (-5, +5); we then select the control firms that exist at event year and were not located in the treated counties during the time window of (-5, +5). We further refine the control controls by requiring them to be in the neighboring states of the treated firms so that the treated and control firms will share similar economic conditions. *Treat* takes the value of one if the firm is headquartered in a treated county where a patent library opens, and zero otherwise; *Post* takes the value of one in years post the patent library opening, and zero otherwise. In column (2), we estimate the interaction weighted (IW) estimator proposed by Sun and Abraham (2021). 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 B. We include firm and year fixed effects in all regressions. The unit of analysis is at firm-year level. 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% level, respectively.

	(1)	(2)
	Dept Var = Ln(1+# of M&A Deals)	
*Treat*Post*	0.059**	
	(2.237)	
IW Estimator		0.064**
		(1.983)
Acquirer Firm Control	Yes	Yes
Acquirer County Control	Yes	Yes
Fixed Effects	Firm + Year	Firm + Year
N	51,328	7,735
Estimation Method	Stacked Regression	IW Estimator