Access to Patent Information and Technological Acquisitions: Evidence from the Patent and Trademark Depository Library Program*

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Abstract

Technology acquirers face significant information asymmetry when identifying appropriate acquisition targets. Employing the staggered openings of patent libraries as an exogenous variation in the costs of gathering technological information, we find that firms become more active in acquisitions following the local patent library opening. Furthermore, we find that acquirers prefer targets that are geographically close or are similar in technological space, however to a lesser extent after a local patent library opens. The results imply that the openings of patent libraries reduce the costs of collecting technology information about potential targets, thereby allowing acquirers to broaden their search to more geographically and technologically distant targets. Additionally, the effect on the pairing choices of acquirers and targets appears value-enhancing. After patent library opening, there is a significant increase in the M&A completion rate as well as the acquirers' 5-day abnormal cumulative returns around acquisition announcement day. Overall, our study sheds light on the importance of information search costs in corporate takeovers.

1. Introduction

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

In this study, we investigate the effects of information frictions on takeover activity and performance by exploiting the expansion of the USPTO Patent and Trademark Depository Library (PTDL, hereafter) system.[2] The opening of a USPTO patent library in a county allows local acquiring firms to easily access the technical information disclosed in patent documents of potential targets nationwide, thereby facilitating their assessments of the value of the intellectual

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[1] There are several reasons that targets would not mitigate the information asymmetries, such as proprietary costs of revealing confidential technology information (Frésard, Hoberg, and Phillips, 2020) or strategic motives (e.g., lead to a higher price). Bhattacharya and Ritter's (1983) model indicates that firms could compromise their innovation ability 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.

properties of these targets (Chen, Gao, and Ma, 2020; Dey and White, 2021). Whereas the exclusion rights associated with patents are national in scope, the openings of these patent libraries yielded regional variation in the costs of gathering technological information. By revealing information about the technological landscape and the activities of players within it, the expansion of the patent library plausibly altered the information environment in which technological acquisitions are conducted. Therefore, we propose that the openings of patent libraries mitigate adverse selection by alleviating information frictions between acquirers and targets. This in turn boosts acquisition intensity and improves the optimal pairing choice of acquirers and targets, the deal completion rate, and the performance of acquirers.

We employ the staggered openings of PTDLs during the period 1985-1999 across different geographic locations and investigate their effects on acquisitions using a difference-in-differences approach. Among all public innovative firms, 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 6.4%) in acquisition activities after a patent library opens in the local counties, consistent with the notion that patent library openings reduce the costs of accessing patent documents, hence mitigating information friction. The results remain robust as we refine the control group to the firms located in counties that are in the same state as the treated counties and have the Federal Depository Library capacity but do not have a patent library.

We next investigate how the openings of patent libraries alter the pairing choice of acquirers and targets. Firms often create synergy and value in technology acquisitions 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 complementarity and synergy gain, opting for first best choice. Nevertheless, information friction in M&As forces acquirers to avoid high information asymmetry by electing targets that are geographically proximate, since acquirers can easily access such targets' soft information through site visits or the interactions with their managers and inventors in social, civic, and business meetings (Petersen and Rajan, 2002; Kantor and Whalley, 2019). By the same token, acquirers are more likely to approach technologically proximate targets, as technology proximity reduces information friction between acquirers and targets (Bena and Li, 2014). Nevertheless, such pairing tendencies constraints acquirers' search and prevents them from finding the first best choice of target, leading to economic losses for both acquirers and targets.

The openings of patent libraries enable local acquirers to collect technology information about potential targets, hence alleviating information asymmetry and lowering the costs of evaluating targets that are geographically distant or are less similar in technology. As a result, patent libraries openings allow acquirers to broaden their search of potential targets. We thus conjecture that the reliance on geographic or technologic proximity in 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, the positive relation between geographical (or technological) proximity and the likelihood of M&A is weakened after the opening of a patent library in the acquirer's headquarter county. Put differently, acquirers continued 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 examine the effect of patent library openings on the completion rate and performance of M&A deals. Due to the adverse selection problem, information frictions hinder deal completion and the success rate of identifying an optimal acquirer-target match. Per discussions above, reduced costs of evaluating technology information of potential targets facilitate acquires to broaden their search without limiting to the candidates that are geographically or technologically close to them. This in turn results in better matches between acquirers and targets, such as better technology complementarity and greater synergy, hence creating greater economic value. In addition, reduced information asymmetry will mitigate adverse selection, helping successful completion of the acquisitions. Taken together, we propose that the opening patent libraries leads to a higher deal completion rate and a higher acquirer announcement return. Consistent with the propositions, we find that patent library openings significantly increase the probability of deal competition: Specifically, the odds of deal completion rise 25.9% post patent library opening. We also find that patent library opening is associated with a 1.3% higher cumulative abnormal return (CARs) for acquirers 7-day around acquisition announcements, indicating that the stock market greets with a higher valuation of the M&A deals that are completed by acquirers in counties with a patent library, compared to the deals completed by acquirers that do not have a local access of patent documents. We finally show M&A deals done by acquirers with nearby patent libraries can foster innovation activities, as well as collaboration in the combined companies among inventors previously working for acquirers and targets, inferring strong synergy creations.

Our paper contributes to the literature in the following ways. First, we add to research on the effect of information frictions on mergers and acquisitions (Rhodes-Kropf and Robinson, 2008; Wang, 2018). Different from the prior literature that focuses on the costs and benefits of information disclosure of acquirers (Bonetti et al., 2020) or targets (Officer et al., 2009; Martin and Shalev, 2016; Chen, 2019), we study the effect of acquirers' increased access to the publicly disclosed information in the USPTO patent documents. As acquirers are better informed about their counterparts' technology through their easier access to patent documents, adverse selection arising from information asymmetry is mitigated, hence yielding value-enhancing M&A deals (Moeller et al., 2007; Jansen, 2020).

Second, prior literature has documented a variety of factors that drive technology firms' acquisition decisions, such as 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), recruiting key talent (Chen et al., 2021; Dey and White, 2021), and exploiting work-in-progress intellectual properties (Beneish et al., 2021; Landsman, Liss, and Sievers, 2020). Our paper shows that technology firms are more actively engaged in acquisitions and complete better-quality acquisitions as they have a better access to the published scientific knowledge (patent documents), highlighting the importance of scientific knowledge in the success of technology acquisitions.

Third, we join the debate over the usefulness of patent disclosure (Ouellette, 2011; Glaeser and Landsman, 2021; Kim and Valentine, 2021) and the patent system (Williams, 2017; Furman, Nagler, and Watzinger, 2021). Despite of the critics that the benefits of reading patents might be limited,[3] we find that better accesses to patent documents by acquirers not only enhance the likelihood of acquisition and completion rate, but also lead to better acquisitions through broadened the search of targets. Our findings generally support the idea that patents promote the

[3] As discussed in legal studies, one example of the downside of reading patents is exposing inventors to willful infringement that might incur financial penalties (e.g., Roin, 2005; Lee and Cogswell III, 2004).

diffusion of technological information and accelerate technological growth in the economy (e.g., Machlup and Penrose, 1950; Romer, 1990).

Lastly, we extend the literature on spatial influences 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 decisions (Malloy, 2005), bank loans (Berger et al., 2005), corporate payout decisions (John, Knyazeva, and Knyazeva, 2011). In the market for takeovers, approaching local targets can reduce bidders' information asymmetry while increase the benefit of soft information exchange and improve monitoring (Kang and Kim, 2008; Uysal, Kedia, and Panchapagesan, 2008). McCarthy and Aalbers (2016) finds post-acquisition innovative performance is better when the technology acquirer and target are located closer to each other, which is consistent with the notion that geographic proximity enhances the sharing of ideas and talent pool (Orlando, 2004; Chu, Tian, Wang, 2019). Our study sheds light on the fundamental friction underlying the preference for geographical proximity—information cost. We show that the reliance of geographical proximity in M&A decision is attenuated as the costs of information search decline, i.e., after the openings of patent libraries. Our paper therefore contributes to the literature by showing that reduced costs of acquiring scientific information can fuel knowledge diffusion across geographic locations and improve the economic value of acquisitions.

Our study is related to Chondrakis, Serrano, and Ziedonis (2021), which shows that accelerated patent disclosure promotes acquisition activities, particularly in more technologically distant pairs of acquirers and targets. However, our paper differs from it in several aspects. First, the identification in Chondrakis et al. (2021) rests on industry-level differences in patent pendency around the implementation of the American Inventor's Protection Act (AIPA) in 2000, which affects patent disclosure of all firms at the same time.[4] We instead exploit the staggered expansions of the USPTO Patent Library system, yielding regional variation in the costs to access technical information in patent documents. Different from the one-time shock like AIPA, our shocks are staggered over time across different geographic locations, which allows for a better control of potentially confounding effects and alleviate the omitted variable problem. Second, the identification in Chondrakis et al. (2021) rests on industry-level variations, which limits their sample to horizontal acquisitions (i.e., acquirers and targets are in the same industry). In contrast, our identification approach enables us to capture both horizonal and vertical acquisitions.[5] Third, in contrast to our finding of greater acquirer returns after easier access to patent documents, Chondrakis et al. (2021) report that increased disclosure of patents post AIPA leads to lower acquirer returns, since greater disclosure under AIPA may spur competition in the M&A market hence reducing acquirers' strategic gain. Our study of staggered expansions of the patent library system allows us to focus on the impact of patent information without the confounding effect on takeover market competition. This is because an opening of a patent library enhances the access of patent information in the local area, thus less likely to intensify a broad market competition.

The rest of the paper is organized as follow. Section 2 describes the background of the Patent and Trademark Depository Library (PTDL) system. We discuss data sources in section 3, and describe sample construction, methods, and empirical results in section 4. Section 5 concludes the paper.

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[4] AIPA speeds up the disclosure of technological developments via the publication of patent applications, yielding cross-industry variation in the magnitude of patent information disclosure.

[5] Vertical acquisition, as an approach to reshape firm boundaries, could eliminate contractual incompleteness hence spurring downstream innovation that also benefit upstream innovation. As an example, Chu et al. (2019) show that knowledge spillover from customers to suppliers is instrumental to supplier innovation. Another example is Dasgupta, Zhang, and Zhu (2021), who find that social connections between the suppliers' managers and board members and those of their customers could alleviate holdup problem and restore trust between customers and supplies, hence leading to greater innovative activities by suppliers.

2. Institutional Background of USPTO Patent and Trademark Depository Library (PTDL)

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, in the early 1870s, USPTO started to distribute copies of patent documents across the United States by establishing a nationwide Patent and Trademark Depository Library (PTDL) system. The PTDLs offers public access to all resources necessary to conduct a full search of patents and trademarks, and meanwhile, increases the awareness in and the use of intellectual property systems.

As demand for access to patent documents has increased since the 1970s, 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 state. 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.[6]

Furman et al. (2021) argue that the decision to join the patent library system is typically 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

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

attractiveness of annual patent librarian training in Washington D.C. and the professional and personal benefits of joining the PTDL librarian community.[7] In addition, the introduction of microfilm in the 1970s made library capacity requirement less of a concern, making more libraries eligible to join the patent library system (rather than just the university libraries or public libraries in large cities). Therefore, the openings of patent libraries were less correlated with local economic and innovation activities. For example, patent libraries opened in Honolulu, HI and Big Rapids, MI in 1989 and 1991, respectively, before it opened in San Francisco CA (which is a more populated and more technology-demanding area) in 1994.

Our study uses the staggered openings of PTDLs across geographic locations and time as a source of variation in the availability of patent information. A key premise is the patent information will be largely utilized by *local* inventors, analysts, investors, 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 traveled between 11 and 20 miles, and 38% of the users traveled fewer than ten miles (Patent and Office, 1999). Similarly, the 1999 survey reports roughly 70% of the users traveled 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 of 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.

[7] 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.

3. Data

Our mergers and acquisitions (M&A) data are from Thomson Financial Securities Data Company (SDC). We started our sample of M&A deals in 1985 since SDC began to provide high quality M&A data in that year. We end our sample in 1999 for two reasons. First, we want to focus on our analysis prior to the internet boom, as Furman et al. (2021) show that the effect of patent library on local innovation diminish during the internet age. Second, we intend to avoid overlapping with the American Inventor Protection Act (AIPA) that became effective in November 2000, alleviating the concerns that our results might be driven by the AIPA.[8]

Following the prior literature (e.g., Bena and Li, 2014; Nguyen and Phan, 2017), we apply the following filters as we build our dataset 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 asset. We also require the acquirers to own less than 50% of the target prior to the bid,[9] seek to own at least 50% and finally own at least 90% of the target after deal completion. 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 financial 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 during 1985 to 1999.

[Insert Table 1 Here]

[8] One of the significant changes by the AIPA, among many others, is requiring 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 became publicly available after they were granted. The average time from a patent's filing date to its grant date was approximately 36 months prior to the AIPA. Effectively, the AIPA accelerates the overall patent disclosure process.

[9] About 98% of acquirers in our sample have zero ownership in the target prior to the bid.

The expansion of patent library serves as an information shock, arguably, only to local innovative firms that have the adequate knowledge and skills to evaluate technology information in patent documents so as 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 acquirers that are innovative (i.e., firms that have been awarded at least one patent during the past five years). We also focus on innovative targets since patent libraries is not relevant to non-innovative target firms. However, about 77% of the M&A deals in our sample involves private targets. Restricting to public innovative targets therefore leads to a small 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 where at least one firm was awarded a patent in the past five years.[10] Patent data are from USPTO PatentsView, and firm identifiers that every patent belongs to are from Noah Stoffman's website (http://kelly.iu.edu/nstoffma/). Restricting to innovative acquirers and targets from innovative industries yields a total of 2,910 M&A deals. Table 1 column (2) shows the distribution by year of a subsample of deals with public traded innovative acquirers.

We obtain the lists of patent depository libraries from Jenda (2005), Martens (2021), and Furman et al. (2021), which include names, location (i.e., state, county, city), and the opening date of each library. Appendix B provides a list of 84 patent library openings between 1870 and 1999. There were 32 counties joined the patent library system during our sample period of 1985-1999, which falls into the wave of USPTO patent library system expansion during this period.

[10] 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).

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.[11] County-level population data and personal income data are from National Cancer Institute and Bureau of Economic Analysis (BEA), respectively.

4. Sample Construction, Methods, and Empirical Results

In this section, we describe sample construction, methodology, and results for each of the empirical tests. We start by investigating the effect of patent library openings on local firms' acquisition activities. We then examine how the openings of patent libraries affect the pairing choices of acquirers and targets. Finally, we assess the impact of patent library opening on deal completion rate and acquirers' announcement returns.

4.1. Patent Library Openings and Local Firm Acquisitiveness

4.1.1. Baseline Results

To examine acquisition intensity, we start with a sample that consists of all publicly traded innovative firms in Compustat from 1985 to 1999. We limit the sample to only innovative firms that had been awarded at least one patent in the previous five years, since we focus on technology acquisitions. We employ a difference-in-differences approach to investigate the effect of staggered openings of patent libraries across different time and different geographic locations on firms' acquisition activities. In our analysis, treated firms are those that are headquartered in counties

[11] To merge the SDC data with that of Compustat and CRSP, we first use the mapping file in Ewens, Peters and Wang (2018) 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. (2018), 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.

where a patent library is open, whereas control firms are those headquartered in counties without any patent libraries.[12] Specifically, we estimate the following OLS regression model:

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

where i represents the firm, c represents the county where firm i's headquarter is located, and t represents the year. The dependent variable is the natural logarithm of one plus *# of M&A Deals* which is the number of acquisitions of innovative targets (hereafter, innovative target acquisitions) completed by a firm in a given year (based on the M&A announcement year). We set the value of *# of M&A Deals* to zero if there are no acquisitions of innovative targets in a year. All the right-hand-side variables are lagged by one year. The key independent variable, *Pat Library*, takes the value of one if the firm is headquartered in a county where a patent library is open, and zero otherwise.[13] We follow the extant 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 Asset)*), research and development expenses scaled by total assets (*RD/Asset*), total debts to total assets (*Leverage*), cash and cash equivalents scaled by total assets (*Cash/Asset*), 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 A. We also include firm

[12] 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.
[13] As noted in Heider and Ljungqvist (2015), using the headquarter location directly from Compustat (which keeps only the most recently location) will mislabel 10% of firm-years' historical headquarter locations. For public acquirers, we use the historical headquarter 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.

(μ_i) and year-fixed (μ_t) effects to control for the time-invariant firm characteristics and time-varying macroeconomics shocks. We cluster standard errors at the county level.

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.[14] On average, a firm completes approximately 0.19 deals as an acquirer in a year. About 43.3% of our sample firms are located in counties with patent libraries. An average firm in our sample has $1,315 million in assets and has been public for about 20 years, both of which are comparable to Nguyen and Phan (2017). The mean values of our 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 also comparable to are comparable to those reported in the prior literature (e.g., Nguyen and Phan, 2017).

[Insert Table 2 Here]

The regression results based on Equation (1) are reported in Table 3. In column (1), where we control for a vector of firm-level characteristics and firm and year fixed effects, we find a positive and statistically significant coefficient estimate on *Pat Library*. As we further add county-level control variables in column (2), the coefficient estimate on *Pat Library* is very similar to that in column (1) in terms of the statistical and economic magnitudes. The results indicate that firms located in counties with patent libraries opened complete more acquisitions than firms located in counties without patent libraries. The effect is also economically large. On average, the openings of patent libraries spur local M&A activities by 6.4%.

[Insert Table 3 Here]

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

The coefficient estimates of the control variables exhibit expected signs. 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 Model

One crucial assumption for the difference-in-differences approach is the parallel trends condition (Roberts and Whited, 2013). To validate the parallel pre-trends assumption, we estimate a dynamic model by including a set of dummy variables that represent each year prior to and post of the year of patent library opening. The dynamic analysis allows us to examine whether our results are driven by reverse causality, i.e., local economic growth and acquisition activities increase the demand for a patent library, hence leading to openings of patent libraries in the county. To address the concern, we follow Bertrand and Mullainathan (2003) and Cornaggia et al. (2015) to conduct a temporal dynamic analysis surrounding the year of patent library opening. Specifically, we construct six time-indicator variables representing the three years before and after the patent library opening: *Pat Library(≤-3)* 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. Below is the dynamic regression model:

$$Ln(1+\#\ of\ M\&A\ Deals)_{i,t} = \beta_0 + \beta_1 Pat\ Library(\leqslant -3)_c + \beta_2 Pat\ Library(-2)_c + \beta_3 Pat\ Library(-1)_c$$
$$+ \beta_4 Pat\ Library(+1)_c + \beta_5 Pat\ Library(+2)_c + \beta_6 Pat\ Library(\geqslant +3)_c$$

$$+ \gamma_1 X_{i,t-1} + \gamma_2 W_{c,t-1} + \mu_i + \mu_t + \varepsilon_{i,t} \,. \tag{2}$$

To avoid multicollinearity, we set the year of library opening as the base year, which is reflected in the intercept. If reverse causality is indeed a concern, 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 no evidence of reverse causality. It also indicates that acquisitions activities display parallel trend prior to the treatment effect (patent library opening). In contrast, the coefficient estimates on *Pat Library(+2)* and *Pat Library (≥+3)* are positive and statistically significant, indicating that patent library openings spur local acquisition activities, as early as two years after the patent library openings.

[Insert Table 4 Here]

To visualize the parallel trend, we follow Gormley and Matsa (2011) and Gopalan, Gormley, and Kalda (2021) and plot the coefficient estimates obtained from the dynamic model in Figure 1. The X-axis represents the years relative to the year of the library opening. The Y-axis represents the coefficient estimates of the time indicator variables surrounding patent library opening ($\beta_1 \sim \beta_6$). 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 pre-trend assumption. However, acquisition activities significantly rise starting in the second year following the opening of the patent library.

[Insert Figure 1 Here]

4.1.3. Post Internet Boom

As argued above, we limit our sample to the period of 1985 to 1999 since prior research (e.g., Furman et al. 2021) finds that the effect of patent library on local innovation diminish during the internet age, where patent documents became available to the public online. To assess whether this is the case on technology acquisitions, we estimate the baseline model using a sample over the post-internet boom period—2002 through 2006. We start the period in 2002 to avoid overlapping with AIPA that became effective in 2000, and end the period in 2006 to avoid overlapping with the 2007-2009 Great Financial Criss. The OLS regression results are reported in Appendix Table A1. In column (1), we report our baseline results for the pre-Internet Boom period of 1985 to 1999, which is the same model as column (2) in Table 3. The results for the post-Internet Boom period of 2002 to 2006 are presented in column (2) of Appendix Table A1. The coefficient on *Pat Library* is negative and statistically insignificant, suggesting little impact of patent library openings on local takeover activities, which is consistent with the prior research. Internet became widely available after 2002, which allows firms, investors, researchers, and lawyers all across the U.S. to easily access USPTO patent documents online. As a result, openings a patent library have little impact on locals' ability to gather patent information.

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, results are reported in Appendix Table A2 Panel A. We control for the same sets of firm-level and county-level variables, as well as firm and year fixed effects. In columns (1) and (2), we run Poisson and Negative Binomial regression, respectively, where the dependent variables is *# of M&A Deals*. The coefficient estimate on *Pat Library* is positive and significant in both columns. In column (3), we estimate an OLS regression with *# of M&A Deals* being the dependent variable and find qualitatively similar result. 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.[15,16] We find that the opening of a local patent library significantly increases the likelihood of local firms' acquisition by 10.7%.[17]

Second, per Harford (2005), acquisitions come in waves in different industries across different time periods. We thus use industry and year fixed effects to control for the merger waves, As shown in Appendix Table A2 Panel B, our results remain robust in both columns (1) and (2), where 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, or 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 assess whether our results are sensitive to the methods of clustering standard errors, we repeat our baseline estimations, but this time we 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 A2 Panel C, we continue to find a significant increase in firms' acquisitiveness following the openings of patent libraries in the headquarter counties.

Fourth, 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

[15] 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.
[16] The results are qualitatively the same if we estimate Probit regressions.
[17] 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 33.5%. That is a 10.7-percent-point increase in acquisition probability (33.5% - 22.8%).

companies. This likely causes a spurious correlation between the opening of patent libraries and technology 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 A3. The openings of non-university patent libraries remain significantly increasing local firms' acquisition activities, implying that our results are not driven by the spurious correlation between universities and local innovation activities.

Finally, some counties have established patent libraries prior to 1985, thus some "treated" firms are "treated" for the entire sample period. As a robustness check, we exclude firms that are headquartered in the aforementioned counties. As shown in Appendix Table A4, our results hold robust.

4.1.5. Refined Control Group

In the analysis above, we employ firms located in counties without any patent library as the counterfactual to estimate what would have happened to M&A activities if the library had not opened. Given that patent libraries might be more likely to open in metropolitan areas or regions with greater economic activities, an adequate control group should be areas that have a similar likelihood of having a patent library, hence having similar regional economic prospects. For this purpose, we identify the control group for each treated county with patent library as the counties that are in the same state, are geographically proximate to the treated county, and have at least one medium or large Federal Depository Library (FDLs). Such counties serve as a better control group, since their medium or large Federal Depository Library have already handled government documents and had the physical space, human capital, and library infrastructure that are required for becoming patent libraries. In fact, 82% (53 of 64) of the patent libraries opened after 1975 are also FDLs (Furman et al., 2021).

Following Furman et al. (2021), we refine our control group as follows. We start with a list of treated counties where a patent library is open, and the library is also an FDL. For each treated county, we require control counties to satisfy the following criteria: (1) are located in the same state as the treated county; (2) have no patent libraries; (3) have an FDL with library volume of medium (250,000 - 1,000,000) or larger (more than 1,000,000) in size; (4) are between 15 and 250 miles away from the patent library in the treated county. Finally, we drop treated counties where we cannot find any qualified control counties. As a result, we end up with 58 treated counties and 141 control counties.

We focus on a sample of public innovative firms that headquarter in this refined groups of treated and control counties. We define *Pat Library* as a dummy variable that takes the value of one if the firm is headquartered in a treated county after the patent library opens, and zero if the firm is located in a treated county before the patent library opens, or located in a control county. We re-estimate Equation (1) and include the same sets of control variables and fixed effects. Results are reported in Table 5. In the refined sample, the coefficient estimates on *Pat Library* continue to be positive and statistically significant, both with and without county-level control variables in columns (1) and (2), respectively. The estimated economic magnitude is comparable to our baseline results—local patent library openings lead to 5.1% more technological acquisitions based on column (1).

[Insert Table 5 Here]

Overall, we find robust evidence that innovative firms become more active in acquiring other firms following the openings of local patent libraries. That finding is consistent with the conjecture that the openings of patent libraries facilitate local technology-intensive firms' access to patent documents and technology information of potential targets, hence alleviating information frictions between potential acquirers and targets, which in turn reduces adverse selection and boosts technological M&A activities.

4.2. The Effect of Patent Library Openings on Acquirer-Target Pairings

In the absence of the aforesaid information frictions, acquiring firms are better able to consider all available targets with various resource complementarity and synergy, and opt for first best choice. Nevertheless, information friction in M&A forces acquirers to avoid high information asymmetry by electing targets that are geographically proximate or in similar technology space so as to lower the costs of information gathering. In this section, we intend to investigate how the openings of patent libraries affect the pairing of acquirers and targets with respect to geographical and technological distance.

4.2.1. Matched Sample for Analyzing Acquirer-Target Pairing

To gain insights on how the openings of patent libraries affect the matching of acquirer and target in 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 2,910 M&A deals that involve public innovative acquirers and targets from innovative industries during the period 1985–1999. 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,[18] then based on the closest size (total assets) in the year prior

[18] 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

to the deal.[19] We also require the control firms to be neither an acquirer nor a target in the past three years prior to the year of deal announcement. 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 Bena and Li (2014), 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 Acquisition

Prior literature has shown that geographical distance aggravates information friction, 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 geographically distant. This in turn reduces the marginal

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there are fewer than five industry peers to the actual acquirer (target firm), we next search for matching 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.

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

cost of information search associated with distant targets, and ultimately encourage local firms to expand their search of targets in distance. As a result, we propose that the positive relation between acquisition 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.[20] Following Bena and Li (2014) and Bereskin et al. (2018), we estimate the following conditional logic model to gauge the likelihood of the actual M&A deal occurring.

$$\begin{aligned} \textit{Actual M\&A Deal}_{i,t} = f(&\beta_0 + \beta_1 \textit{Geo Prox}_{i,j,t-1} \times \textit{Pat Library}_{c,t-1} + \beta_2 \textit{Geo Prox}_{i,j,t-1} \\ &+ \beta_3 \textit{Pat Library}_{c,t-1} + \gamma_1 X_{i,t-1} + \gamma_2 W_{c,t-1} + \mu_d + \varepsilon_{i,t}), \end{aligned} \tag{3}$$

where *i* and *j* index the acquirer and the target, respectively. The dependent variable, *Actual M&A Deal* is 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 a list of acquirer ($X_{i,t-1}$) and county characteristics ($W_{c,t-1}$) as in Table 3.[21] 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 6. We employ 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). As with the prior results, *Pat Library* is significantly positively related to the likelihood of M&A pairing in both columns. We find a strong positive coefficient on *Geo Prox*,

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

[21] 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).

implying that M&A deals are more likely to take place between acquirers and targets that are geographically closer. That is consistent with the extant literature that information search costs are lower between geographically proximate acquirers and targets, hence facilitating acquisition of nearby targets. As for our variable of interest, the coefficient on the interaction term *Geo Prox*×*Pat Library* is negative and statistically significant, suggesting that the positive relation between geographical proximity and the likelihood of M&A is attenuated after the openings of patent libraries. Post library opening, 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 lesser extent after their local patent library opens. To put the economic magnitude into perspective and take column (1) as an example, the marginal effect of geographical proximity spurring actual M&A pairing declines by 50% following the openings of local patent libraries.[22]

[Insert Table 6 Here]

4.2.3. Technological Proximity and Acquisition

Similar to the idea of geographic proximity, technological proximity can also serve as a catalyst to reduce information searching costs. Following Jaffe (1986) and Bena and Li (2014), we construct a measure of technological proximity of acquirer or pseudo-acquirer *i* and target *j* as the following:

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[22] 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 86.1% when *Geo Prox* is at its median value; the likelihood of actual M&A increases to 91.6% when *Geo Prox* is one standard deviation above the median. That indicates an increase of the likelihood by 6.4% (=91.6%/86.1%-1). Similarly, with patent library (*Pat Library*=1), the likelihood of actual M&A increases by 3.2% (=93.0%/90.1%-1) as the acquirer-target pair is more geographically close. Altogether, that is a 50% reduction (3.2%/6.4%-1) in the likelihood of actual M&A.

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

$X_{i,t} = (X_{i1,t}, X_{i2,t}, \ldots, \ldots, X_{iK,t})$ 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 similarly of an acquirer and a target's patent portfolio, which ranges between 0 to 1. A higher (lower) value indicates a higher (lower) degree of technological overlap between the acquirer and the target. Since there are targets in an innovative industry that did not 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 four-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. The results are reported in Table 7. We find that technologically proximate acquirers and targets are more likely to engage in acquisitions, indicated by the significant positive coefficient on *Tech Prox*. More importantly, we find significant negative coefficients on the interaction term *Tech Prox×Pat Library* in both columns, implying that the effect of technological proximity becomes weaker in motivating acquisitions following a local patent library opening. The moderating effect of patent library openings on technological proximity is economically significant, causing the positive marginal effect of technological proximity on M&A pairing declining by 34.4%.[23]

[23] Following the same practice as in the previous table, 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

[Insert Table 7 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 more easily, hence broadening their search to more geographically and technologically distant targets.

4.3. Deal-Level Analysis

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.

4.3.1. Patent Library Opening and the Likelihood of Deal Completion

M&A deals that are announced do not always reach to completion. Per Savor and Lu (2009) and Bena and Li (2014), a variety of reasons (such as disagreement between the acquirers and the targets on deal valuation) could lead to deals withdrawn. To investigate whether access to patent libraries affects the deal completion rate, we stack the completed deals with the withdrawn deals during our sample period.[24] Our sample includes a total of 3,195 completed deals and 439 withdrawn deals, the latter accounting for 12.08% of the total.[25]

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

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

M&A increases by 9% (=91.7%/84.1%-1) as the acquirer-target pair is more technologically close. With patent library (*Pat Library*=1), the likelihood of actual M&A increases by 5.9% (=93.5%/88.3%-1) as the acquirer-target pair is more technologically close. Altogether, that is a 34.4% reduction (5.9%/9%-1) in the likelihood of actual M&A.

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

[25] 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) and Nguyen and Phan (2017), 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.[26] Regression results are reported in Table 8.

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), for firms located in counties with patent libraries, the odds of deal completion are 25.9% higher than that of firms located in counties without a patent library. The results indicate that, following the openings of local patent libraries, innovative acquirers are better at finding appropriate targets and face less adverse selection problems, all of which leads to a successful deal completion.

[Insert Table 8 Here]

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[26] Since those deal-level tests are not panel data, and given that firms are less likely to repetitively get engaged in M&A deals, adding firm fixed effect will drop a large number of the firms out of the regression analysis. We use industry fixed effects in those actual deal level analysis instead.

4.3.2. Patent Library Opening and Announcement Return

To assess whether the acquisition activities following patent library openings are value enhancing for shareholders, we follow the prior literature to gauge market reactions to M&A announcements. First, following the extant literature (e.g., Bonaime et al., 2018), we compute the cumulative abnormal return 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.[27] We estimate the following OLS model:

$$CARs\ [-3,\ +3]_d = \beta_0 + \beta_1 Pat\ Library_{i,t-1} + \gamma_1 X_{i,t-1} + \gamma_2 W_{i,t-1}$$

$$+\gamma_3 Z_d + \mu_m + \mu_t + \varepsilon_d\ , \qquad (6)$$

If patent libraries enable local firms to access patent documents nationwide, hence broadening their searches of targets, acquirers could identify better targets that create greater synergies and economic value post-mergers, compared to the acquirers who do not have access to patent information. Our results are supportive of the conjecture. As shown in column (1) of Table 9, *Pat Library* is positively associated with the acquirers' 7-day abnormal announcement return, indicating that the M&A deals completed by acquirers close to a patent library generate a higher market value for the acquirers' shareholders, relative to the deals completed by acquirers who do not have a local access to patent documents. Economically, our estimate suggests the 7-day CAR of acquirers is 1.3% higher after the local patent library opens, implying M&A deals of greater economic value.

[Insert Table 9 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

[27] Our results hold using an alternative estimation model (e.g., market model used in Bereskin et al. (2018)).

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 remains an empirical question. The regression results are reported in column (2). Since we are limited to public 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 reaction in target firms. Nevertheless, the insignificant coefficient on *Pat Library* could be due to the smaller sample of public targets, hence lacking the statistical power to find significant result.

Finally, we examine the effect of *Pat Library* on the combined stock returns of both acquirers and targets. Follow the extant literature (e.g., Bereskin et al., 2018; Chen et al., 2021), we compute a weighted average of the 7-day cumulative abnormal returns of acquirer and 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 9. *Pat Library* is positively associated with *Combined CARs [-3,+3]*, reflecting greater synergies generated from the M&A deals that are completed by acquirers close to a patent library.

4.4. Patent Library Opening and Post-M&A Performance

The combined abnormal return (*Combined CAR[-3,+3]*) shed some lights on the ex-ante expected synergy creation resulted from the access to patent libraries. To gain insights on the ex-post value of synergy, we conduct two 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 in the 5-year window. We re-estimate Equation (6) using *Acquirer BHAR [5y]* as the dependent variable. Results are reported in column (4) of Table 9, where the coefficient estimate on *Pat Library* is positive and statistically significant, indicating that acquirers with local access to a patent library experience a greater post-M&A long-term stock returns, compared to acquirers that do not have access to a local patent library.

Second, we investigate the innovation activities in the post-merger firms. Since we focus on technology acquisitions, synergy creation is expected to be reflected in innovation outputs. Following Bena and Li (2014) and Chen et al. (2021), we construct a 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:

$$\begin{aligned} Innovation\ Activities_{i,t} = {} & \beta_0 + \beta_1 Treat_i \times Post_{i,t} + \beta_2 Post_{i,t} \\ & + \gamma_1 X_{i,t-1} + \gamma_2 W_{c,t-1} + \mu_t + \mu_d + \varepsilon_{i,t}\,, \end{aligned} \tag{9}$$

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*".[28] In the pre-acquisition period, "*Combined # of Patents*" is the

[28] We follow the method in Kogan, Papanikolaou, Seru, and Stoffman (2017) for the construct of citation weighted patents.

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. Similarly, in the pre-acquisition (post-acquisition) period, "*Combined # of Citation Weighted Patents*" is the total number of citation-weighted patents from acquirers and targets (from combined firms), where the weight of each patent is its number of forward citations received scaled by the average number of forward citations received by all patents granted in the same 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. We also include deal- and year- fixed effects in the model.[29] Regression results are reported in columns (1) and (2) of Table 10 Panel A, respectively.

[Insert Table 10 Here]

The interaction term *Treat*×*Post* captures the differences in the changes of innovation outputs before and after the mergers between deals completed by acquirers that have local access to a patent library vs. those without local access to a patent library. We find positive and statistically significant coefficient estimates in both columns (1) and (2), suggesting that innovation activities are higher among post-merger firms when the acquirers had access to a local patent library. The result is consistent with the higher abnormal announcement returns, implying that improved innovation productivity is the source of synergy gains.

We further consider the collaborations in innovation projects between the acquirers and the targets. Following the construct of Chen et al. (2021), for every acquirer firm-year, we count the

[29] 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.

number of co-patents among the inventors working for acquirers and targets, scaled by the total number of patents applied by the acquirers and the targets.[30] For robustness, we also compute the number of citations received by co-invented patents, scaled by the total number of citations received by patents applied by the acquirers and the targets. Similar to Panel A, in the pre-acquisition period, the total number of patents (or citations) is the sum of the total number of patents from acquirers and targets, and in the post-acquisition period, it is the number of patents (or citations) from the post-merger combined firms. Those results are reported in Panel B of Table 10. The statistically significant and positive coefficient estimates on the interaction term, *Treat×Post*, reinforces that acquirers close to a patent library explore complementarity that incubate more collaboration between their existing inventors and incoming research team from the targets.

5. Conclusions

In this paper, we examine how information costs affect technology acquisitions. Employing the staggered openings of patent libraries as an exogenous variation in the costs of gathering technological information, we find that firms become more active in acquisitions following a decline in information costs due to the openings of local patent libraries. In addition, information costs appear affecting the pairing choice of acquirers and targets. Consistent with prior studies that acquirers are more likely to takeover targets that are geographically close (Kang and Kim, 2008) or technologically similar (Bena and Li, 2014), we document a strong preference of acquirers to geographically or technologically proximate targets, since proximity in both geographic location

[30] In the pre-M&A period, we can identify the patents applied by acquirers alone, by the targets alone, and co-invented by the inventors from acquirers and targets. In the post-M&A period, though the targets are combined into the acquirer, for every patent, we can still identify whether it is by inventors entirely from pre-M&A acquirers, or by inventors entirely from pre-M&A targets, or by inventors from pre-M&A acquirers and inventors from pre-M&A targets jointly.

and technological space reduces the costs of gathering information. However, such a preference is significantly attenuated after local patent libraries are opened, highlighting that patent library openings broaden acquirers' search to more geographically and technologically distant targets. Further analysis reveals that openings of patent libraries enhance the economic values of the M&A transactions. After patent libraries open, the deal completion rate rises, the abnormal cumulative announcement returns for acquirers becomes higher, and more collaboration between acquirers' and targets' inventors is fostered, implying better matches between acquirers and targets in terms of better technology complementarity and greater synergy, hence creating greater economic value. Overall, our study provides causal evidence on the impact of information costs on the decision, choices, and economic value of technological acquisitions. Our findings also shed light on the importance of information search costs in corporate investment decisions.

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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 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.

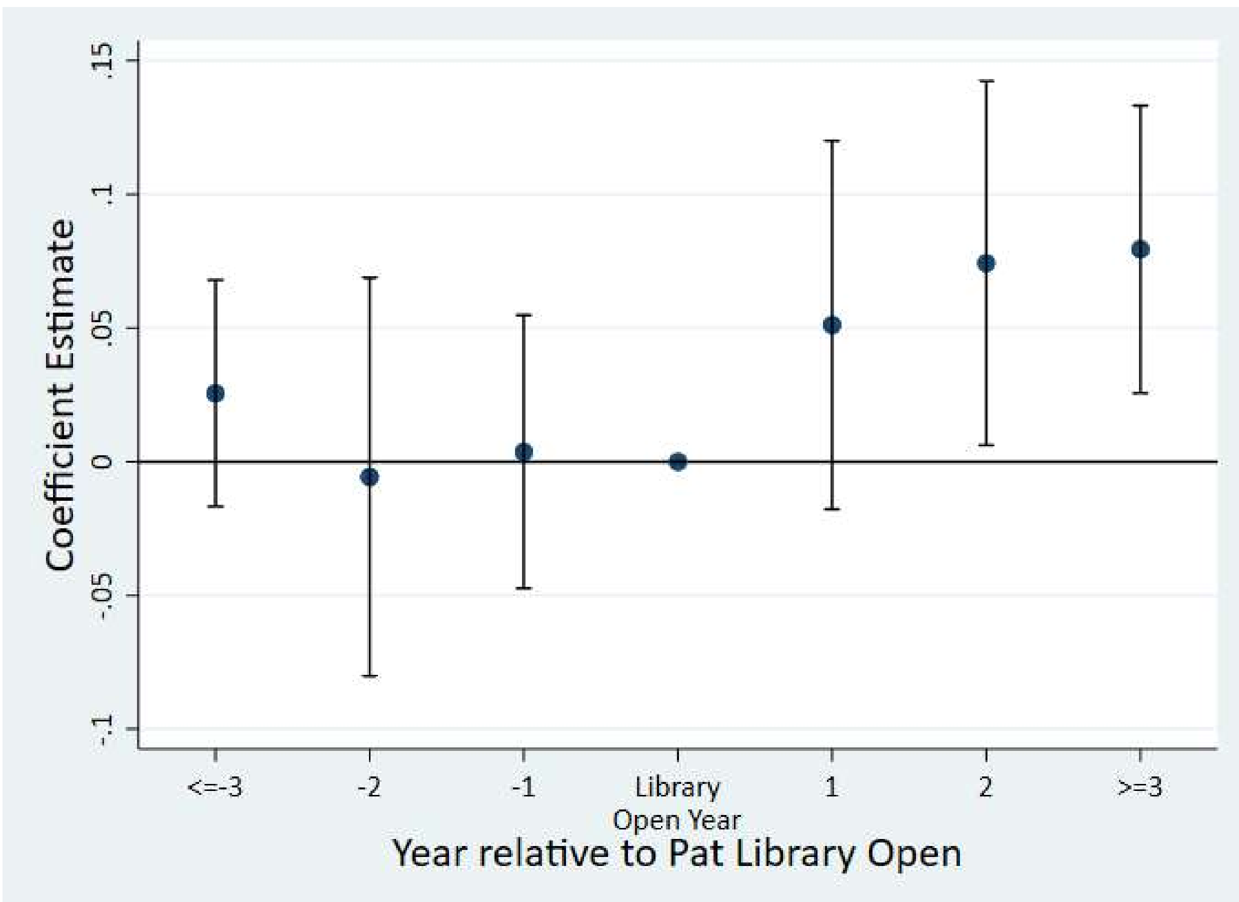

Table 1. M&A Deals Distribution

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).

Year	(1) # of M&A Deal All Public Acquirers	(2) # 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	104
1991	294	105
1992	396	131
1993	609	179
1994	705	210
1995	850	259
1996	1,017	338
1997	1,324	361
1998	1,327	417
1999	1,169	450
Total	8,744	2,910

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 A.

	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	0.433	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 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 A. 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	0.064***	0.064***
	(2.938)	(2.725)
Ln(Age)	-0.025	-0.025
	(-1.099)	(-1.094)
Ln(Total Asset)	0.009	0.009
	(0.993)	(0.996)
RD/Asset	-0.066	-0.066
	(-1.150)	(-1.149)
ROA	-0.002	-0.002
	(-0.081)	(-0.081)
Leverage	-0.169***	-0.169***
	(-6.160)	(-6.150)
Cash/Asset	0.167***	0.167***
	(7.897)	(7.901)
Market-to-Book	0.002**	0.002**
	(2.478)	(2.468)
Sales Growth Rate	-0.003	-0.003
	(-0.967)	(-0.965)
Net Working Capital	-0.007	-0.007
	(-0.380)	(-0.376)
Return	0.017***	0.017***
	(4.036)	(4.038)
Ln(Population)		-0.006
		(-0.051)
Income Per Capita		0.000
		(0.080)
Constant	0.119*	0.115
	(1.706)	(1.318)
Fixed Effects	Firm + Year	Firm + Year
Model	OLS	OLS
N	15,262	15,262
adj. R-sq	0.238	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 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 A. 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)	0.024	0.026
	(0.969)	(0.997)
Pat Library(-2)	-0.007	-0.006
	(-0.160)	(-0.125)
Pat Library(-1)	0.002	0.004
	(0.075)	(0.121)
Pat Library(+1)	0.049	0.051
	(1.199)	(1.224)
Pat Library(+2)	0.072*	0.074*
	(1.795)	(1.800)
Pat Library(≥+3)	0.076***	0.079**
	(2.643)	(2.438)
Constant	0.117*	0.117
	(1.682)	(1.337)
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 Local M&A Activities: Refined Control Group

This table presents the results of the effect of patent library opening on local firms' M&A activities using refined control group following Furman et al. (2021). We start with a list of treated counties where a patent library is opened, and the library must also be a federal depository library (FDL). For each treated county, we require control counties to be located in the same state as the treated county and between 15 and 250 miles away from the patent library; have no patent libraries opened; have a FDL with of medium or large size. Our final sample consists of public innovative firms located in treated counties and public innovative firms located in control counties that are identified based on the aforesaid criteria. The dependent variable, *Ln(1+# of M&A Deals)*, is the natural logarithm of one plus 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 A. 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	0.051**	0.049**
	(2.234)	(2.103)
Ln(Age)	-0.021	-0.023
	(-0.766)	(-0.841)
Ln(Total Asset)	0.002	0.002
	(0.209)	(0.199)
RD/Asset	-0.050	-0.051
	(-0.680)	(-0.693)
ROA	0.018	0.018
	(0.664)	(0.659)
Leverage	-0.163***	-0.163***
	(-4.887)	(-4.901)
Cash/Asset	0.188***	0.189***
	(6.824)	(6.848)
Market-to-Book	0.001	0.001
	(1.337)	(1.358)
Sales Growth Rate	-0.003	-0.003
	(-0.801)	(-0.788)
Net Working Capital	-0.001	-0.002
	(-0.038)	(-0.091)
Return	0.018***	0.018***
	(3.135)	(3.129)
Ln(Population)		0.016
		(0.133)
Income Per Capita		-0.002
		(-1.069)
Constant	0.140*	0.186**
	(1.759)	(2.049)
Fixed Effects	Firm + Year	Firm + Year
Model	OLS	OLS
N	10,477	10,477
adj. R-sq	0.219	0.219

Table 6. 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) of both panels, we select pseudo-acquires that have the closest size to and from the same industry as the actual acquirer. In column (2) of both panels, 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 A. 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)	-2.211***	-2.402***
	(-3.259)	(-3.510)
Geo Prox (β_2)	6.181***	6.495***
	(11.542)	(12.048)
Pat Library (β_3)	0.712***	0.761***
	(5.416)	(5.760)
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= 85.15	χ^2= 76.32
	(p-value=0.000)	(p-value=0.000)
N	10,304	10,304
Pseudo. R-sq	0.165	0.163

Table 7. 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 A. 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)	-0.528*	-0.505*
	(-1.702)	(-1.671)
Tech Prox (β_2)	4.434***	4.379***
	(14.360)	(14.529)
Pat Library (β_3)	0.378***	0.396***
	(4.989)	(5.220)
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= 186.68 (p-value=0.000)	χ^2= 187.12 (p-value=0.000)
N	10,304	10,304
Pseudo. R-sq	0.177	0.175

Table 8. 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 A. 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	0.199*	0.230*
	(1.664)	(1.803)
Ln(Total Asset)	0.142***	0.149***
	(3.367)	(3.484)
Market-to-Book	0.011	0.012
	(0.617)	(0.744)
Return	-0.075	-0.068
	(-0.493)	(-0.432)
Sales Growth Rate	0.191**	0.187**
	(2.004)	(2.035)
Leverage	-0.587	-0.569
	(-1.492)	(-1.440)
ROA	0.768	0.736
	(1.417)	(1.378)
Cash/Asset	0.374	0.396
	(0.955)	(1.012)
RD/Asset	1.530*	1.577*
	(1.684)	(1.728)
Relative Size	-0.155**	-0.147**
	(-2.147)	(-1.980)
All Cash Dummy	0.487***	0.497***
	(2.987)	(2.992)
High Tech Dummy	0.187	0.172
	(0.838)	(0.790)
Diversify Dummy	-0.081	-0.074
	(-0.632)	(-0.578)
Hostile Dummy	-1.666***	-1.678***
	(-5.395)	(-5.512)
Challenge Dummy	-1.774***	-1.786***
	(-7.217)	(-7.223)
Public Target Dummy	-0.563***	-0.564***
	(-3.602)	(-3.588)
Ln(Population)		-0.232
		(-0.638)
Income Per Capita		-0.013*
		(-1.851)
Constant	-1.465	-1.445
	(-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 9. Patent Library Openings and Announcement Returns

The table presents the results of the effect of patent library opening on cumulative abnormal announcement returns. The sample consists of completed innovative target acquisition deals by all public innovative acquirers. In column (1), the dependent variable is *Acquirer CARs [-3,+3]*, which is the 7-day cumulative abnormal returns surrounding the announcement day for acquirers, computed using a market adjusted model with the CRSP value-weighted index as the market. In column (2), the dependent variable is *Target CARs [-3,+3]*, which is the 7-day cumulative abnormal announcement returns for public traded targets. In column (3), the dependent variable is *Combined CARs [-3,+3]*, which is the weighted average of the 7-day cumulative abnormal announcement returns of both acquirer and target, with the weights being the market values of the acquirer and the target one 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 market 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. 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 A. 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**	0.018	0.013*	0.109**
	(2.081)	(0.982)	(1.684)	(2.181)
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	0.009	0.365

Table 10. Patent Library Openings and 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. In Panel A, we examine the overall innovation activities, where the dependent variable is the natural logarithm of one plus "*Combined # of Patents*" and the natural logarithm of one plus "*Combined # of Citation Weighted Patents*" in columns (1) and (2), 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. In Panel B, we examine the extent of collaboration between inventors from acquirers and targets. In column (1), the dependent variable is "*%Coinvented Patents*", which is the number of patents coinvented by the acquirers' and targets' inventors scaled by the sum of the number of patents applied by the acquirers and the targets (pre-merger) or the total number of patents of the post-merger firms. In column (2), the dependent variable is "*%Citations to Coinvented Patents*", which is the number of citations received by coinvented patents scaled by the sum of the total number of citations received by all patents of the acquirers and the targets (pre-merger) or the total number of citations of all patents from the post-merger firms. *Treat* takes the value of one if the firm is headquartered in a county where a patent library opens by the year of 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*. 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.

Panel A: Overall Innovation Activities

	(1) *Ln(1+ Combined # of Patents)*	(2) *Ln(1+ Combined # of Citation Weighted Patents)*
Treat×Post	0.238***	0.248***
	(4.791)	(4.288)
Post	-0.606***	-0.681***
	(-10.004)	(-9.654)
Acquirer Firm Control	Yes	Yes
Acquirer County Control	Yes	Yes
Deal Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Model	OLS	OLS
N	7,356	7,356
adj. R-sq	0.851	0.839

Panel B: Cooperation between Acquirers' and Targets' Inventors

	(1) *%Coinvented Patents*	(2) *%Citations to Coinvented Patents*
Treat×Post	0.010***	0.009***
	(2.775)	(2.607)
Post	-0.000	-0.003
	(-0.065)	(-0.802)
Acquirer Firm Control	Yes	Yes
Acquirer County Control	Yes	Yes
Deal Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Model	OLS	OLS
N	7,356	7,356
adj. R-sq	0.684	0.683

Appendix A. Variable Definitions

Variable	Definition
<u>Firm Characteristics</u>	
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.
<u>Deal Characteristics</u>	
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.
<u>County Characteristics</u>	
Population	Total population in one county.
Income Per Capita	The personal income per capita in 1000 dollars in one county.

Appendix B. List of Patent Depository Libraries

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

Table A1. Pre and Post Internet Boom

This table presents the results on the effect of patent library opening on local firms' M&A activities pre and post the internet boom. We restrict to publicly traded and innovative firms that have been 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 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 focus on the pre-internet boom period (1985-1999) in column (1) and the post-internet boom period (2002-2006) in column (2). 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 A. 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)	
	1985-1999	2002-2006
Pat Library	0.064***	-0.058
	(2.725)	(-1.294)
Acquirer Firm Control	Yes	Yes
Acquirer County Control	Yes	Yes
Model	OLS	OLS
Fixed Effects	Firm + Year	Firm + Year
N	15,262	6,670
adj. R-sq	0.238	0.326

Table A2. 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 A. 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, 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	0.533***	0.533***	0.122***	0.729***
	(2.922)	(3.097)	(3.155)	(2.892)
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)
	Dept Var = Ln(1+# of M&A Deals)	
Pat Library	0.012**	0.013**
	(1.981)	(2.032)
Acquirer Firm Control	Yes	Yes
Acquirer County Control	Yes	Yes
Model	OLS	OLS
Fixed Effects	Industry (SIC3) + Year	Industry (FF48) + Year
N	15,643	15,616
adj. R-sq	0.134	0.110

Panel C: Alternative Clustering of Standard Errors

	(1)	(2)	(3)
		Dept Var = Ln(1+# of M&A Deals)	
Pat Library	0.064**	0.064**	0.064***
	(2.409)	(2.166)	(5.124)
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

Table A3. 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 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 A. 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	0.070**	0.075**
	(2.349)	(2.239)
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

Table A4. Exclude Firms Located in Counties with Patent Library Opened Prior to 1985

This table presents the results on the effect of patent library opening on local firms' M&A activities 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)*, is the natural logarithm of one plus 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 A. 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	0.056**	0.060***
	(2.565)	(2.687)
Acquirer Firm Control	Yes	Yes
Acquirer County Control	No	Yes
Model	OLS	OLS
Fixed Effects	Firm + Year	Firm + Year
N	9,076	9,076
adj. R-sq	0.226	0.227