**Internet Appendix for**

**"Does access to patent information help technological acquisitions? Evidence from patent library openings"**

**(Not to be published)**

This Internet Appendix (IA) provides supplemental analyses and robustness tests to the main results presented in "Does access to patent information help technological acquisitions? Evidence from patent library openings". Section A presents detailed model specifications regarding the determinants of patent library openings. Section B presents detailed discussions of additional falsification tests. Section C presents detailed discussions of robustness checks. Towards the end of the IA, we present the tabulated results that are organized as follows:

**Section A. Determinants of Patent Library Openings (Detailed Model Specifications)**

To formally check whether local patent library opening is indeed unrelated to local economic characteristics, we follow the method in Acharya, Baghai, and Subramanian [2014] by estimating a Cox proportional hazard model, which examines whether any county-level characteristics could predict the opening of a patent library in a county. We start with a sample of county-year observations during 1985-1999 up to the year when a patent library opens in the county.[1] The dependent variable (or the "failure event") equals one if a patent library opens in a county-year and zero otherwise. Similar to Guernsey, John, and Litov [2022] and Green and Shenoy [2022], we include a set of county demographic and economic variables as the potential determinants that might predict local patent library openings. Specifically, we include the natural logarithm of county population (*Ln(Population)*), the personal income per capita in 1,000 dollars in a county (*Income Per Capita*), percent change in unemployment rate ($\Delta$ *Unemployment Rate (%)*), and the percent change in the number of business establishments ($\Delta$ *# of Establishments (%)*).[2] Since our empirical strategy in the main test relies on the assumption that the openings of patent libraries are exogenous with respect to local innovation activities, we investigate whether there is a reverse causality, i.e., whether local demand for technological information (proxied by local innovation activities) predicts patent library openings. As a result, we include the natural logarithm of one plus the total number of patents generated by public firms located in a county-year (*Ln(1+# of Patents)*). To examine whether past M&A activities can predict patent library openings, we count the number of firms being acquirers (or targets) in M&A deals in a county-year and add *Ln(1+# of M&A Deals as Acquirers)* and *Ln(1+# of M&A Deals as Targets)* as predictors in the model, respectively. Lastly, given that the USPTO aims for at least one patent library in each state as they expand the PTDL program, the chance of having a local patent library is expected to be lower in states with existing patent libraries. We thus create a binary variable, *Same State Pat Library* that takes the value of one if there has already been a patent library opened

---

[1] We start our sample of M&A deals in 1985 since SDC began to provide high-quality M&A data in that year. As a result, we restrict the sample for this test to post-1985. There are 32 patent libraries opened during 1985-1999. The patent library in Mayaguez Minicipio, PR is not in the sample because of missing county characteristics. The patent library in Washington, D.C. is not included because of the missing establishment data from CBP. In the end, we have 30 patent library opening events ("failure events") in the hazard model.

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

in the state where the county is located and zero otherwise. Following Guernsey, John, and Litov [2022], we include year dummies in the Cox proportional hazard model.

**Section B. Additional Falsification Tests**

One additional falsification test we undertake is to examine the post-internet boom period. As internet becomes widely available, firms, investors, researchers, and lawyers across the U.S. have easy access to the USPTO patent documents online. As a result, we expect that opening a patent library has little effect on locals' ability to gather patent information. For this purpose, we estimate the baseline model using a sample over the post-internet boom period—2000 through 2020, and report the results in Internet Appendix Table IA3 columns (1)-(2). To mitigate the effect of the financial crisis in 2007-2008, we exclude the period of 2007-2008. In contrast to the results for the pre-Internet Boom period of 1985 to 1999, we find no evidence of patent library openings on local takeover activities during 2000 through 2020. To ensure the muted results are not driven by the internet bubble around 2000, we rerun the regressions using a sample period of 2002-2020, also excluding 2007-2008. As shown in columns (3)-(4), the results remain insignificant. Overall, we find that patent libraries have little effect on local firms' M&A activities in more recent years, given the improved dissemination technology of patent information via the internet (e.g., through Google Patents).

Additionally, since we presume that patent libraries are only relevant to technological acquisitions that involve innovative acquirers, we limit the sample to only innovative firms that have been granted at least one patent in the previous five years. To validate this presumption, we examine whether patent library opening has any effect on the M&A activities of non-innovative acquiring firms. We rerun the baseline models using a sample consisting of non-innovative public firms (i.e., those acquirers that have not been granted any patent in the previous five years). The results are reported in Internet Appendix Table IA4, where the dependent variables are the number of M&A deals of non-innovative acquirers with innovative targets in columns (1) and (2), and the number of M&A deals of non-innovative acquirers with any targets in columns (3) and (4), respectively. We find no significant effect of patent library openings on M&A activities that involve non-innovative acquirers, confirming that patent information is relevant only to innovative acquirers.

We further investigate the effect of patent libraries on the extent of acquisitions involving non-innovative targets. Since their information would not show up in the patent library in the first place, the openings of libraries will not be useful in acquiring non-innovative targets. As shown in columns (5) and (6), the sample consists of innovative public firms, and the dependent variable is the number of M&A deals of innovative acquirers with non-innovative targets. Consistent with our expectation, columns (5) and (6) show no significant effect of patent library opening on the number of acquisitions of non-innovative targets, which is a direct contrast to the effect on the acquisitions of innovative targets shown in our baseline results.

**Section C. Robustness Checks**

To ensure the robustness of our results, we conduct a battery of additional tests. First, instead of taking natural logarithm of our outcome variable and estimate OLS regressions, we estimate alternative regression models for count data. Results are reported in Internet Appendix Table IA5 Panel A. Cohn, Liu, and Wardlaw [2022] demonstrate that the common practice of adding a constant to the outcome variable and then estimating log-linear regressions might produce estimates with the wrong sign. Additionally, Chen and Roth [2023] argue that log-like transformations are problematic in assessing the average treatment effect (ATE) as approximating percentage effects. To address these concerns, we follow the suggestions by Cohn et al. [2022] and Chen and Roth [2023] and estimate Poisson model in which the dependent variable is *# of M&A Deals*. Results are reported in column (1). We control for the same sets of firm-level and county-level variables, as well as firm and year fixed effects. The coefficient estimate on *Pat Library* remains positive and significant. In column (2), we run a Negative Binomial regression in which the dependent variable is *# of M&A Deals* and find qualitatively similar results. In column (3), we estimate an OLS regression with *# of M&A Deals* being the dependent variable and find robust results. In column (4), we run a logit regression to model the likelihood of a public innovative firm completing at least one innovative target acquisition in a year.[3] We find that the opening of a patent library significantly increases the likelihood of local firms' technological acquisitions by 10.8%.[4]

Second, Harford [2005] documents acquisitions coming in waves in different industries across different time periods. We thus use industry and year fixed effects to control for merger waves. As shown in Internet Appendix Table IA5 Panel B, our results remain robust in both columns (1) and (2) in which we add industry fixed effects based on three-digit SIC or the Fama-French 48 industry classifications, respectively. The results remain robust to the use of two-digit or four-digit SIC industry classifications, the Fama-French 12 or 30 industry classifications, or industry-times-year fixed effect that captures the time-varying unobservable factors within the industry (untabulated and available upon request). Third, to account for time varying local unobservable factors, we add state×year fixed effects in column (3), and in column (4) we control county and year fixed effects. Our results are robust to these alternative specifications. Fourth, to assess whether our results are sensitive to the clustering methods of standard errors, we repeat our baseline estimations and cluster standard error at the firm- or industry-level, or double cluster standard errors at both county- and year-level. As shown in Internet Appendix Table IA5 Panel C, we continue to find a significant increase in firms' acquisition activities following the openings of patent libraries in their headquarters counties.

Fifth, among the 69 patent libraries in our sample, 29 of them are university libraries. Universities are often hubs of innovation, which in turn boosts innovation activities in the local firms. This likely causes a spurious correlation between the opening of patent libraries and technological acquisition activities. To address this concern, we exclude, from our sample, all the firms located in the counties where university patent libraries reside and rerun the baseline model in Equation (1). Results are presented in Internet Appendix Table IA6 Panel A. The openings of non-university patent libraries continue to increase local firms' technological acquisition activities, suggesting that our results are not driven by the spurious correlation between universities and local innovation activities.

[3] 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.

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

Sixth, there are two types of firms that have the *Pat Library* treatment effect for the entire sample period. One type is the firms located in Washington D.C., which could have been accessing patent information at the USPTO headquarters since 1870. The other type is the firms located in counties that have established patent libraries prior to the beginning of our sample period, 1985. To ensure that our results are not driven by these firms that always had patent libraries, we rerun the DiD regressions by excluding the firms that are headquartered in Washington D.C. in Internet Appendix Table IA6 Panel B or excluding the firms headquartered in counties where patent libraries established before 1985 in Panel C. The results remain robust.

Seventh, Baker et al. [2022] point out that staggered DiD regressions are susceptible to biases resulting from treatment effect heterogeneity. To address this concern, we follow their recommendation and perform two diagnostic tests in Internet Appendix Table IA7: 1) we conduct a stacked regression and obtain qualitatively similar result as the baseline result; 2) we estimate the interaction weighted (IW) estimator and constructs pointwise confidence interval for the estimation of dynamic treatment effects, a method that is initially proposed by Sun and Abraham [2021] in the presence of treatment effects heterogeneous across cohorts, and obtain similar results.

Finally, our model specifications may underestimate the treatment effect, since control counties that are geographically close to a treated county are likely affected by the treatment effect.[5] To assess whether the treatment effects gradually dissipate as firms are more distant to a treated county, we construct a continuous distance variable that measures the distance in miles between a firm's headquartered county and the closest treated county where a library is opened. We then rerun our baseline tests by replacing *Pat Library* with the distance variable. As shown in Internet Appendix Table IA8, the coefficient estimate on the distance variable is significantly negatively related to firms' M&A activities, suggesting that the treatment effect is smaller as firms are farther away from a treated county. This finding confirms that geographic distance is an underlying mechanism of our findings.[6]

---

[5] We are grateful for an anonymous referee's suggestion to provide the test to alleviate the concern on violations of the Stable Unit Treatment Value Assumption (SUTVA) (Rubin [1980], Imbens and Rubin [2015]).

[6] In untabulated results, we find that the effect of a local patent library opening is greater in firms that are farther away from an existing patent library than in firms that are closer to existing patent libraries.

**Table IA1. Determinants of Patent Library Openings (Tabulated Results)**

The table reports the hazard ratios from Cox proportional hazard models to examine the determinants of patent library openings. The sample consists of county-year observations during 1985-1999 up to the year when a patent library opens. The dependent variable (or the "failure event") equals to one if a patent library opens in a given county-year. Explanatory variables (all lagged by one year) include the natural logarithm of total population in a county-year (*Ln(Population)*), percentage change in unemployment rate (Δ *Unemployment Rate (%)*), percentage change in the number of establishments (Δ *# of Establishments (%)*), the natural logarithm of one plus total number of patents by public firms located in a given county-year (*Ln(1+# of Patents)*), the natural logarithm of total number of firms located in a county-year being acquirers in M&A deals (*Ln(1+# of M&A Deals as Acquirers)*), the natural logarithm of total number of firms located in a county-year being targets in M&A deals (*Ln(1+# of M&A Deals as Targets)*). In column (2), we include an additional binary variable that takes the value of one if a patent library has already opened in the state where the county is located (*Same State Pat Library*). We include year fixed effects in all regressions. T-statistics based on robust standard errors clustered at county-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) |
|---|---|---|
| *Ln(Population)* | 3.424*** | 4.958*** |
| | (9.566) | (5.325) |
| *Income Per Capita* | 0.937 | 0.889 |
| | (-1.151) | (-0.715) |
| Δ *Unemployment Rate (%)* | 1.000 | 0.996 |
| | (0.018) | (-0.288) |
| Δ *# of Establishments (%)* | 1.048 | 1.084 |
| | (0.796) | (1.232) |
| *Ln(1+# of Patents)* | 1.252 | 1.142 |
| | (1.477) | (0.424) |
| *Ln(1+# of M&A Deals as Acquirers)* | 0.798 | 0.986 |
| | (-0.547) | (-0.034) |
| *Ln(1+# of M&A Deals as Targets)* | 1.454 | 1.032 |
| | (0.780) | (0.068) |
| *Same State Pat Library* | | 0.038*** |
| | | (-6.726) |
| Year FE | Y | Y |
| N | 45,125 | 45,125 |
| Pseudo. R-sq | 0.213 | 0.322 |
| # Unique Counties | 3,033 | 3,033 |
| # of Pat Library Opened | 30 | 30 |

**Table IA2. Alternative Dependent Variables**

This table presents the results on the effect of patent library opening on local firms' M&A activities using alternative dependent variables. In Panel A, the dependent variables is *Ln(1 + $ Value of M&A Deals),* which is the natural logarithm of one plus the dollar value of firms' M&A deals in a year. In Panel B, the dependent variable, *Ln(1+# of M&A Deals, t+1 to t+3)*, is the natural logarithm of one plus the number of innovative target acquisitions completed by a firm in the next three 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 independent variable *Pat Library* takes the value of one if the firm is headquartered in a county where a patent library opens, and zero otherwise. We include the same set of control variables as those in Table 3, but do not report them for brevity. We use the same sample as in Table 3. Definitions of other variables are in Appendix C. 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.

**Panel A. Dollar Value of M&A Deals**

| | (1) | (2) |
|---|---|---|
| | *Dept Var = Ln(1 + $ Value of M&A Deals)* | |
| *Pat Library* | 0.322*** | 0.332*** |
| | (2.912) | (2.690) |
| Acquirer Firm Controls | Y | Y |
| Acquirer County Controls | N | Y |
| Fixed Effects | Firm + Year | Firm + Year |
| Model | OLS | OLS |
| N | 15,262 | 15,262 |
| adj. R-sq | 0.249 | 0.249 |

**Panel B. Cumulative Number of M&A Deals**

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

**Table IA3. Effect of Patent Library Openings during Post-Internet Period**

This table presents the results on the effect of patent library opening on local firms' M&A activities during the post-internet period. The dependent variable, *Ln(1+# of M&A Deals)*, is the natural logarithm of one plus the number of innovative target acquisitions completed by a firm in a given year. Innovative targets are those from a three-digit SIC coded industry where at least one firm was awarded a patent during the past five years. The independent variable *Pat Library* takes the value of one if the firm is headquartered in a county where a patent library opens, and zero otherwise. We include the same set of control variables as those in Table 3, but do not report them for brevity. The sample covers the period from 2000 to 2020 in columns (1) and (2), and spans 2002 to 2020 in columns (3) and (4). We exclude the 2007-2008 Financial Crisis period in both samples. Definitions of other variables are in Appendix C. 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) | (3) | (4) |
|---|---|---|---|---|
| | *Dept Var = Ln(1+# of M&A Deals)* | | | |
| *Pat Library* | -0.018 | -0.012 | -0.020 | -0.015 |
| | (-1.453) | (-1.094) | (-1.404) | (-1.179) |
| Sample Period | 2000-2020 | | 2002-2020 | |
| Acquirer Firm Controls | Y | Y | Y | Y |
| Acquirer County Controls | N | Y | N | Y |
| Fixed Effects | Firm + Year | Firm + Year | Firm + Year | Firm + Year |
| Model | OLS | OLS | OLS | OLS |
| N | 20,547 | 20,547 | 17,766 | 17,766 |
| adj. R-sq | 0.215 | 0.215 | 0.211 | 0.211 |

**Table IA4. Non-innovative Acquirers and Targets**

This table presents the results on the effect of patent library opening on local M&A activities of non-innovative acquirers as well as M&A activities involving non-innovative targets. Our sample in columns (1) – (4) consists of non-innovative public firms, i.e., those acquirers that have not been granted any patent in the previous five years. In columns (1) and (2), the dependent variable is the logarithm of one plus the number of M&A deals of non-innovative acquirers with innovative targets. In columns (3) and (4), the dependent variable is the logarithm of one plus the number of M&A deals of non-innovative acquirers with any targets. In columns (5) and (6), the sample consists of innovative public firms, and the dependent variable is the logarithm of one plus the number of M&A deals of innovative acquirers with non-innovative targets. Definitions of the variables are in Appendix C. T-statistics based on robust standard errors clustered at county-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Dept Var = Ln(1+# of M&A Deals)* | | *Dept Var = Ln(1+# of M&A Deals)* | | *Dept Var = Ln(1+# of M&A Deals)* | |
| | *M&A Deals* of non-innovative acquirers & innovative targets | | *M&A Deals* of non-innovative acquirers & all targets | | *M&A Deals* of innovative acquirers & non-innovative targets | |
| *Pat Library* | -0.004 | -0.009 | 0.006 | 0.009 | 0.001 | 0.000 |
| | (-0.223) | (-0.456) | (0.344) | (0.478) | (0.778) | (0.126) |
| Acquirer Firm Controls | Y | Y | Y | Y | Y | Y |
| Acquirer County Controls | N | Y | N | Y | N | Y |
| Fixed Effects | Firm + Year | Firm + Year | Firm + Year | Firm + Year | Firm + Year | Firm + Year |
| Model | OLS | OLS | OLS | OLS | OLS | OLS |
| N | 26,998 | 26,998 | 26,998 | 26,998 | 12,895 | 12,895 |
| adj. R-sq | 0.287 | 0.287 | 0.305 | 0.305 | 0.043 | 0.043 |

**Table IA5. Alternative Model Specifications**

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

**Panel A: Alternative Regression Models**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | *Dept Var =* *# of M&A Deals* | | *Dept Var =* *Acquirer Dummy* |
| *Pat Library* | 0.541*** | 0.541*** | 0.116*** | 0.741*** |
| | (2.976) | (3.199) | (3.148) | (3.093) |
| Acquirer Firm Control | Y | Y | Y | Y |
| Acquirer County Control | Y | Y | Y | Y |
| Model | Poisson | Negative Binomial | OLS | Logit |
| Fixed Effects | Firm + Year | Firm + Year | Firm + Year | Firm + Year |
| N | 7,969 | 7,969 | 15,262 | 7,830 |

**Panel B: Alternative Fixed Effects**

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

**Panel C: Alternative Clustering of Standard Errors**

| | (1) | (2) | (3) |
|---|---|---|---|
| | | *Dept Var = Ln(1+# of M&A Deals)* | |
| *Pat Library* | 0.062** | 0.062** | 0.062*** |
| | (2.445) | (2.184) | (4.757) |
| Acquirer Firm Control | Y | Y | Y |
| Acquirer County Control | Y | Y | Y |
| 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 IA6. Alternative Samples**

This table presents the results on the effect of patent library opening on local firms' M&A activities using alternative samples. In Panel A, we exclude firms located in the counties where university patent libraries reside. In Panel B, we exclude firms located in Washington, D.C. In Panel C, we exclude firms located in counties with patent libraries opened prior to 1985. The dependent variable, *Ln(1+# of M&A Deals)*, is the natural logarithm of one plus the number of innovative target acquisitions completed by a firm in a given year. Innovative targets are those from a three-digit SIC coded industry where at least one firm was awarded a patent during the past five years. The independent variable *Pat Library* takes the value of one if the firm is headquartered in a county where a patent library opens, and zero otherwise. We include the same set of control variables as those in Table 3, but do not report them for brevity. Definitions of other variables are in Appendix C. 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.

**Panel A: Exclude Firms Located in Counties with University Patent Libraries**

| | (1) | (2) |
|---|---|---|
| | *Dept Var = Ln(1+# of M&A Deals)* | |
| *Pat Library* | 0.066** | 0.070** |
| | (2.348) | (2.221) |
| Acquirer Firm Control | Y | Y |
| Acquirer County Control | N | Y |
| Model | OLS | OLS |
| Fixed Effects | Firm + Year | Firm + Year |
| N | 13,853 | 13,853 |
| adj. R-sq | 0.243 | 0.243 |

**Panel B: Exclude Firms Located in Washington, D.C.**

| | (1) | (2) |
|---|---|---|
| | *Dept Var = Ln(1+# of M&A Deals)* | |
| *Pat Library* | 0.062*** | 0.062*** |
| | (2.985) | (2.772) |
| Acquirer Firm Control | Y | Y |
| Acquirer County Control | N | Y |
| Model | OLS | OLS |
| Fixed Effects | Firm + Year | Firm + Year |
| N | 15,241 | 15,241 |
| adj. R-sq | 0.238 | 0.238 |

**Panel C: Exclude Firms Located in Counties with Patent Libraries Opened Prior to 1985**

| | (1) | (2) |
|---|---|---|
| | *Dept Var = Ln(1+# of M&A Deals)* | |
| *Pat Library* | 0.054*** | 0.058*** |
| | (2.677) | (2.817) |
| Acquirer Firm Control | Y | Y |
| Acquirer County Control | N | Y |
| Model | OLS | OLS |
| Fixed Effects | Firm + Year | Firm + Year |
| N | 9,076 | 9,076 |
| adj. R-sq | 0.226 | 0.227 |

**Table IA7. Alternative DiD Estimates**

This table presents the alternative DiD estimates results on the effect of patent library opening on local firms' M&A activities. The dependent variable is the natural logarithm of one plus the number of innovative target acquisitions completed by a firm in a given year. Innovative targets are those from a three-digit SIC coded industry where at least one firm was awarded a patent during the past five years. In column (1), we conduct a stacked regression. In particular, we first identify each library opening event (at t=0) and the treated counties as well as the firms located in those counties; next, we choose five years before to five years after the opening event as the event time window (-5, +5); we then select the control firms that exist at event year and were not located in the treated counties during the time window of (-5, +5). We further refine the control controls by requiring them to be in the neighboring states of the treated firms so that the treated and control firms will share similar economic conditions. *Treat* takes the value of one if the firm is headquartered in a treated county where a patent library opens, and zero otherwise; *Post* takes the value of one in years post the patent library opening, and zero otherwise. In column (2), we estimate the interaction weighted (IW) estimator proposed by Sun and Abraham [2021]. We include the same set of control variables as those in Table 3, but do not report them for brevity. Definitions of other variables are in Appendix C. We include firm and year fixed effects in all regressions. The unit of analysis is at firm-year level. T-statistics based on robust standard errors clustered at county-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

**Table IA8. Geographical Distance to the Nearest Patent Library**

This table presents the results on the effect of firms' geographical distance to their nearest patent library on firms' M&A activities. The dependent variable is the natural logarithm of one plus the number of innovative target acquisitions completed by a firm in a given year. Innovative targets are those from a three-digit SIC coded industry where at least one firm was awarded a patent during the past five years. *Ln(1+Distance to Treated County)* is the natural logarithm of one plus the distance in miles between a firm' headquartered county and the closest treated county where a library is opened. We include the same set of control variables as those in Table 3, but do not report them for brevity. Definitions of the variables are in Appendix C. T-statistics based on robust standard errors clustered at county-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) |
|---|---|---|
| | *Dept Var = Ln(1+# of M&A Deals)* | |
| *Ln(1+ Distance to Treated County)* | -0.013** | -0.012** |
| | (-2.444) | (-2.222) |
| Acquirer Firm Controls | Y | Y |
| Acquirer County Controls | N | Y |
| Fixed Effects | Firm + Year | Firm + Year |
| Model | OLS | OLS |
| N | 15,262 | 15,262 |
| adj. R-sq | 0.238 | 0.238 |

**Table IA9. Patent Library and Local Firms' Takeover Exposure**

This table presents the results on the effect of patent library opening on the extent of local firms being acquired as targets. The sample consists of county-year observations. Since many U.S. counties are in rural areas with few business activities, we limit our sample to the county-year observations where at least one public firm is headquartered. Since patent information is relevant only to technological innovation, we focus on innovative acquirers. In column (1), for every county-year, we count the total number of target firms from innovative industries that are acquired by innovative public firms. An innovative industry is defined as a three-digit SIC coded industry where at least one firm was awarded a patent during the past five years. In column (2), for every county-year, we count the total number of target firms from innovative industries that are acquired by public firms. In column (3), for every county-year, we count the total number of local target firms that are acquired by publicly traded innovative public firms. In columns (4), for every county-year, we count the total number of local target firms that are acquired by publicly traded public firms. 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 control for every county-year's total population, income per capita, unemployment rate, total number of establishments, and the total number of patents. T-statistics based on robust standard errors clustered at county-level are reported in parentheses under the corresponding estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Ln(1+# Innovative Tgt Acquired by Innovative Acquirer)* | *Ln(1+# Innovative Tgt)* | *Ln(1+# Tgt Acquired by Innovative Acquirer)* | *Ln(1+# Tgt)* |
| *Pat Library* | -0.038 | 0.067 | -0.020 | 0.080 |
| | (-1.070) | (0.981) | (-0.591) | (1.183) |
| *Ln(Population)* | -0.292*** | -0.616*** | -0.294*** | -0.626*** |
| | (-6.494) | (-9.125) | (-6.512) | (-9.056) |
| *Income Per Capita* | 0.011*** | 0.022*** | 0.011*** | 0.023*** |
| | (3.083) | (4.270) | (2.996) | (4.104) |
| *Unemployment Rate (%)* | 0.006*** | 0.016*** | 0.006*** | 0.017*** |
| | (3.427) | (5.779) | (3.344) | (6.012) |
| *# of Establishments* | 0.080*** | 0.157*** | 0.081*** | 0.164*** |
| | (8.628) | (13.401) | (8.681) | (13.607) |
| *# of Patents* | 0.003*** | 0.003*** | 0.003*** | 0.003*** |
| | (6.950) | (5.523) | (6.897) | (5.703) |
| Constant | 2.784*** | 5.954*** | 2.812*** | 6.039*** |
| | (5.767) | (8.091) | (5.803) | (8.035) |
| Fixed Effects | County + Year | County + Year | County + Year | County + Year |
| Model | OLS | OLS | OLS | OLS |
| N | 11,877 | 11,877 | 11,877 | 11,877 |
| adj. R-sq | 0.550 | 0.643 | 0.557 | 0.654 |

**Table IA10. Summary Statistics of the Public Acquirers and Public Targets**
This table presents the summary statistics of the public innovative acquirers (Panel A) and public innovative targets (Panel B). Definitions of the variables are in Appendix C.

Panel A: Summary statistics of public innovative acquirers

| | N | Mean | Median | Std. Dev. |
|---|---|---|---|---|
| *CAR (Acquirer)* | 2,798 | 2.1% | 0.8% | 11.6% |
| *MVE (Acquirer, Million)* | 2,798 | 6,721 | 617 | 23,691 |
| *Deal Size (Million)* | 2,798 | 416 | 38 | 2,981 |
| *Relative Size* | 2,798 | 0.248 | 0.081 | 0.566 |
| *All Cash Dummy* | 2,798 | 0.264 | 0.000 | 0.441 |
| *High Tech Dummy* | 2,798 | 0.390 | 0.000 | 0.488 |
| *Diversify Dummy* | 2,798 | 0.490 | 0.000 | 0.500 |
| *Hostile Dummy* | 2,798 | 0.011 | 0.000 | 0.103 |
| *Challenge Dummy* | 2,798 | 0.020 | 0.000 | 0.140 |

Panel B: Summary statistics of public innovative targets

| | N | Mean | Median | Std. Dev. |
|---|---|---|---|---|
| *CAR (Target)* | 745 | 19.8% | 14.6% | 25.5% |
| *MVE (Target, Million)* | 745 | 4,467 | 222 | 17,509 |
| *Deal Size (Million)* | 745 | 1,285 | 150 | 5,693 |
| *Relative Size* | 745 | 0.352 | 0.117 | 0.697 |
| *All Cash Dummy* | 745 | 0.384 | 0.000 | 0.487 |
| *High Tech Dummy* | 745 | 0.362 | 0.000 | 0.481 |
| *Diversify Dummy* | 745 | 0.472 | 0.000 | 0.500 |
| *Hostile Dummy* | 745 | 0.035 | 0.000 | 0.184 |
| *Challenge Dummy* | 745 | 0.067 | 0.000 | 0.250 |

## Reference


ACHARYA, V., R. BAGHAI, and K. SUBRAMANIAN. 'Wrongful Discharge Laws and Innovation.' *The Review of Financial Studies*. 27 (2014): 301-346.

BAKER, A., D. LARCKER, and C. WANG. 'How Much Should We Trust Staggered Difference-in-differences Estimates?.' *Journal of Financial Economics*. 144 (2022): 370-395.

CHEN, J., and J. ROTH. 'Logs with Zeros? Some Problems and Solutions.' *The Quarterly Journal of Economics*. 139 (2024): 891-936.

COHN, J., Z. LIU, and M. WARDLAW. 'Count (and Count-like) Data in Finance.' *Journal of Financial Economics*. 146 (2022): 529-551.

GREENE, D., and J. SHENOY. 'How Do Anti-discrimination Laws Affect Firm Performance and Financial Policies? Evidence from the Post-World War II Period.' *Management Science.* 68 (2022): 3813-3833.

GUERNSEY, S., K. JOHN, and L. LITOV. 'Actively Keeping Secrets from Creditors: Evidence from the Uniform Trade Secrets Act.' *Journal of Financial and Quantitative Analysis.* 57 (2022): 2516-2558.

HARFORD, J. 'What Drives Merger Waves?' *Journal of Financial Economics.* 77 (2005): 529-560.

IMBENS, G. W., and D. B. RUBIN. *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction*: Cambridge University Press, 2006.

RUBIN, D.B. 'Randomization Analysis of Experimental Data: The Fisher Randomization Test Comment.' *Journal of the American Statistical Association.* 75 (1980): 591-593.

SUN, L., and S. ABRAHAM. 'Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects.' *Journal of Econometrics.* 225 (2021): 175-199.