Innovation and Acquisition:

Can M&A improve innovation capacity for the Chinese Companies?

By

Xinyue Chen

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Professor Marti G. Subrahmanyam	Professor Yiqing Lv
Professor Yiqing Lv	
Faculty Advisor	Thesis Advisor

Abstract:

Innovation capacity is one of the core assets that a company preserves. As one of the indicators of innovation capacity, the number of patent applications in China has increased dramatically last year. Another notable trend observed in China is the rapid growth in Merger and Acquisition (M&A) transactions. Some researchers claim that innovation capacity can be improved by M&A transactions, because such activity generates synergies between target firm and acquiring firm by sharing resources from both sides. However, such studies only covered companies in the United States, where regulations for M&A transactions and patent system are comparatively mature. Therefore, I want to understand whether M&A transaction affects the innovation capacity of Chinese companies. Based on the empirical research on a series of datasets of Chinese companies, I find that M&A activities in China have little influence on the innovation capacity of the Acquiring side. Instead, some company characteristics such as research & development expenditure and EBIT showcased strong significance in the relevant regressions. Moreover, different behaviors among industries are observed in the regressions. Several industries were influenced by M&A activities more than other industries, especially in terms of patent quality. To a certain degree, my study indicates that for Chinese companies nowadays, taking M&A deals to improve innovation capacity is not so efficient as investing in their R&D department.

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1. Introduction:

Innovation capacity is one of the core assets that a company preserves. As one of the indicators of innovation capacity, the number of patent applications in China has increased dramatically last year. In 2016, China's State Intellectual property Office (SIPO) stated that it received 1.3 million patent applications in total, as opposed to the patent application number of the United States (605,571), Japan (318.381) and Korea (208,830)[1].

Another notable trend observed in China is the rapid growth in Merger and Acquisition (M&A) transactions. According to a relevant report,[2] 2016 witnessed record levels of M&A transactions in China, both in terms of the number of deals and the volume of transactions.

Some researchers claim that innovation capacity can be improved by M&A transactions, because such activity generates synergies between target firm and acquiring firm by sharing resources from both sides. Other researchers claim that M&A transactions decrease the innovation capacity because the consolidated resource will generate extra internal competition, discouraging the innovative development. However, such studies only covered companies in the United States, where M&A transactions and Patent system are comparatively mature. Therefore, I want to study how M&A transaction affects the innovation capacity of Chinese companies.

According to my regression result, it seems that the frequency and amount of M&A transactions have little to do with the innovation capacity of acquiring firms. On the contrary, other variables such as R&D expenditure and EBIT show the high possibility to influence the innovation capacity of the acquiring firm. Moreover, I observed different behaviors among different industries

1 See "China leads in patent, trademark and design filings in 2016: WIPO", Xinhua Net, December 2017
2 See "M&A 2016 review and 2017 outlook", PwC China, January 2017

in the regressions. Several industries were influenced by M&A activities more than other industries in terms of post-M&A innovation quality.

In section 2, I will analyze three major theories about the influence of M&A on innovation capacity and how these three theories differ from my study. In section 3, I will introduce the dataset I use for this study, the methodology regarding data processing, the regression model, relevant variable sets, and a preview of the result. In section 4, I will talk about the regression results. Finally, in section 5, I will conclude my study and end the paper with some reflections.

2. Literature Review:

One school of studies concluded that M&A may have a negative effect on the innovation capacity of acquiring firm. M&A activity may trigger agency problems such as resource allocation dispute and greater competition for corporate resources, thus discouraging the employee to generate ideas of economic value. Therefore, M&A activity may prevent the acquirer from improving its innovation capacity.[3] (Rotemberg and Saloner, 1994; Rajan, Servaes and Zingales, 2000; Scharfstein and Stein,2000)

Another study claimed that M&A activity may have a positive effect on the acquirer's innovation capacity. Aghion and Tirole (1994) stated their rationale as "Established firms with a low ability to innovate organically may undertake acquisitions with the objective of acquiring firms with significant technological know-how or firms with already existing patents." [4] They also

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3 See Rotemberg, J., and Saloner G, 1994, "Benefits of Narrow Business Strategies", American Economic Review, Vol. 84, 1330-1349
Rajan, R., Servaes, H., and Zingales, L, 2000, "The Cost of Diversity: The Diversification Discount and Inefficient Investment," Journal of Finance, Vol. 55, 35-80.
Scharfstein, D., and Stein, J, 2000, "The Dark Side of Internal Capital Markets: Divisional Rent-Seeking and Inefficient Investment," Journal of Finance, Vol. 55, 2537-2564.
4 Aghion, P., and Tirolem J., 1994, "On the Management of Innovation," Quarterly Journal of Economics, Vol. 109, 1185-1209.

found, after a theoretical analysis of their idea, that it may be more efficient if the acquiring firm sources innovation from the target firms. In other words, the acquirer can improve their innovation capacity better by using the external innovation resource of the target firm than investing R&D internally in the firm. This theory indicates that in M&A deals, target firm has better innovation capacity and that acquiring innovation is one of the incentives of the acquirer. Sevilir and Tian (2012) pointed out that this theory implies that "M&A enhances innovation output through a selection mechanism where the acquirer buys an innovative target firm— a firm which has already obtained an innovation before the acquisition." [5]

However, according to my regression result, the theory mentioned in the last paragraph does not work for Chinese companies. Neither the number of deals nor the M&A volume has any positively significant effect on innovation capacity in terms of growth of patent number and growth of patent grant ratio. If M&A can generate synergy, and if the acquiring firms conduct M&A to improve the innovation capacity, then it is highly likely that the frequency and volume of M&A deals will positively and greatly influence the innovation capacity of the acquiring firms. I do not observe a strong negative effect of M&A on the firm's innovation performance. It seems that the theory that "M&A has a negative effect on innovation capacity" does not apply to Chinese companies either.

The positive effect of M&A on innovation is explained in another study. Rhodes-Kropf and Robinson (2008) concluded from their research that M&A improve innovation by generating synergy. [6] To be more specific, if acquiring company merge with a target company with complementary knowledge and technologies, then such M&A may enable the two companies to

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5 Sevilir, M, and Tian, X, Acquiring Innovation (May 24, 2012). AFA 2012 Chicago Meetings Paper.
6 Rhodes-Kropf, M. and Robinson, D., 2008, "The Market for Mergers and the Boundaries of the Firm," Journal of Finance, Vol. 63, 1169-1211.

combine their innovation capacity and new ideas that will not exist should M&A did not take place. However, such argument is hard to prove theoretically. First, it is hard to conclude that two companies merge because they have complementary resources. A case study may provide the ideal answer, but such approach is not reachable for a long list of companies. Moreover, it is hard to evaluate synergy objectively and estimate what is the consequence of not conducting M&A. One may argue that we can study the innovation performance of the companies with similar financial indicators while have not conducted M&A. This approach is not feasible for my study because it is over-idealistic, and the data source is limited.

One of my concerns during this literature review is that all the theory is developed based on the U.S database, where both M&A activity and patent documentation system are relatively mature. Therefore, no matter how M&A influences the innovation capacity, the theories mentioned previously serve only as a reference in the study of the influence M&A activities have on innovation output for the Chinese companies.

Innovation ownership is another concern. This topic is studied by few people. During an M&A Intellectual Property due diligence[7], one must check the ownership of the patents of the target firm. If the patent is owned not only by the target firm (such as jointly owned by a third party), or the patent is owned by an individual instead of by the target firm, then it is highly likely that the acquiring firm will encounter legal issue over the patent acquisition. If an acquirer buys a target firm that does not own part of its patent and innovation capacity, then M&A activity may have little to do with innovation output and capacity. Such problems can be solved by the selection

7 See “The importance of IP due diligence”, Taylor Wessing, https://united-kingdom.taylorwessing.com/synapse/ip_duediligence.html

mechanism mentioned previously. However, no current study can prove that all the acquirers conduct M&A activity rationally according to the selection mechanism.

3. Data, Methodology and Preliminary results:

3.1 Data

3.1.1 A general introduction to my dataset

I collected the M&A related variables from Bloomberg terminal. The criteria I used to filter the candidates are:

1) The acquiring side is a Chinese firm;
2) The acquiring firm is publicly traded;
3) Deal status is "successful" and,
4) The transaction took place between 2013/11/1 and 2017/11/1 (five years).

I counted the number of M&A transaction every acquiring firm conducted and calculated the weighted average transaction volumes for each acquiring firm. Apart from these two M&A related variables, I also collected many extra variables including Payment method (Cash or Stock), EBIT, Industry Sector, R&D Expenditure, ROA (based on the bottom EPS) and Financial Leverage. These variables are mainly control variables for my regression model.

I collected the patent related variables from Google Patent. Data collection for a patent in China is hard because of the unfriendly Chinese databases, making data collection extremely hard without a subscription. Luckily, Google Patent records the patent information for most of the firms listed in my dataset. In the end, 1377 companies are listed in my database. Please refer to table 1 for detailed data description.

3.1.2 The literature that contributes to my final dataset:

To find the proper indicators of innovation capacity is not an easy work since innovation capacity is vague in definition. Patent statistics are frequently used to indicate the innovation capacity of a company. Whether patent statistics can accurately reflect the innovation capacity of a company is thoroughly studied.

According to one study, patent statistics are not perfect indicators of innovation capacity because not all innovation can be recorded as patents; whether an invention is patentable or patented partly depend on the industry the patent issuer is in. For example, patents from industries such as pharmaceutical, chemical, and electronics technology are more effective in terms of patent protection, making patents from such industries have a higher economic value than those from other industries. (Dang and Motohashi 2015)[8] Moreover, among the innovative ideas that were patented, the quality of such patent varies because of different factors. (Griliches et al 1998)[9]

As Griliches and his co-editors stated, the first problem is solved by controlling for industry differences; it can be solved by introducing industry dummy variables as control variables, or by conducting analysis only within a specific industry. The concern over patent quality is much trickier to tackle. “Patent quality is generally assessed using detailed patent information, including citation, renewal information, and patent claims.” (Dang and Motohashi 2015) However, these indicators all have their respective disadvantages that prevent me from quantifying the quality of patent filed by Chinese companies:

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8 Dang, J., and Motohashi, K, Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. China Economic Review 35 (2015) 137-155

9 Griliches, Z., Pakes, A., and Hall, B. 1988, “The Value of Patents as Indicators of Inventive Activity,” Working Paper, University of California at Berkeley.

1) Citation: Citation shows how popular and valuable a certain patent is since patent of high quality tends to be cited by others more frequently. The number of forwarding citations is widely used to value patent quality and has been theoretically and empirically proved to have a strong correlation with patent value. (Trajtenberg, 1990) [10] One drawback of using citation to value patent quality is that citation is limited by timeliness. In other words, the citation numbers would keep increasing as time goes by. Moreover, the citation data for Chinese patent is not accessible since SIPO does not disclose such information. Though Google Patent documents citation numbers for each patent, the source of such data is questionable and is hard to collect in large quantity.

2) Renewal information: Renewal information stands for the number of years a patent is renewed since a patent stay valid for only several years. (Lanjouw, Pakes and Putnam 1998)[11] If a patent has high quality, it is highly likely to be renewed so that the intellectual property stays protected for a longer period of time. Many papers (Thoma, 2013[12] and Zhang & Chen 2012[13]) claimed that patent value can be quantified using renewal information. However, renewal information is restricted by timeliness as well, making it hard to reflect recent changes in the value of a patent. Moreover, such information is not disclosed in SIPO database.

3) Patent Claims: A patent claim defines what is protected by the patent. It functions as a warning to the patent reader to avoid patent infringement. Since a patent with a good quality tends to be protected more thoroughly with a longer claim section, a patent claim can be quantified by

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10 Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. The Rand Journal of Economics, 21(1), 172–187.

11 Lanjouw, J.O., Pakes, A, and Putnam, J (1998). How to Count Patents and Value Intellectual Property: The Uses of Patent Renewal and Application Data. The Journal of Industrial Economics Volume XLVI, 1998(12).

12 Thoma, G. (2013). Quality and value of Chinese patenting: An international perspective. Seoul Journal of Economics, 26(1).

13 Zhang, G., & Chen, X. (2012). The value of invention patents in China: Country origin and technology field differences. China Economic Review, 23(2), 357–370

counting the number of claims a patent has to measure how good the quality is. (Lanjouw & Schankerman, 2004)[14] Measuring the length of the claim by recording word counts is another way to only roughly measure the patent quality. (Malackowski and Barney 2008)[15] However, neither of these two measures is feasible for a large dataset. Moreover, the logic of such methods remains to be questioned.

4) Grant Ratio: If a patent is of high value, it will be granted by local patent authorities. Therefore, grant ratio (patent granted over patent applied) can be an ideal indicator for the patent quality indicator. Based on the studies mentioned previously and taking into consideration the limited database, I chose the patent grant ratio as an indicator of patent quality. On average, it takes 3.87 years to grant a patent after filling in China with SIPO. (Dang and Motohashi 2015)[16] However, such statistical results can hardly apply to a small subset of the Chinese firms that conducted M&A deals. Another study claims that SIPO does not have any regulation as to when a patent should be granted. (Yang, 2008)[17] Moreover, patent grant ratio is limited by timeliness and a filing-grant time gap. Considering grant ratio is the only indicator available for me to serve as a patent quality indicator, I decided to use this indicator for my study. Since grant ratio is closely related to the number of patents granted as well as the numbers of patents applied, I collected both variables for pre-M&A and post-M&A scenarios.

14 Lanjouw, J.O., & Schankerman, M. (2004). Patent quality and research productivity: Measuring innovation with multiple indicators. The Economic Journal, 114(495), 441–465.
15 Malackowski, J.E., & Barney, J.A. (2008). What is patent quality? A merchant banc's perspective. Les Nouvelles, 2008(6), 123–134.
16 Dang, J., and Motohashi, K, Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. China Economic Review 35 (2015) 137-155
17 Yang, D. (2008). Pendency and grant ratios of invention patents: A comparative study of the US and China. Research Policy, 37(6-7), 1035–1046.

3.2 Methodology:

To explore whether M&A transaction influences the innovation capacity of the acquiring firm, I developed the following regression model. The model and the data processing approach are based on my literature review and other relevant studies. I estimated the following empirical model in my regression:

$$Innovation_{i,t+5} = \alpha_i + \beta_i \times (M\&A\ Activity)_{i,t} + Industry_i + Firms_i + Year_t + \varepsilon_{i,t}$$

3.2.1 Dependent Variables:

One dependent variable in terms of innovation capacity is the number of patent applications. I collected the numbers of the patent applications within the same time length before and after the acquiring companies finished their first M&A deals. For example, if Company (A) acquired a company on 2016/1/1, then I will count the numbers of patent applications company (A) has filed from 2015/1/1 to 2016/1/1 (f-pre) and from 2016/1/1 to 2017/1/1 (f-post). I calculated the growth rate as:

$$\frac{(f-post)-(f-pre)}{(f-pre)}.$$

If the acquiring firm does not file any patent application during the pre-M&A time interval, then (f-pre) would be 0, resulting in an invalid number for patent growth. Therefore, I set such (f-pre) as $\frac{1}{3}$ based on the theory of (Sevilir and Tian (2012))[18].

According to my data description, the 25th percentile growth rate is -0.5882, and median of growth rate is 0 and the 75th percentile growth rate is 0.4671. Therefore, among 1377 Chinese companies that conducted M&A in the past fo years, half of the companies suffered a decrease in patent application filing and half of the companies had an increase in the numbers of patent

18 Sevilir, M, and Tian, X, Acquiring Innovation (May 24, 2012). AFA 2012 Chicago Meetings Paper.

application filing. On average, the growth rate for the acquiring firms is 2.2293. This digit indicates that for the companies that had increased patent applications, the rate of increase is very high.

Another dependent variable is the grant ratio before and after M&A and the growth of such ratio. Even though the number of patent application increases dramatically, the quality of the patents is worth questioning because patent applications are largely supported by Chinese local government's patent subsidy programs. (Dang and Motohashi 2015)[19] I collected the numbers of the patent applications filed and granted within the same time intervals before and after an M&A deal took place. For example, if Company (A) acquired a company on 2016/1/1, in addition to the dataset I have collected for the number of patent applications, I also checked how many patent applications filed respectively in the pre and post-M&A time interval was granted. Assume that the patent granted in the pre-M&A time interval is g-pre and that in the post-M&A time interval is g-post. I calculated the grant ratio as $\frac{(g)}{(f)}$. Since the number of the granted patents will not be greater than the patent application filed, the grant ratio is no greater than 1. If the company did not file anything in pre-M&A or post-M&A time interval, then the grant ratio would be 0, resulting in an invalid grant ratio. Therefore, I set such grant ratio as $\frac{1}{6}$ based on the theory of Sevilir and Tian (2012)[20].

The 25th percentile post-M&A grant ratio is 0.4000, the median of this ratio is 0.5000 and the 75th percentile ratio is 0.6667. The 25th percentile pre-M&A grant ratio is 0.4286, the median of this ratio is 0.5189 and the 75th percentile ratio is 0.8620. The average for post-M&A grant ratio is 0.5187 and that for pre-M&A grant ratio is 0.5886. These statistics all indicate that the

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19 Dang, J., and Motohashi, K, Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. China Economic Review 35 (2015) 137-155
20 Sevilir, M, and Tian, X, Acquiring Innovation (May 24, 2012). AFA 2012 Chicago Meetings Paper.

number of patent application that was granted decreases after M&A activity. However, this decrease cannot say that the quality of patent application decreases after M&A activity, because I do not measure the time lag between filing and granting an application. Moreover, the average of the Grant Ratio Growth Rate is 0.5750, with the 25th percentile growth rate being -0.4090, the median growth rate being 0, and the 75th percentile growth rate being 0.0459. Even though I did not take into consideration the timeliness problem, the growth rate of patent grant ratio still indicated that half of the acquiring firms had increased in their patent grant ratio. Since the average growth rate is much higher than the 75th percentile growth rate, it seems that some acquiring firms had a dramatic increase in patent growth.

3.2.2 Independent Variables and Control Variables:

I collected the number of M&A deals a company has conducted from 2013/11/1 to 2017/11/1 and the respective transaction volumes. The 25th percentile number of deals conducted by these companies is 1, the median number of deals conducted is 1 and 75th percentile of this variable is 2. On average, a company conducted 1.89 M&A deals in the past 5 years. The transaction volumes were a weighted average variable. The 25th percentile weighted average transaction volume is \$16.14 million, the median volume is \$50.44 million and 75th percentile of this variable is \$136.99 million. On average, a company has an average of \$712.73 million weighted average transaction volume.

3.2.3 Regression models:

Based on the dataset I collected, I ran four regressions using same independent and control variables and different dependent variables:

Regression 1): $Post\ M\&A\ Patent\ Application\ Number_{i,t+5} = \alpha_i + \beta_i \times (M\&A\ Activity)_{i,t} + Industry_i + Firms_i + Year_t + \varepsilon_{i,t}$

Regression 2): $Growth\ of\ Patent\ Numbers_{i,t+5} = \alpha_i + \beta_i \times (M\&A\ Activity)_{i,t} + Industry_i + Firms_i + Year_t + \varepsilon_{i,t}$

Regression 3): $Post\ M\&A\ Grant\ Ratio_{i,t+5} = \alpha_i + \beta_i \times (M\&A\ Activity)_{i,t} + Industry_i + Firms_i + Year_t + \varepsilon_{i,t}$

Regression 4): $Growth\ of\ Patent\ Grant\ Ratio_{i,t+5} = \alpha_i + \beta_i \times (M\&A\ Activity)_{i,t} + Industry_i + Firms_i + Year_t + \varepsilon_{i,t}$

The M&A activity variables include Number of Deals and M&A Transaction Volumes and the payment type (if buying a company by stock or cash would influence the innovation output of the acquiring company). The Industry Variables include Acquirer Industries Fixed, Target-Acquirer Industry difference (to test if cross-industry M&A would influence the innovation of acquirer company). Lastly, the Firm variables include Acquirer EBIT, Acquirer R&D Expenditures, Acquirer ROA, Acquirer Financial Leverage. I also add the year-fixed control to control the time series influence.

In Regression 1) and 2), I tested the innovation performance in terms of patent application numbers. In Regression 3) and 4), I testified the quality of innovation of the acquiring firms.

Table 2 is a correlation table between variables used in the regression. I found that the M&A Volume (Weighted Average) is highly correlated with Acquirer's EBIT and R&D Expenditures (0.31 and 0.36). These correlations indicate that M&A transaction volume may slightly increase the profitability of a company and the R&D investment. Conversely, a more profitable company may tend to conduct M&A with large transaction volumes. Moreover, the EBIT and R&D Expenditures are highly correlated (0.73). This indicates that Acquirer EBIT tends to increase if the company spends more on research and development. However, according to the firm level regression in Table 3, EBIT and R&D Expenditures show opposite influence on acquiring firm's post-M&A innovation performance. This is rather confusing since how these two variables behave somehow generates a paradox that needs further study.

3.3 Preliminary results:

Generally, M&A activities have little influence on the innovation capacity of Chinese companies, if only measured by the frequency and volumes of the deals. After a preliminary study of my dataset, I found little correlation between a company's M&A activities and its innovation capacity. Considering the immature players and the chaos in the Chinese markets of both M&A and intellectual properties, I wanted to challenge the theories mentioned in my literature reviews.

Rather than being influenced by M&A activity, the innovation capacity of the acquiring firm is determined mainly by the amount of R&D investment and the industry sector it belongs. Even though there are many differences between companies from China and United States, innovation capacity in terms of intellectual patent plays an important role no matter what. Moreover, since many Chinese regional governments have set aside a huge amount of incentives for the patent with better quality. The importance of investment in the research and development department has therefore been gradually emphasized. Since patent quality differs because of the special industry characteristics, innovation capacity of a company is partly determined by the industry sector that it belongs.

4. Result

Please refer to table 3 for the result of the overall regression. The overall regression result does not fit my expectation; the R-squares are low for all four regressions and there are only a few variables that show strong significance. Moreover, according to the overall regression result, we can see that M&A activities do not have a strong influence on the innovation capacity of acquiring firm, unlike the result Sevilir and Tian (2012) [21] have from companies listed in the United States. However, there are several points that draw my interest.

In regression 1), there are four variables that show significance apart from the year-fixed variables. According to the regression result, Number of deals and the M&A volumes both have a slightly positive influence on the post-M&A patent application number, indicating that if a company conducts M&A more frequently and having larger transaction volumes, the acquiring firm will have a slight increase in the post-M&A patent application number.

The third variable is the EBIT of the acquirer companies. This variable negatively influences the number of patent applications. In other words, if the acquiring company has a higher profitability, then it is more likely for this company to apply for less patent after the M&A deals.

Another variable that shows strong significance is the R&D expenditure of the acquiring firm. The R&D Expenditure positively influences the number of patent applications. To be more specific, the increase in patent application numbers may result from the investment in R&D activities, not M&A activities. The positive correlation between R&D expense and post-M&A patent application number can also indicate that Merger and Acquisition do not contribute directly

21 Sevilir, M, and Tian, X, Acquiring Innovation (May 24, 2012). AFA 2012 Chicago Meetings Paper.

to acquiring companies' innovation capacity. On the other hand, these deals might not for innovation improvement purpose.

In regression 2), there are only three variables showing strong significance. The first variable is the payment type; it seems that deals paid by stock positively improve the patent growth of the acquiring firm. R&D expenditure is another variable --- increasing investments in Research and Development activities may result in an improvement in the growth of patent application number after M&A. The last variable that shows strong significance is the EBIT of the acquiring firm. The acquirer EBIT negatively influences the growth of the patent, which is unexpected.

One reason that may account for this result is that these three variables are intertwined with one another. First, the payment type may influence acquiring firm's R&D expenditure and EBIT. In a deal that is paid by stock, the acquiring firm usually pays less than the market capitalization of the target firm and the amount of market capitalization is usually what the acquiring firm should pay in cash. On one hand, such acquiring firm burdens less risk for potential M&A synergy[22]. On the other hand, such acquiring firm will have more funds for R&D investment, comparing to paying for M&A deals by cash.

Moreover, the increase in R&D expense may cause a decrease in EBIT. It is likely that Chinese companies improve their innovation capacities by increasing investment in R&D and somehow sacrificing part of their profit, as a side effect. While on the contrary, an increase in EBIT may indicate that the acquiring company does not invest enough in their R&D department and thus, resulting in fewer patent application numbers. Whatever the reasons might be behind the

22 See "Stock or Cash?: The Trade-Offs for Buyers and Sellers in Mergers and Acquisitions", Harvard Business Review, November 1999.

negative correlation between post-M&A patent performance, we can still conclude that M&A activity is not the key fact that influence the innovation capacities of the acquiring firms.

In regression 3), it seems that acquiring firm from some specific industries have a greater improvement when it comes to the post-M&A grant ratio: Consumer (Cyclical), Industrial and Utilities. However, when I ran the same regression for each industry respectively, I found that none of the variables accounts for their better improvement in patent quality. (Please see table 5 & 6 for the industry-specific regression results, I excluded the Utility industry because there are only 22 firms in this industry). After exploring the data for each industry, I found the following reason that may accounts for the industry specification: These three industries are among the top industries having good patent quality both before and after M&A. In other words, patents from Consumer (Cyclical), Industrial and Utilities are entitled to higher patent quality with or without any M&A deal. However, in table 4, I plotted the growth of patent grant ratio by industry. I found that even though Consumer (Cyclical), Utilities and Industrial have both high pre-M&A and post-M&A grant ratio comparing to other industries, the growth rates of grant ratio of these three industries do not stand out.

Surprisingly, the grant ratio growth rate of Technology industry ranks third among other industries (the Diversified industry has the highest patent grant ratio growth rate, but since this dataset is rather small and diversified in terms of product and service, I excluded this industry in this data analysis). I paid special attention to Technology industry because naturally, companies from Technology industry pay a rather high emphasis on patent innovation. In table 7, we can see that Technology companies on average have the highest patent growth rate. Therefore, combining table 4 and 7, Technology industry may have a good innovation capacity on average, considering its high growth rate on both patent application number and patent grant ratio. However, my regressions indicate that M&A has little influence on the innovation capacity of Technology firms.

The other two variables having strong significance are Acquirer ROA and Financial Leverage. According to the regression result, Acquirer ROA is negatively correlated with post-M&A grant ratio, while the Acquirer's Financial Leverage is positively correlated with the grant ratio. The reason for a negative correlated ROA can be similar to the one for EBIT, however, the positive correlation between acquirer's financial leverage and grant ratio is rather confusing. Ideally, a company with less potential for financial distress indicates a stronger cash flow for internal investment (the company does not have to allocate funds for interest payment). Therefore, how financial leverage influences the patent quality of the acquiring firm remains to be studied.

In regression 4), There are two variables that have moderate significance and one variable having a rather strong significance. Unlike the result of regression (2), payment type in regression (4) demonstrated a negative correlation. Even though paying in Stock increases the growth rate of patent application number, it decreases the growth rate of grant ratio on the contrary. In other words, paying in stock can encourage patent application, but the quality of such patent applied would be lowered. The other variable is the Number of Deals. Similar to payment type, this variable is negatively correlated with the growth of grant ratio. Comparing to the positive correlation between Number of Deals and Post M&A patent number in regression (1), conducting more M&A deals will lower the growth of grant ratio of the acquiring firm. Therefore, having more M&A activities can increase the patent application amount, but it would lower the quality improvement of patent applied. These two variables only have a moderate significance in regression (4), therefore, it is hard to claim that these two variables pose opposite influence on patent application number and patent quality improvement.

In table 3, I also added a year fixed control in all four regressions. I found that both the post-M&A patent application number and the post-M&A grant ratio are highly influenced by the year in which acquiring firm's first deal took place. According to the regression result, the more recent a deal is completed, less patent is applied and the lower the grant ratio is. This may be explained by the timeliness problem and the filing-granting gap because the patent indicators keep changing as time goes by. If a deal is completed recently, it is highly likely that the patent indicators would change dramatically in the future. However, time series control variable has no significance on either growth of the patent number, or the growth of the grant ratio.

5. Conclusion:

Based on my regression results, it seems that M&A activities with Chinese companies as buy-side generally have little influence on the innovation capacity of the acquiring firm. According to my study, the frequency a company initiates M&A transaction will slightly increase the patent application number after the deal completes but decrease the post-M&A grant ratio. Moreover, payment type of the deal also slightly determines the patent quantity and quality; the acquiring firms paying by stock are more likely to apply for more patent after M&A while suffer from a lower grant ratio.

More importantly, the empirical study indicates that R&D expenditure plays a vital role in acquiring firm's innovation capacity. This variable is positively related to both patent quantity and quality. Therefore, I want to assume that R&D investment is more important than initiating M&A transactions if a company wants to improve their innovation capacity.

There are also several variables with rather unexpected behavior: the two control variables as well as acquiring firm's profit indicators, EBIT and ROA, are both negatively correlated with patent quantity and quality. This negative influence may be explained by the expense spent on R&D and a higher financial leverage, but whether this proposed explanation is true needs further study.

According to the result, industry behaves differently in patent quality related regression. After a simple analysis of their respective datasets, I found that patents from these three industries have high quality both before and after M&A completes. The result from rerunning regression (3) for all these industries also indicates that the "high patent quality" characteristic does not result from M&A activity. Recalling my literature review, the specific industry characteristics might account for the quality difference, considering some industries being much more effective in terms of patent protection, making patents from such industries have a higher economic value than those from other industries.

It seems that the frequency and amount of M&A transactions have little to do with the innovation capacity of acquiring firms. On the contrary, other variables such as R&D expenditure and EBIT show the high possibility to influence the innovation capacity of the acquiring firm. Moreover, the innovation capacity of the acquiring firms from different industries differs according to their respective industry characteristics.

Finally, my thesis is incomplete since many new problems occurred in the process of my study. The first problem remains to be solved is how to improve the quality of my dataset. As mentioned in section 3.1, the patent data is collected from Google Patent and the data source of this database is questionable since it even has the data that SIPO does not disclose to the public. One great difficulty I encountered during my data collection is that Google Patent does not support API, making crawling data impossible. Thanks to this fact, I must collect data manually, which is time-consuming.

The second problem to solve is the independent variable choice. According to my literature review, many studies claim that citation stands for patent quality the best since such dataset is not available for me, I chose grant ratio instead. This variable has several disadvantages. Not only because it is limited by timeliness, but also, it is up to the relevant authority to decide whether to grant a patent or not. Therefore, grant ratio is not the best candidate for the patent indicator.

The third problem is how to design a more systematic dataset for data analysis and a more reasonable regression. Since I spent a lot of time collecting data manually, my dataset is small, covering only a short time period with only a few variables. (mostly consolidated or taken average based on deals and dates) However, even though my dataset does not cover a broad range of information, it still has a great potential for future study.

In conclusion, my thesis needs a lot of supporting studies, but it still shows that merger and acquisition activities have little to do with innovation capacity improvement. The reason might be that most of the companies do not conduct M&A with the purpose of improving innovation, or that Chinese buyers behave differently with their American counterparts. It is also possible that the patent market in China is newly constructed, making patent-related data chaotic. To a certain degree, my study indicates that for Chinese companies nowadays, taking M&A deals to improve innovation capacity is not so efficient as investing in their R&D department.

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Table 1 Data Description

	count	mean	std	min	25%	50%	75%	max
Number of Deals	1377	1.8954248	1.320385	1	1	1	2	11
M&A Volumes	1377	187.44652	712.73054	1	16.14	50.44	136.985	14289.02
Acquirer EBIT	1377	113.17302	614.39926	-2356.28	9.15706	25.3476	66.1801	11624.3
Acquirer R&D Expenditures	1377	38.769342	161.40093	0.0007064	4.02812	9.32938	21.8804	2536.4
Acquirer ROA based on bottom EPS	1377	4.3011085	6.5261399	-70.0576	1.64594	4.05517	6.99674	36.1436
Acquirer Financial Leverage	1377	2.2007886	1.9611747	1.02487	1.40546	1.73867	2.39111	53.1458
Post M&A Patent Number	1377	26.654805	55.423393	0.3333333	0.3333333	6	26	561
Pre M&A Patent Number	1377	25.903413	47.500185	0.3333333	1	7	26	342
Post M&A Grant Number	1377	16.71968	43.192908	0.1666667	0.1666667	1	12	561
Pre M&A Grant Number	1377	18.54793	38.075942	0.1666667	0.1666667	3	17	325
Patent Number Growth Rate	1377	2.2293375	21.87659	-0.996212	-0.588235	0	0.4671053	560
Post M&A Grant Ratio	1377	0.5186922	0.2830519	0.001292	0.4	0.5	0.6666667	3
Pre M&A Grant Ratio	1377	0.5886267	0.295858	0.004065	0.4285714	0.5188679	0.862069	1
Grant Ratio Growth Rate	1377	0.5750366	4.7750447	-0.998708	-0.409091	0	0.0458839	122

Table 2 Correlation Table

	Number of Deals	M&A Volumes	Post M&A Patent Number	Growth Rate	Post M&A Grant Ratio	Growth Rate of Grant Ratio	Acquirer EBIT	Acquirer R&D Expenditures	Acquirer ROA based on bottom EPS	Acquirer Financial Leverage
Number of Deals	1									
M&A Volumes	-0.05	1								
Post M&A Patent Number	0.05	0.07	1							
Growth Rate	0	0.06	0.46	1						
Post M&A Grant Ratio	-0.01	-0.02	0.18	0.04	1					
Growth Rate of Grant Ratio	-0.05	-0.02	-0.05	0.02	0.1	1				
Acquirer EBIT	0.04	0.31	-0.02	-0.05	-0.03	-0.01	1			
Acquirer R&D Expenditures	0.03	0.36	0.08	0.07	-0.01	-0.01	0.73	1		
Acquirer ROA based on bottom EPS	0.04	0.05	-0.02	-0.05	-0.1	0.03	0.06	0.01	1	
Acquirer Financial Leverage	0.04	0.08	0.05	0.05	0.1	0	0.08	0.13	-0.18	1

Table 3Firm Level Regression Result

	Dependent variable:			
	(1)	(2)	(3)	(4)
Number of Deals	2.20*	0.29	-0.001	-0.22**
	(1.13)	(0.45)	(0.01)	(0.10)
M&A Volumes (Weighted Average)	0.004*	0.001	-0.0000	-0.0001
	(0.002)	(0.001)	(0.0000)	(0.0002)
Payment Type - Stock	4.75	5.82***	-0.01	-0.72
	(5.54)	(2.21)	(0.03)	(0.48)
Communications	-8.12	-3.80	-0.01	0.32
	(7.50)	(3.00)	(0.04)	(0.65)
Consumer, Cyclical	-8.06	0.82	0.11***	-0.28
	(5.81)	(2.32)	(0.03)	(0.51)
Consumer, Non-cyclical	-8.29	-2.03	-0.04	0.23
	(5.51)	(2.20)	(0.03)	(0.48)
Diversified	-18.28	-4.46	-0.04	9.70***
	(16.13)	(6.45)	(0.08)	(1.41)
Energy	-5.66	-0.55	0.08	-0.11
	(9.87)	(3.94)	(0.05)	(0.86)
Industrial	2.66	-1.95	0.10***	0.03
	(4.86)	(1.94)	(0.02)	(0.42)
Technology	-3.44	0.60	-0.05	0.13
	(6.50)	(2.60)	(0.03)	(0.57)
Utilities	3.84	1.21	0.16**	0.08
	(12.34)	(4.93)	(0.06)	(1.08)
Acquirer EBIT	-0.02***	-0.01***	-0.0000	-0.0002
	(0.004)	(0.001)	(0.0000)	(0.0003)
Acquirer R&D Expenditures	0.06***	0.03***	0.0000	0.001
	(0.01)	(0.01)	(0.0001)	(0.001)
Acquirer ROA based on bottom EPS	0.13	-0.09	-0.003**	0.03
	(0.23)	(0.09)	(0.001)	(0.02)
Acquirer Financial Leverage	0.55	0.21	0.01**	0.002
	(0.77)	(0.31)	(0.004)	(0.07)

Year 2014	-8.86	1.05	-0.05	0.38
	(7.05)	(2.82)	(0.04)	(0.62)
Year 2015	-24.54***	-1.95	-0.11***	0.01
	(6.95)	(2.78)	(0.04)	(0.61)
Year 2016	-28.35***	-0.04	-0.10***	0.08
	(7.08)	(2.83)	(0.04)	(0.62)
Year 2017	-34.13***	-1.56	-0.15***	0.66
	(7.22)	(2.89)	(0.04)	(0.63)
Constant	43.81***	2.47	0.56***	0.58
	(8.22)	(3.29)	(0.04)	(0.72)
Observations	1,377	1,377	1,377	1,377
R2	0.07	0.05	0.09	0.04
Adjusted R2	0.06	0.03	0.08	0.03
Residual Std. Error (df = 1357)	53.83	21.52	0.27	4.70
F Statistic (df = 19; 1357)	5.34***	3.40***	7.13***	3.36***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4 Average Grant Ratio Growth Rate (by Industry)

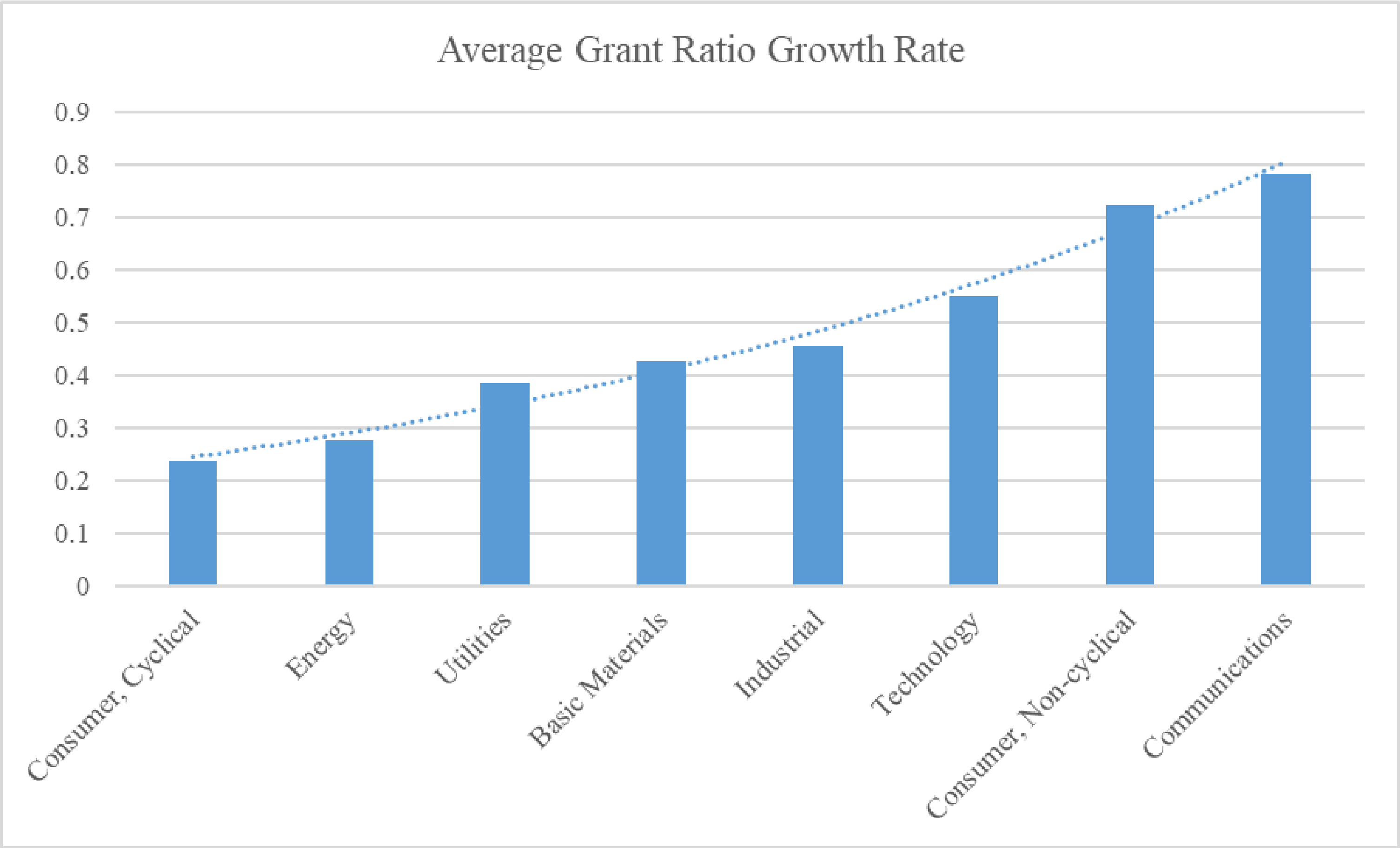

Table 5 Industry Level Regression Result-Industrial

	Dependent variable:			
	(1)	(2)	(3)	(4)
Number of Deals	5.775***	0.910***	0.0005	-0.218
	(1.707)	(0.310)	(0.009)	(0.146)
M&A Volumes	0.001	-0.001**	-0.00003*	-0.00001
	(0.004)	(0.001)	(0.00002)	(0.0003)
Payment Type - Stock	-3.848	2.720*	-0.037	-0.464
	(8.275)	(1.505)	(0.045)	(0.709)
Acquirer EBIT	-0.043***	-0.001	0.00002	-0.0005
	(0.011)	(0.002)	(0.0001)	(0.001)
Acquirer R&D Expenditures	0.166***	0.015***	0.00000	0.001
	(0.032)	(0.006)	(0.0002)	(0.003)
Acquirer ROA based on bottom EPS	0.913*	0.068	-0.007***	0.110***
	(0.476)	(0.087)	(0.003)	(0.041)
Acquirer Financial Leverage	-0.077	0.016	0.009**	0.020
	(0.872)	(0.159)	(0.005)	(0.075)
Year 2014	-32.874***	-3.440*	-0.041	0.162
	(11.135)	(2.025)	(0.060)	(0.954)
Year 2015	-35.970***	-3.426*	-0.122**	-0.534
	(10.846)	(1.973)	(0.059)	(0.929)
Year 2016	-40.438***	-3.296	-0.099*	-0.412
	(11.053)	(2.010)	(0.060)	(0.947)
Year 2017	-53.817***	-3.951*	-0.184***	0.749
	(11.253)	(2.047)	(0.061)	(0.964)
Constant	53.271***	2.454	0.692***	0.519
	(11.062)	(2.012)	(0.060)	(0.947)
Observations	511	511	511	511
R2	0.128	0.057	0.069	0.030
Adjusted R2	0.108	0.036	0.049	0.008
Residual Std. Error (df = 499)	50.617	9.206	0.273	4.335
F Statistic (df = 11; 499)	6.631***	2.720***	3.365***	1.384

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6 Industry Level Regression Result-Consumer, Cyclical

	Dependent variable:			
	(1)	(2)	(3)	(4)
Number of Deals	-2.145	0.603	0.006	0.047
	(3.425)	(2.579)	(0.015)	(0.086)
M&A Volumes	0.003	0.009	0.00004	0.0001
	(0.008)	(0.006)	(0.00003)	(0.0002)
Payment Type - Stock	27.602*	27.309**	0.046	0.148
	(14.015)	(10.554)	(0.061)	(0.352)
Acquirer EBIT	-0.076***	-0.091***	0.0001	-0.0005
	(0.022)	(0.016)	(0.0001)	(0.001)
Acquirer R&D Expenditures	0.169***	0.173***	-0.00004	0.001
	(0.043)	(0.032)	(0.0002)	(0.001)
Acquirer ROA based on bottom EPS	0.535	0.380	-0.0002	0.004
	(0.675)	(0.508)	(0.003)	(0.017)
Acquirer Financial Leverage	-0.797	0.444	0.001	-0.063
	(3.825)	(2.880)	(0.017)	(0.096)
Year 2014	17.674	3.862	-0.061	-0.297
	(20.581)	(15.498)	(0.089)	(0.517)
Year 2015	-18.003	-10.501	-0.141	-0.239
	(20.611)	(15.521)	(0.089)	(0.518)
Year 2016	-6.439	-2.007	-0.115	-0.785
	(20.880)	(15.724)	(0.090)	(0.525)
Year 2017	-22.346	-5.527	-0.167*	-0.732
	(21.503)	(16.192)	(0.093)	(0.540)
Constant	26.370	-0.245	0.668***	0.698
	(22.831)	(17.192)	(0.099)	(0.574)
Observations	185	185	185	185
R2	0.196	0.238	0.060	0.052
Adjusted R2	0.145	0.190	0.0004	-0.008
Residual Std. Error (df = 173)	50.076	37.709	0.217	1.258
F Statistic (df = 11; 173)	3.839***	4.916***	1.007	0.863
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 7 Patent Application Number Growth Rate

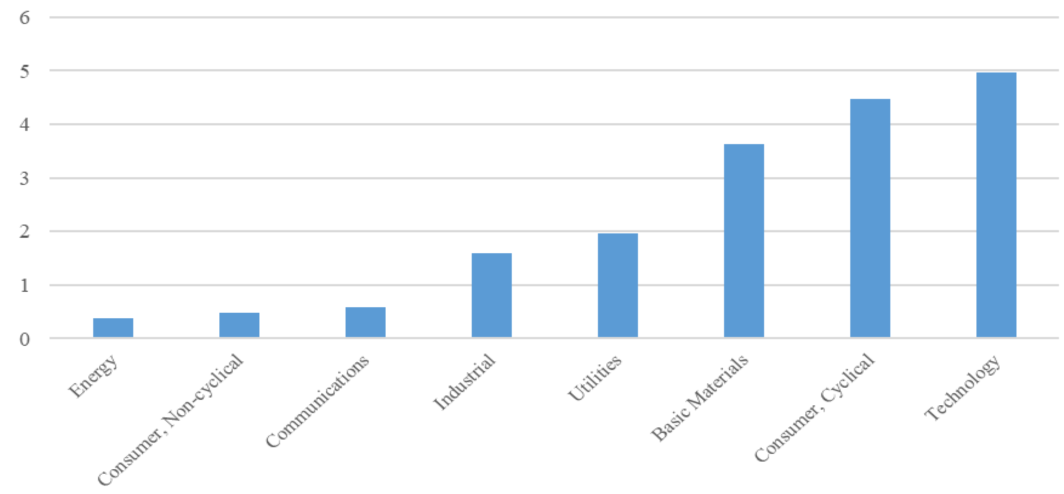

Table 8 Rate of Cross Industry M&A

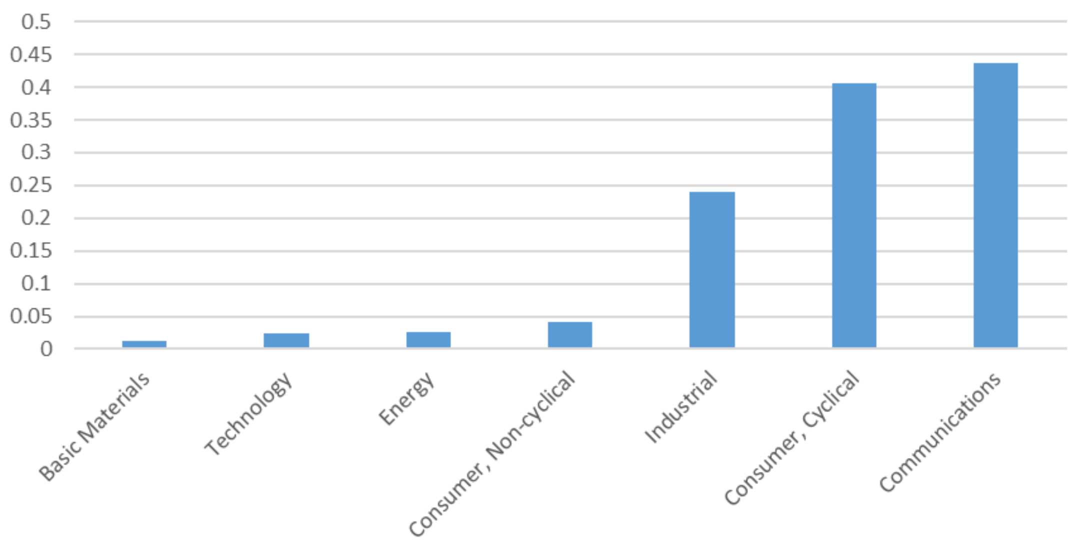

Table 9 Industry Level Regression Result-Technology

	Dependent variable:			
	(1)	(2)	(3)	(4)
Number of Deals	-3.131	-2.092	-0.028	-0.342*
	(3.822)	(2.870)	(0.021)	(0.201)
M&A Volumes	-0.002	0.004	-0.0001**	-0.0001
	(0.008)	(0.006)	(0.00004)	(0.0004)
Payment Type - Stock	-15.009	-6.087	0.006	-0.454
	(23.222)	(17.439)	(0.129)	(1.222)
Acquirer EBIT	-0.096	-0.096	0.001**	-0.001
	(0.078)	(0.059)	(0.0004)	(0.004)
Acquirer R&D Expenditures	0.089	0.093**	-0.001**	0.002
	(0.060)	(0.045)	(0.0003)	(0.003)
Acquirer ROA based on bottom EPS	0.488	0.190	-0.003	-0.017
	(0.567)	(0.426)	(0.003)	(0.030)
Acquirer Financial Leverage	2.098	0.113	0.044**	-0.001
	(4.022)	(3.020)	(0.022)	(0.212)
Year 2014	-12.420	-4.941	0.128	0.663
	(20.145)	(15.128)	(0.112)	(1.060)
Year 2015	-8.072	2.552	0.105	-0.094
	(19.849)	(14.906)	(0.110)	(1.045)
Year 2016	-25.751	10.694	0.098	0.723
	(19.927)	(14.964)	(0.110)	(1.049)
Year 2017	-46.091**	-3.949	0.121	2.105*
	(22.585)	(16.961)	(0.125)	(1.189)
Constant	48.245**	5.660	0.321***	0.690
	(21.448)	(16.107)	(0.119)	(1.129)
Observations	123	123	123	123
R2	0.096	0.069	0.114	0.102
Adjusted R2	0.006	-0.023	0.027	0.012
Residual Std. Error (df = 111)	54.074	40.609	0.300	2.846
F Statistic (df = 11; 111)	1.068	0.745	1.304	1.140

Note: *p<0.1; **p<0.05; ***p<0.01