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Master Thesis Draft 5
The Relationship between M&A and Innovation Output

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Abstract

In theory, synergies can lead to knowledge spillovers with the effect to be positive for both parties since transferring knowledge yields higher growth opportunities. Although many studies focused on the positive learning effect between the two firms, it is unclear whether M&A activity increases innovation and technological developments. In this thesis I will analyse the M&A activity as a contributor to innovation by comparing innovation output of successful to that of failed deals. In order to do that, the number of patents reported annually by firms is used as a proxy for innovation. The updated dataset from 2010-2019 suggests that there is a negative relationship short term, and the magnitude depends on the industry in which firms are classified. On the year of the M&A innovation is negative, but it increases slowly one year after and becomes steadier three years after the M&A. Also, there was no evidence that portfolio diversification increases innovation.

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1. Introduction

The last decade an impressive increase in mergers and acquisitions was documented globally (IMAA Org., 2020). Some of the most valuable mergers and acquisitions (M&As) that shaped the business world the last decade are the merger of AT&T with Time Warner ($108 billion), Verizon with Verizon Wireless ($130 billion) and Dow with DuPont combined businesses ($130 billion transaction). The total aggregate value of the deals from 2010 to 2019 is 34 trillion US dollars. This enormous increase raises the question why do firms seek mergers and acquisitions? To start with, Trautwein, (1990), Berkovitch and Narayanan (1993) discussed that the main benefits from an M&A are the increase in market share, the expansion in new markets and the creation of corporate diversification. This paper explores the knowledge spillover effect which drives innovation activity. This benefit has caught lately more attention by researchers who consider it as an indirect positive effect from M&As (e.g. Gerpott, 1995; Chakrabarti et al., 1994; Cloodt et al., 2006). For example, Hitt et al., (2006), drew their attention on the positive learning effect between the two firms and the impact it has on innovation and technological developments. Moreover, the effect is mutual since transferring knowledge yields higher growth opportunities for both (Karim and Mitchell, 2000).

Innovation is important not only from an economic point of view but from a welfare perspective too. Taking as an example the pharmaceutical industry, the development of new drugs and vaccines are improving the quality of human lives. The global pandemic we currently phase, requires the utilization of different patents and developments in the industry in order to produce a vaccine against the virus. Therefore, M&As play a key role in allowing knowledge and technological spillover effects to contribute to the development of such patents. During major crisis and recessions, the economic landscape is described by uncertainties regarding the direction of technological change, supply, demand, and entry in new markets (Archibugi et al., 2013). Therefore, the need for cost sharing, especially for innovations which require high funds, can be achieved through the channel of an M&A. Schumpeter and his followers claimed that the relationship of economic cycles and innovation is two-way, economic cycles are the result of innovation, but also innovation is re-shaped by economic crises (Schumpeter, 1935).

Conversely, there is considerable theoretical and empirical evidence that M&As have a negative effect on innovation activity. For example, in pharmaceutical industry innovation activity after an M&A decreases or grow at a slower rate at least for the first three years (Ruffolo, 2006). Pharmaceuticals is not an exception, evidence from the electronics industry suggests that ex post an M&A, innovation drops significantly (Blonigen and Taylor, 2000). One possible explanation is that after an M&A, there is a high pressure for returns and business activities point towards this direction. As a result, investments for long term returns decrease. The lack of those investments may harm the company in the future. For example, Valentini (2011) highlighted the negative effect of M&As on innovation quality (originality and generality) for medical devices and camera material.

Prior literature and empirical findings in M&A research discuss both risks and rewards on a short on long term scope (Cassiman et al., 2005; Galpin, 2014; Cunningham et al., 2019). This paper examines whether M&A activity, positively influence innovation output using a recent dataset from 2010 to 2019.

Overall, this paper makes three contributions. Firstly, it sheds light on the debate of a new and growing literature that examines interactions between innovation and M&As. With starting point the paper from Sevilir and Tian's (2012), this paper attempts to shed light on the relationship by following a different methodology and using an updated patent dataset from 2011-2019. Secondly, this thesis presents empirical evidence by examining the M&A activity for companies from 12 different industries. I explore the relationship of M&A and innovation output from the economic growth perspective where knowledge spillover externalities are positive. Delmar et al., (2003) explained that growth can be organic, formed by new companies, mergers, and acquisitions or through innovation. Majority of the previous studies have focused on the value creation and profitability of M&A activities but have not taken into consideration the benefits arising from innovation. Finally, this paper provides new evidence related to corporate diversification and its role in innovation.

This paper is organized as follows. Section 2 discusses the related literature and develops the hypotheses. Section 3 describes the data, underlines few assumptions, and presents balance checks. Section 4 describes the development of the models used to answer the research question whether mergers and acquisitions yield higher innovation output (measured by patents). The findings of the empirical analysis are reported also in this segment as well as some robustness checks. Then the last part, summarizes the findings but also presents some limitations and ideas for future research. Variable descriptions, tables and figures can be found in the Appendix.

2. Related Literature and Hypothesis

Mergers and acquisitions contribute to the growth of business activities by allowing knowledge to be transferred across divisions while increasing efficiency and decreasing costs. M&As foster innovation through the channel of complementary knowledge. Economists often use the theory of the firm to discuss allocation of property rights after M&As. Grossman, Hart, (1986) and Moore (1990) found that for complementary assets, common ownership is efficient. Drawing of their work, Rhodes-Kropf and Robinson (2008) emphasised on the synergy creation by acquirer and target firms in their model. A major take away of the model is that innovation is positively related to M&As. The introduction of innovation in literature was in 1940s by Schumpeter. As the first economist who discussed about innovation and entrepreneurship, his work on the theory of economic development has been the starting point for this field. There, he highlighted the importance of innovation as a contributor in economic growth (Ruttan, 1959; Śledzik, 2013). Later, on Tilton (1971) emphasized on the ability that firms have to utilize internal technical capabilities to increase innovation. Aghion and Tirole (1994) discusses how M&As affect the rate of occurrence as well as and the magnitude of innovation. The growing empirical evidence supports the discussed arguments and provides evidence for a positive relationship between M&A innovation. For example, Cefis (2009) found a positive relationship between M&A activities and R&D intensity. Moreover, patent outcome has been reported to be larger ex post an M&A (Sevilir and Tian, 2012). Based on the above theoretical and empirical framework I hypothesise the following:

Hypothesis I: M&A activity is positively related to the innovation output of the firms involved in the deal.

Another interesting angle to understand innovation and M&As is through the diversification of the target and acquirer. The theoretical framework of portfolio diversification is based on the agency theory and transaction cost economics (for example Williamson, 1975). From the Resource Based view, diversification yields higher performance though the channel of resources maximization across different businesses (Wan et al., 2011). Belenzon and Berkovitz (2010) examined the innovation activity between group and non-group firms and found that the output is higher for group firms. In contradiction to the knowledge spillover as the main contributor according to the agency theory, this study found that financial resource advantages of the groups positively affect innovation. Nelson (1959) explains that firm diversification plays an important role, providing with higher innovation incentives. More specifically, he claimed that a firm with a more diverse profile can utilize innovation to a better extend that a specialized one. Empirical study in alliances supports this line or research and found that diversified alliances have 13 times higher innovation activity in comparison to non-diversified (Sampson, 2007). According to Sampson, diversity between partners is required in increasing innovation, but it may be also an obstacle when partners are highly diversified because in that case, learning opportunities are low. Katila and Ahuja (2002) suggested that diversification enhances innovation though the utilization of internal know-how. A few years later, Miller et al., (2007) explored whether knowledge spillovers in diversified companies increase innovation and found that transferring knowledge across divisions for companies with a diversified portfolio increases innovation. They also pointed out the importance of internal knowledge since it is less costly and less risky. Moreover, Aghion and Tirole (1994) discussed that for acquirers which are less competent at innovating themselves, acquiring an innovative target increases innovativeness. Based on the above, I hypothesize the following:

Hypothesis II: Portfolio diversification of the acquirer increases innovativeness ex post an M&A.

Contrary to the above empirical findings and literature, M&As may impede innovation output. Ruffulo (2006) presented a negative relationship between pharma M&As and innovation. Moreover, prior study in medical and camera materials found that innovation quality drops after an M&A (Valentini, 2011). Evidence from high-technology industries also points out the inverse relationship between R&D intensity and M&A (Blonigen and Taylor, 2000). The most common explanation is the agency problem in resource allocation after an M&A (Rotemberg and Saloner, 1994; Rajan, Servaes, and

Zingales, 2000). Moreover, Hitt et al., (1991) found a negative decrease in patent input and R&D intensity after an M&A. He also stressed the importance of many different resources in the crucial stage of integration after an M&A which results in less available resources for innovation (1996). The magnitude of the effect in years ex post varies in empirical literature. Szücs (2014) by examining the impact of M&A on R&D found that target firms reported a drop in R&D after the transaction and at least for the following 6 years. More recently, Desyllas and Hughes (2010) revealed a decrease in R&D intensity one year after the M&A but after three years it increases again. Please refer to section one for the predictions of the effect in the main variables of interest.

Why do announced M&As fail?

There are many reasons why an announced M&A fails (withdraw). The deal can be mutually withdrawn/terminated, or it can be one sided either the acquirer withdrew, or the target company rejected the offer. A change of view in the review or reassessment can lead to a deal termination. This is highly influenced by the board composition since those changes might reflect management rent-seeking behavior or control over decisions (Raad & Ryan, 1995). Moreover, it may withdraw due to unfavorable market conditions. The failure to obtain a bank agreement or other sufficient payment method is also a common reason discussed by Franks et al., (1988) and Sudarsanam (1995). Sometimes, antitrust authority or other regulatory reasons affect the completion of a deal. This was the case for one of the largest German companies, Thyssenkrupp. Recently, the European Union’s antitrust authority blocked the merger of Tata Steel with Thyssenkrupp to avoid a cartel.[1]
It is also important to consider the costs of withdrawing an M&A deal. First of all, there are penalties and other termination fees which sometimes can reach 6% of the deal value (Rosenkranz and Weitzel, 2005). Additionally, all the costs from the negotiation stage are added for example payments for lawyers, financial advisors, and other costly executive management activities. Luo (2005) explained that another indirect cost is the negative effect the withdrawal of a deal has on the reputation and credibility especially

[1] More information can be found here: https://scroll.in/latest/926688/european-unions-antitrust-authority-blocks-tata-steel-thyssenkruppmerger#:~:text=The%20European%20Union's%20antitrust%20authority, Vestager%20said%20in%20a%20statement.

for the acquirer.[2] Overall, withdrawing an announced deal can harm both target and acquirer.

The above arguments are important because innovation is found to be related to the success or failure of the M&A activities. Empirical study showed that withdrawn M&A deals are negatively related to patent output (Sevilir and Tian, 2012). On the other hand, Seru (2014) found that failed M&A deals have higher innovation output than successful diversified M&As. The latter shows that a failed M&A transaction may not be necessarily harmful to innovation.

3. Data and Balance Tests

3.1 Data

A large number of studies in this field have used the number of patents as a proxy for innovation output (eg. Sevilir and Tian, 2012; Valentini, 2012). The same approach has been followed in this paper. Patent data are obtained from the Dimensions Patent database. I restrict those data to 180 companies with successful patent submissions, for the period of 2010-2019. For the M&A activity, transaction data are collected from the Securities Data Company (SDC) Mergers and Acquisitions database via ThomsonOne (54,458 observations). With those data, I construct the treatment and control group, with treatment being the firms which experienced a successful merger or acquisition from 2010 to 2019 and control those firms whom M&A failed (withdrawn). The latter is classified in the dataset under the description completed or withdrawn. Moreover, a few dummies are generated to capture the changes over a short period of time t, one year before and up to three years after the deal. Another dummy was added related to the industry of the target and acquirer to capture diversified acquisition, equals one if the acquirer and the target are not within the same two-digit SIC industry codes and zero otherwise. Furthermore, financial statement items are collected from the Compustat database, via Wharton Research Data Services (WRDS). This dataset allows the use of control variables for sales, research and development expenditures, assets, and acquisition related information. After merging the three datasets, the final sample consists of 1,155 observations. **Table 1** presents the overview of the three datasets and information on the number of M&As and

[2] Empirical study showed that the existence of break-up fees yields a 20% higher probability of M&A completion (Officer, 2003).

companies in treatment and control group. There are 179 completed M&As and 163 failed ones (withdrawn) during the sample period. There were 45 completed M&As for companies from a different industry. Although there are a few European and Asian companies, the large majority of this sample are US companies which trade with stocks (and registered bonds) in the U.S. The sample consisted of a few outliers in company size variables which were dropped and therefore do not affect the analysis. In the analysis the number of patents is added for the treatment and the control group. The number of patents corresponds to the patents reported for the target firm. Using companies for which M&A withdrew is more appropriate than considering companies which did not experience M&A at all because there is a comparison for innovation output for companies which completed the M&A and those for which would have completed otherwise. This approach is recommended by many researchers in establishing causality in M&A empirical studies (e.g. Savor and Lu, 2009; Sevilir and Tian, 2012).

Table 2 presents the descriptive statistics of this sample. The average number of patents is 820 per year with Qualcomm Inc. and Toyota Motor Corp. to be the two most innovative companies for this sample period. Research and Development average expenditures are reported 1071 thousand US Dollars and average sales 18.778 thousand dollars. Sale is the operating revenue of a company. Assets refers to any resource owned by a company. Capex or capital expenditure, captures the used funds to buy, maintain or upgrade company's assets. This includes the acquisition of land, buildings equipment and computer software. Taking the latter, a new software acquisition for example has long term impact on company's innovation activity and hence it is relevant for this paper. Research and Development (R&D) expenditure go hand in hand with innovation and for some researchers R&D was used as innovation indicator. R&D intensity is the ratio of Research and Development expenditure divided by total book value of firm assets. ROA is the ratio of operating income before depreciation divided by the book value of firm assets. For detailed definition of all variables used as well as the databases please see section 1 in Appendix.

3.1.1 Assumptions

In order to merge the Dimensions database with SDC and Compustat some assumptions need to be made. Dimensions database has different format in comparison to the other two and there is no information related to cusip codes or other company identification. Therefore, the merge is made based on the first name of the company. As a result, companies like “American Airlines” matched with “American Express”. To eliminate this risk, an additional manual check is performed to ensure that there are no duplications and those observations were dropped. Another assumption made is related to the origin of the patents. Dimensions consists of patent data for companies based on the country those were submitted. In the sample a few companies had multiple patent outcomes per country for example “Toyota (Japan)”, and “Toyota (Unites States)”. On those cases the patent outcome of the specific country is used instead of the total.

3.1.2 Balance Tests

In order to check whether the sample is balanced and more specifically if the companies of the treatment group have similar characteristics to those of the control group, a few balance checks were performed. Since the dependent variable is the number of patents, it is essential to check the patent means on the two groups. Additionally, the Research and Development Expenses give a good indication of the intensity of the innovative activities. Moreover, the size of the firm whether it is estimated based on the sales, capex or assets is an important characteristic of the companies. Finally, since later on the diverse portfolio hypothesis is checked, this variable has been added to the balance test. **Figure 1** illustrates the average patents for the treatment and control group. The control group has on average 681 patent submissions one year before the M&A and treatment 1002. On the year of M&A, the treatment group increases the mean to 1048 patents and control drops to 650. The difference of the two groups increases one year after the M&A but becomes steadier the following years. This indicates that there are differences in the two groups. **Table 3** reports the differences of the main variables of interest before the M&A took or was supposed to take place. Column (2) reports the means for the control group, whereas column (5) for the treatment. For patents, the average difference between the groups is 235 units. For R&D expenditure there is a difference of 375 thousand US dollars on average. Similarly, for the rest of the variables. **Table 3** also checks whether those differences are statistically significant. The last column shows the t-statistics for the main variables of interest. A negative t-statistic means that treatment has higher values than control group. For 5 variables the t-statistic is large which means that the null hypothesis of same means between the two groups can be rejected. The t-statistics for R&D expenditures and R&D intensity are statistically significant at 10% level. Companies in the treatment group, (before treatment) invested on average 906 thousand dollars in R&D which is 40% higher than in control group. However, this does not seem to affect the number of patent submissions since the t-statistic is not statistically significant. Also, capital expenditures, assets and sales are statistically significant at 5% and 1% respectively. This shows that ex ante the transaction, companies which completed a successful M&A (treatment group) were larger in size and with higher sales volume in comparison to the those which M&A failed (control group).

Someone could easily argue that patent submissions are relevant for only a limited amount of industries. To address this concern, an analysis was performed on the industry level (of the target companies) and the number of patents per industry were reported well spread across 12 different industries. As expected, in total, Industrials and High Technology account for the highest number of patents, both around 17% respectively. Once the treatment group is separated from the control, the picture is slightly different. As reported in **Figure 2.A,** Industrials and Financials account for 27% and 16% in the treatment group. In the control group, Healthcare and High technology represent 46% and 20% of the sample. **Figure 2.B** presents the average number of patents per industry for the two groups. For the treatment group, Industrials and Consumer staples lead in 1601 and 1337 average number of patents respectively. In the control group, Telecommunications, and Industrials account for the highest number of average patents. **Table 4** reports the industry classification of the sample, including the total number of patents and percentages per group. Overall, the variation of industries across the sample suggests that there is limited risk of selection bias on the industry level and generalizability of the results in more industries is possible.

4. Methodology and Findings

This section describes the empirical models used to reveal evidence for the two hypotheses. Moreover, the main findings are presented and discussed.

4.1 M&A activity and innovation output

This paper attempts to uncover a causal effect between M&A transactions and innovation outcome. In order to do this, the Difference-in-Differences (DD) method is used. DD exploits the fact that some treatments send companies on a different path in terms of how their outcomes evolve over time. In this paper treatment group consists of companies who experienced a successful M&A and control group those which the announced M&A failed from 2010-2019. In the absence of the treatment, if companies' outcomes on innovation would have followed the same trends as companies who did not have an M&A, causal effects on the evolution of innovation can be identified.

The dependant variable patent is highly right skewed with a mean almost 4 times larger than median (see **Figure 5** for illustration). In order to normalize the distribution of the patent variable the natural logarithm of the variable is used. Another reason that makes the natural logarithm a better fit is that it reduces the influence of potential outliers in the sample. Drawing on this, the natural logarithm is used also for the control variables R&D, sales, capex, and assets. The natural logarithm has not been used in the ratio variables.

I start with the following empirical model:

$$Ln(Patent_{i,t}) = \beta_0 + \beta_1 MAdummy_{i,t} + \beta_2 Postdummy_{i,t} + \beta_3 MAdummy_{i,t} * Postdummy_{i,t} + \beta_4 V_{i,t} + FE_{industry_i} + FE_{year_t} + e_{i,t}$$

where dependent variable is the natural logarithm of patents. $MAdummy_{i,t}$ is a generated dummy variable equal to 1 for the firms which had a successful M&A during the sample period and zero otherwise. $Postdummy_{i,t}$ is a dummy variable equals to one in periods after a successful or failed M&A, and zero in periods before (the successful or failed M&A). $FE_{industry_i}$ and FE_{year_t} are fixed effects for industry and year. $V_{i,t}$ is a vector of firm and industry characteristics consisting of standard control variables used in prior studies related to firm innovation. The first coefficient will reveal the average difference in patents between the two groups of companies that is common to both pre and post treatment periods. The coefficient β_2 will show the average change in patents from pre to post-treatment periods that is common to both companies which had or not an M&A deal during the sample period. Finally, the coefficient of the interaction term β_3 is the difference in difference estimate for the average differential change in patents from the pre to post treatment period for the for the companies which had a successful M&A transaction relative to the change in patents for the untreated group.

The main assumption of Differences in Differences method is that in the absence of treatment, the change in treated outcome would have been same to the change in untreated outcome. This parallel trend assumption is graphically presented in **Figure 4**. This graph illustrates the innovation output for t-1, t and up to 3 periods after the M&A. Based on this, the innovation in the treatment group would have had a parallel trajectory to the innovation of the control group, in the absence of the M&A (treatment). Although the patent output for treatment is larger, it seems that both groups are following same trends. The visual inspection suggests that the assumption holds despite the fact that the groups are different.

Table 5 presents evidence on the relationship between the M&A activity of a firm and its innovation output. Column (1) presents the baseline regression and column (2) reports the changes when control variables are added. Column (3) and (4), show the coefficients and standard errors in parentheses when industry and year fixed effects are included. Column (1) shows that M&A activity whether successful or not, increases patents by approximately 10%, however this finding is not statistically significant (t-stastistic=0,75). Interestingly, after the M&A took place or was supposed to take place, patents increase by 32% (significant at 5% level). This finding is consistent also when the control variables are added, slightly lower at 30%. However, the above finding vanishes after the introduction of the industry and year fixed effects. I think that the increase in innovation after a successful or failed M&A may be influenced by the expenses associated with the M&A. As mentioned in the theory segment, M&A activity is associated with additional costs and fees (e.g. lawyers, financial advisors) and most likely, there are less resources available for innovation. Once the M&A phase is over, the firms increase their ability for higher investments in innovation since more money are available. This conjecture lies on the agency problem in resource allocation (Rotemberg and Saloner, 1994; Rajan, Servaes, and Zingales, 2000).

In column (1) the interaction term (dif-in-dif) is positive and the expected average change in patents from before to after the M&A is 10%, but statistically insignificant. When industry and year fixed effects are included, the patent increase reaches 20,7%. On the other hand, in columns (2) and (4) the interaction term is negative. Since column

(2) explains 44% of the patent variation in the sample, the findings are drawn from here. The interaction term (dif-in-dif) is negative, but insignificant and therefore the first hypothesis cannot be rejected. The negative sign points this paper closer to the studies of Hitt et al., (1991), Valentini (2011), Szücs (2014). The evidence suggests that firms with larger R&D expenditures and assets but lower ROA and R&D intensity, are more innovative. The first two variables are closely related to the size of the company, but ROA to the profitability. The negative relationship between ROA and patents can be explained due to the fact that the return on a recently acquired asset can be low in the first few years. The last findings are consistent with prior studies by Sevilir and Tian (2012), Ahuja and Katila (2001) Blonigen and Taylor (2000).

4.2 Portfolio diversification of acquirer and innovation

In order to test the second hypothesis whether portfolio diversification of the acquirer increases innovativeness, similar approach to the above has been followed. For this empirical model a new dummy was generated the so called $Diversified\ Acquisition\ _{i,t}$ which is equal to 1 if the industry of the target company is different to the one of the acquiror and otherwise 0. V is a vector of firm and industry characteristics and includes R&D expenses and intensity, sales, capex, assets, and ROA. The following model will show whether diversified firms benefit in patent submission from the M&A activity regardless of whether the deal was successful or not.

$$\begin{aligned} Ln(Patent_{i,t}) = \beta_0 + \beta_1 Diversified\ Acquisition\ _{i,t} + \beta_2 Postdummy_{i,t} \\ + \beta_3 Diversified\ Acquisition\ _{i,t} * Postdummy_{i,t} + \beta_4 V_{i,t} \\ + FE_{industry_i} + FE_{year_t} + e_{i,t} \end{aligned}$$

Table 6 presents the findings for the empirical model above. Dependent variable is the natural logarithm of patents. As illustrated on Figure 3, the sample is diverse on industry level and consists of 12 different industries. Out of the 178 completed M&As, 45 were with a company from a different industry. Column (1) shows the baseline regression and column (2) includes the firm controls. Column (3) and (4) includes industry and year fixed effects. In the baseline regression, column (1) the acquisition of a company from a different industry is negatively related to the number of patents. After the successful or failed M&A, the number of patents increases by 34%, a trend reported also in the previous regression. The difference in difference coefficient is 0.07

and it indicates that the industry diversity in M&As increases innovation output by 7%. Similarly, when industry and year fixed effects are added, this relationship becomes stronger, however still statistically insignificant. The opposite relationship is reported in column (2). There the coefficient of the interaction term suggests that companies with a diversified acquisition (successful or not) decrease their number of patents by almost 44% after the completion. Since none of the t-statistics is larger than 2, there is not enough evidence to reject the second hypothesis. In columns (1), (3) and (4) reports a negative relation between a diversified acquisition and the number of patents. It is also important to note that R&D expenditures and assets are still positively related to the number of patents but also sale once fixed effects are added. Larger R&D intensity, and ROA decrease the number of patents. Overall, the results are closer to the findings of Sampson (2007), which claimed that intermediate diversification is better than high because too diverse companies are not able to learn from each other.

4.3 Innovation Development over time

In order to explore the dynamic for the first few years after the M&A deal, successful or not, an additional model is estimated. I construct dummy variables that capture the years after the M&A and restrict the analysis on the first three years. T corresponds to the year of the M&A whether it was successful or not and t+1 for one year after, similarly for the rest. As before, the $MAdummy_{i,t}$ and $Postdummy_{i,t}$ are used and $V_{i,t}$ is a vector of firm and industry characteristics. The regression explores the changes between the two groups per year after a successful or failed M&A. The following empirical model is estimated:

$$Ln(Patent_{i,t+n}) = \beta_0 + \beta_1 MAdummy_{i,t} + \beta_2 Postdummy_{i,t} +$$

$$\beta_3 MAdummy_{i,t} * Postdummy_{i,t} + \beta_4 V_{i,t} + e_{i,t}$$

where $\mathrm{Ln}(\mathrm{Patent}_{i,t+n})$ is the natural logarithm of patent submissions for firm i on period t+n. $Postdummy_i$ a is a dummy equals to zero if the period is before the M&A (successful or failed) and one if it is after. $MAdummy_{i,t}$, is a dummy which captures the timing of the M&A transaction either it was successful or failed for t periods. V is a vector of firm and industry characteristics consisting of standard control variables used in prior studies related to firm innovation. It consists of R&D intensity, sales, roa, firm assets and capex.

Table 7 presents the results of the above model. For each period t, there are two columns reported, so for the year of the M&A column (1) and (2). Similarly, for the next periods. The first column in each period denotes the baseline regression results for that period and the second column takes into consideration the control variables. In column (2), for the year of M&A, a successful M&A increases patent output by 45%.

However, one year after, the patent output for those companies decreases to negative 37% and follows a downward trend for at least the following two years with negative 44% and negative 42%. The postdummy coefficients show a steady innovation development over time, around 20% at least for the first three years after the transaction. All coefficients are statistically significant either at 5% or 1% level. Consistent with the findings from the first model, companies which go through an M&A, increase their innovation output after, irrespective to whether the M&A was successful or not. There is an interesting dynamic on the interaction term of madummy and postdummy. In the year of the M&A, the number of patents decreases by 38%. The negative relationship may be caused by issues arising during the integration phase and barriers in communication. This is often the case in industries like chemicals where knowledge spillover opportunities take longer (Cloodt et al., 2006). One year after the M&A, the patent output increases by 7,5%. In the following two years, the impact of a successful M&A on patent output becomes stronger with an increase of 47% and 41% respectively. Although the coefficients are not statistically significant, this finding is closer to the line of research by Aghion and Tirole (1994), Sirower (1997), Cefis (2009), Sevilir and Tian (2012) who claim that M&A activity is a positive contributor to company's innovation. Also, companies with larger R&D expenditures and assets but lower R&D intensity and ROA report higher innovation outputs.

4.4 Robustness checks

In this section the robustness of the results is being tested. Although someone would expect that the financial industry would follow unique trends, after a robustness check this does not seem to be not the case in this sample. In **Table 8** panel A, the t-statistic for financials is -1,46 and therefore not statistically significant. Instead, the industrials, high technology and telecommunications [3] are statistically significant and healthcare marginally insignificant but close to 2. Prior studies in the healthcare industry reported major differences from other industries due to the unique innovation process (eg. Cloodt et al., 2006 and Ruffolo, 2006). Moreover, in this sample the healthcare industry is overrepresented with 46% in the control group, therefore it is important to see the change in findings once those observations are dropped. Another two statistically significant industries are high technology and industrials. **Table 8** panel B reports the results of the first regression model. Column (1) shows the coefficients and standard errors for the baseline regression with all 12 industries. Column (2) shows the results when Industrial industry observations are dropped. Moreover, column (3) and (4) correspond to the findings excluding the healthcare and high technology industry respectively. Starting with column (2), even when industrial industry observations are removed, the coefficients are very similar to the baseline (all industries). Innovation after the successful or failed M&A increases to 36,6% (relative to 30%). In the case of the healthcare industry exclusion, the latter relationship increases to 48% whereas the interaction term drops to 33% however statistically insignificant. In the case of high technology exclusion, the relationship between patents M&A activity and patents is negative and statistically significant at 10% level. In this case, a successful M&A decreases patents by 38,6% which is consistent with prior literature by Hitt et al., (1991) and Szücs (2014). Overall, the robustness checks suggest that the magnitude of the relationship between M&A activity and innovation is also subject to the industry.

5. Conclusion

My thesis contributes to the growing literature of innovation and M&A activity. In theory, synergies enhance knowledge spillovers and create equal growth opportunities. However, the empirical findings for the relationship between M&A activity and innovation contradict each other. The findings point this paper to the direction of the negative relationship between the two on a short-term scope which is consistent with previous work by Hitt et al., (1991) and Valentini (2011). Although the results are not statistically significant, they seem to hold across different industries. There is no evidence that portfolio diversification of the acquirer increases innovativeness. The results are closer to the findings of Sampson (2007), which claimed that intermediate

[3] The number of observations for telecommunications was low in the sample and since there were no related empirical findings, no additional check for this industry was performed in panel B.

diversification is optimal because high diversity creates communication barriers. This paper reveals an interesting dynamic on the innovation development over a short period of time. On the year of the M&A innovation is negative, but it increases slowly one year after and becomes steadier three years after the M&A. The evidence suggests that firms with larger R&D expenditures and assets but lower ROA and R&D intensity, are more innovative which is consistent with prior studies by Sevilir and Tian (2012), Ahuja and Katila (2001) Blonigen and Taylor (2000). Also, the magnitude of the relationship between M&A activity and innovation is subject to the industry. When high technology industry was removed, a statistically significant negative relationship was documented.

The agency problem in resource allocation after an M&A is the most common explanation of the negative relationship (Rotemberg and Saloner, 1994; Hitt et al., 1996). There is a trade-off between resources allocated in integration and available resources for other business activities, like R&D. From a policy perspective, the latter raises many questions related to the factors that may cause this drop. Policy makers should take this into consideration and implement strong integration procedures for a smooth transition. Some of those practices are to create new communication channels, manage cultural integration and change management. Especially in cases of pharmaceutical companies which merge to invent a new drug, policies enforcing a seamless integration process will yield higher innovation outcome faster and increase welfare.

This paper is subject to a few *Limitations and Extensions:*

External Validity

The Securities Data Company (SDC) dataset contains 1.1 million global M&A transactions since the 1970s however majority of the data correspond to American and Canadian companies. As a result, the generalizability of the findings is questionable since firms in Europe or Asia may present a different dynamic on the relationship of M&As and innovation. Recent study in Europe revealed differences in the timing of the effect. Fernández et al., (2019) reported a positive impact of successful M&As on R&D intensity two years after the M&A and an increase in sales five years after the transaction. Overall, this is a great starting point for further research.

Proxy for Innovation

The main assumption of this paper is that the number of patents is a good indicator of innovation. Someone could easily argue that an alternative measure for innovation would be the sales percentage from products introduced in the last X year(s). One should consider whether R&D activity and innovation is informative enough, or whether the impact of that more efficient output can define more effectively innovation. Also, innovation can be related either to the process (adaption of existing products) or product (new product launch). The size of a company plays a role on the research and development budget distribution between process and product innovation. Smaller companies focus more on product that process development according to Fritsch and Meschede (2001). In each type of innovation, there is a large focus on the company's innovation strategy in order to benefit from both types of innovation (Bhoovaraghavan, et al., 1996).

Short/Long term

The models used in this thesis examine the relationship of M&A activity and innovation from a short-term perspective. In reality the impact of such a change becomes more evident on a longer rather than a shorter time span. Empirically, Aluja and Katila (2001) found a long-term effect of the acquired knowledge. The integration process may differ from firm to firm due to industry barriers. For example, chemical M&As require longer time to evaluate and benefit from knowledge spillover opportunities from the acquisition (Cloodt et al., 2006).

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Appendix

1. Variable Definitions and Predictions

1.1 Predictions for the effect of the variables

Variable	Expected effect on innovation	Actual effect on innovation	Related literature
M&A activity	+	-	Nelson (1959), Aghion and Tirole (1994), Sirower (1997), Cefis (2009), Sevilir and Tian (2012)
	-		Hitt et al., (1991), Ruffolo (2006), Valentini (2011), Szücs (2014)
R&D	+	+	Ahuja and Katila (2001)
	-		Szücs (2014)
R&D intensity	+	-	Cefis (2010), Tilton (1971)
	-		Blonigen and Taylor (2000), Desyllas and Hughes (2010)
Assets	+	+	Hitt et al., (1996), Rhodes-Kropf and Robinson (2008), Sevilir and Tian (2012)
Diversifying acquisition	+	+/-	Nelson (1959), Aghion and Tirole (1994), Miller et al., (2007), Sampson (2007)
Sales	+	+	Schumpeter (1935), Coad and Rao (2010), Fernández, et al., (2019)

1.2 Variable Description

Dependent Variable	Description	Data Source
Patent	Innovation indicator	Dimensions
Explanatory variable		
M&A dummy	Is a dummy variable equals one if a firm completed the M&A deal and zero if the announced deal was withdrawn.	SDC
Post dummy	Is a dummy variable equals to one in periods after a successful or failed M&A, and zero in periods before (the successful or failed M&A).	SDC
Diversified Acquisition	A dummy variable that equals one if the acquirer and the target are not within the same industry code and zero otherwise.	SDC
Control Variables		
Firm Characteristics		
R&D	Annual Research and Development expenditure	Compustat

R&D intensity	Ratio of Research and Development expenditure divided by total book value of firm assets.	Compustat
Capex	Annual capital expenditure	Compustat
CapEx in assets	Capital expenditure divided by book value of firm assets.	Compustat
Sales	Firm's annual sales in $thousands	Compustat
ROA	Operating income before depreciation divided by book value of firm assets.	Compustat
M&A characteristics		
One year before M&A	A dummy variable that equals one if the year is one year before the M&A took or was supposed to take place.	SDC
Year of M&A	A dummy variable that equals one if on the year the M&A took or was supposed to take place.	SDC
One year after M&A	A dummy variable that equals one if it is one year after the M&A took or was supposed to take place.	SDC
Two years after M&A	A dummy variable that equals two if it is one year after the M&A took or was supposed to take place.	SDC
Three years after M&A	A dummy variable that equals three if it is one year after the M&A took or was supposed to take place.	SDC

2. Tables

2.1 Dataset Overview

Table 1 | Dataset Overview

This table presents the number of observations from each dataset as well some information on the number of completed and withdrawn M&As reported in the sample.

Dataset information	Observations
Securities Data Company (SDC)	150.395
Compustat	54.458
Dimensions	19.477
Final dataset	1.155
Completed M&As	178
Withdrawn M&As	163
Companies with M&A	112
Companies with withdrawn M&A	70
Diversified companies with M&A	45
Diversified companies with withdrawn M&A	11

Table 1: Dataset Overview

2.2 Descriptive Statistics

Table 2 | Descriptive Statistics

This table reports the summary of the descriptive statistics of the variables of interest in the sample. All financial related variables are measured in thousands of US dollars.

	Observations	Mean	Std. Dev	Min	Max
Patents	1,155	819.650	1773.776	57	16633
M&A dummy	1,155	0.589	0.492	0	1
Post Dummy	1,155	0.642	0.479	0	1
Diverse Dummy	1,155	0.048	0.215	0	1
One year before	1,155	0.174	0.380	0	1
Year of M&A	1,155	0.295	0.456	0	1
One year after M&A	1,155	0.231	0.422	0	1
Two years after M&A	1,155	0.204	0.403	0	1
Three years after M&A	1,155	0.186	0.389	0	1
Sale	1,137	18778.450	39963.370	0	280522
Capital Expenditures	1,136	1284.980	3972.639	0	36108
Capex/assets	989	0.138	0.229	0	1.809
Assets	989	9879.522	21023.950	1.298	170929
R&D expenditures	881	1071.244	2526.434	-0.648	35931
R&D intensity	989	0.151	0.569	-0.017	17.172
ROA	989	0.340	0.906	-19.255	9.461

Table 2: Descriptive Statistics

2.3 Balance Test

Table 3 | Balance Test

This table reports the balance test for the main variables of interest. The first three columns refer to the control group. The next three columns correspond to the treatment group. For each group, N is the number of observations, mean the average and Std. Dev. The standard deviation. The last column reports the combined t-statistic. All financial items are measured in thousands of US dollars. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Variable	Control			Treatment			t- statistic
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	
Patents	192	523	920.5	221	758	1862	-1.59
R&D expenditures	178	531.8	972.5	168	906.5	1883	-2.32*
R&D intensity	178	0.314	1.293	180	0.120	0.102	2.20*
Sale	192	6971	11870	216	18267	43904	-3.45***
Capital Expenditures	192	413.9	1225.	216	1222	4414	-2.46**
Assets	178	3986	7455	180	9802	27084	-2.76**
Capex divided by assets	178	0.102	0.189	180	0.131	0.225	-1.30
ROA	178	0.106	1.551	180	0.308	0.617	-1.63
Diversified acquisition	192	0.009	0.095	221	0.009	0.094	-0.46

Table 3: Balance Test

2.4 Industry Classification

Table 4| Industry Classification

This table reports the industry classification of the sample. In total the sample consisted of 12 industries. For both treatment and control group the number of patents, the mean and the percentage of the patents are presented in the columns.

Industry	Treatment			Control		
	N	Mean	%	N	Mean	%
Consumer Products and Services	539	135	2,25%	563	282	1,23%
Consumer Staples	6686	1337	2,81%	879	440	1,23%
Energy and Power	7925	660	6,74%	3330	666	3,07%
Financials	11500	411	15,73%	8982	499	11,04%
Healthcare	7387	336	12,36%	25507	340	46,01%
High Technology	24092	964	14,04%	68341	2071	20,25%
Industrials	76855	1601	26,97%	13648	1516	5,52%
Materials	7438	676	6,18%	1323	265	3,07%
Media and Entertainment	704	176	2,25%	1235	206	3,68%
Real Estate	12274	1023	6,74%	174	174	0,61%
Retail	94	94	0,56%	2529	843	1,84%
Telecommunications	7403	1234	3,37%	8024	2006	2,45%

Table 4: Industry Classification

2.5 Innovation output and M&A

Table 5| Innovation output and M&A

This table presents regressions of innovation output on merger activity. The dependent variable is natural logarithm of patents, which equals the total number of annual patent submissions. Postdummy is a dummy variable equals to one in periods after a successful or failed M&A, and zero in periods before. The interaction term of Postdummy and Madummy is the Dif-in-Dif. Column (1) presents the baseline regression and column (2) includes control variables. The natural logarithm is used also for the control variables, with the exception of the ratios. Column (3) and (4), show the coefficients and standard errors when industry and year fixed effects are added. All variable definitions and data resources can be found in the Appendix. Standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Madummy	0.0982	0.0790	-0.1262	-0.0258
	(0.1120)	(0.1115)	(0.1227)	(0.1195)
Postdummy	0.3244**	0.3022**	0.0657	-0.0627
	(0.1061)	(0.1159)	(.1310)	(0.1343)
Madummy* postdummy	0.1061	-0.1479	0.2071	-0.0717
	(0.1410)	(0.1515)	(0.1556)	(0.1600)
Ln(R&D expenditures)		0.1330***		0.5004**
		(0.0357)		(0.0716)
Ln(Sale)		0.0757		0.3301***
		(0.0696)		(0.1139)
Ln(Capex)		-0.0291		-0.1903*
		(0.0759)		(0.0895)
Ln(Assets)		0.2178**		-0.0797
		(0.0984)		(0.1288)
R&D intensity		-0.3958*		-1.8165***
		(0.1915)		(0.4619)
capex/assets		-0.6136		0.2088
		(0.6317)		(0.7304)
ROA		-0.4674***		-1.1814***
		(0.1619)		(0.2286)
Observations	1,155	744	1,090	684
R^2	0.0217	0.3358	0.0072	0.4373
Adj. R-squared	0.0191	0.3267		
Industry FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
Constant	5.524***	3.037***	5.795***	2.725***
	(0.0819)	(0.3368)	(0.1015)	(0.4603)

Table 5: Innovation output and M&A

2.6 Innovation output and Diversity

Table 6 | Innovation output and Diversity

This table shows evidence on the second hypothesis. The dependent variable is the natural logarithm of patents. Diversified Acquisition is a dummy variable that equals one if the acquirer and the target are not within the same industry code and zero otherwise. In total there are 12 different industry codes. Column (1) presents the baseline regression and column (2) includes control variables. Column (3) and (4), show the findings of the previous columns when industry and year fixed effects are added. Standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Diversified Acquisition	-0.1833	0.1296	-0.7636	-0.4240
	(0.6583)	(0.6986)	(0.6535)	(0.6584)
Postdummy	0.3428***	0.2516***	0.2067**	-0.0864
	(0.0708)	(0.0771)	(0.0883)	(0.0989)
Diversified Acquisition * postdummy	0.0715	-0.4398	0.5529	0.2330
	(0.6779)	(0.7174)	(0.6789)	(0.6846)
Ln(R&D expenditures)		0.1431***		0.5129***
		(0.0353)		(0.0707)
Ln(Sale)		0.0757		0.3398***
		(0.0692)		(0.1132)
Ln(Capex)		-0.0199		-0.1937*
		(0.0756)		(0.0890)
Ln(Assets)		0.2002*		-0.1012
		(0.0984)		(0.1282)
R&D intensity		-0.4441**		-1.8695***
		(0.1928)		(0.4599)
capex/assets		-0.5421		0.2654
		(0.6314)		(0.7313)
ROA		-0.4983***		-1.1924***
		(0.1625)		(0.2284)
Observations	1,155	744	1,090	684
R^2	0.0202	0.3383	0.0084	0.4381
Adj. R-squared	0.0177	0.3293		
Industry FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
Constant	5.578***	3.123***	5.721***	2.7525***
	(0.0561)	(0.3339)	(0.0677)	(0.4467)

Table 6: Innovation output and Diversity

2.7 Short time Innovation Development

Table 7| Short time Innovation Development

This table describes the relationship of innovation output for the year of the M&A, up to three years ex post. The dependent variable is the natural logarithm of patents. Madummy equals 1 if there was an M&A on that year and zero otherwise. Postdummy is a dummy variable equals to one in periods after a successful or failed M&A, and zero in periods before. Each column denotes the period (year). In every period there are two sub columns to account for the baseline regression and the regression with control variables. The natural logarithm is used for the control variables but not for the ratios. Standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	t		t+1		t+2		t+3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Madummy	0.7308**	0.4570	-0.3137	-0.0376	-0.5123	-0.4442	-0.4746	-0.4211
	(0.2799)	(0.3238)	(0.4663)	(0.4453)	(0.4322)	(0.4071)	(0.3317)	(0.3185)
Postdummy	0.4547***	0.2024**	0.3969***	0.2049**	0.3828***	0.2020***	0.3857***	0.2057**
	(0.0792)	(0.0854)	(0.0763)	(0.0817)	(0.0753)	(0.0803)	(0.0746)	(0.0795)
Madummy* postdummy	-0.9333	-0.3835	0.1281	0.0752	0.3330	0.4714	0.2432	0.4104
	(0.2921)	(0.3382)	(0.4744)	(0.4574)	(0.4415)	(0.4229)	(0.3446)	(0.3310)
Ln(R&D expenditures)		0.1357***		0.1356***		0.1359***		0.1351***
		(0.0352)		(0.0353)		(0.0353)		(0.0352)
Ln(Sale)		0.0764		0.0799		0.0836		0.0831
		(0.0693)		(0.0694)		(0.0695)		(0.0695)
Ln(Capex)		-0.0212		-0.0339		-0.0381		-0.0404
		(0.0763)		(0.0757)		(0.0758)		(0.0758)
Ln(Assets)		0.2085***		0.2167*		0.2162*		0.2195*
		(0.0984)		(0.0983)		(0.0982)		(0.0982)
R&D intensity		-0.3890***		-0.3945*		-0.3939*		-0.3926*
		(0.1911)		(0.1915)		(0.1914)		(0.1917)
capex/assets		-0.8036		-0.6174		-0.6108		-0.5374
		(0.6435)		(0.6322)		(0.6314)		(0.6343)
ROA		-0.4687**		-0.4645**		-0.4648**		-0.4600
		(0.1616)		(0.1619)		(0.1618)		(0.1622)
Observations	1,155	744	1,155	744	1,155	744	1,155	744
R^2	0.0305	0.3372	0.0240	0.3350	0.0243	0.3360	0.0267	0.3365
Adj. R-squared	0.0279	0.3282	0.0215	0.3260	0.0218	0.3270	0.0242	0.3274
Constant	5.547***	3.092***	5.581***	3.061***	5.585***	3.061***	5.590***	3.052***
	(0.0567)	(0.3350)	(0.0562)	(0.3345)	(0.0562)	(0.3336)	(0.0565)	(0.3333)

Table 7: Short time Innovation Development

2.8 Robustness checks

Table 8| Robustness checks

This table presents robustness checks of innovation output on merger activity. Panel A shows the statistical significance for innovation output per industry. The last column presents the t-statistic. Panel B shows the results of the robustness regressions. The dependent variable is natural logarithm of patents, which equals the total number of annual patent submissions. Postdummy is a dummy variable equals to one in periods after a successful or failed M&A, and zero in periods before. The interaction term of Postdummy and Madummy is the Dif-in-Dif. Column (1) presents the baseline regression for all industries. Column (2) excludes companies who were classified as Industrials. Column (3) and (4), show the coefficients and standard errors when Healthcare and High Technology observations are dropped. The natural logarithm is used also for the control variables, with the exception of the ratios. All variable definitions and data resources can be found in the Appendix. Standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Robustness checks on industry level

Industry	N	Control mean	Treatment mean	t-statistic
Consumer Products and Services	32	163	150	1.3676
Consumer Staples	22	246	678	-1.1084
Energy and Power	75	1140	791	1.3676
Financials	157	333	679	-1.4601
Healthcare	221	380	385	1.9321
High Technology	208	684	1555	-2.2524*
Industrials	152	1010	1936	-2.042*
Materials	87	371	385	-0.1139
Media and Entertainment	45	220	174	1.3816
Real Estate	28	159	1927	-1.5932
Retail	22	1983	94	N/A
Telecommunications	41	2400	780	3.1867**

Panel B: Regressions excluding industries	All industries	Without Industrials	Without Healthcare	Without High Technology
	(1)	(2)	(3)	(4)
Madummy	0.0789	0.0641	0.2623	0.1544
	(0.1115)	(0.1153)	(0.135)	(0.1258)
Postdummy	0.3022**	0.3664***	0.4844***	0.4133***
	(0.1159)	(0.1194)	(0.1362)	(0.1366)
Madummy* postdummy	-0.1479	-0.1548	-0.333	-0.3859*
	(0.1515)	(0.1596)	(0.1799)	(0.1783)
Ln(R&D expenditures)	0.1330 ***	0.1366**	0.1487***	0.0515
	(0.0357)	(0.0362)	(0.0395)	(0.0406)

Ln(Sale)	0.0757	0.125	-0.0530***	0.0442
	(0.0697)	(0.0706)	(0.0797)	(0.0739)
Ln(Capex)	-0.0292	-0.0449	-0.0697	0.0006
	(0.0759)	(0.0758)	(0.0910)	(0.0839)
Ln(Assets)	0.2179**	0.1067	0.3724***	0.3022**
	(0.0984)	(0.1002)	(0.1245)	(0.1116)
R&D intensity	-0.3958*	-0.4154*	-0.2595	-0.7899***
	(0.1915)	(0.200)	(0.2331)	(0.2160)
capex/assets	-0.6137	-0.436	-0.3714	-0.4271
	(0.6317)	(0.6234)	(0.7045)	(0.6640)
ROA	-0.4674***	-0.4607**	-0.2971	-0.8119***
	(0.1619)	(0.1714)	(0.1984)	(0.1837)
Observations	744	621	596	540
R^2	0.3358	0.2509	0.3475	0.3669
Adj. R-squared	0.3267	0.2387	0.3363	0.355
Industry FE	No	No	No	No
Year FE	No	No	No	No
Constant	3.037***	3.528 ***	2.860***	2.901***
	(0.3368)	(0.3372)	(0.4125)	(0.3847)

Table 8: Robustness checks

3. Figures

3.1 Patent output for Control and Treatment Group

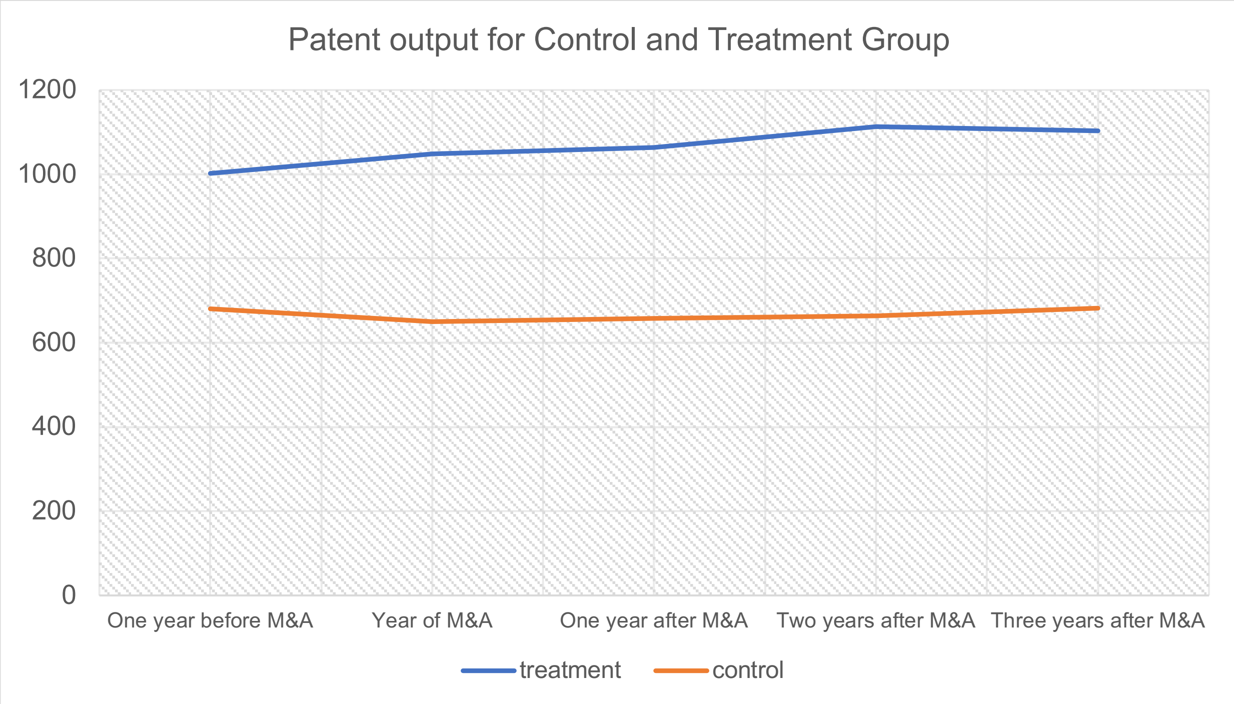

Figure 1: Patent output for Control and Treatment Group

Note: Mean number of patent submissions per year for treatment and control group

3.2 Industry classification of the sample

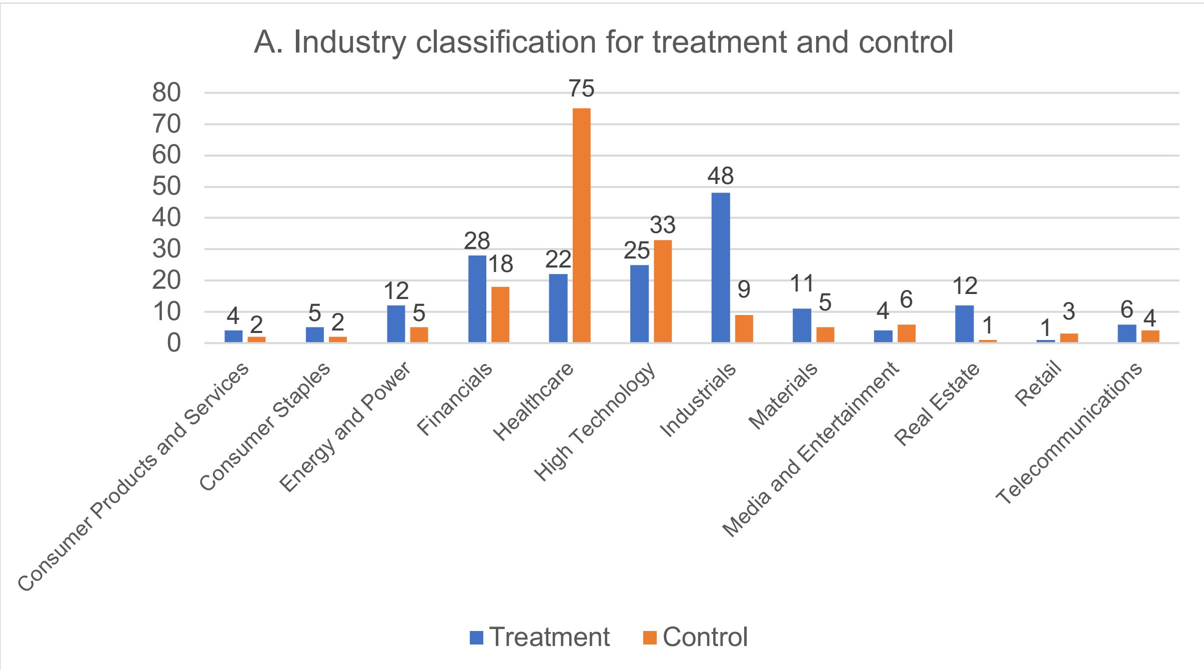

Figure 2: Industry classification of the sample

Note: This chart reports the variety of the industries in the sample across the two groups.

3.3 Average number of patents per Industry

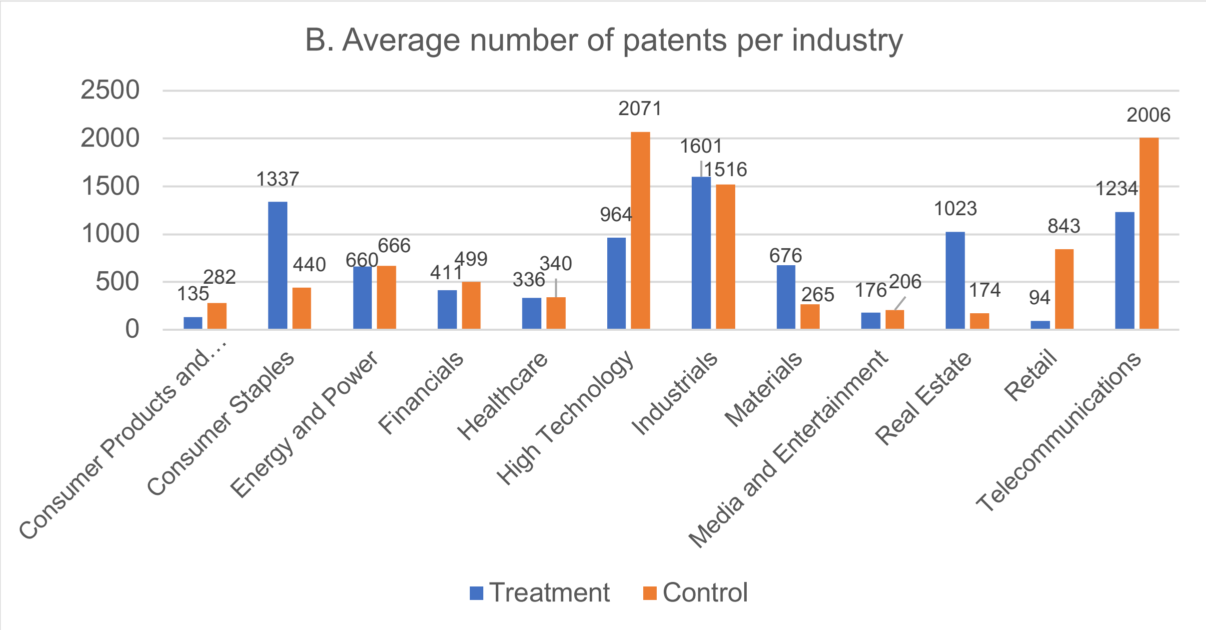

Figure 3: Average number of patents per industry

Note: This chart reports the average number of patents per industry in the sample across the two groups.

3.4 Parallel trend assumption

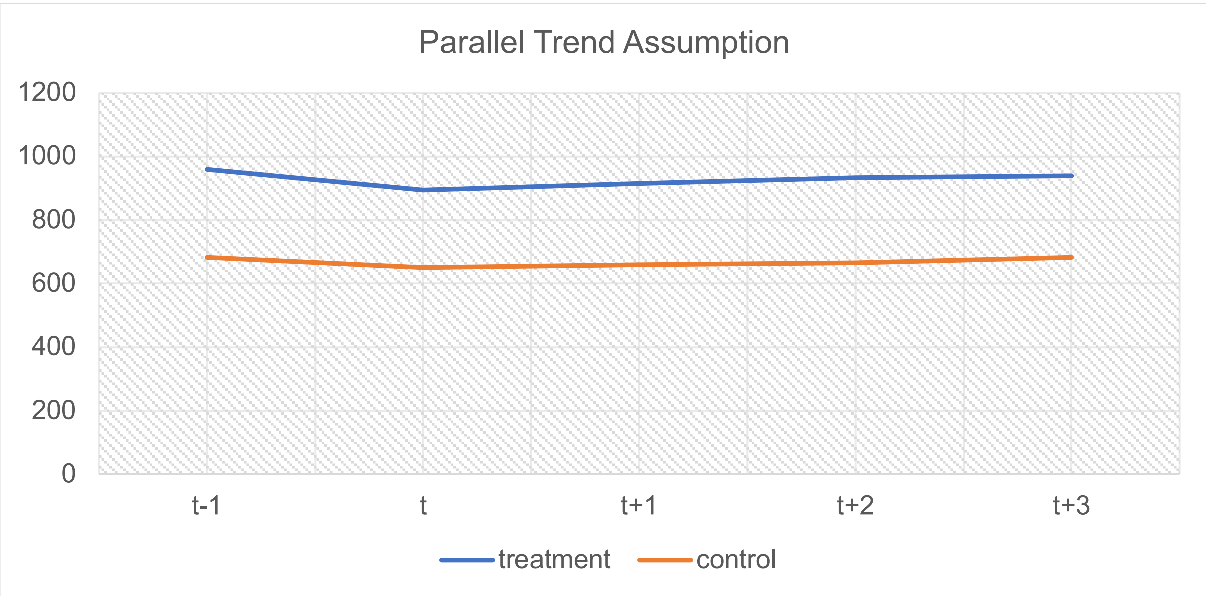

Figure 4: Parallel Trend Assumption

Note: The innovation in the treatment group would have had a parallel trajectory to the innovation of the control group, in the absence of the M&A (treatment).

3.5 Patent Density Estimate

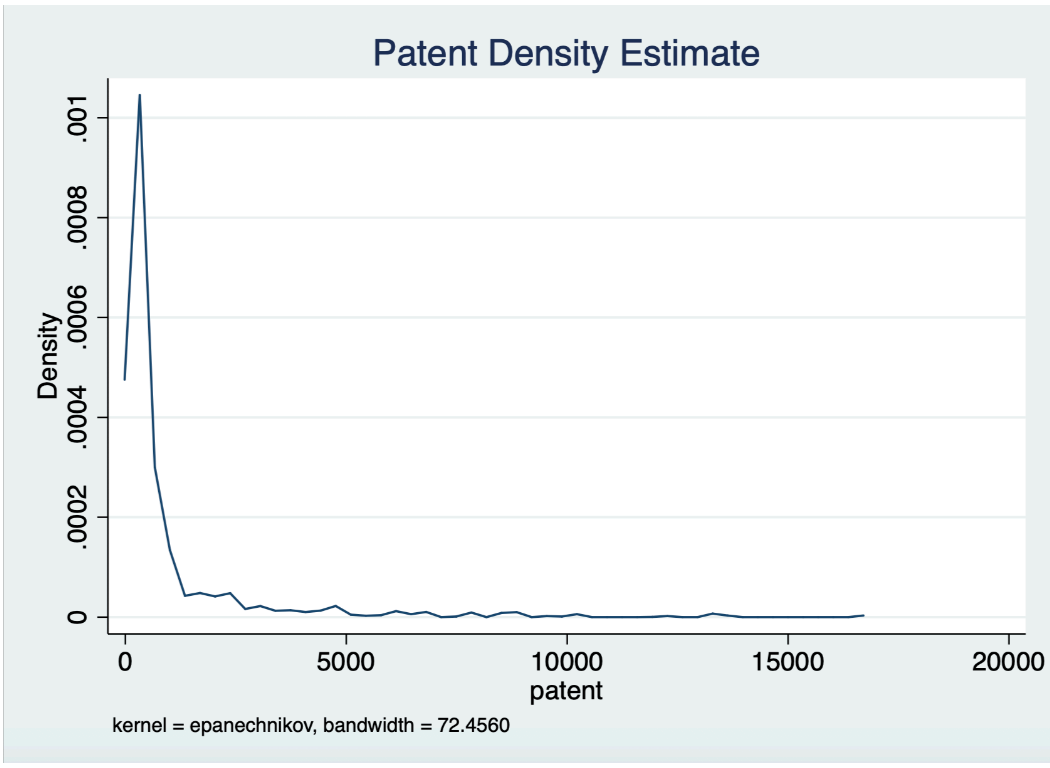

Figure 5: Patent Density Estimate

Note: The patent variable is highly right skewed. When the natural logarithm of patents is used, the distribution is normalized.