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From Motivation to Innovation: Examining the Impact of Technological and Non-Technological Acquisitions in the U.S. High-Tech Sector

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Abstract

This study examines the impact of technological and non-technological acquisitions on the innovation performance of companies in the U.S. high-tech industry. Previous literature shows mixed results regarding the impact of acquisitions on both innovation input and output, with most empirical research focusing on data from companies within a single sector. This study contributes to the literature by creating a recent panel dataset consisting of companies from four sectors of the high-tech industry from 2000 until 2019, the four industries studied in this paper are Pharmaceutical and Medicine Manufacturing (NAICS 3254), Semiconductor and Other Electronic Component Manufacturing (NAICS 3344), Computer and Peripheral Equipment Manufacturing (NAICS 3343) and Computer Systems Design and Related Services (NAICS 5415). Furthermore, a staggered Difference-in-Difference (DID) approach is used to test the impact on the innovation input, providing more robust results than the often-used Two Way Fixed Effect (TWFE) models. To test the impact on innovation output, a Poisson QMLE model is used. The findings of this paper provide evidence that technological acquisitions positively impact innovation input and output post-acquisition, while no significant impact is found for non-technological acquisitions. Additionally, the findings suggest that larger firms are more efficient in incorporating the acquired knowledge leading to a higher innovation output.

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Chapter 1

Introduction

In 2023, companies globally engaged in mergers and acquisitions (M&A) deals worth a total of 3.2 trillion dollars (Bain and Company, 2024) this large amount of resources spend on M&A highlights the importance of M&A deals for companies. The motivations behind acquisitions are diverse, with some companies aiming to enter new markets and others seeking to acquire new technologies and knowledge (Ahuja and Katila, 2001; Ranft and Lord, 2002). By acquiring new technologies, firms aim to enhance their market power through improved technological capabilities (Schweizer et al., 2023; Uhlenbruck et al., 2006). This paper investigates the post-acquisition impact of technological and non-technological acquisitions on the innovation input and output of acquiring firm across four different sectors in the U.S. high-tech industry.

Firms are constantly seeking methods to enhance their competitive advantage. Innovation is a key method which often involves large investments in Research and Development (R&D). The United States, having the highest private R&D expenditures worldwide, with an estimated value of 885.6 billion USD in 2022, saw an increase of 12% compared to 2021, with the business sector performing 78% of the total R&D expenditure (National Science Foundation, 2024). The high-tech industry, characterized by rapid innovation and a constantly changing business environment, is particularly notable for its high R&D expenditure. Specifically, the four industries studied in this paper are Pharmaceutical and Medicine Manufacturing (NAICS 3254), Semiconductor and Other Electronic Component Manufacturing (NAICS 3344), Computer and Peripheral Equipment Manufacturing (NAICS 3343) and Computer Systems Design and Related Services (NAICS 5415) who collectively accounted for more than 40% of the total U.S. R&D expenditure in 2022 (National Science Foundation, 2024).

Firms employ M&A not only as a strategy for market expansion but also as a means to acquire new technologies, thereby boosting their innovative capabilities (Cassiman et al., 2005). There is also evidence that firms use M&A as a substitute for direct investment in R&D (Hitt et al., 1990; Phillips and Zhdanov, 2012). Following the framework estab-

lished in previous studies e.g. (Ahuja and Katila, 2001; Schweizer et al., 2023), this paper differentiates between M&A deals driven by technological and non-technological motives. The main aim of Non-technological acquisitions are market expansion or improving operational processes, while technological acquisitions aim to obtain new technologies and knowledge (Schweizer, 2005). Consistent with prior research, an acquisition is classified as technological if the acquired company was granted at least one patent in the five years prior to the acquisition (Ahuja and Katila, 2001; Cloodt et al., 2006).
Given the importance of acquisitions in the high-tech industry and the mixed findings in the literature on the outcome of M&As (de Man and Duysters, 2005; Rossi et al., 2013) this study aims to fill the gap in understanding how acquisitions impact the innovation input (measured by R&D intensity) and output (measured by annual granted patents) of the acquiring firm. By examining the impact of both technological and non-technological acquisitions on innovation input and output within different sectors from the U.S. high-tech industry.

To examine the impact of non-technological and technological acquisitions on the R&D intensity of the acquiring firm this study uses a staggered Difference-In-Difference (DID) approach as introduced by Callaway and Sant'Anna (2021). The method addresses the limitations associated with the traditional To Way Fixed Effect (TWFE) methodology, particularly issues related to negative weighs in TWFE. The results from this analysis support the hypothesis that technological acquisitions increases R&D intensity post-acquisition, a 66.7% increase has been found. Whereas no statistically significant effect is found for non-technological acquisitions.

To analyze the impact on the number of annually granted patents post-acquisition, a Poisson Quasi-Maximum Likelihood Estimation (QMLE) method is employed. The findings indicate that a technological acquisition leads to a 6-8% increase in the number of patents granted post-acquisition, whereas no significant effect is observed for non-technological acquisitions. For a deeper understanding of the impact of acquisitions, this study also examines the differential impact of technological acquisitions between large and smaller firms. The results show that technological acquisitions conducted by larger firms leads to 24.4% higher number of patents, in the first year after the acquisition compared to those conducted by smaller firms. This suggests that larger firms are better able to incorporate the acquired knowledge.

To validate the robustness of the results, several robustness checks are employed. For the impact on R&D intensity, a placebo test randomly assigns technological acquisitions to the treatment group, a second analysis examines the effect of the second (non-)technological acquisition and a third check investigates potential anticipation effects. These robustness checks support the initial findings, enhancing their reliability. For the impact on patents, robustness checks include using a Negative Binomial regression, examining the total number of technological acquisitions and applying the staggered DID method by Callaway and Sant'Anna (2021). These checks also support the initial findings, increasing confidence in the results.

The findings of this study are of interest for firms aiming to improve their innovation performance as well as to policymakers. The insights can help policymakers make better informed decisions regarding the approval of acquisitions under antitrust regulations. Due to the positive impact of technological acquisitions on innovation, policies could be less strict for these type of acquisitions to stimulate innovation. In addition to direct R&D investments, this paper shows that technological acquisitions can be a valuable part of the firm's innovation strategy.

The remainder of this paper is structured as follows: Chapter 2 presents a literature review elaborating on the existing research on M&A and innovation. Chapter 3 discusses the relevant economic theory and introduces the hypotheses. Chapter 4 details the methodology used to test the hypotheses and elaborate on the data used. Chapter 5 presents the results of the empirical analysis, followed by the robustness checks in Chapter 6 to ensure the reliability and validity of the findings. Finally Chapter 7 provides the limitations, suggestions for future research and the conclusion, with a discussion of the main findings and implications for practice and policy.

Chapter 2

Literature Review

M&A and innovations can serve as key strategies for companies aiming to increase their growth and enhance their competitive advantages (Galende, 2006; Porter, 1990). Understanding the impact of an acquisition on a company's innovation process is therefore important. Despite this importance, the number of studies that examine the direct relationship between M&A and innovation remains small, with findings often presenting mixed outcomes (de Man and Duysters, 2005; Rossi et al., 2013). This section synthesizes the existing literature to offer a clear understanding of the dynamics between M&A and R&D processes.

The relationship between M&A and R&D is complex and depends on several factors. On the one hand, M&A can lead to economies of scale and scope in R&D, encouraging firms to intensify their R&D activities (Cassiman et al., 2005; de Man and Duysters, 2005; Hitt et al., 1991; Rossi et al., 2013). On the other hand, some studies (Haucap et al., 2019; Hitt et al., 1991) suggest that acquisitions might negatively impact both R&D input and output. Hitt et al. (1991) argues that acquisitions have a negative impact on both the R&D input and output. Consequently, acquisitions do not always have a positive impact on the performance of a firm, since according to Franko (1989) the long-term performance of a company is related to the company's R&D investments. The main reason R&D input and output are affected by acquisitions is due to a shift in managerial focus (Ahuja and Katila, 2001; Hitt et al., 1991).

Hitt et al. (1991) argues that, contrary to R&D investments acquisitions will have an immediate benefit for the company. For example when a company enters a new market this can lead to an increase in profit in the short term, where investments in R&D will pay off in the long term. Furthermore, Hitt et al. (1990) argues that acquisitions lead to an increase in risk-aversion by a firm's management. Consequently, the focus can shift away from R&D investments. This is supported by the empirical analysis conducted by Hitt et al. (1991) and a more recent paper by Haucap et al. (2019), showing that acquisitions have a negative effect on R&D intensity and patent intensity, which are used as the innovation input and output measures. However, these results are opposed by empirical research by Liu (2022) who shows using a broad dataset consisting of public and private companies, that acquiring companies increase their innovation output post-acquisition, using the knowledge received from the acquisition. This shows that there are often mixed findings in the research on the direct impact of acquisitions on the innovation performance of firms (de Man and Duysters, 2005; Rossi et al., 2013). However, it is important to note that Haucap et al. (2019); Hitt et al. (1991); Liu (2022) do not distinguish between technological acquisitions and non-technological acquisitions.

The reason why it is important to make this distinction is because technological acquisitions have as aim to increase a firm's innovation capacity. Hence, one would expect that the management's focus on innovation would at least be the same after the technological acquisition. This is supported by Ahuja and Katila (2001) who studied the impact of technological acquisitions on the output of innovation. They conducted an empirical analysis of 72 leading companies in the chemical industry between 1980 and 1991. From their analysis it follows that technological acquisitions can increase the innovative performance of a company, measured by the number of patents post-acquisition. The effect of technological acquisition on a company's innovation performance depends on the size of the knowledge base obtained through the acquisition. A larger knowledge base enhances performance by allowing more combinations of existing and new knowledge. However, the relative size has a negative effect on the innovation performance (Ahuja and Katila, 2001). The reason for this is because a relatively large knowledge base will demand a lot of time and resources of the company to integrate this knowledge base. As a result, less resources will be available for innovation (Ahuja and Katila, 2001; Cloodt et al., 2006). Ahuja and Katila (2001) argue that on the one hand, the acquisition increases the knowledge base of the acquiring company, thereby creating the possibility of recombining existing and newly acquired knowledge, which can lead to potential new innovations (Schumpeter, 1942). On the other hand Ahuja and Katila (2001) argues that due to the disruption in the innovation routines for both companies, innovation output might decrease post-acquisition.

The importance of post-acquisition management is also highlighted in the research conducted by Puranam and Srikanth (2007). They show that management should determine the extent of integration for the acquired company, based on the goal of the acquisition. After extensive integration, the acquiring company will improve its ability to use the knowledge from the acquired company in order to facilitate the sharing of knowledge and coordination by the management. However, Puranam and Srikanth (2007) argue that this will decrease the innovation capabilities for future inventions of the acquired company, due to the disruption in their routines.

Previous research by Cassiman et al. (2005) finds a mixed impact of a technological acquisition on R&D input and output. Based on interviews with key personnel, involving 31 M&A deals in medium and high-tech companies, they conduct an in-depth analysis using a case study design. They found that the market and technological relatedness between the acquiring and target company influences the impact of an acquisition, specifically when the companies have complementary technologies, they experience an increase in R&D performance. Conversely, when the technologies are substitutes, R&D performance tends to decline post-acquisition. If the deal is between competitors in the same market, the decrease in R&D levels is even more evident.

In conclusion, the impact of an acquisition on innovation performance finds mixed results from the literature. When assessing the direct impact, research by Hitt et al. (1991) and Haucap et al. (2019) finds a direct negative impact of acquisitions on the innovation input and output of firms, while others find a positive direct impact (Liu, 2022). Studies focusing the on conditions when M&A could improve innovation performance find mixed results (de Man and Duysters, 2005). For example, Ahuja and Katila (2001) and Puranam and Srikanth (2007) indicate that the impact can be positive. However, this positive outcome depends upon several factors such as the relatedness of the acquired technology and the management decisions made during the integration process.

This paper aims to fill the gap between the two types of research on M&A and innovation, as mentioned by de Man and Duysters (2005): studies that examine the direct impact of acquisitions on innovation (e.g. Hall et al. 1990; Haucap et al. 2019; Hitt et al. 1991; Liu 2022) and studies that examine conditions under which acquisitions can positively impact a firm's innovation performance (e.g. Hagedoorn and Duysters 2002; Puranam and Srikanth 2007). An important heterogeneity between acquisitions are the motives behind the acquisitions (Bower, 2001; Ranft and Lord, 2002; Schweizer, 2005). However studies examining the direct impact of acquisitions typically consider acquisitions in general and do not take this heterogeneity into account (Bower, 2001; Haucap et al., 2019; Hitt et al., 1991). As a result, Bower (2001); Schweizer (2005) argue that this leads to an overgeneralization when examining the impact of technological acquisitions.

Therefore this paper will use the framework of technological and non-technological acquisitions (Ahuja and Katila, 2001; Cloodt et al., 2006; Puranam and Srikanth, 2007) and examine the impact of both types of acquisitions on the innovation input and output of the acquiring firm. To the best of my knowledge, this paper is the first paper to investigate both the impact on input and output for technological and non-technological acquisitions. This has as benefit that the results can be compared and the different impacts of both type of acquisitions, give an possible explanation of the often mixed findings in the literature (de Man and Duysters, 2005; Haucap et al., 2019; Liu, 2022; Rossi et al., 2013). Additionally, the study investigates the distinctions between larger and smaller acquiring firms in the used dataset, to further improve the understanding of acquisitions.

Chapter 3

Theory

3.1 Innovation

This section explores the main motives behind corporate investments in innovation, the challenges associated with capitalizing on these investments and the mechanisms companies employ to protect and benefit from their innovations.

Innovation is a critical driver of economic growth and competitive advantage for companies (Hall, 1993; Porter, 1990; Schumpeter, 1934). Despite its importance innovation has not always received academic attention (Fagerberg, 2013). The academic focus on innovation and acknowledge of the importance of innovation in the development of the economy started with Schumpeter (1934).

The technological knowledge of a company, combined with its ability to innovate, is one of its most valuable resources (Galende, 2006). Companies primarily invest in innovation to enhance their performance, as it serves as a key driver of sustained competitive advantage. This is important since a competitive advantage ultimately leads to increased profitability (Hall, 1993; OECD, 2005).

To achieve this, firms must be able to capitalize on their innovations, because it is only profitable for a firm to invest in innovation if profits rise as a result. However, once an innovation becomes publicly available, a firm cannot prevent others from using it. Often imitators profit the most from the innovation (Teece, 1986). This inability to capture the value created by an innovation underscores the importance of appropriate mechanisms to encourage innovation activities, by protecting the intellectual property rights (OECD, 2005). To mitigate the risks associated with value appropriation, companies often rely on intellectual property rights such as patents, trademarks and copyrights. Patents play a crucial role in protecting innovations by granting inventors exclusive rights to their inventions for a specified period (Hall and Harhoff, 2012). This exclusivity prevents competitors from using their innovations without authorization, thereby securing a competitive advantage and help receiving positive returns on their investments. This mechanism addresses the issue highlighted by (Teece, 1986), where imitators often profit more from an invention than the inventors themselves.

3.2 Mergers and Acquisitions

Companies not only use innovation to maintain their competitive advantage but also engage in M&A deals. M&A deals are strategic business decisions where a firm acquires the entire or specific parts of another firm (Cassiman et al., 2005).

There are several motivations for companies to engage in M&A. One common strategy is market expansion, whereby a firm acquires another company in a market that it seeks to enter. This approach allows the acquiring firm to leverage the existing market knowledge and customer base of the acquired company. Another reason to acquire a company is to increase market power (Schweizer, 2005). By acquiring a competitor or another firm within the same industry, a company can consolidate its position, reduce competition and potentially increase its pricing power and market influence (Ahuja and Katila, 2001; Hagedoorn and Duysters, 2002; Schweizer, 2005).

This study examine technological acquisitions, where the primary motivation is to enhance the innovation capabilities of the acquiring company. In such cases, firms acquire companies with advanced technological assets, intellectual property, or R&D capabilities, thereby accelerating their own innovation processes (Puranam and Srikanth, 2007; Schweizer, 2005). Additionally, to provide a comprehensive comparison and a deeper understanding of acquisitions' effects, this study also examines the impact of non-technological acquisitions. By including both types of acquisitions, the research aims to further clarify the different mechanisms through which acquisitions influence innovation.

3.3 Resource Based View

The Resource-Based View (RBV) theory, introduced by Wernerfelt (1984), provides a framework for understanding how innovation and M&A deals can align within a company's innovation strategy. The RBV emphasizes the importance of internal resources such as R&D capabilities, highlighting that unique resources are important for sustaining a competitive advantage. Consequently, a company's innovation capabilities results from unique internal intangible assets rather than assets readily available outside the firm (Barney, 1991; Galende, 2006; Uhlenbruck et al., 2006). If such resources were widely accessible to other companies, any competitive advantage would disappear (Galende, 2006).

The RBV distinguishes between two types of resources: tangible resources, such as physical assets like machinery and intangible resources, like patents and know-how (Wernerfelt, 1984). In the context of innovation the intangible like the innovation process of a firm, are particularly important. These resources are difficult to sell independent on the market because the resources are integrated into the firm itself. The only way to acquire those intangible resources is by purchasing the entire firm (Galende, 2006; Wernerfelt, 1984). Therefore a company's innovation capability must be developed internally and cannot be simply bought on the open market. The only exception is through the acquisition of another company, whereby intangible assets are integrated into the acquiring firm (Eisenhardt and Martin, 2000; Makadok, 2001; Uhlenbruck et al., 2006). Consequently, acquiring companies for their technological knowledge or innovation capabilities can be a key component of a company's innovation strategy.

3.4 Development of Hypotheses

3.4.1 Economies of Scale and Scope

Economies of Scale can be used to explain how M&A influence a company's R&D strategy. In R&D, economies of scale are realized when fixed costs, such as those associated with research facilities and personnel can be distributed across a larger output, such as an increased number of patents. An M&A deal aimed at enhancing a company's R&D capabilities offers the advantage of eliminating redundant R&D resources post-acquisition (Cassiman et al., 2005). This cost elimination leads to a more cost-efficient R&D process. Furthermore, post-acquisition restructuring often involves centralizing knowledge from both companies, which aligns with Schumpeter (1934) theory that innovation is driven by the recombination of existing knowledge and learning. This integration of knowledge bases can catalyze synergies, resulting in higher R&D output.

The reduced cost per R&D output is achieved by spreading fixed costs over a larger output, as a consequence the expected profit of an R&D investment will increase. This creates an incentive for management to place greater focus on innovation. Additionally, (Henderson and Cockburn, 1996) show in their study of the pharmaceutical industry that economies of scope generated more cost efficiencies than the removal of redundant resources. This was primarily due to the free flow of information within larger companies, where the interaction between various R&D projects had a more substantial positive impact than the cost reductions achieved through economies of scale. Due to the higher expected profit from R&D projects, management is likely to prioritize innovation following a technological acquisition (Cassiman et al., 2005). Which leads to the first hypothesis:

Hypothesis 1a *A technological acquisition increases the innovation input of the acquiring company post-acquisition.*

However, acquiring a company costs significant financial resources that therefore can not be used for innovation. Even if the firm has enough resources to do both, integrating an acquired company requires significant management attention, due to the integration of new resources, systems and people, potentially shifting the focus of the management away from innovation (Ahuja and Katila, 2001; Hitt et al., 1990). Using this argumentation, the following hypothesis is proposed:

Hypothesis 1b: *Non-technological acquisitions will have a negative impact on the innovation input of the acquiring firm.*

In addition to economies of scale, the larger size of a company's knowledge base also enhances the efficiency of the R&D process through economies of scope. Economies of scope arise when a diversified portfolio of R&D projects allows for significant knowledge spillovers between different projects, which can be beneficial as the recombination of this knowledge can lead to new inventions (Schumpeter, 1934).

It is important to study the post-acquisition changes in the number of patents, since the main motivation of technological acquisitions is to increase the innovation performance of a firm (Schweizer, 2005). Especially since empirical studies show mixed outcomes of the impact of a technological acquisition on the innovation performance of a company (Ahuja and Katila, 2001; Cassiman et al., 2005; de Man and Duysters, 2005; Hitt et al., 1991). Therefore, this study proposes the following hypothesis to empirically test the impact of technological acquisitions on the number of granted patents:

Hypothesis 2a: *A technological acquisition increases the innovation output of the acquiring company post-acquisition.*

In contrast to technological acquisitions, non-technological acquisitions are likely to have different effects on the innovation output since their primary focus is not on enhancing the acquiring company's knowledge base (Schweizer, 2005). Similar to the argument made previously, due to a shifting focus away from innovation by the management, a negative impact could be expected (Hitt et al., 1990; Hoskisson et al., 1994). However, it is more nuanced since non-technological acquisitions do not directly influence the innovation process of the acquiring firm, unlike technological acquisitions (Ahuja and Katila, 2001). Therefore, it is possible that non-technological acquisitions might not significantly impact a firm's innovation input and output, leading to the following hypothesis:

Hypothesis 2b: *Non-technological acquisitions will have either a negative or no impact on the innovation output of the acquiring firm.*

The success of a technological acquisition also depends on the acquiring company's ability to utilize the acquired knowledge effectively (Cohen and Levinthal, 1990). Literature suggests that post-acquisition management plays a significant role in the success rate of the acquisition (Puranam and Srikanth, 2007). Extensive resources enable firms to allocate the necessary infrastructure and capabilities to support integration processes. Additionally, large firms benefit more from the synergies created by economies of scale and scope, as they can spread fixed costs over a larger output and leverage diversified portfolios of R&D projects for significant knowledge spillovers. This is confirmed by empirical research which shows that research programs within large firms have a higher output because they can capitalize on these synergies (Cohen and Levinthal, 1990). Therefore, the following hypothesis is proposed to test if this view can be extended to the incorporation of newly acquired technologies:

Hypothesis 3: *Larger companies will experience a greater impact on innovation output after a technological acquisition compared to smaller companies.*

Chapter 4

Methodology

4.1 Data

The dataset comprises of high-tech companies located in the US. This research specifically looks at large established companies, which is in line with previous research (e.g. Puranam and Srikanth (2007); Ranft and Lord (2002)). In order to select the companies the following selection criteria are used, the company should have a minimum EBITA of 5 billion USD and the company should be publicly listed. The reason this paper only looks at publicly listed companies is due to the availability of data. The companies in this dataset are operating within four high-tech sectors, classified according to the NAICS 2022 codes: 3254 (Pharmaceutical and Medicine Manufacturing), 3343 (Computer and Peripheral Equipment Manufacturing), 3344 (Semiconductor and Other Electronic Component Manufacturing) and 5415 (Computer Systems Design and Related Services). I have specifically chosen companies in these four high-tech sectors since these sectors are characterized by companies that use M&A deals in order to acquirer knowledge and these industries are known for their high patent activity (National Science Foundation, 2024; Puranam and Srikanth, 2007).

I gathered data for each company from the Orbis database and used the Orbis M&A database, formerly known as Zephyr, to identify the acquisitions made by these companies. Companies without available data were excluded from the dataset, resulting in a total of 43 companies that completed 394 acquisitions. Of these 394 acquisitions, 200 are identified as technological acquisitions and 194 as non-technological acquisitions, highlighting the strategic importance of technological acquisitions in these industries. My study covers the period from 2000 to 2019, for which I collected data annually for each acquiring company.

4.1.1 Variables

Dependent Variables:

R&D Intensity:[1] Measured as the ratio of R&D expenditure to EBITA (Cloodt et al., 2006; Puranam and Srikanth, 2007), this variable captures the investment in R&D relative to the size of the company. R&D intensity is used as a measure for the innovation input. The R&D intensity was calculated using company data from Orbis. For the regressions the logarithm of the R&D intensity is used because the density of the R&D intensity is positive skewed, for details see the descriptive statistics section.

Number of Patents: To measure the innovation output of the companies I use annual granted patents, as it is commonly used as a measure for innovation output (Ahuja and Katila, 2001; Cloodt et al., 2006; Hitt et al., 1991; Puranam and Srikanth, 2007). The reason I use granted patents as a measure of innovation output is based on the distinction between invention and innovation. Innovation is the successful commercialization of an invention (Fagerberg, 2013). A patent application indicates a potential invention, but it does not guarantee that the invention will be feasible, valuable, or successfully brought to market. Granted patents, on the other hand, indicate a higher likelihood that the invention has practical applications and commercial potential since it is already granted. Furthermore, studies have show that there is a strong relationship between granted patents and other used measures for innovation such as creating new product and once patents are granted a large part will be commercialized (Comanor and Scherer, 1969; Griliches, 1990). The U.S. high-tech sector is characterized by high patent activity to protect their innovations Webb et al. (2018).

Explanatory Variable:

Technological Acquisition: is the explanatory variable in my research. The variable is a binary variable indicating whether the acquisition is classified as technological (1 if technological, 0 otherwise). An acquisition is classified as technological if the acquired company has had any patents granted in the five years prior to the acquisition (Cloodt et al., 2006). If a firm acquired a department of another company, the acquisition was labeled as technological if patents were mentioned as part of the deal. The M&A deals between the acquiring company and the target are drawn from the Orbis M&A dataset and the patent data of the acquired firm is drawn from Orbis. This paper also incorporates lagged versions of this variable, spanning from one year to four years, to examine the impact of technological acquisitions over time.

[1] R&D Intensity is also used as a control variable in the Poisson QMLE regression that examines the impact of (non-) technological acquisitions on the number of annual granted patents.

Non-Technological Acquisitions: Acquisitions that did not meet the criteria for being labeled as technological acquisitions, as explained above, were labeled as non-technological acquisitions. Similar to technological acquisitions, lagged variables of non-technological acquisitions are also utilized.

Control Variables:

Size: According to Schumpeter (1934) large firms are more innovative than small firms, therefore the size of a firm could influence both the R&D input and output. Furthermore, Hitt et al. (1990) argues that there is a strong relationship between the size of a firm and the R&D of a firm. To control for this effect this research uses the logarithm of the number of employees as a control for a firm's size and operational capacity (Ahuja and Katila, 2001; Cloodt et al., 2006; Hitt et al., 1991).

R&D Intensity: Using the same definition for R&D intensity as mentioned earlier, this variable is included as a control in the Poisson QMLE regression. Including R&D intensity as a control variable helps asses the effect of the (non-) technological acquisition on innovation output. This control accounts for the possibility that any observed increase in post-acquisition innovation output might be driven by an increase in innovation input (R&D intensity) following the acquisition Ahuja and Katila (2001); Cloodt et al. (2006). Therefore, by controlling for R&D intensity, the true impact of the acquisition on innovation performance will be assessed more accurate.

Fixed effects: Despite the fact that all four industries are from the U.S. High-Tech sector, sector dummy variables are included to control for structural differences in R&D and patent activity between the industries (Cloodt et al., 2006). To control for the yearly trends, year fixed effects are included in the regression. Lastly, to control for yearly industry specific trends the interaction term between industry and year fixed effects is included.

Correlation Table

Table 4.1.1 shows the correlation of the variables used to test the hypotheses of this research. In general the correlations between the variables are low, raising no concerns regarding multicollinearity. There is only a moderate correlation between the size of the firm and the number of patents, indicating that larger firms have higher patent activity in general.

Table 4.1: Correlation Matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Number of patents	1.0000												
2. Technological Acquisition	0.2501	1.0000											
3. Technological Acquisition$_{t-1}$	0.2502	0.1530	1.0000										
4.Technological Acquisition$_{t-2}$	0.2685	0.2193	0.1431	1.0000									
5. Technological Acquisition$_{t-3}$	0.2515	0.2599	0.2527	0.1519	1.0000								
6. Technological Acquisition$_{t-4}$	0.2520	0.1889	0.2352	0.2575	0.1529	1.0000							
7. Non-Technological Acquisition	0.1406	-0.2093	0.0171	0.0295	0.0224	-0.0082	1.0000						
8. Non-Technological Acquisition$_{t-1}$	0.1383	0.0822	-0.2100	-0.0159	0.0055	0.0202	0.0846	1.0000					
9. Non-Technological Acquisition$_{t-2}$	0.1201	0.0391	0.0684	-0.2161	-0.0059	-0.0318	0.1522	0.1349	1.0000				
10. Non-Technological Acquisition$_{t-3}$	0.1297	0.0093	0.0130	0.0537	-0.2369	-0.0292	0.2113	0.1911	0.1622	1.0000			
11. Non-Technological Acquisition$_{t-4}$	0.1445	0.0272	0.0323	-0.0023	0.0390	-0.2362	0.1777	0.2211	0.2048	0.1731	1.0000		
12. Size	0.4638	0.2684	0.2505	0.2463	0.2470	0.2411	0.1386	0.1526	0.1561	0.1535	0.2031	1.0000	
13. Log(R&D)	0.0611	0.0656	0.0547	0.0731	0.0788	0.0662	0.0290	-0.0135	-0.0494	-0.0245	-0.0365	-0.2695	1.0000

Descriptive Statistics

Table 4.1.1 provides the descriptive statistics of the panel data used in this research. In Appendix A Figure A.1 shows the density of the R&D. From this follows that the data is positively skewed. Therefore will the log transformation of the R&D density be used as dependent variable. Figure A.2 shows the density of the number of patents. To test the impact of technologial and non-technological acquisitions a Poisson QMLE method, a count model is used. Therefore it is not necessary to use a log transformation for the number of patents (Wooldridge, 2012). Furthermore, since 2.1% of the number of patents has the value zero the data is not zero inflated.

Table 4.2: Descriptive Statistics

	N	**Mean**	**SD**	**Min**	**Max**
Tech Acquisition	734	0.208	0.406	0	1
#Technological Acquisitions	734	0.272	0.600	0	5
Non-Tech Acquisition	734	0.137	0.345	0	1
#Non-Technological Acquisitions	734	0.264	1.071	0	17
R&D Expenses	734	2,005	2,704	3	16,217
R&D Intensity	734	0.665	0.853	0.006	7.29
Log(R&D)	734	-0.932	1.073	-5.050	1.987
# Employees	734	42,883	65,170	92	434,246
# Patents	693	1,231	1,859	0	10,534
EBITA	734	5,159	9,406	2,864	81,801
Size	734	9.878	1.364	4.522	12.98

Notes: The table provides the descriptive statistics of the panel dataset used to test the impact of (non-)technological acquisitions on the number of patents. Tech Acquisition is a binary variable equal to one if a firm made a technological acquisition in year t. An acquisition is defined as technological if the acquired firm had at least one granted patent three years prior to the acquisition. #Technological Acquisitions are the number of technological acquisition a company made in year t. Non-Tech Acquisition, is a binary variable that equals one if the acquisition did not meet the criteria of being labelled as technological. #Non-Technological acquisitions are the number of non-technological acquisitions a company made in year t. R&D Expenses are the R&D investments made by a company in year t, measured in million USD. R&D Intensity is defined as R&D expenses divided by EBITDA in year t. Log(R&D) is the logarithm function of R&D intensity. #Employees represents the total number of employees a firm has in year t. #Patents represents the number of patents granted to a firm in year t. EBITDA is the EBITDA of a firm in year t, denoted in million USD. Size is the logarithm of the number of employees.

4.2 Methodology

4.2.1 DID Callaway & Sant'Anna

Testing the impact of a technological or non-technological acquisition on R&D intensity using traditional Ordinary Least Squares (OLS) regressions can lead to biased estimates due to endogeneity issues (Roberts and Whited, 2011). One common endogeneity problem is omitted variable bias, which can result from unobserved heterogeneity at the company level (Angrist and Pischke, 2009). While the standard DID methodology can address some of these endogeneity concerns (Angrist and Pischke, 2009), the standard DID methodology is not suitable for testing my hypothesis because the companies in my dataset experience technological acquisitions (the treatment) at different times. Therefore, the staggered DID method of Callaway and Sant'Anna (2021) is more suitable as it accounts for different treatment timings and allows for heterogeneous treatment effects. Additionally, this method resolves issues associated with Two-Way Fixed Effects (TWFE) models, particularly the assumption of homogeneous treatment effects, which may lead to negative weights for long-run treatment effects that can bias treatment coefficients (Borusyak et al., 2024; de Chaisemartin and D'Haultfœuille, 2023).

In this section, I will explain the methodology and the assumptions underlying this method. The assumptions, derived from Callaway and Sant'Anna (2021), have been adapted to the context of this research.
DID is one of the most popular methods used in research for evaluating the causal effects of policy interventions. Traditionally, the DID methodology evaluates two groups over two time periods. Initially, neither group is treated and in the second time period one of the groups receives a treatment. The untreated group serves as the control group, while the other is the treated group. Under the parallel trend assumption, which states that in the absence of the treatment, the outcomes for both groups would have been the same on average, the causal effect of the treatment can be estimated using this approach.

The method introduced by Callaway and Sant'Anna (2021) offers an framework in which DID can be used with variations in treatment timing, allowing the companies to have technological acquisitions in different years. Additionally, this method provides the advantage that even if the parallel trend assumption holds only after conditioning on certain covariates, such as the industry of the companies, it can still estimate the causal effects of the acquisitions. This method, a staggered DID, ensures that once a company has received the treatment (i.e., conducted a technological acquisition), it remains in the treatment group in the subsequent periods.

Especially because the method allows for heterogeneity in the effect of the treatment, it is preferable to use this method compared to a traditional DID approach. The impact of a technological acquisition is expected to vary among different companies, making this method more suitable for capturing these variations. The method specifically examines the Average Treatment Effect for a group g at time t (ATT(g,t)). In my dataset, a group consists of companies that conducted a technological acquisition in a particular year. For instance, one group includes all companies that made their first technological acquisition in 2005, while a different group includes those that did so in 2006. Additionally, this method accounts for the possibility that the treatment effect evolves over time. For example, the impact of a technological acquisition may diminish after a few years as the acquired knowledge is fully utilized.

Before the staggered DID method can be applied, a few assumptions are needed. Prior to introducing these assumptions, some notations should be discussed. Let T be the number of time periods, since the research period spans from 2000 to 2019, T will equal to 20. Let $\mathrm{D}_{i,t}$ be a binary variable that equals one if unit i is treated in period t, otherwise this variable equals zero. Hence, if $\mathrm{D}_{i,t}$ equals one in my dataset for the first time, it indicates that company i did a technological acquisition in time period t. This leads to the first assumption (Callaway and Sant'Anna, 2021).

Assumption 1 (Irreversibility of Treatment)

$\mathrm{D}_1 = 0$, For t $=2, ..., T$
$\mathrm{D}_{t-1} = 1$ implies that $\mathrm{D}_t = 1$

This assumption is called the staggered treatment adoption, meaning that once a unit is treated it remains treated in the subsequent time periods. This assumption is likely to hold in this papers research since, once a company has conducted a technological acquisition (the treatment), the knowledge gained from the acquisition is expected to persist over time.

To introduce the second assumption, some additional notation is necessary. In order to create different groups of companies for the staggered DID, let G represent the first time period in which a company conducts a technological acquisition. The variable G will denote the group to which a company belongs. For example, if $G = 2005$, this group consists of all companies that undertook their first technological acquisition in 2005. If a company does not conduct any technological acquisition during the study period, G will equal to infinity.(Callaway and Sant'Anna, 2021). Let G_g be a binary variable that equals one if a company made a technological acquisition in period g, which can be denoted as $G_{i,g} = \mathbf{1}_{\{G_i=g\}}$. Let C be a binary variable that equals one for all companies that did not a technological acquisition during the study period, hence $C_i = \mathbf{1}_{\{G_i=\infty\}} = 1 - D_{i,T}$.
Let $Y_{i,t}(0)$ denote company i's untreated potential outcome at time t if they did not conduct any technological acquisitions during the study period. For g = 2,...,T let $Y_{i,t}(g)$

denote the potential outcomes accounting for potential dynamic treatment selection. This gives the relationship between observed and potential outcomes for each company i as:

$$Y_{i,t} = Y_{i,t}(0) + \sum_{g=2}^{T} (Y_{i,t}(g) - Y_{i,t}(0)) \cdot G_{i,g} \tag{4.1}$$

This means that only one potential outcome for each company is observed. For companies that do not undertake any technological acquisitions, all observed outcomes are the untreated potential outcomes in all periods. For the companies that do conduct a technological acquisitions during the study period, observed outcomes correspond to the company's specific potential outcome for the particular time period in which the acquisition occurred. This leads to the second assumption (Callaway and Sant'Anna, 2021):

Assumption 2 (Random Sampling)

$$\{Y_{i,1}, Y_{i,2}, \ldots, Y_{i,\tau}, X_i, D_{i,1}, D_{i,2}, \ldots, D_{i,\tau}\}_{i=1}^{n} \tag{4.2}$$

is independent and identically distributed.

This implies that panel data is used and assumption 2 states that all potential outcomes can be seen as random.
The treatment effect parameter in this research is the group time average treatment effect (ATT(g,t)) for companies who are member of a specific group g at a particular time period t. Hence the ATT(g,t) refer to the group of companies that all made a technological acquisition in time period t. This can be denoted as $ATT(g,t) = \mathbb{E}[Y_i(g) - Y_i(0) \mid G_g = 1]$ An advantage of the ATT(g,t) is that is does not impose any limitations on treatment effect heterogeneity across different groups or time-period (Callaway and Sant'Anna, 2021).

The following assumptions are proposed by Callaway and Sant'Anna (2021) to identify the ATT(g,t)'s and their functionals.

Assumption 3 (Limited Treatment Anticipation)

There is a known $\delta \geq 0$ such that

$$\mathbb{E}[Y_i(g) \mid X, G_g = 1] = \mathbb{E}[Y_i(0) \mid X, G_g = 1] \tag{4.3}$$

a.s. for all $g \in \mathcal{G}, t \in \{1, \ldots, \tau\}$ such that $t < g - \delta$.

Assumption 3 states that there should be no anticipation effect among the companies. This means that a company should not adjust its R&D expenses in anticipation of an acquisition in the following period. However, according Callaway and Sant'Anna (2021); Laporte and Windmeijer (2005); Malani and Reif (2015) assumption three still holds if $\delta = 1$, indicating that there may be some anticipation effect one year before the acquisition. If the results are robust for an anticipation effect of one year is tested in the robustness section.

To use as a control group companies that did not undertake a technological acquisition between the years 2003 and 2009, the following assumption should hold (Callaway and Sant'Anna, 2021).

Assumption 4 (Conditional Parallel Trends Based on a Never Treated Group)

Take $\delta \geq 0$, For each $g \in \mathcal{G}$ and $t \in \{2, \ldots, T\}$ such that $t \geq g - \delta$

$$\mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid X, G_g = 1] = \mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid X, C = 1] \tag{4.4}$$

Assumption 4 generalizes the parallel trend assumption of the standard two-period DID method to a multiple-period and multiple-treatment groups parallel trend assumption. This assumption holds after conditioning on covariates, denoted by X in equation 4.4. In this research, the relevant covariates include the industry in which the company operates and the company's size.

Assumption 4 states that, in the absence of an acquisition, the acquiring and non-acquiring companies would have, on average, a similar outcome in R&D intensity (Callaway and Sant'Anna, 2021). The methodology employed in this paper diverges slightly from Callaway and Sant'Anna (2021). Instead of using "never treated" companies as the control group, this paper uses "later treated" companies, which made acquisition after 2009. This adjustment makes them a better control group, as both the treated and control group are active in making technological acquisitions, with the primary difference being the timing of the acquisitions. This approach addresses the concerns mentioned in Callaway and Sant'Anna (2021) regarding potential fundamental differences between the control and treatment group, as the treatment group conducts acquisitions while the companies in the control group do not. Therefore, to avoid ambiguity, the term "later treated companies" will be used throughout this paper instead of "never treated companies".

Group-time Average Treatment Effect

The parameter of interest in this research is the ATT(g,t). This section will outline the ATT(g,t) parameters used in this paper. Since as a control group the later treated companies are used and the outcome regression (OR) methodology is employed, as described by Callaway and Sant'Anna (2021) the ATT(g,t) can be denoted as follows:

$$ATT_{\mathrm{OR}}^{\mathrm{later}}(g,t;\delta) = \mathbb{E}\left[\frac{G_g}{\mathbb{E}[G_g]}\left(Y_t - Y_{g-\delta-1} - m_{g,t,\delta}^{\mathrm{never}}(X)\right)\right] \tag{4.5}$$

with $m_{g,t,\delta}^{\mathrm{never}}(X) = \mathbb{E}\left[Y_t - Y_{g-\delta-1} \mid X, C = 1\right]$

4.2.2 Staggered Difference in Difference

To test the impact of technological and non-technological acquisition on the impact of the R&D intensity of the acquiring company post-acquisition. I employ a staggered Difference-in-Differences (DID) approach. I utilize the method developed by Callaway and Sant'Anna (2021), introduced by previous chapter 4.2.1, for the following reasons. Firstly, the companies in my dataset have technological acquisitions occurring at different time periods, making a standard two-period DID unsuitable. Hence, a staggered DID approach is required. Secondly, this method allows for heterogeneous treatment effects, which is crucial since the impact of a technological acquisition on R&D intensity is likely to vary across companies and over time. Finally, the method conditions on covariates, addressing potential violations of the parallel trends assumption. To test the first hypothesis this paper uses a balanced panel data set.

This dataset is a subset of the original dataset for which the summary statistics are given in Table 4.1.1. The selection criteria is the availability of data for all periods between 2000 and 2019. Table 4.3 states the descriptive statistics of this subset and the companies that are in the subset can be found in the appendix C.2. Comparing the descriptive statistics tables shows that the overall averages in the subset are slightly higher compared to the original dataset. All averages are around the 20% higher with the exception of the average number of employees which increases from 42,883 to 54,779 an increase of around 25%. The differences between the datasets are not problematic high since the difference is smaller than the standard deviation. However the difference should be taken into account when interpreting the magnitude of the results.

I looked at acquisitions that happened between 2003 and 2009 ensuring that there is a pre- and post-acquisition period. The treatment group in this study consists of companies that made a technological acquisition between 2003 and 2009. An important deviation from the methodology proposed by Callaway and Sant'Anna (2021) is the use of ”later treated” companies as the control group, rather than ”never treated” companies. In this study, the control group comprises companies that conducted their first technological acquisition after 2010. This approach is preferred because companies that never engage in acquisitions may differ fundamentally from those that do, potentially leading to biased results. Hence, employing later treated companies provides a more accurate comparison, since acquisitions are occurring for both groups, although at different times.

Variables:

Table 4.3: Descriptive Statistics Variables of Hypothesis 1

	N	**Mean**	**SD**	**Min**	**Max**
Tech Acquisition	500	0.0860	0.281	0	1
Non-Tech Acquisition	500	0.300	0.459	0	1
R&D Expenses	500	2,323	2,863	4.839	13,543
R&D Intensity	500	0.629	1.401	0.00641	23.26
Log(R&D)	500	-1.080	0.922	-5.050	1.802
# Employees	500	54,779	74,219	392	434,246
# Patents	480	1,462	2,076	0	10,534
EBITDA	500	5,345	7,048	15.60	33,254
Size	500	10.28	1.180	5.971	12.98

Notes: The table provides the descriptive statistics of the panel dataset used to test the impact of (non-)technological acquisitions on R&D intensity (Hypotheses 1 and 3). Tech Acquisition is a binary variable equal to one if a firm made a technological acquisition in year t. An acquisition is defined as technological if the acquired firm had at least one granted patent three years prior to the acquisition. Non-Tech Acquisitions is a binary variable that equals one if the acquisitions did not meet the criteria of being labelled as a technological acquisition. R&D Expenses are the R&D investments made by a company in year t, measured in million USD. R&D Intensity is defined as R&D expenses divided by EBITDA in year t. Log(R&D) is the logarithm function of R&D intensity. #Employees represents the total number of employees a firm has in year t. #Patents represents the number of patents granted to a firm in year t. EBITDA is the EBITDA of a firm in year t, denoted in million USD. Size is the logarithm of the number of employees.

To examine the impact of technological acquisitions on the R&D intensity of the acquiring company the following equation is estimated:

$$\log(RD\_intensity_{it}) = \beta_0 + \sum_g \sum_t \beta_{gt} D_{gt} + \beta_3 X_{it} + \lambda_t + \mu_i + \epsilon_{it} \tag{4.6}$$

In equation 4.6, i indexes the acquiring company and t denotes the time period. $\log(RD\_intens_{it})$ represents the logarithm function of thr R&D intensity of firm i in year t. D_{gt} is a dummy variable that equals 1 if company i is in group g (the group of companies treated in year g) at time t and 0 otherwise. β_{gt} represents the group-time specific treatment effect, which is the parameter of interest The vector X_{it} consists of the covariates for company i at time t (such as company size and industry sector). μ_i and λ_t represents the company and time fixed effects, respectively. Finally, β_0 is the constant and ϵ_{it} is the error term. The standard errors are clustered at the company level, to account for serial correlation of the errors within companies.

As mentioned before, the treatment group consists of companies that completed a technological acquisition between 2003 and 2009. The control group consists of companies that have not undertaken a technological acquisition in the period of interest.

4.2.3 Poisson Regression

To test the impact of both technological and non-technological acquisitions on innovation output, measured by the number of annual granted patents, this study employs two separate models designed for count data. One model uses technological acquisitions as the independent variable, while the other uses non-technological acquisitions. The dependent variable in both models, the annual number of granted patents of a firm, is a non-negative integer count variable. Since count variables are not continuous, a standard linear regression model is inappropriate due to the assumption that the dependent variable should follow a normal distribution (Wooldridge, 2012). Given that annual granted patents are discrete, they cannot follow a continuous normal distribution. Therefore, a Poisson regression model is the preferred method for analyzing count data. Consistent, with prior research, this study uses a Poisson model for the above mentioned reasons (Ahuja and Katila, 2001; Henderson and Cockburn, 1996; Puranam and Srikanth, 2007; Wooldridge, 2012).
The probability density function of the Poisson distribution is given by (Bain and Engelhardt, 1992; Cameron and Trivedi, 2005):

$$P[y = x] = \frac{\mu^x e^{-\mu}}{x!} \tag{4.7}$$

where y is the number of patents granted, μ is the mean number of patents and x is a specific count of patents. From this and extending to a panel data set gives(Cameron and Trivedi, 2005; Wooldridge, 2012):

$$\mathbb{E}(y \mid x_1, x_2, \ldots, x_k) = \exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k) \tag{4.8}$$

In order to interpret the coefficients, the log of equation 4.10 should be taken which gives (Wooldridge, 2012):

$$\log(\mathbb{E}(y \mid x_1, x_2, \ldots, x_k)) = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k \tag{4.9}$$

Hence equation 4.9 is linear, therefore in order to calculate the percentage change in the expected number of patents post-acquisition ($\mathbb{E}$[Number of Patents]), let β_{acq} be the coefficient for the technological acquisition variable, then the percentage change of the number of patents would equal $(e^{\beta_{\text{acq}}} - 1) * 100\%$ (Cameron and Trivedi, 2005; Wooldridge, 2012).

In order to use the The Poisson model, the equidispersion assumption is required, i.e. the Poisson model assumes that the variance equals the mean, so it this case it would be that $\mathbb{E}$[Number of Patents] = Var[Number of Patents] (Cameron and Trivedi, 2005). From table 4.4 it can be seen that the variance is larger than the mean of annual granted patents, hence the dataset has over-dispersion. This causes an issue because over dispersion can lead to underestimated standard errors. Consequently, the t-statistics are overestimated using a standard Poisson model. Therefore this increases the chance of a Type I error, meaning that the results are interpreted as statistically significant when in reality they are not (Cameron and Trivedi, 2005).

To address this issue, this study employs Poisson quasi-maximum likelihood estimation (QMLE), which provides robust standard errors even when the equidispersion assumption does not hold, thereby enhancing the robustness of the results (Wooldridge, 2012). In addition, to further test the robustness of the results, section 6.3 employs a Negative Binomial model and the staggered DID approach from Callaway and Sant'Anna (2021). The findings from these additional analyses are consistent with those obtained using the Poisson QMLE method.

Table 4.4: Statistics for Number of Patents

Statistic	**Value**
Mean	1109.897
Variance	3213787.7

I estimate the following equation to examine the effect of a technological or non-technological acquisition on the number of annual patents granted to a firm:

$$\begin{aligned} \log(\mathbb{E}[\text{Patents}_{it}]) = {} & \beta_0 + \beta_1 \text{Acquisition}_{it} + \beta_2 \text{Acquisition}_{it-1} \\ & + \beta_3 \text{Acquisition}_{it-2} + \beta_4 \text{Acquisition}_{it-3} \\ & + \beta_5 \text{Acquisition}_{it-4} + \beta_6 \text{X}_{it} + \gamma_i + \lambda_t + \epsilon_{it} \end{aligned} \tag{4.10}$$

In equation 4.10, i indexes the acquiring company and t denotes the time period. $\mathbb{E}[\text{Patents}_{it}]$ represents the expected number of patents granted to firm i in year t. The binary variable Acquisition_{it} equals one if company i made a technological to test hypothesis 1a. To test hypothesis 1b the variable Acquisition equals one if the acquisition is a non-technological acquisition in year t. Since companies must first integrate the acquired knowledge before it can improve innovation output, (non-)technological acquisitions are expected to impact innovation over several years (Ahuja and Katila, 2001). Therefore, a distributed lag model is used, with lags ranging from one to four years, to understand the dynamics of such acquisitions. This has as benefit that time patterns could be observed. For instance, if a technological acquisition does not significantly impact innovation output in the first two years due to the time required to incorporate the knowledge, a positive effect might be observed afterward. This would be reflected in the coefficients of the lagged variables, where the one and two-year lags would be insignificant, but the three-year and four-year lags would be positive and significant.

Further, the vector X_{it} are the control variables explained in the previous section. γ_i and λ_t represents industry and time fixed effects, respectively. Finally, β_0 is the constant and ϵ_{it} is the error term. The standard errors are clustered at the company level, to account for serial correlation of the errors within companies.

Chapter 5

Results

5.1 Innovation Input

5.1.1 Parallel Trend Assumption

Before interpreting the results, it is important to first discuss the parallel trend assumption. Appendix D.1 provides illustrations of the pre- and post-acquisition trends for the groups from hypothesis 1a and hypothesis 1b. From the pre-period trends of hypothesis 1a, it appears that the parallel trend assumption holds for most groups. Specifically, the groups G2003, G2004, 2006 and G2008 show no statistically significant pre-period trends. However, there are some significant coefficient for group G2009 three to seven years before the acquisition. Since no clear pre-trend is visible and the last two years are insignificant the parallel trend assumption is likely to hold. To further analyse the pre-acquisition period, there will be a robustness check to see if there is an anticipation effect, in Chapter 6.

For Hypothesis 1b, it follows from the pre-period trends that the parallel trend assumption is likely to hold. With no group that shows a clear pre-acquisition trend. Similar as for hypothesis 1a, there will be a robustness check to further analyse the pre-acquisition period which will test if there is an anticipation effect for non-technological acquisitions, in Chapter 6.

5.1.2 Technological Acquisition

Next, this section presents the results of the staggered DID regression, using the method proposed by Callaway and Sant'Anna (2021) that I used to test the impact of a technological acquisition on the R&D intensity of acquiring companies. In column one of table 5.1 the average treatment effect of the treated ($\text{ATT}(g, t)$) per group are stated, compared to the pre-acquisition period. Each group consists of the companies that did their first technological acquisition in the given year. Furthermore, the average of all groups is included to analyse the average effect of a technological acquisition. Note in the appendix B.1 all the individual coefficients for each year and group are stated.

From the results of table 5.1 evidence is found that supports hypothesis 1a, that technological acquisitions increase innovation input. This follows from the positive coefficient of 0.5111 that is statistically significant at the 5% significance level of the overall average treatment effect (GAverage). This indicates that, on average, companies engaging in technological acquisitions experienced an increase in their R&D intensity post-acquisition of 66.7%$\approx ((e^{0.5111} - 1) * 100\%)$. This contradicts findings from previous literature, which argued that technological acquisitions negatively impact innovation input. For example, since technological acquisitions serve as a substitute for R&D investments (Phillips and Zhdanov, 2012) or causes a shift in managerial focus away from R&D Ahuja and Katila (2001); Hitt et al. (1991). Instead, the results indicate that companies in the high-tech sector that undertook technological acquisitions increased their R&D investments post-acquisition.

Examining the coefficients for specific acquisition years provides further insights. The groups G2003 and G2009 shows a significant positive effect, at the 1% significance level. This indicates an increase in R&D intensity for companies that made their first acquisition in 2003 and 2009. Similarly, the group G2008 has a positive and significant coefficient, at the 5% significance level. These group coefficients show that the result is not driven by one group and increases the validity of the result.

Hence, the results support my first hypothesis that technological acquisitions generally lead to increased R&D intensity in the acquiring companies.

5.1.3 Non-technological Acquisition

In column two of table 5.1 are the results of the staggered DID with as independent variable the non-technological acquisition. Note in the appendix B.2 all the individual coefficients for each year and group are stated.

From the results of column two in table 5.1 it follows that the overall average treatment effect (GAverage) suggests a non-significant positive impact of technological acquisitions on R&D intensity. The positive coefficient, indicates that companies engaging in non-technological acquisitions generally experienced an increase in R&D intensity post-acquisition. However, the coefficient is statistically not significant different from zero. Therefore, we find no evidence for hypothesis 1b that non-technological acquisitions lead to a decrease in innovation input.

Examining the coefficients for specific acquisition years provides further insights. The groups of companies that made a non-technological acquisition in 2004 and 2005 (G2004 & G2005) have a positive and statistically significant coefficient, at the 5% and 1% significance level, respectively. This, is an unexpected results and could potentially be explained that with some non-technological acquisitions economies of scale can be realized although the aim is not to increase the R&D capacity of a firm. Finally the coefficient of the group of 2007 is negative and statistically significant at the 1% significance level.

In conclusion, there is no evidence found that on average non-technological acquisitions have an significant impact on the R&D intensity of a firm. However, the individual group coefficients shows an mixed result, indicating that further analysis of different non-technological acquisitions could be of interest for future research.

Table 5.1: R&D Intensity Post-Acquisition Analysis

Group	**Technological** (1)	**Non-Technological** (2)
GAverage	0.5111**	0.1713
	(0.2096)	(0.1734)
G2003	1.0725***	0.2624
	(0.2662)	(0.2681)
G2004	0.0361	0.7913**
	(0.4515)	(0.3740)
G2005	-	0.8425***
	-	(0.2172)
G2006	0.3192	-0.0426
	(0.3168)	(0.2590)
G2007	-	-0.3134***
	-	(0.1042)
G2008	0.8399**	-0.8301
	(0.3625)	(0.5987)
G2009	0.5583***	-
	(0.1857)	-

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. The staggered DID method introduced by Callaway and Sant'Anna (2021) is used with the dependent variable being the logarithm of the R&D intensity of the acquiring firm. In Model 1, the treatment is the first technological acquisition of the acquiring firm in the years 2003-2009. In Model 2, the treatment is the first non-technological acquisition in the same period. As a control group, "later treated" companies are used, which are those companies that made (non-)technological acquisitions after 2009. The coefficients represent the average post-acquisition impact of the (non-)technological acquisition compared to the pre-acquisition period. GAverage is the average effect across all groups, while G2003-G2009 represent the individual groups. Each group consists of companies that made their first (non-) technological acquisition in the corresponding year. The full regression output of both regressions are available in Appendix B. Standard errors, in parentheses, are clustered at the company level.

5.2 Innovation Output

5.2.1 Technological Acquisition

The Poisson regression estimates examining the effect of technological acquisitions on the number of patents granted post-acquisition are presented in Table 5.2. This table includes four models, progressively incorporating additional control variables and fixed effects.

Model 1, includes the primary independent variable, technological acquisition and its lagged terms without any fixed effects. The results show for all coefficient a positive and statistically significant effect of technological acquisitions on the number of patents granted to the acquiring firm, post-acquisition. *Model 2*, incorporates fixed effects for both years and industries, accounting for unobserved heterogeneity across different time periods and industry sectors. The coefficients for the one and three-year lagged acquisition variables become insignificant after controlling for fixed effects, while the two-year and four-year lagged effects remain statistically significant. *Model 3*, adds the control variables for firm size and R&D intensity. The results show that firm size is positive and statistically significant at the 5% significance level. This result indicates that larger firms tend to have more patents granted post-acquisition, which is in line with Schumpeter (1942) who argued that larger firms are more innovative. The log of R&D intensity has a negative and statistically significant, at the 5% significance level, coefficient suggesting that companies with a higher R&D intensity have fewer granted patents, contrary to expectations. When controlling for firm size and R&D, the two and four year lagged effects of technological acquisitions remain positive and significant, respectively at the 5 and 10% significance level. *Model 4*, includes the interaction effect between industry and time fixed effects, controlling for potential trends over time or in specific industries. The results show that technological acquisitions increase the number of granted patents by 9.2%($\approx (e^{0.088} - 1) * 100\%$) after four years, a statistically significant effect at the 5% significance level. *Model 5*, tests Hypothesis 3 by adding the interaction effect between technological acquisition and a binary variable, Large, indicating if the company's size one year prior to acquisition is larger than the sample average. The one-year lagged coefficient of the interaction term is positive and statistically significant at the 1% significance level, indicating that larger firms have 28.4% ($\approx (e^{0.25} - 1) * 100\%$) more patents granted one year after acquisition compared to smaller firms. Therefore, we find evidence for Hypothesis 3, that larger firms have indeed a higher post-acquisition increase in the number of granted patents compared to smaller companies.

Overall, the results support Hypothesis 2a, which predicts a positive relationship between technological acquisitions and the number of granted patents post-acquisition. The significant effects observed two to four years post-acquisition indicate that technological acquisitions are a valid strategic part of the innovation strategy of a firm, with an increase in granted patents ranging from 6-8%. Additionally, the findings support Hypothesis 3, indicating that larger companies experience a short-term benefit over smaller companies when utilizing technological acquisitions. However, this advantage disappears after one year.

5.2.2 Non-Technological Acquisition

The Poisson regression estimates examining the impact of non-technological acquisitions on the post-acquisition number of granted patents are presented in Table 5.3. This table includes four models, progressively incorporating additional control variables and fixed effects, similar to the approach in 5.2.

Model 1, includes the primary independent variable, non-technological acquisition and the lagged terms without any fixed effects. The results indicate a negative but statistically non-significant impact of non-technological acquisitions on the number of patents granted, at the 10% significance level, post-acquisition both for the immediate and lagged coefficients. *Model 2*, incorporates fixed effects for both years and industries to account for unobserved heterogeneity across time periods and industry sectors. After controlling for these fixed effects the coefficients remain statistically insignificant at the 10% significance level. *Model 3*, adds control variables for firm size and R&D intensity. Similar as the results found in 5.2, firm size is positive and statistically significant and the log of R&D intensity has a negative and statistically significant coefficient. For the non-technological acquisition all coefficients remain insignificant at the 10% significance level. *Model 4*, includes the interaction effect between the industry and time fixed effects to control for potential trends in patenting activity over time in certain industries. After including these controls, the results show a direct positive and statistically significant effect of non-technological acquisitions at the 10% significance level. However, the other coefficients remain statistically insignificant at the 10% significance level.

Overall, the results support hypothesis 2b, which predicts either a negative or a non-significant effect of non-technological acquisitions on the innovation output of acquiring firm. Hence, it follows from the results that non-technological acquisitions do not significantly impact the number of granted patents post-acquisition.

Table 5.2: Impact of Technological Acquisitions on Patent Counts

	1	2	3	4	5
Number of patents					
Technological Acquisition	0.103*	0.099*	0.069	0.020	-0.054
	(0.063)	(0.056)	(0.054)	(0.043)	(0.079)
Technological Acquisition$_{t-1}$	0.138*	0.091	0.049	0.052	-0.150
	(0.075)	(0.069)	(0.061)	(0.055)	(0.098)
Technological Acquisition$_{t-2}$	0.168***	0.108**	0.079**	0.058	0.098
	(0.055)	(0.046)	(0.039)	(0.047)	(0.082)
Technological Acquisition$_{t-3}$	0.129**	0.075	0.054	0.039	0.120
	(0.057)	(0.047)	(0.039)	(0.047)	(0.037)
Technological Acquisition$_{t-4}$	0.099**	0.080*	0.060*	0.088**	0.122***
	(0.044)	(0.043)	(0.033)	(0.038)	(0.037)
Size			0.276**	0.311***	0.294**
			(0.118)	(0.121)	(0.122)
Log(R&D)			-0.116**	-0.145**	-0.148***
			(0.047)	(0.051)	(0.053)
Tech*Large					0.093
					(0.073)
Tech$_{t-1}$*Large					0.250***
					(0.092)
Tech$_{t-2}$*Large					-0.047
					(0.077)
Tech$_{t-3}$*Large					-0.094
					(0.092)
Tech$_{t-4}$*Large					-0.034
					(0.056)
Constant	6.851***	6.670***	3.732***	3.506***	3.670***
	(0.231)	(0.345)	(1.262)	(1.292)	(1.30)
Industry FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Year*Industry FE	No	No	No	Yes	Yes
N	548	548	548	548	548

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. The dependent variable is the count of annual granted patents for the acquiring firm. The explanatory variable, Technological Acquisition, is a binary variable that equals one in year t if the company made a technological acquisition in that year. Technological Acquisition$_{t-1}$ with i={1,...,4}, represents the lagged variables of technological acquisition, ranging from one to four years. The control variable Size is defined as the logarithm of the number of employees in a firm. The control variable, Log(R&D), measures the logarithm function of the firm's R&D Intensity and is defined as R&D expenses divided by EBITDA in year t. Standard errors, in parentheses are clustered at the company level.

Table 5.3: Impact of Non-Technological Acquisitions on Patent Counts

	1	2	3	4
Number of patents				
Non-Technological Acquisition	-0.068	-0.006	0.001	0.145**
	(0.072)	(0.079)	(0.076)	(0.063)
Non-Technological Acquisition$_{t-1}$	-0.002	0.069	0.067	0.093
	(0.044)	(0.060)	(0.065)	(0.064)
Non-Technological Acquisition$_{t-2}$	-0.088	-0.011	-0.042	0.029
	(0.055)	(0.076)	(0.074)	(0.066)
Non-Technological Acquisition$_{t-3}$	-0.036	0.018	-0.011	0.032
	(0.060)	(0.058)	(0.056)	(0.057)
Non-Technological Acquisition$_{t-4}$	-0.036	0.008	-0.024	0.008
	(0.069)	(0.053)	(0.050)	(0.059)
Size			0.292*	0.205
			(0.150)	(0.144)
Log(R&D)			-0.144***	-0.171***
			(0.043)	(0.051)
Constant	7.129***	6.788***	3.637**	4.681***
	(0.257)	(0.380)	(1.587)	(1.556)
Industry FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Year*Industry FE	No	No	No	Yes
N	548	548	548	548

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. The dependent variable is the count of annual granted patents for the acquiring firm. The explanatory variable, Non-Technological Acquisition, is a binary variable that equals one in year t if the company made a non-technological acquisition in that year. Non-Technological Acquisition$_{t-1}$ with i=$\{1,\ldots,4\}$, represents the lagged variables of non-technological acquisition, ranging from one to four years. The control variable Size is defined as the logarithm of the number of employees in a firm. The control variable, Log(R&D), measures the logarithm function of the firm's R&D Intensity and is defined as R&D expenses divided by EBITDA in year t. Standard errors, in parentheses are clustered at the company level.

Chapter 6

Robustness Checks

6.1 Hypothesis 1a

6.1.1 Placebo Test

To ensure that the results presented in Table 5.1 column one, are indeed due to the technological acquisition and not influenced by some underlying effect, a placebo test was conducted. In this test, the treatment (technological acquisition) timing was randomly assigned to the treated group and the analysis was repeated 100 times to make sure that the result of the placebo test is not caused by chance. As shown in the appendix E Figure E.1, the majority of the coefficients (73%) from the group ATT(g,t) in the placebo tests are insignificant. These findings reinforce the robustness of the results reported in Table 5.1 column one, indicating that the observed effects are likely caused by the technological acquisition rather than to an unobserved confounding factor.

6.1.2 Anticipation

The main objective of this robustness check is to ensure that the observed increase in post-acquisition R&D intensity from Table 5.1 column one is not driven by an anticipation effect. An anticipation effect would occur if acquiring companies reduce their R&D expenses one year before the technological acquisition, making the subsequent post-acquisition increase appear larger than it actually is.

To test for the anticipation effect, the same staggered DID method used in the initial analysis is employed. However, instead of using the actual year of the technological acquisition as the treatment date, one year prior to the acquisition is taken as the treatment date. This adjustment allows to observe any changes in R&D intensity that occur before the acquisition, hence identifying potential anticipation effects.

The results of this modified regression analysis are presented in Table E.1. The findings indicate a positive, statistically significant anticipation effect at the 1% significance level. Specifically, on average companies increase their R&D investments by 137%($\approx$ $(e^{0.8626} - 1) * 100\%$) one year prior to a technological acquisition. A possible explanation for this large increase in R&D intensity is that companies already start investing in specific research areas where they anticipate gaining new knowledge post-acquisition. By investing in related R&D companies can increase their absorptive capacity, which would lead to a better capacity to integrate the new acquired knowledge (Cohen and Levinthal, 1990; Lane et al., 2006; Zahra and George, 2002).

Although there is an significant anticipation effect, this is not necessarily an issue since the effect has a positive coefficient. A reduction in R&D investments one year before the acquisition would have inflated the observed post-acquisition increase in R&D intensity, leading to a biased outcome. However, since Table E.1 shows on average no negative significant anticipation effect, this indicates that even if there is an anticipation effect this could mean that the initial findings are an underestimation. Hence this supports the findings of my initial results from Table 5.1 column one, that a technological acquisition increases the post-acquisition R&D intensity.

Therefore, these results enhances the robustness of my initial findings from Table 5.1 column one, which indicate that a technological acquisition leads to an increase in post-acquisition R&D intensity.

6.1.3 2nd Acquisition

To validate the hypothesis that a technological acquisition increases the acquiring company's R&D intensity, a robustness check was conducted by examining a second technological acquisition. Table E.2 shows the average treatment effect of the second acquisition, confirming the positive impact observed in Table 5.1, column one. The second acquisition's effect is larger, with an average coefficient of 0.5714, statistically significant at the 10% level, indicating a 77.1% increase in R&D intensity, compared to the first acquisition's 66.7%. A possible interpretation is that firms benefit more from their second acquisition due to the experience gained from their first. This suggests a potential learning effect. Recent literature indicates that prior acquisition experience can lead to above-average acquisition performance, as firms develop relevant skills and knowledge on how to effectively integrate an acquired company (Schweizer et al., 2023; Trichterborn et al., 2016). However, further analysis is required to confirm this.

The group-specific effects provide a more detailed view of the impact. The group that conducted their second acquisition in 2004 shows a negative and statistically significant coefficient, at the 10% significance level. In contrast, the other groups exhibit positive and statistically significant effects, with 2005, 2006 and 2007 significant at the 10% level and 2006 significant at the 1% level. From this it follows that the result is not been driven by one group and the results reinforce the hypothesis that technological acquisitions have a positive impact on R&D intensity post-acquisition.

In summary, the results from the three robustness checks validate my initial findings that technological acquisitions increase the R&D intensity of acquiring firms.

6.2 Hypothesis 1b

6.2.1 Anticipation

The main objective of this robustness check is to ensure that the observed increase in post-acquisition R&D intensity from Table 5.1, column two is influenced by an anticipation effect. An anticipation effect would occur if acquiring companies reduce their R&D expenses one year before the technological acquisition, making the subsequent post-acquisition increase appear larger than it actually is. To test for the anticipation effect, the same staggered DID method used in the initial analysis is employed. However, instead of using the actual year of the technological acquisition as the treatment date, one year prior to the acquisition is taken as the treatment date. This adjustment allows to observe any changes in R&D intensity that occur before the acquisition, hence identifying potential anticipation effects. The results of this modified regression analysis are presented in Table E.3. From the results it can be seen that, on average there is a positive and insignificant anticipation effect. This lack of a significant decrease in R&D investments one year prior to the acquisition suggests that companies do not strategically reduce their R&D expenses in anticipation of the acquisition. So from the results it follows that companies do not have an anticipation effect on non-technological acquisitions, which increases the robustness of the initial findings that non-technological acquisitions do not have a significant impact on R&D intensity.

6.2.2 2nd Acquisition

To further validate the initial findings, instead of the first acquisition the same staggered DID as in the initial analysis used is conducted however, now the treatment data is the year of the second acquisition. The results are given in Table E.4, the groups average coefficient is positive and statistically insignificant. Hence, both models find a non-significant effect, hence this robustness check supports the findings that a non-technological acquisition does not have a significant impact on the innovation input.

In conclusion, the result of the two robustness checks validate the initial findings that non-technological acquisitions do not have a significant effect on R&D intensity post-acquisition.

6.3 Hypothesis 2a

6.3.1 Negative Binomial

To assess the robustness of the outcomes for hypothesis 2a, I examined the effect of technological acquisitions on the number of post-acquisition granted patents using a Negative Binomial model. The results are presented in Appendix E, Table E.5, incorporating four models that progressively add control variables and fixed effects, similar to the initial results in Table 5.2.

The robustness check supports the initial findings that technological acquisitions positively impact the number of granted patents post-acquisition. The result for the lagged coefficients are similar to the initial results. Across all models, the four-year lagged variable remains consistently statistically significant, indicating a delayed yet positive effect of 7.6% $((\approx e^{0.073}-1) * 100\%)$ increase in granted patents post-acquisition. The magnitude is slightly lower compared to the 9.1% from the Poisson QMLE but the difference is not large enough to undermine the overall conclusion.
Hence, this robustness check supports the initial findings that technological acquisitions have a positive impact on the number of patents granted post-acquisition to acquiring firms.

Goodness of Fit

To assess the goodness of fit for the Poisson and Negative Binomial model that this paper uses to predict the number of patents, the fitted values from these models were compared to the observed data to determine which model provides a better fit. The results can be found in Table 6.1

Table 6.1: Goodness of Fit Comparison

Model	R^2
Poisson Regression	0.2168
Negative Binomial Regression	0.0211

The comparison of the R-squared from the Poisson and Negative Binomial models reveals that the Poisson model provides a better fit to the data than the negative binomial model. Specifically, the Poisson model R-squared equals 0.2168, while the negative binomial model has a R-squared of only 0.0211. This suggests that the Poisson distribution is more appropriate for modelling the number of patents in this dataset.

6.3.2 Number of Technological Acquisitions

As a second robustness check for hypothesis 2a, I examined the effect of the number of technological acquisitions a company undertakes in a given year on the number of granted patents, post-acquisition using a Poisson distribution model. The results are presented in Appendix E, Table E.6, which includes four models that progressively incorporate additional control variables and fixed effects, similar as for the initial results in Table 5.2.

As shown in Table E.6, the coefficients for the number of technological acquisitions are positive across all four models. This indicates that a higher number of technological acquisitions has a positive impact on the number of granted patents. However, the magnitude of the coefficients suggests that the effect diminishes over time. This finding differs from the initial model, which found a stronger effect, especially for the four-year lagged coefficient. In this robustness check, especially the second-year coefficient is the statistically significant at the 1% significance level, in the first three models but becomes insignificant in the fourth model.

Overall, these results offer partial support to the hypothesis that technological acquisitions positively impact the number of granted patents. Although the coefficients are positive across all four models and the two-year lag variable is statistically significant in the first three models, the coefficient loses significance in the fourth model.

6.3.3 Staggered Difference in Difference

As a third robustness check, the staggered DID method introduced by Callaway and Sant'Anna (2021) is employed. This method is particularly effective in accounting for variations in treatment timing across groups, providing a more nuanced analysis. Although the initially used Poisson model is a common approach in the literature for count data (see section 4.2.3), the DID method offers an additional layer of validation for the robustness of the results by controlling for time-varying unobserved heterogeneity (Callaway and Sant'Anna, 2021).

Appendix E, Table E.7 shows that the group average treatment effect is positive and statistically significant at the 5% significance level. This finding indicates that technological acquisitions lead to an increase in the number of post-acquisition granted patents for the acquiring firm. These results further support the hypothesis that acquisitions positively impact the innovative output of the acquiring firm.

In conclusion, the three robustness checks validate the initial results presented in Table

5.2. The consistency of results across different methodologies increases the robustness of my result that technological acquisitions increase the number of granted patents post-acquisition.

6.4 Hypothesis 2b

6.4.1 Negative Binomial

To assess the robustness of Hypothesis 2b, I examine the impact of non-technological acquisitions on the number of granted patents post-acquisition using a Negative Binomial model. The results are presented in Appendix E, Table E.8, which includes four models similar to the initial method. These models progressively incorporate additional control variables and fixed effects.

The results from Table E.8 support the initial findings that non-technological acquisitions have either a negative or no significant impact on the number of granted patents post-acquisition. A notable difference with the initial results is observed in models 2 to 4, where a direct positive and significant effect on the number of patents is measured. However, this effect is not consistent over time, following from the insignificant results for the lagged coefficients. Additionally, the four-year lagged variable in model 3 is negative and statistically significant at the 10% significance level, indicating on the long run a negative impact of non-technological acquisitions.

Overall, the results of this robustness check supports the initial findings that non-technological acquisitions have either a non-significant or negative impact on the number of granted patents post-acquisition.

Goodness of Fit

To examine which results are the most trustworthy between the initial used Poisson model or the Negative Binomial model to predict the post-acquisition number of annual granted patens after a non-technological acquisition. The fitted values are compared to the observed data to determine which model provides a better fit. The results can be found in Table 6.2. Comparing the R-squared from the Poisson and Negative Binomial

Table 6.2: Goodness of Fit Comparison

Model	R^2
Poisson Regression	0.1620
Negative Binomial Regression	0.0116

model given in Table 6.2 it follows that the Poisson model provides a better fit to the data than the Negative Binomial model, since the R-squared from the Poisson model equals

0.1620 which is larger than the R-squared of the Negative Binomial Regression which equals 0.0116.

6.4.2 Number of Non-Technological Acquisitions

As a second robustness check for validating the non-significant impact of non-technological acquisitions, I examined the effect of the number of non-technological acquisitions a company made in a year. This approach differs from the initial analysis, which used a binary variable indicating whether a company made at least one non-technological acquisition in that year. In this analysis, the number of non-technological acquisitions is used as the independent variable. The results are provided in Table E.9. Similar to the initial regression, four models are used, progressively adding control variables and fixed effects.

The results in Table E.9 indicate that non-technological acquisitions generally do not have a significant effect on the innovation output of acquiring firms. However, the fourth model shows that non-technological acquisitions have a positive and significant effect on the number of granted patents post-acquisition in the short term. Following from the coefficients of the direct and first two lagged variables. The direct and one year lagged variable are positive and significant at the 1% significance level. The two year lagged variable is positive and significant at the 5% significance level. However, the three and four year lagged variable are insignificant. This suggests that in the short term, non-technological acquisitions may positively impact a firm's innovation output, but this effect becomes insignificant in the long run.

Therefore, the results do not improve the robustness of the initial findings because, after controlling for yearly industry-specific trends, there is a positive impact of non-technological acquisitions in the short run. However, the results do not fully undermine the initial findings because the positive and significant effect is observed only in the short term in model 4.

6.4.3 Staggered Difference in Difference

Applying the staggered DID method introduced by Callaway and Sant'Anna (2021) serves as a third robustness check. This method offers a more nuanced analysis by effectively accounting for differences in treatment timing between groups. While the Poisson model that is used in the initial analysis, is a common approach in the literature for count data. By accounting for time-varying unobserved heterogeneity the DID method offers an additional layer of validation for the robustness of the results (Callaway and Sant'Anna, 2021).

From the results in Table E.10 it can be seen that the coefficient of the groups average is negative and statistically insignificant at the 10% significance level. This finding align with the initial results, thereby, reinforcing the robustness of the conclusion that non-technological acquisitions have no statistically significant impact on the number of granted patents post-acquisition.

In conclusion, although a positive and significant effect is found in the short term, when taking the number of non-technological acquisitions into account. The Negative Binomial and staggered DID show a non significant effect of non-technological acquisitions therefore the overall findings supports my initial results.

Chapter 7

Discussion and Conclusion

7.1 Limitations and Future Research

The results of this study are subject to the following limitations. First, the dataset used in this study consist exclusively of publicly listed companies due to the missing data from private firms. Publicly listed firms are typically better at integrating acquired firms compared to private firms Maksimovic et al. (2010) which may lead to different impacts of acquisitions on the innovation output. Additionally, publicly listed firms have easier access to capital Makadok (2001) which could lead in less restrictions on R&D budgets post-acquisition compared to private firms. Consequently, acquisitions could have a more positive impact on the R&D input of public companies compared to private companies. As a result, the findings may not be generalizable to private firms. Future research should aim to include data from private firms to determine if the observed effects of acquisitions on the R&D performance of firms holds for both types of firms.

Secondly, this study focuses on four sectors within the high-tech industry, which increases the generalizability of the results within the high-tech industry. However, the emphasis of the high-tech industry on R&D may mean that acquisitions have a different impact on companies in outside the high-tech industries. For instance the argument by Ahuja and Katila (2001)that acquisitions may decrease R&D intensity post-acquisition due to a shift in managerial focus may hold for industries outside the high-tech industry. Therefore, future research could examine if the observed impact of acquisitions hold using data from different industries.

Thirdly, the definition of a technological acquisitions states that an acquisition is technological if the acquired company has a at least one granted patent in the 5 year prior to the acquisition. However, this definition does not necessarily capture the acquiring company's motivation, which may not be to use the acquired knowledge. For instance, the aim could be that of a non-technological acquisitions like expanding to a certain market. Furthermore, recent research has shown that some companies acquire innovative companies to kill the innovation to prevent future competition (Cunningham et al., 2018). These acquisitions would falsely increase the number of technological acquisitions and minimize the true impact of real technological acquisitions because they are meant to neutralize potential threats rather than to capitalize on technological benefits. To address this limitation, future studies could adopt the methodology used by Cassiman et al. (2005), who conducted in-depth questionnaires with acquiring firms to understand their acquisition motives better.

The lack of control variables for the acquired knowledge could possible lead to the overestimation of the causal effects due to omitted variable bias. Future research, should aim to control for the heterogeneity of the acquired knowledge, for example for the relatedness between the acquired and already existing knowledge (Cassiman et al., 2005).

While patents are often used in literature as a measure for innovation output (Ahuja and Katila, 2001; Cassiman et al., 2005; Hitt et al., 1991) they inherently measure invention rather than the full innovation process Fagerberg (2013). This can lead to a misalignment between measured patent output and actual innovation. Future research could search for better ways to measure innovation, like the development of new products. Another improvement could be by determining the success of a technological acquisitions through patent citations, to assess whether newly acquired patents contribute to further patent creation, offering a more precise measure of the impact of acquisitions on innovation

7.2 Conclusion

This study examines the impact of technological and non-technological acquisitions on innovation input and output post-acquisition, using a newly created dataset of high-tech companies in the U.S. from 2000-2019. To test the impact of technological and non-technological acquisitions on the innovation input a staggered DID approach, as introduced by Callaway and Sant'Anna (2021), was employed. To assess the impact on innovation input a Poisson QMLE was used and the staggered DID is used as a robustness check. This approach is novel, as recent literature typically relies on a TWFE model, which does not account for heterogeneity in the treatment effect or differences in treatment timing. The staggered DID approach addresses these issues, providing more robust results.

Existing literature shows mixed findings on the impact of acquisitions on the innovation performance of firms (e.g. Ahuja and Katila 2001; Cassiman et al. 2005; Haucap et al. 2019; Hitt et al. 1991). The mixed findings and lack of consensus on the impact is caused by the fragmented literature and the many different methodologies used to study the impact on innovation input and output (de Man and Duysters, 2005; Rossi et al., 2013). This paper aim to fill this gap, by examining the impact on innovation input and output of both technological and non-technological acquisitions, to the best of my knowledge this research is the first to analyze both the impact on innovation input and output simultaneously of non-technological and technological. This has as benefit that the same dataset and method are used to analyze the difference between technological and non-technological acquisitions. In this way a more, comprehensive understanding of the impact of acquisitions is created.

The results of the staggered DID support Hypothesis 1a that a technological acquisition increases the innovation input of the firm post-acquisition. The results finds an average increase of 66.7% in R&D intensity post-acquisition. This finding is supported by the robustness checks conducted, from the placebo test it follows that the result is not caused by an underlying effect showed by the insignificance of the placebo test. Looking at the second acquisitions shows an even higher increase of 77.1% in R&D intensity and from the anticipation test it follows that firms start investing in R&D a year before the acquisition. This could potentially indicate that firms, expecting to receive certain knowledge from the acquisition and already make investments in this area.

The results of the Poisson QMLE supports Hypothesis 2a that a technological acquisition increases the innovation output of the acquiring firm post-acquisition. This is in line with the economies of scope that suggest that recombination of knowledge bases leads to an increase in innovation Schumpeter (1942). The results are consistent with other methodologies, the robustness checks uses the staggered DID and Negative Binomial, supporting the results.

These results are in line with the Resource Based View Barney (1991); Uhlenbruck et al. (2006); Wernerfelt (1984) that technological acquisitions improve the innovation performance of a firm and therefore can be a key component of a firm's innovation strategy (Eisenhardt and Martin, 2000; Makadok, 2001). These results oppose the findings from existing literature that argued and empirically showed that acquisitions have a negative impact on the innovation input and output of acquiring firms Haucap et al. (2019); Hitt et al. (1991). This difference in results highlights the importance of distinguishing between technological and non-technological acquisitions, since the papers that did found a negative impact did not make this distinction Haucap et al. (2019); Hitt et al. (1991).

The results from the staggered DID regression for non-technological acquisitions did not support Hypothesis 1b, that non-technological acquisitions have a negative impact on the innovation input of acquiring firm. Literature suggests that non-technological acquisitions negatively impact innovation input due to the shift in managerial focus (Ahuja and Katila, 2001; Hitt et al., 1991). However, this has only been tested for acquisitions in general, which shows a negative impact (Haucap et al., 2019; Hitt et al., 1991). The non-significant impact could be explained due to the innovative characteristics of the high tech industry, therefore managers will stay focused on R&D since it is important for the

long-term performance firms (Franko, 1989; National Science Foundation, 2024). This could also explain the results of the Poisson QMLE used to test Hypothesis 2b, that non-technological acquisitions do not have a significant impact on innovation output. The results supports Hypothesis 2b showing no significant effect. The insignificant results of Hypothesis 1b and 2b are supported by the conducted robustness checks.
Finally, this paper shows that technological acquisitions conducted by larger firms are more efficient, which has been showed by a higher post-acquisition number of patents one year after the acquisition. From this follows that the results of Cohen and Levinthal (1990) who showed that research programs are more efficient in larger firms, can be extended to technological acquisitions.

Policymakers and managers should consider the practical implications of the findings of this paper. When assessing acquisitions under antitrust laws, policymakers may want to be less restrictive when it comes to technological acquisitions in order to stimulate innovation in particular industries. Society may benefit if large firms are allowed to acquirer smaller firms, particularly when fast innovative solutions for societal challenges are desired, like sustainable technologies (Silvestre and Ţîrcă, 2019).

The findings underscore the significance of integrating technology acquisitions into innovation strategies for managers and stakeholders of companies. A technological acquisition has the potential to be a crucial component of a firm's innovation strategy, as evidenced by the 6–8% increase in granted patents that follow the acquisition. The findings also indicated that patience is required, as it typically takes four years for a technological acquisition to have a positive impact on innovation output.

In conclusion, this paper shows that technological acquisitions have a positive impact on both the innovation input and output of a firm. Compared to no impact on both the innovation input and output of non-technological acquisitions. Therefore, the motivation behind an acquisition significantly influences a firm's post-acquisition innovation performance.

References

Ahuja, G. and Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: a longitudinal study. *Strategic Management Journal*, 22(3):197–220. http://www.jstor.org/stable/3094458.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Bain, L. J. and Engelhardt, M. (1992). *Introduction to probability and mathematical statistics*. Duxbury/Thomson Learning, 2 edition.

Bain and Company (2024). Global M&A Report 2024. Accessed through: https://www.bain.com/insights/topics/m-and-a-report/.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1):99–120. 10.1177/014920639101700108.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting Event-Study Designs: Robust and Efficient Estimation. *The Review of Economic Studies*, pages 1–33. https://doi.org/10.1093/restud/rdae007.

Bower, J. L. (2001). Not all M&As are alike – and that matters. Harvard Business Review. Accessed through: https://hbr.org/2001/03/not-all-mas-are-alike-and-that-matters.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230. https://doi.org/10.1016/j.jeconom.2020.12.001.

Cameron, A. C. and Trivedi, P. K. (2005). *Supplement to Microeconometrics: Methods and Applications*. Cambridge University Press, New York.

Cassiman, B., Colombo, M., Garrone, P., and Veuglers, R. (2005). The impact of mergers and acquisitions on the R&D process: an empirical analysis of the role of technological- and market-relatedness. *Research Policy*, 34(2):195–220. https://doi.org/10.1016/j.respol.2005.01.002.

Cloodt, M., Hagedoorn, J., and Van Kranenburg, H. (2006). Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries. *Research Policy*, 35(5):642–654.

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, 35(1):128–152. http://

www.jstor.org/stable/2393553.

Comanor, W. S. and Scherer, F. M. (1969). Patent Statistics as a Measure of Technical Change. *Journal of Political Economy*, 77(3):392–398. http://www.jstor.org/stable/1828910.

Cunningham, C. M., Ederer, F., and Ma, S. (2018). Killer acquisitions. *Journal of Political Economy*, 129:649 – 702. https://doi.org/10.1086/712506.

de Chaisemartin, C. and D'Haultfœuille, X. (2023). Two-way fixed effects and differences-in-differences estimators with several treatments. *Journal of Econometrics*, 236(2):105480. https://doi.org/10.1016/j.jeconom.2023.105480.

de Man, A.-P. and Duysters, G. (2005). Collaboration and innovation: a review of the effects of mergers, acquisitions and alliances on innovation. *Technovation*, 25(12):1377–1387. https://doi.org/10.1016/j.technovation.2004.07.021.

Eisenhardt, K. M. and Martin, J. A. (2000). Dynamic Capabilities: What Are They? *Strategic Management Journal*, 21(10/11):1105–1121. http://www.jstor.org/stable/3094429.

Fagerberg, J. (2013). Innovation–a new guide. *Working paper*. http://www.sv.uio.no/tik/InnoWP/tik_working_paper_20131119.pdf.

Franko, L. G. (1989). Global Corporate Competition: Who's Winning, Who's Losing, and the R&D Factor as One Reason Why. *Strategic Management Journal*, 10(5):449–474. http://www.jstor.org/stable/2486472.

Galende, J. (2006). Analysis of technological innovation from business economics and management. *Technovation*, 26(3):300–311. https://doi.org/10.1016/j.technovation.2005.04.006.

Griliches, Z. (1990). Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, 28(4):1661–1707. http://www.jstor.org/stable/2727442.

Hagedoorn, J. and Duysters, G. (2002). External Sources of Innovative Capabilities: The Preferences for Strategic Alliances or Mergers and Acquisitions. *Journal of Management Studies*, 39(2):167–188. http://dx.doi.org/10.1111/1467-6486.00287.

Hall, B. H., Berndt, E., and Levin, R. C. (1990). The Impact of Corporate Restructuring on Industrial Research and Development. *Brookings Papers on Economic Activity. Microeconomics*, 1990:85–135. http://www.jstor.org/stable/2534781.

Hall, B. H. and Harhoff, D. (2012). Recent research on the economics of patents. *Annual Review of Economics*, 4:541–565.

Hall, R. (1993). A Framework Linking Intangible Resources and Capabilities to Sustainable Competitive Advantage. *Strategic Management Journal*, 14(8):607–618. http://www.jstor.org/stable/2486860.

Haucap, J., Rasch, A., and Stiebale, J. (2019). How mergers affect innovation: Theory and evidence. *International Journal of Industrial Organization*, 63:283–325. https://doi.org/10.1016/j.ijindorg.2018.10.003.

Henderson, R. and Cockburn, I. (1996). Scale, Scope, and Spillovers: The Determinants of Research Productivity in Drug Discovery. *The RAND Journal of Economics*, 27(1):32–59. https://doi.org/10.2307/2555791.

Hitt, M. A., Hoskisson, R. E., Ireland, D. R., and Harrison, R. D. (1991). Effects of acquisitions on R&D inputs and outputs. *Academy of Management Journal*, 34(3):693–706. https://www.jstor.org/stable/256412.

Hitt, M. A., Hoskisson, R. E., and Ireland, R. D. (1990). Mergers and acquisitions and managerial commitment to innovation in m-form firms. *Strategic Management Journal*, (Special Issue 11):29–47.

Hoskisson, R. E., Hitt, M. A., and Ireland, R. D. (1994). *The Effects of Acquisitions and Restructuring (Strategic Refocusing) Strategies on Innovation*, pages 144–169. Palgrave Macmillan, London. https://doi.org/10.1007/978-1-349-13016-0_7.

Lane, P. J., Koka, B. R., and Pathak, S. (2006). The reification of absorptive capacity: A critical review and rejuvenation of the construct. *Academy of Management Review*, 31(4):833–863. https://doi.org/10.5465/amr.2006.22527456.

Laporte, A. and Windmeijer, F. (2005). Estimation of panel data models with binary indicators when treatment effects are not constant over time. *Economics Letters*, 88(3):389–396. https://doi.org/10.1016/j.econlet.2005.04.002.

Liu, O. (2022). The dynamics of firm size inequality: The role of acquisition and innovation. https://ssrn.com/abstract=4279062.

Makadok, R. (2001). Toward a synthesis of the resource-based and dynamic-capability views of rent creation. *Strategic Management Journal*, 22(5):387–401. http://www.jstor.org/stable/3094265.

Maksimovic, V., Phillips, G. M., and Yang, L. A. (2010). Private and public merger waves. *Available at SSRN*. https://ssrn.com/abstract=1625848.

Malani, A. and Reif, J. (2015). Interpreting pre-trends as anticipation: Impact on estimated treatment effects from tort reform. *Journal of Public Economics*, 124:1–17. https://doi.org/10.1016/j.jpubeco.2015.01.001.

National Science Foundation (2024). Research and development: U.S. Trends and International Comparisons. https://ncses.nsf.gov/pubs/nsb20246/u-s-business-r-d.

OECD (2005). Oslo manual, guidelines for collecting and interpreting technological innovation data - third edition. https://ec.europa.eu/eurostat/documents/3859598/5889925/OSLO-EN.PDF.

Phillips, G. M. and Zhdanov, A. (2012). R&d and the incentives from merger and acquisition activity. https://ssrn.com/abstract=2181152.

Porter, M. E. (1990). *The Competitive Advantage of Nations*. Free Press, New York. https://hbr.org/1990/03/the-competitive-advantage-of-nations.

Puranam, P. and Srikanth, K. (2007). What they know vs. what they do: how acquirers leverage technology acquisitions. *Strategic Management Journal*, 28(8):805–825. https://doi.org/10.1002/smj.608.

Ranft, A. L. and Lord, M. D. (2002). Acquiring new technologies and capabilities: A grounded model of acquisition implementation. *Organization Science*, 13(4):420–441. http://www.jstor.org/stable/3085975.

Roberts, M. R. and Whited, T. M. (2011). Endogeneity in Empirical Corporate Finance. *Banking Financial Institutions eJournal*. https://doi.org.10.2139/ssrn.1748604.

Rossi, M., Yedidia Tarba, S., and Raviv, A. (2013). Mergers and acquisitions in the hightech industry: a literature review. *International Journal of Organizational Analysis*, 21(1):66–82. doi.org/10.1108/19348831311322542.

Schumpeter, J. (1934). *The Theory of Economic Development*. Harvard University Press, Cambridge, MA.

Schumpeter, J. A. (1942). *Capitalism, Socialism and Democracy*. Harper & Brothers.

Schweizer, L. (2005). Organizational integration of acquired biotechnology companies into pharmaceutical companies: The need for a hybrid approach. *The Academy of Management Journal*, 48(6):1051–1074. https://www.jstor.org/stable/20159729.

Schweizer, L., Wang, L., and Koscher, E. (2023). Long-term performance of technology acquisitions: The role of acquisition program diversity, innovation, and alliance portfolio size – evidence from the pharmaceutical industry. *European Management Journal*. https://doi.org/10.1016/j.emj.2023.07.002.

Silvestre, B. and Ţîrcă, D.-M. (2019). Innovations for sustainable development: Moving toward a sustainable future. *Journal of Cleaner Production*. https://doi.org/10.1016/J.JCLEPRO.2018.09.244.

Teece, D. J. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, 15(6):285–305. https://doi.org/10.1016/0048-7333(86)90027-2.

Trichterborn, A., Zu Knyphausen-Aufseß, D., and Schweizer, L. (2016). How to improve acquisition performance: The role of a dedicated m&a function, m&a learning process, and m&a capability. *Strategic Management Journal*, 37(4):763–773. https://doi.org/10.1002/smj.2364.

Uhlenbruck, K., Hitt, M. A., and Semadeni, M. (2006). Market value effects of acquisitions involving internet firms: A resource-based analysis. *Strategic Management Journal*, 27(10):899–913. http://www.jstor.org/stable/20142386.

Webb, M., Short, N., Bloom, N., and Lerner, J. (2018). Some facts of high-tech patenting. Working Paper 19-014, Harvard Business School. https://ssrn.com/abstract=3233722.

Wernerfelt, B. (1984). A Resource-Based View of the Firm. *Strategic Management Journal*, 5(2):171–180. http://www.jstor.org/stable/2486175.

Wooldridge, J. M. (2012). *Introductory Econometrics: A Modern Approach.* Cengage Learning.

Zahra, S. A. and George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review*, 27(2):185–203. https://www.jstor.org/stable/41343515.

Appendix A

Distribution Graphs

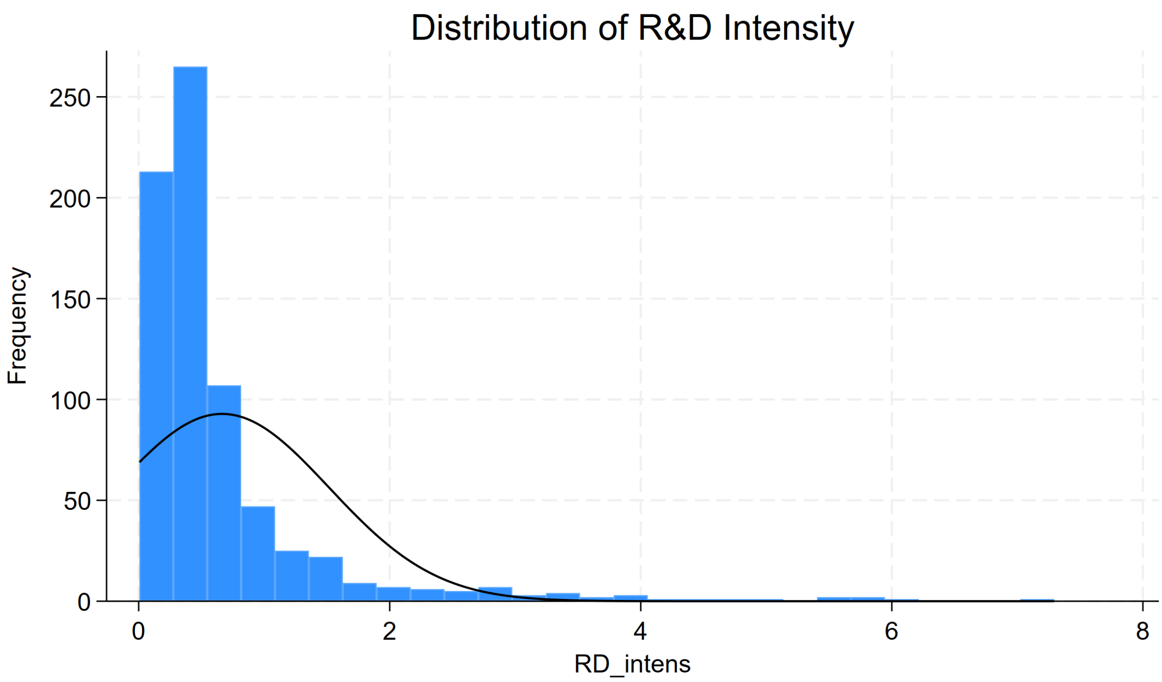

Figure A.1: R&D Denisty

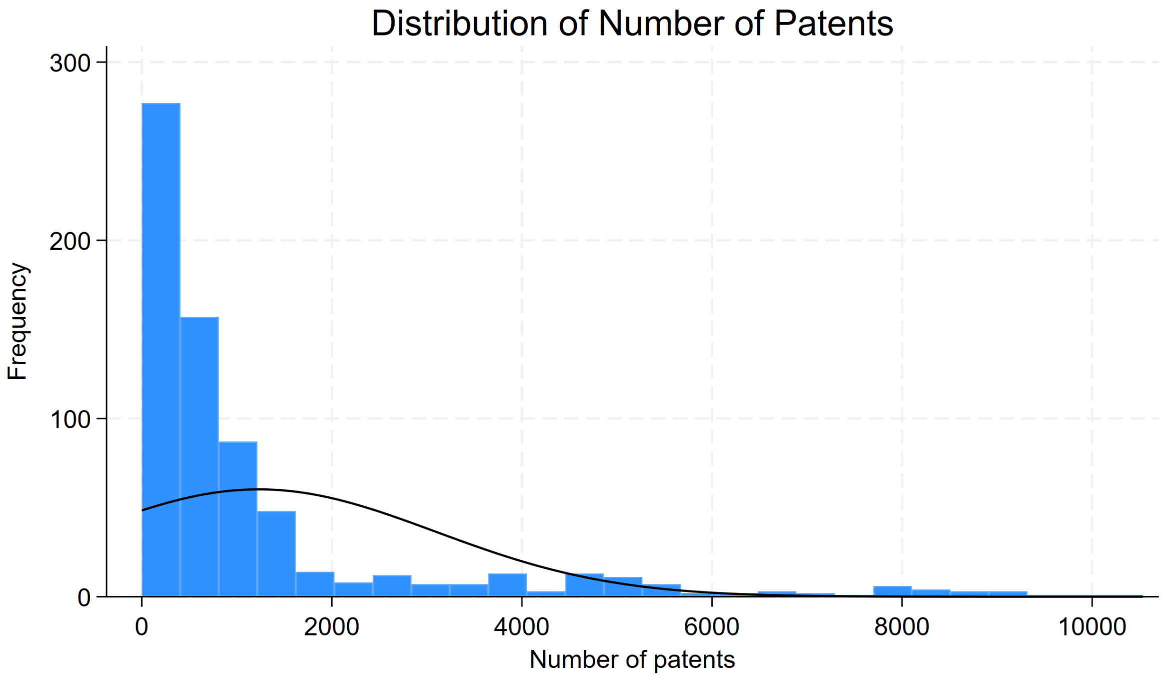

Figure A.2: Patent Denisty

Appendix B

Main Regression results

Table B.1: Technological Acquisitions and R&D Intensity: DID Regression Results

VARIABLES	(1) g2003	(2) g2004	(3) g2006
t_2000_2001	-1.451274**	-0.2078911	0.3080778
	(0.6669915)	(0.7853723)	(0.3920469)
t_2001_2002	0.3237456	0.5318892**	0.1196584
	(0.3454323)	(0.2697557)	(0.4731018)
t_2002_2003	0.9278017*	0.6428777	0.0272829
	(0.4985122)	(0.4325169)	(0.1738371)
t_2003_2004	0.6671011***	-0.412002	-0.2201563
	(0.2123507)	(0.2628007)	(0.1817056)
t_2004_2005	0.1476368	-1.071874**	0.2024289
	(0.4380768)	(0.5289806)	(0.1601519)
t_2005_2006	0.296465	-0.5616329	0.2636013
	(0.2842017)	(0.437747)	(0.2004114)
t_2006_2007	1.133243	-0.4129889	0.4618156**
	(0.6248533)	(0.4351177)	(0.2011328)
t_2007_2008	0.9049331	-0.0901644	0.2698471
	(0.599295)	(0.4194216)	(0.1561035)
t_2008_2009	1.457693**	0.823737	0.4656804
	(0.6961536)	(0.9034511)	(0.6363382)
t_2009_2010	1.58294***	0.4115137	0.6257669
	(0.3350678)	(0.5543774)	(0.4622257)
t_2010_2011	1.08771***	-0.1221963	0.2981303
	(0.3532581)	(0.5681204)	(0.3788053)
t_2011_2012	1.34838*	-0.0220372	0.2585264
	(0.6925959)	(0.5591528)	(0.3411987)
t_2012_2013	1.251551***	0.3401605	0.3344965
	(0.4836694)	(0.4739093)	(0.3847355)
t_2013_2014	1.316216***	0.1728298	0.4979616
	(0.3161477)	(0.5112524)	(0.3702778)
t_2014_2015	1.387259***	0.3083458	0.2428468
	(0.4342731)	(0.5126363)	(0.310806)
t_2015_2016	1.299328***	0.3980143	0.262215
	(0.4389266)	(0.5435453)	(0.397891)
t_2016_2017	1.21338**	0.4329936	0.1532655
	(0.6166572)	(0.7164487)	(0.3692536)
t_2017_2018	0.867261*	-0.1363158	0.1167633
	(0.4650583)	(0.7876415)	(0.3221897)
t_2018_2019	1.343456	0.5196445	0.2182953
	(0.7369004)	(0.7534239)	(0.4210065)
Observations	500	500	500

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.1: Continued

VARIABLES	(5) g2008	(6) g2009
t_2000_2001	0.4596183	-0.6546516
	(0.7834342)	(0.4847403)
t_2001_2002	-0.341263	0.5380335*
	(0.5873037)	(0.2414192)
t_2002_2003	0.2696184	0.9098222**
	(0.2277795)	(0.3468337)
t_2003_2004	-0.2233023	-0.4793305**
	(0.1821418)	(0.1762116)
t_2004_2005	-0.0511523	-0.944911***
	(0.2031585)	(0.2960146)
t_2005_2006	-0.0520582	1.162621**
	(0.2537149)	(0.3893662)
t_2006_2007	0.2101529	0.0629911
	(0.1698732)	(0.3568362)
t_2007_2008	0.2251196	-0.0193112
	(0.1989708)	(0.0749223)
t_2007_2009	0.5031049	0.8088269
	(0.8438382)	(0.8654675)
t_2007_2010	0.5138073	0.2911619
	(0.3120866)	(0.2139223)
t_2007_2011	0.4850979	-0.1616169
	(0.4125876)	(0.3119515)
t_2007_2012	0.3899732	0.1173445
	(0.3482794)	(0.2660157)
t_2007_2013	2.433394*	0.6514028*
	(1.379931)	(0.2662416)
t_2007_2014	2.263521*	0.8657849***
	(1.251035)	(0.1912799)
t_2007_2015	0.5964125**	1.6897***
	(0.2231551)	(0.1942414)
t_2007_2016	0.7036522**	0.6244225*
	(0.2500959)	(0.2921578)
t_2007_2017	0.5869702	0.4964646
	(0.3908255)	(0.3637927)
t_2007_2018	0.4532795	0.1329128
	(0.2726931)	(0.3922227)
t_2007_2019	0.9247418	0.6253449
	(0.5556286)	(0.3695723)
Observations	500	500

Standard errors in parentheses, clustered at company level
*** p<0.01, ** p<0.05, * p<0.1

Table B.2: Non-Technological Acquisitions and R&D Intensity: DID Regression Results

VARIABLES	(1) g2003	(2) g2004	(3) g2005	(4) g2006
t_2000_2001	-0.182325	-0.320305	-0.3964314	-0.5199694
	(0.4880885)	(1.041259)	(0.5940983)	(0.958621)
t_2001_2002	-0.2063185	-0.3545796	0.5967284	-0.4906345
	(0.2143826)	(0.2409884)	(0.2171848)	(0.3468629)
t_2002_2003	-0.0008714	-0.4975231	-0.0223924	0.3709059
	(0.183616)	(0.2929796)	(0.166286)	(0.3138027)
t_2003_2004	0.2646801	0.8699532	0.2206788	0.6568148
	(0.1752159)	(0.1981987)	(0.1527476)	(0.2636382)
t_2004_2005	0.2356218	1.321176	0.5769169	0.1280838
	(0.1900779)	(0.2901268)	(0.217828)	(0.214155)
t_2005_2006	0.3371165	0.8024229	0.7705568	-0.5690007
	(0.2110529)	(0.387157)	(0.2017413)	(0.2675824)
t_2006_2007	0.2175694	0.6272827	0.9885894	-0.3336518
	(0.1830499)	(0.2281658)	(0.0985161)	(0.1331006)
t_2007_2008	0.0576871	0.741121	0.7424592	-0.2927954
	(0.265977)	(0.2073825)	(0.1424023)	(0.3271605)
t_2008_2009	-0.0741763	-0.4165524	0.2130945	-1.115159
	(0.422454)	(0.7146248)	(0.6190094)	(0.8692162)
t_2009_2010	0.5683055	0.5024549	1.11088	0.3804448
	(0.3073828)	(0.5481358)	(0.1384243)	(0.4012594)
t_2010_2011	0.5088615	0.8275669	0.8483871	0.7409062
	(0.3021598)	(0.4946643)	(0.2308559)	(0.2860776)
t_2011_2012	0.3660576	0.6708678	0.8470133	0.2309357
	(0.2467949)	(0.4046295)	(0.4135676)	(0.3216045)
t_2012_2013	-0.1643165	0.5662392	0.7249957	0.0908911
	(0.6939266)	(0.4522976)	(0.2773085)	(0.275762)
t_2013_2014	-0.2046946	0.8336467	0.9271096	0.1944658
	(0.7037562)	(0.5186756)	(0.188486)	(0.345122)
t_2014_2015	0.3300679	0.7808062	0.6395166	-0.0172853
	(0.3174069)	(0.5555702)	(0.3203443)	(0.3666582)
t_2015_2016	0.4486482	0.7807391	0.770645	-0.0511466
	(0.2891889)	(0.4927879)	(0.4379513)	(0.3760209)
t_2016_2017	0.6056535	1.202164	0.9849771	-0.0100658
	(0.3921902)	(0.7073452)	(0.4388023)	(0.3693818)
t_2017_2018	0.4755698	1.567774	1.290912	0.142862
	(0.4267951)	(0.7803512)	(0.3065152)	(0.451289)
t_2018_2019	0.4887808	0.9829915	1.202174	0.0119387
	(0.4054121)	(0.8440263)	(0.4548455)	(0.3911653)
Observations	500	500	500	500

Standard errors in parentheses, clustered at the company level
*** p<0.01, ** p<0.05, * p<0.1

Table B.2: Continued

VARIABLES	(5) g2007	(6) g2008
t_2000_2001	0.6091211***	-1.525605
	(0.1447746)	(1.085489)
t_2001_2002	-0.2427028***	-0.2636166
	(0.0620204)	(0.3103246)
t_2002_2003	-0.3035131*	-0.0277922
	(0.1698843)	(0.2309297)
t_2003_2004	0.2976984*	0.7187207***
	(0.1621914)	(0.2098555)
t_2004_2005	-0.0480668	0.192572
	(0.088017)	(0.2590873)
t_2005_2006	0.7418582***	0.461472***
	(0.0367799)	(0.0838005)
t_2006_2007	-0.1817877***	0.7643426
	(0.0683965)	(0.8219782)
t_2006_2008	-0.510337	-0.2377517
	(0.3169725)	(0.2661179)
t_2006_2009	-0.4036412***	-1.308839
	(0.1049488)	(1.453908)
t_2006_2010	-0.5755332***	-0.7988052
	(0.0658349)	(0.8543115)
t_2006_2011	-0.6981454***	-1.048946
	(0.0901849)	(0.7096287)
t_2006_2012	-0.3605466***	0.0445645
	(0.120273)	(0.1661623)
t_2006_2013	-0.1345405	-0.9947835
	(0.106401)	(0.6435154)
t_2006_2014	0.0614689	-1.017268*
	(0.1490673)	(0.5568388)
t_2006_2015	0.7214018***	-1.012453*
	(0.1405104)	(0.5884631)
t_2006_2016	-0.2660605*	-1.085154*
	(0.1412681)	(0.6003007)
t_2006_2017	-0.4946251***	-0.8106475
	(0.1310632)	(0.6058671)
t_2006_2018	-0.653363***	-0.7708904
	(0.1145346)	(0.5301773)
t_2006_2019	-0.577968***	-0.9206241
	(0.084411)	(0.757059)
Observations	500	500

Standard errors in parentheses, clustered at the company level
*** p<0.01, ** p<0.05, * p<0.1

Appendix C

Companies

Table C.1: Companies Hypothesis 1

No.	Company Name
1	ABBOTT LABORATORIES
2	AMKOR TECHNOLOGY INC
3	AMPHENOL CORP
4	ANALOG DEVICES INC
5	AUTOMATIC DATA PROCESSING
6	BRISTOL-MYERS SQUIBB COMPANY
7	CISCO SYSTEMS INC
8	ELI LILLY AND COMPANY
9	INTEL CORP
10	INTERNATIONAL BUSINESS MACHINES CORP
11	JABIL, INC.
12	JOHNSON & JOHNSON
13	KLA CORPORATION
14	L3HARRIS TECHNOLOGIES, INC.
15	MERCK & CO., INC.
16	MICROCHIP TECHNOLOGY INC
17	MICRON TECHNOLOGY INC
18	NVIDIA CORP
19	ON SEMICONDUCTOR CORP
20	PFIZER INC
21	QUALCOMM INC
22	SANMINA CORPORATION
23	SYNOPSYS INC
24	TEXAS INSTRUMENTS INC
25	VIATRIS INC

The 25 companies that are in the dataset used for the results of Table 5.1

Table C.2: Companies Hypothesis 2

	Company Name		Company Name
1	ABBOTT LABORATORIES	23	JUNIPER NETWORKS INC
2	ABBVIE INC.	24	KLA CORPORATION
3	ADVANCED MICRO DEVICES INC	25	L3HARRIS TECHNOLOGIES, INC.
4	AMGEN INCORPORATED	26	LEIDOS HOLDINGS, INC.
5	AMKOR TECHNOLOGY INC	27	LUMENTUM HOLDINGS INC.
6	AMPHENOL CORP	28	MERCK & CO., INC.
7	ANALOG DEVICES INC	29	MICROCHIP TECHNOLOGY INC.
8	APPLE	30	MICRON TECHNOLOGY INC.
9	ARISTA NETWORKS INC.	31	MOTOROLA SOLUTIONS, INC.
10	AUTOMATIC DATA PROCESSING	32	NVIDIA CORP
11	AVAYA	33	ON SEMICONDUCTOR CORP
12	BROADCOM INC.	34	PFIZER INC
13	BRISTOL-MYERS SQUIBB COMPANY	35	QUALCOMM INC
14	CISCO SYSTEMS INC	36	QORVO INC
15	COMMSCOPE	37	SALESFORCE INC
16	ECHOSTAR CORPORATION	38	SANMINA CORPORATION
17	ELI LILLY AND COMPANY	39	SCIENCE APPLICATIONS
18	GILEAD SCIENCES INC	40	SYNOPSYS INC
19	INTEL CORP	41	TEXAS INSTRUMENTS INC
20	INTERNATIONAL BUSINESS MACHINES CORP	42	UBIQUITI INC.
21	JABIL, INC.	43	VIATRIS INC
22	JOHNSON & JOHNSON		

The 43 companies that are in the dataset used for the results of 5.2

Appendix D

Parallel Trend Assumption

D.1 Technological Acquisition - Hypothesis 1a

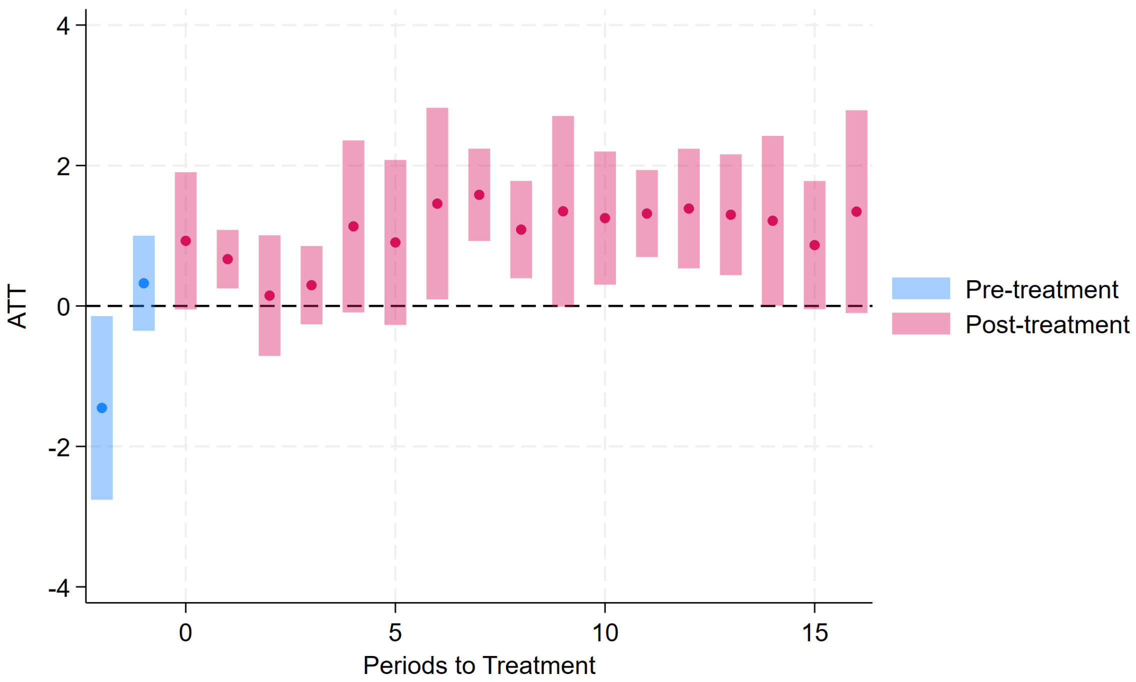

Figure D.1: pre- and post periods to treatment, Group: 2003

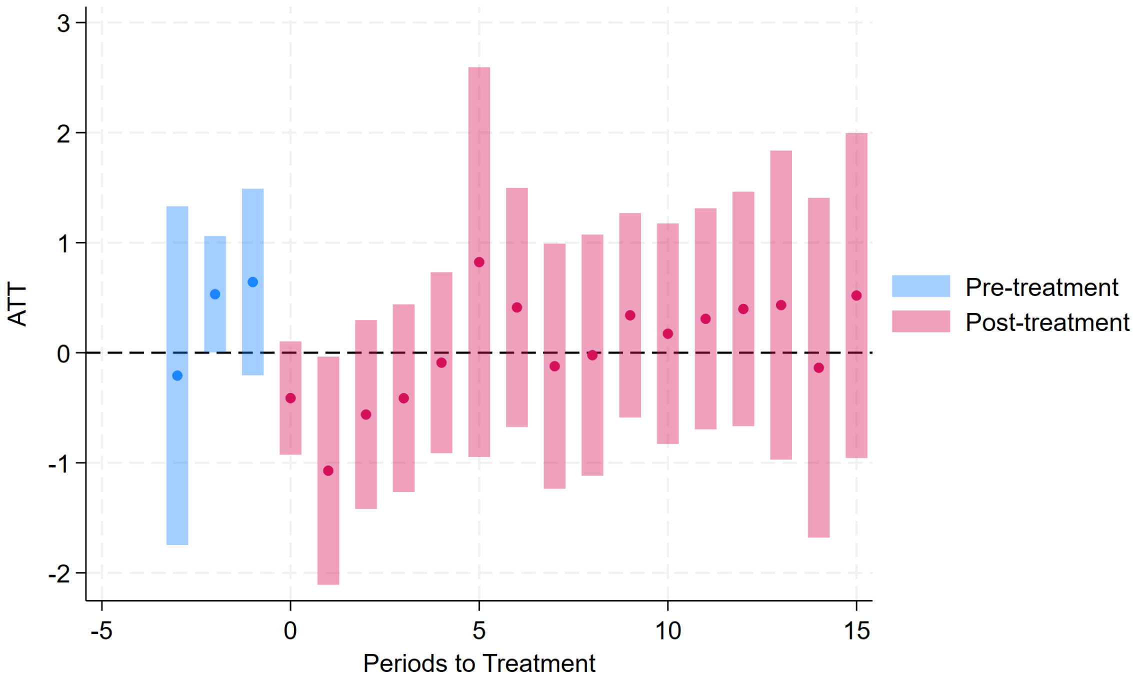

Figure D.2: pre- and post periods to treatment, Group: 2004

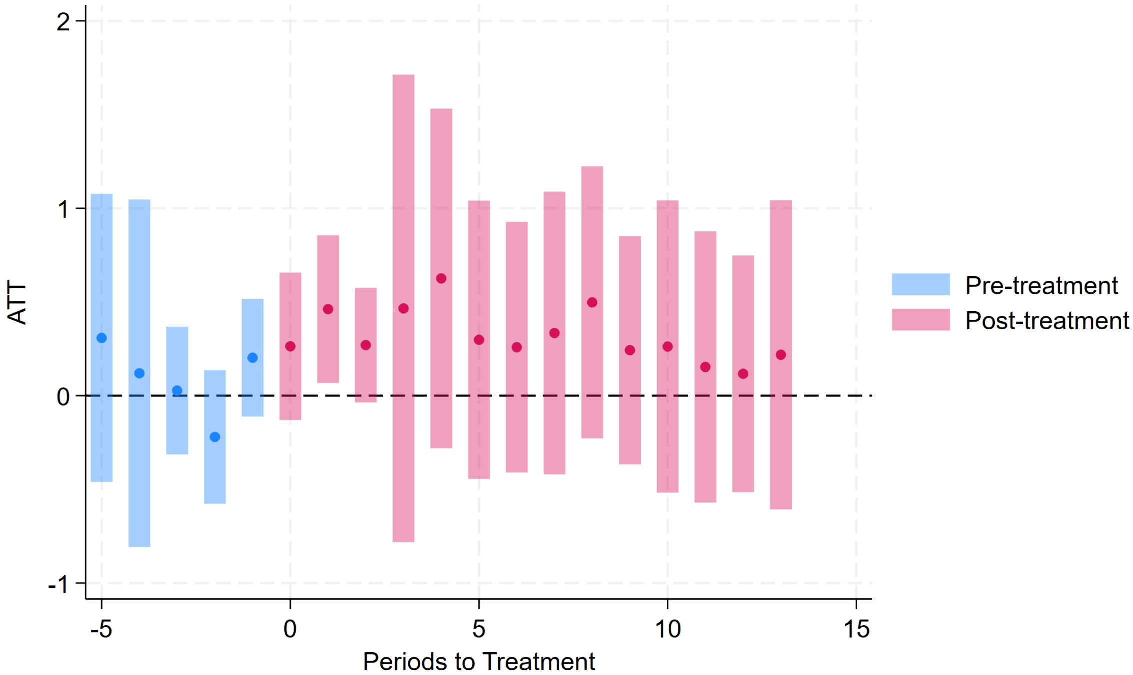

Figure D.3: pre- and post periods to treatment, Group: 2006

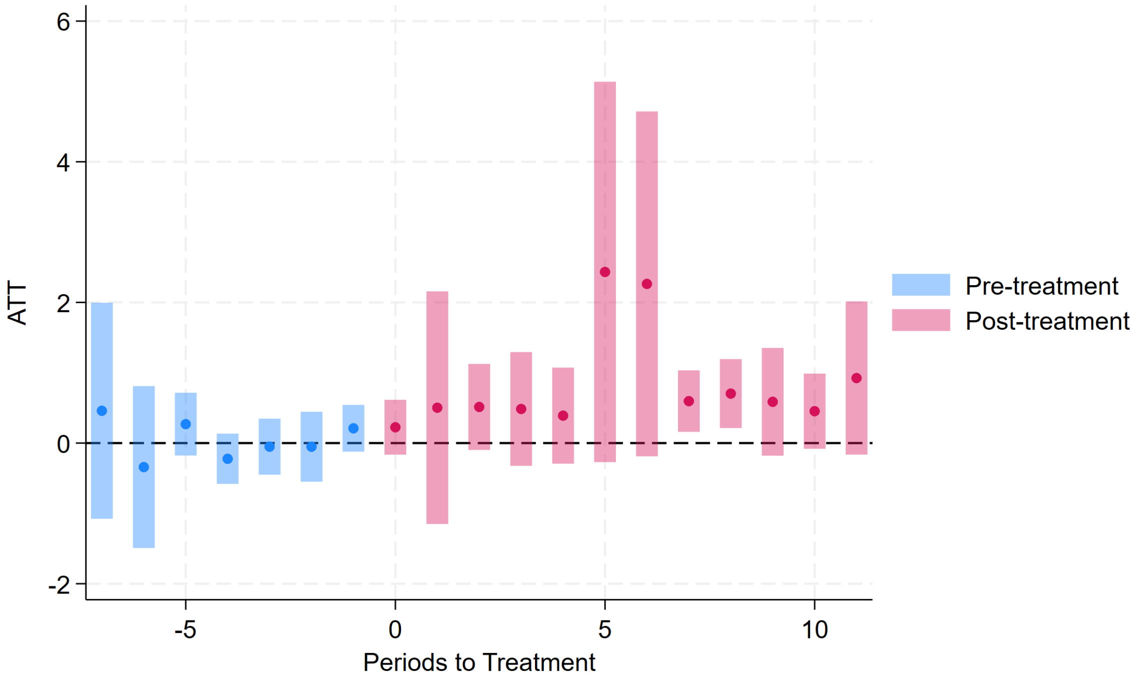

Figure D.4: pre- and post periods to treatment, Group: 2008

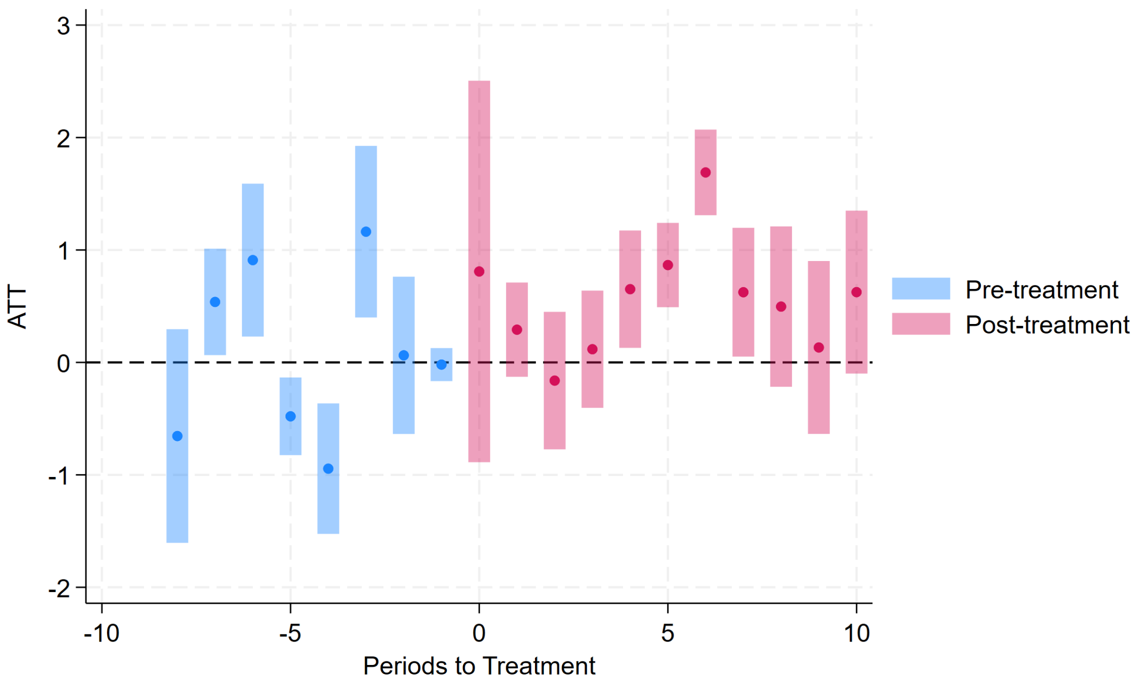

Figure D.5: pre- and post periods to treatment, Group: 2009

D.2 Non-Technological Acquisition - Hypothesis 1b

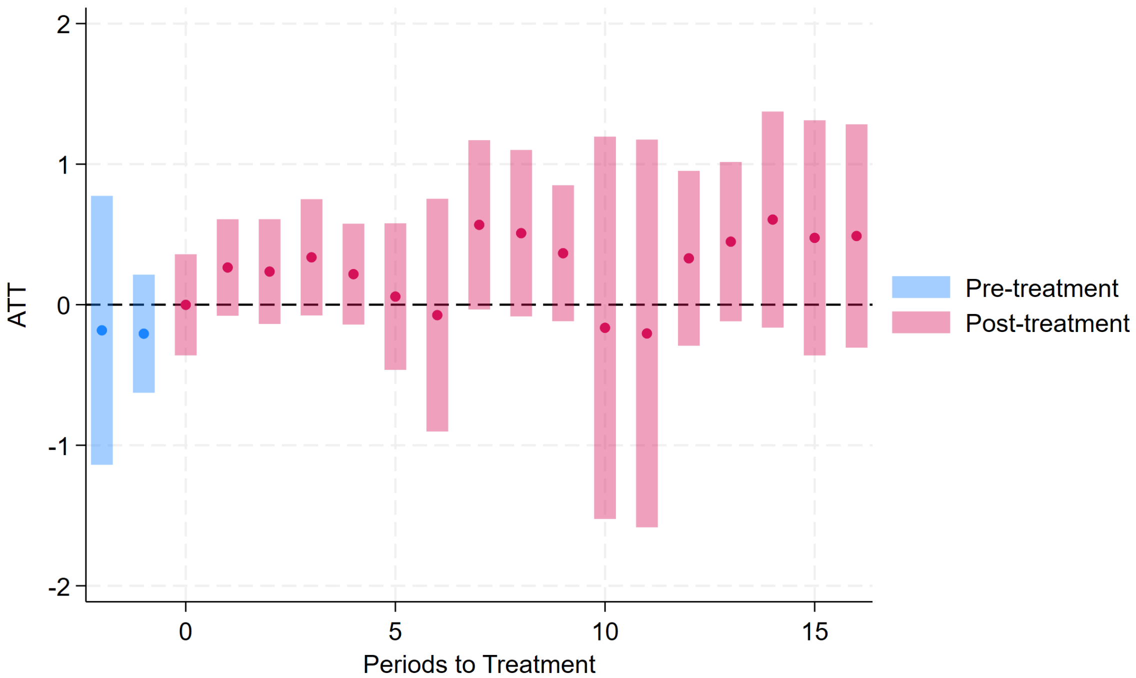

Figure D.6: pre- and post periods to treatment (non-technological acquisition), Group: 2003

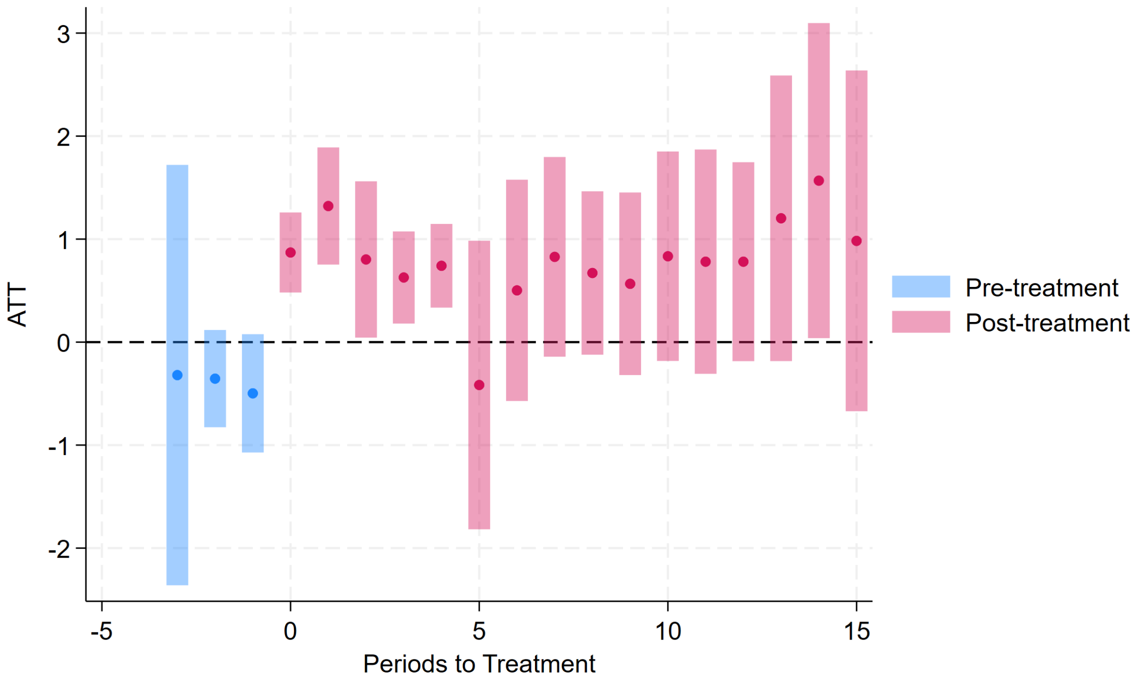

Figure D.7: pre- and post periods to treatment (non-technological acquisition), Group: 2004

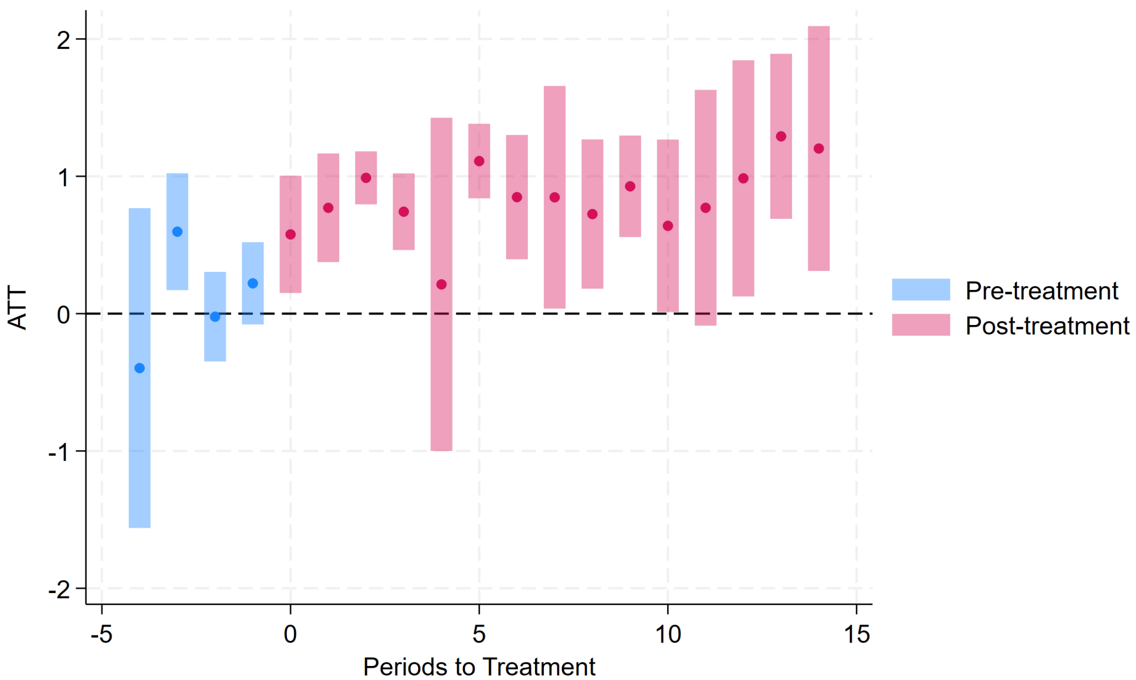

Figure D.8: pre- and post periods to treatment (non-technological acquisition), Group: 2005

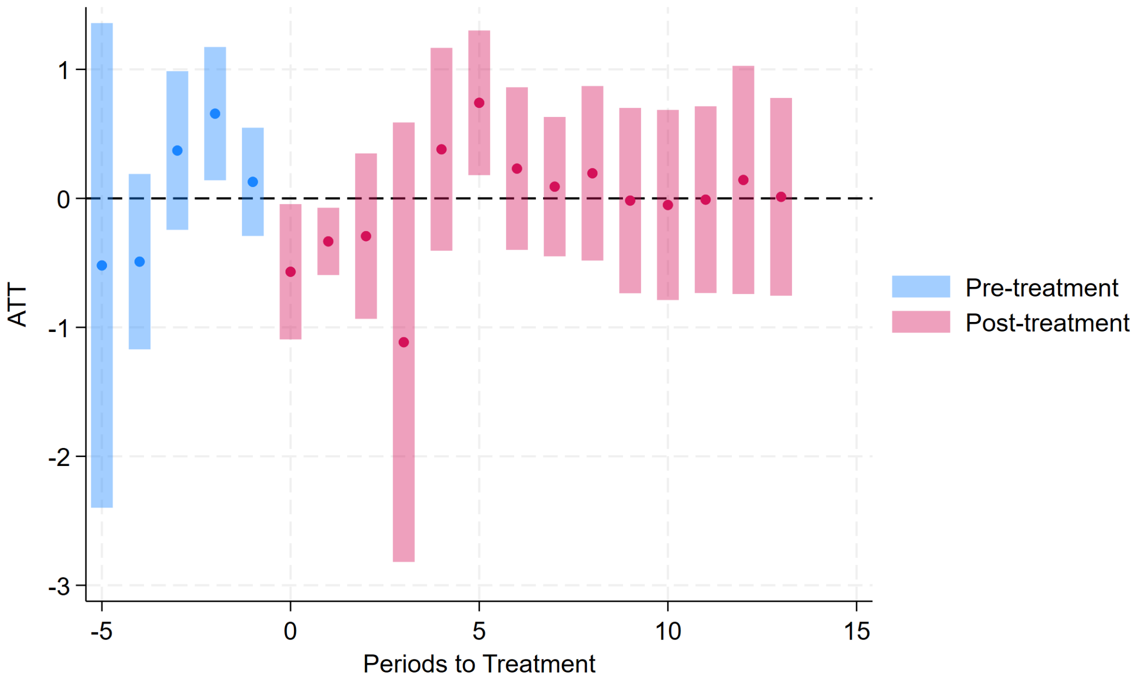

Figure D.9: pre- and post periods to treatment (non-technological acquisition), Group: 2006

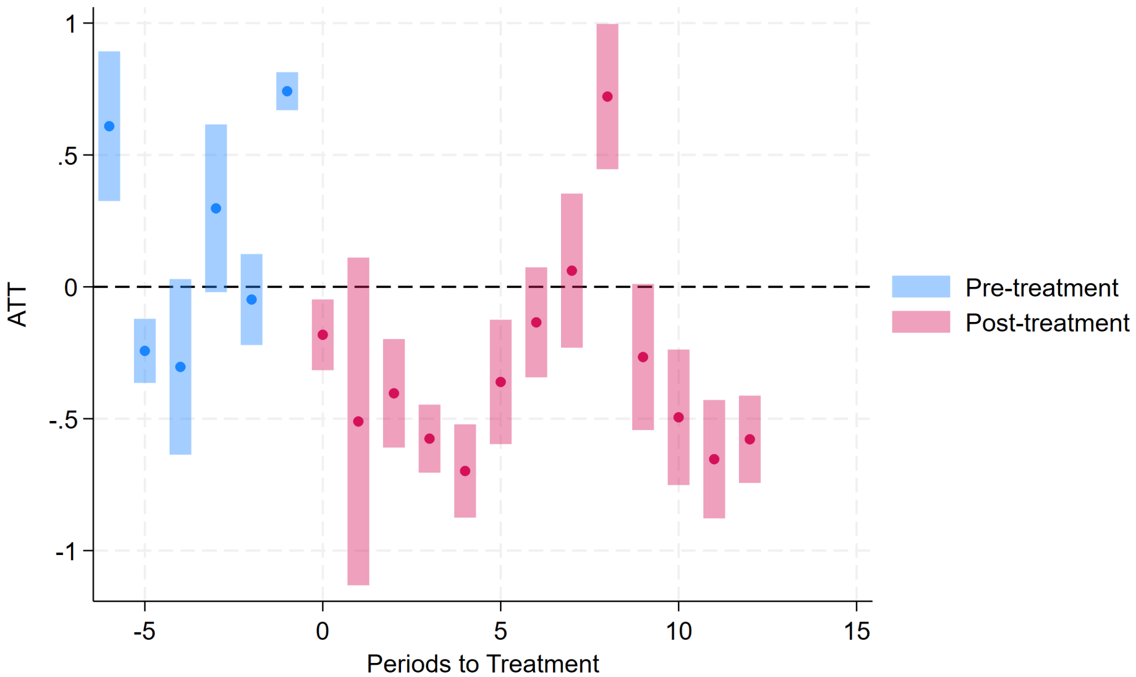

Figure D.10: pre- and post periods to treatment (non-technological acquisition), Group: 2007

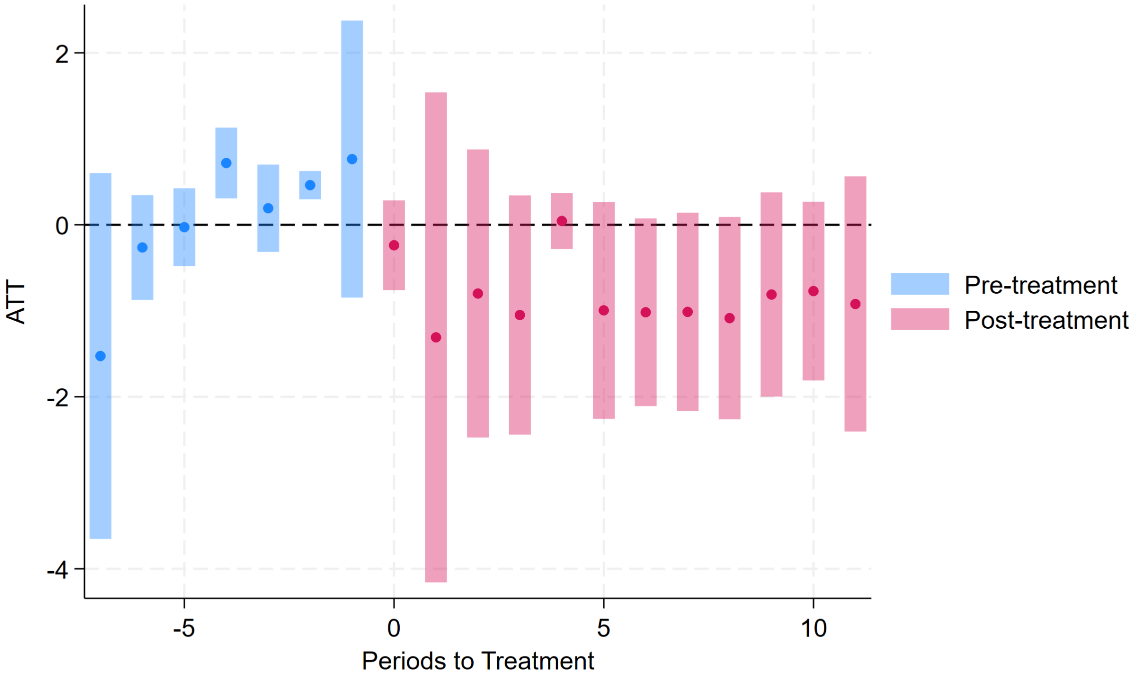

Figure D.11: pre- and post periods to treatment (non-technological acquisition), Group: 2008

Appendix E

Robustness Checks

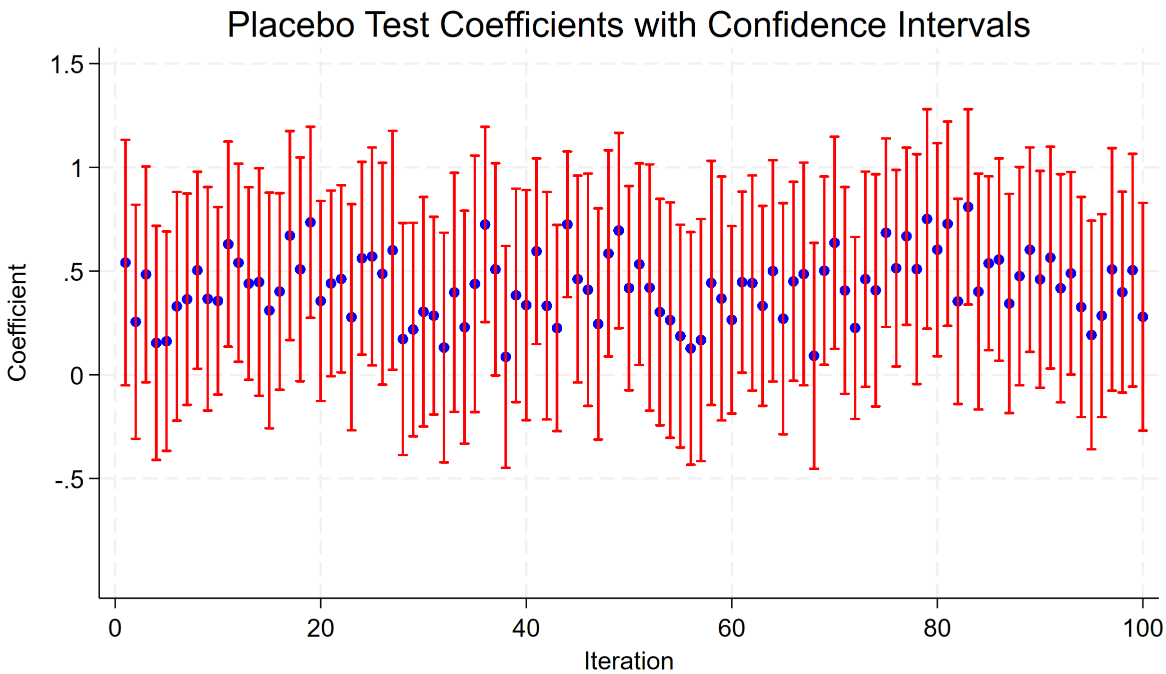

Figure E.1: Placebo Test, Hypothesis 1a

Table E.1: Anticipation Effects of Technological Acquisitions on R&D Intensity

Group	**Coefficient**
GAverage	0.8626***
	(0.2247)
G2002	1.3229**
	(0.4888)
G2003	0.7078
	(0.5027)
G2005	0.4966**
	(0.1985)
G2007	0.9500***
	(0.2402)
G2008	0.7187**
	(0.2610)

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. The staggered DID method introduced by Callaway and Sant'Anna (2021) is used with as dependent variable the logarithm of R&D intensity of the acquiring firm. The treatment is set at one year prior to the first technological acquisition of the acquiring firm in the years 2003-2009 to test if there is an anticipation effect. As a control group, "later treated" companies are used, which are those companies that made technological acquisitions after 2009. The coefficients represent the average post-acquisition impact of the technological acquisition compared to the pre-acquisition period. GAverage is the average effect across all groups, while G2002-G2008 represent the individual groups. Each group consists of companies that made their first technological acquisition one year after the corresponding year. Standard errors, in parentheses, are clustered at the company level.

Table E.2: Effect of Second Technological Acquisition on R&D Intensity

Group	**Coefficient**
GAverage	0.5714*
	(0.3067)
G2004	-0.9000*
	(0.4663)
G2005	0.8263*
	(0.4897)
G2006	0.9824***
	(0.3586)
G2007	0.7689*
	(0.4022)
G2010	-0.0660
	(0.9226)

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. The staggered DID method introduced by Callaway and Sant'Anna (2021) is used with as dependent variable the logarithm of the R&D intensity of the acquiring firm. The treatment is the second technological acquisition of the acquiring firm in the years 2004-2010. As a control group, "later treated" companies are used, which are those companies that made either their first or second technological acquisitions after 2010. The coefficients represent the average post-acquisition impact of the technological acquisition compared to the pre-acquisition period. GAverage is the average effect across all groups, while G2004-G2010 represent the individual groups. Each group consists of companies that made their second technological acquisition in the corresponding year. Standard errors, in parentheses, are clustered at the company level.

Table E.3: Anticipation Effects of Non-Technological Acquisitions on R&D Intensity

Group	**Coefficient**
GAverage	0.2075
	(0.2039)
G2002	0.0339
	(0.3487)
G2003	0.2250
	(0.4822)
G2004	1.0050***
	(0.3503)
G2005	0.0898
	(0.2831)
G2006	0.4499***
	(0.0839)
G2007	-0.0313
	(0.2798)

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. The staggered DID method introduced by Callaway and Sant'Anna (2021) is used with as dependent variable the logarith of the R&D intensity of the acquiring firm. The treatment is set at one year prior to the first non-technological acquisition of the acquiring firm in the years 2003-2009 to test if there is an anticipation effect. As a control group, "later treated" companies are used, which are those companies that made non-technological acquisitions after 2009. The coefficients represent the average post-acquisition impact of the non-technological acquisition compared to the pre-acquisition period. GAverage is the average effect across all groups, while G2002-G2007 represent the individual groups. Each group consists of companies that made their first non-technological acquisition one year after the corresponding year. Standard errors, in parentheses, are clustered at the company level.

Table E.4: Effect of Second Non-Technological Acquisition on R&D Intensity

Group	**Coefficient**
GAverage	0.0315
	(0.1741)
G2004	0.2496
	(0.4257)
G2005	-0.1304
	(0.3539)
G2007	-0.3934***
	(0.1339)
G2008	0.3094***
	(0.0285)
G2009	0.2283
	(0.2530)

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. The staggered DID method introduced by Callaway and Sant'Anna (2021) is used with as dependent variable the logarithm of the R&D intensity of the acquiring firm. The treatment is the second non-technological acquisition of the acquiring firm in the years 2004-2010. As a control group, "later treated" companies are used, which are those companies that made either their first or second non-technological acquisitions after 2010. The coefficients represent the average post-acquisition impact of the non-technological acquisition compared to the pre-acquisition period. GAverage is the average effect across all groups, while G2004-G2009 represent the individual groups. Each group consists of companies that made their second non-technological acquisition in the corresponding year. Standard errors, in parentheses, are clustered at the company level.

Table E.5: Negative Binomial Regression: Technological Acquisitions and Patent Counts

	1	2	3	4
Number of Patents				
Technological Acquisition	0.052	0.012	0.000	-0.014
	(0.043)	(0.036)	(0.033)	(0.031)
Technological Acquisition$_{t-1}$	0.114***	0.071**	0.061*	0.044
	(0.044)	(0.036)	(0.033)	(0.032)
Technological Acquisition$_{t-2}$	0.126***	0.050	0.034	0.016
	(0.044)	(0.037)	(0.034)	(0.032)
Technological Acquisition$_{t-3}$	0.062	0.001	0.002	-0.012
	(0.044)	(0.037)	(0.033)	(0.032)
Technological Acquisition$_{t-4}$	0.118***	0.065*	0.059*	0.073**
	(0.044)	(0.037)	(0.034)	(0.033)
Size			0.257***	0.250***
			(0.046)	(0.047)
Log(R&D)			0.011	0.022
			(0.032)	(0.033)
Constant	1.724***	2.577***	0.164	0.534
	(0.074)	(0.152)	(0.475)	(0.501)
Industry FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Year*Industry FE	No	No	No	Yes
N	548	548	548	548

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. A Negative Binomial model is used with as dependent variable the count of annual granted patents for the acquiring firm. The explanatory variable, Technological Acquisition, is a binary variable that equals one in year t if the company made a technological acquisition in that year. Technological Acquisition$_{t-1}$ with i={1,. . . ,4}, represents the lagged variables of technological acquisition, ranging from one to four years. The control variable Size is defined as the logarithm of the number of employees in a firm. The control variable, R&D Intensity, measures the firm's R&D Intensity and is defined as R&D expenses divided by EBITDA in year t. Standard errors, in parentheses are clustered at the company level.

Table E.6: Effect of Number of Technological Acquisitions on Patent Counts

	1	2	3	4
Number of patents				
Technological Acquisition	0.068	0.062	0.040	0.024
	(0.054)	(0.038)	(0.035)	(0.031)
#Technological Acquisition$_{t-1}$	0.075*	0.052	0.026	0.021
	(0.044)	(0.037)	(0.033)	(0.034)
#Technological Acquisition$_{t-2}$	0.093***	0.065***	0.048***	0.028
	(0.023)	(0.019)	(0.017)	(0.024)
#Technological Acquisition$_{t-3}$	0.055*	0.031	0.016	0.001
	(0.030)	(0.024)	(0.022)	(0.026)
#Technological Acquisition$_{t-4}$	0.032	0.029	0.016	0.023
	(0.025)	(0.024)	(0.022)	(0.023)
Size			0.270**	0.317**
			(0.122)	(0.127)
Log(R&D)			-0.120***	-0.144***
			(0.045)	(0.051)
Constant	6.927***	6.708***	3.818***	3.462**
	(0.241)	(0.341)	(1.298)	(1.351)
Industry FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Year*Industry FE	No	No	No	Yes
N	548	548	548	548

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. A Poisson QMLE model is used with as dependent variable the count of annual granted patents for the acquiring firm. The explanatory variable, #Technological Acquisition, represents the number of technological acquisitions a company made in year t. #Technological Acquisition$_{t-1}$ with i={1,...,4}, represents the lagged variables of the number of technological acquisitions, ranging from one to four years. The control variable Size is defined as the logarithm of the number of employees in a firm. The control variable, Log(R&D) measures the logarithm of the firm's R&D Intensity and is defined as R&D expenses divided by EBITDA in year t. Standard errors, in parentheses are clustered at the company level.

Table E.7: Average Treatment Effect of Technological Acquisition on Patent Counts

Group	**Coefficient**
GAverage	447.2798*
	(252.2763)
G2003	269.9218
	(476.9646)
G2004	1050.586
	(677.9556)
G2005	-
G2006	-139.0115**
	(70.75354)
G2008	517.0688
	(798.8544)
G2009	501.8938***
	(36.52085)
G2010	76.07096
	(150.7778)

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. The staggered DID method introduced by Callaway and Sant'Anna (2021) is used with as dependent variable the number of annual granted patents of the acquiring firm. The treatment is the first technological acquisition of the acquiring firm in the years 2003-2010. As a control group, "later treated" companies are used, which are those companies that made their first or technological acquisitions after 2010. The coefficients represent the average post-acquisition impact of the non-technological acquisition compared to the pre-acquisition period. GAverage is the average effect across all groups, while G2003-G2010 represent the individual groups. Each group consists of companies that made their first technological acquisition in the corresponding year. Standard errors, in parentheses, are clustered at the company level.

Table E.8: Negative Binomial: Non-Technological Acquisitions and Patent Counts

	1	2	3	4
Number of patents				
Non-Technological Acquisition	0.038	0.075	0.077*	0.102**
	(0.057)	(0.048)	(0.045)	(0.044)
Non-Technological Acquisition$_{t-1}$	0.003	0.020	0.018	0.068
	(0.058)	(0.050)	(0.047)	(0.046)
Non-Technological Acquisition$_{t-2}$	-0.069	-0.039	-0.039	-0.012
	(0.056)	(0.049)	(0.047)	(0.045)
Non-Technological Acquisition$_{t-3}$	-0.075	-0.028	-0.043	-0.020
	(0.054)	(0.047)	(0.045)	(0.044)
Non-Technological Acquisition$_{t-4}$	-0.064	-0.029	-0.058	-0.009
	(0.053)	(0.046)	(0.044)	(0.043)
Size			0.236***	0.190***
			(0.052)	(0.054)
Log(R&D)			0.008	0.026
			(0.033)	(0.034)
Constant	1.871***	2.747***	0.515	1.257**
	(0.073)	(0.165)	(0.537)	(0.582)
Industry FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Year*Industry FE	No	No	No	Yes
N	548	548	548	548

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. A Negative Binomial model is used with as dependent variable the count of annual granted patents for the acquiring firm. The explanatory variable, Non-Technological Acquisition, is a binary variable that equals one in year t if the company made a non-technological acquisition in that year. Non-Technological Acquisition$_{t-1}$ with i={1,. . . ,4}, represents the lagged variables of non-technological acquisition, ranging from one to four years. The control variable Size is defined as the logarithm of the number of employees in a firm. The control variable, R&D Intensity, measures the firm's R&D Intensity and is defined as R&D expenses divided by EBITDA in year t. Standard errors, in parentheses are clustered at the company level.

Table E.9: Effect of Number of Non-Technological Acquisitions on Patent Counts

	1	2	3	4
Number of patents				
#Non-Technological Acquisition	-0.016	0.001	0.007	0.085***
	(0.029)	(0.028)	(0.027)	(0.016)
#Non-Technological Acquisition$_{t-1}$	0.009	0.020	0.020	0.031***
	(0.017)	(0.013)	(0.014)	(0.009)
#Non-Technological Acquisition$_{t-2}$	-0.004	0.015	0.007	0.038**
	(0.020)	(0.017)	(0.019)	(0.016)
#Non-Technological Acquisition$_{t-3}$	-0.012	-0.000	-0.011	0.004
	(0.016)	(0.012)	(0.013)	(0.008)
#Non-Technological Acquisition$_{t-4}$	-0.008	0.004	-0.003	-0.009
	(0.012)	(0.009)	(0.010)	(0.008)
Size			0.281*	0.149
			(0.151)	(0.148)
Log(R&D)			-0.143***	-0.163***
			(0.044)	(0.046)
Constant	7.094***	6.775***	3.724**	5.298***
	(0.253)	(0.367)	(1.593)	(1.594)
Industry FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Year*Industry FE	No	No	No	Yes
N	548	548	548	548

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. A Poisson QMLE model is used with as dependent variable the count of annual granted patents for the acquiring firm. The explanatory variable, #Technological Acquisition, represents the number of non-technological acquisitions a company made in year t. #Technological Acquisition$_{t-1}$ with i={1,. . . ,4}, represents the lagged variables of the number of technological acquisitions, ranging from one to four years. The control variable Size is defined as the logarithm of the number of employees in a firm. The control variable, Log(R&D), measures the logarithm of the firm's R&D Intensity and is defined as R&D expenses divided by EBITDA in year t. Standard errors, in parentheses are clustered at the company level.

Table E.10: Average Treatment Effect of Non-Technological Acquisition on Patent Counts

Group	**Coefficient**
GAverage	135.09
	(554.31)
G2003	379.30
	(1108.75)
G2004	-3838.93**
	(1481.34)
G2005	2795.05
	(1719.91)
G2006	-314.91*
	(147.81)
G2007	154.51
	(190.80)
G2008	1455.91
	(981.43)
G2010	-13.04
	(92.64)

Notes: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. The staggered DID method introduced by Callaway and Sant'Anna (2021) is used with as dependent variable the number of annual granted patents of the acquiring firm. The treatment is the first non-technological acquisition of the acquiring firm in the years 2003-2010. As a control group, "later treated" companies are used, which are those companies that made their first or non-technological acquisitions after 2010. The coefficients represent the average post-acquisition impact of the non-technological acquisition compared to the pre-acquisition period. GAverage is the average effect across all groups, while G2003-G2010 represent the individual groups. Each group consists of companies that made their first non-technological acquisition in the corresponding year. Standard errors, in parentheses, are clustered at the company level.