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1 Introduction

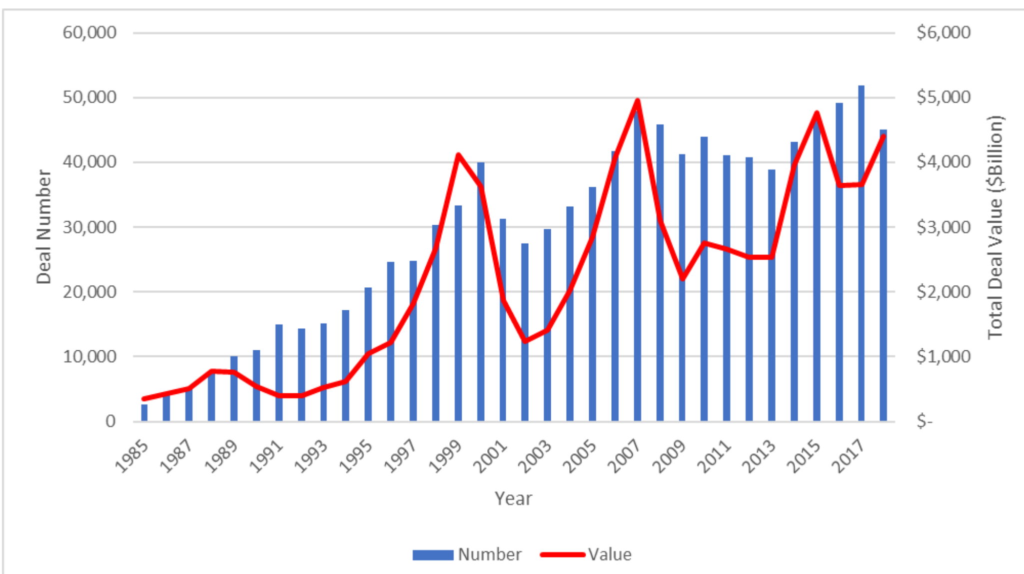
1.1 Research Objectives and structure

The following empirical work aims at analyzing the peculiar characteristics that shape Mergers and Acquisitions (M&A) value creation in High Tech industries. The viewpoint of the analysis is the one of the acquired, or target firms, listed on the NASDAQ and involved in M&A activity in the 2008-2018 period. While target firms have traditionally experienced positive financial returns from being acquired (Asquith & Kim, 1982, Datta et al., 1992, Hansen & Lott, 1996, Malatesta, 1983), few research efforts have yet been dedicated at the investigation of the particular factors that are typical of these firms and that therefore may play significant roles in moderating M&A performance. Given the prominent role and importance of technological progress for the global economy, and the yet low volume of High Tech M&A literature present, the main research objective is to determine the extent to which innovative activities at the firm level determine transaction outcomes for target firm shareholders. Innovative activities in the following work are mainly characterized as R&D expenditures, number of Patents and Technological Sector dynamics. Other factors that moderate M&A performance are the size of the deal, M&A experience by the acquiring firm, financial distress at the target firm, and the year in which the deal is announced. Given the current economic landscape at the time of writing, I believe this work to be theoretically interesting and relevant both in terms of its contribution to M&A literature and in terms of its attempt at understanding major drivers of value creation in the data and software driven economy of the 21st century.

This work in divided in six main sections: the first and current section provides a brief introduction to the examined economic topics of Mergers and Acquisition activity and the High Tech sectors of the global world economy in year 2018. The second section is dedicated to the description of the data used for the empirical analysis. Section 3 illustrates the methodology of the Event Study, a statistical approach to examine stock price data around a certain event of interest, which will be applied to the sample data. Section 4 presents the results of the Event Study analysis conducted at Section 3 and further builds on further statistical investigation in order to determine the role of technology firms' features and activities which possibly play a moderating role in the Event Study analysis. Section 5 illustrates the consequent results of the overall statistical analysis of sections 3 and 4, whereas section 6 concludes the text with final implications, limitations of the conducted study, as well as considerations for further empirical research.

Topics of Corporate Strategy and diversification at the firm level have been longtime favorites of managerial literature (Coase, 1937, Porter, 1985, Barney, 1991, Campbell, 1995, Collis & Montgomery,1998 Kotter et al., 2008, Collis et al, 2012, Campbell et al, 2014), which has tried, time and time again, to develop models for analyzing the overall *raison d'être* of a firm in the global market environment of today's modern economy. Throughout the course of history, trade and business expansion have represented a tool for man to unite the world under more homogeneous economic, social, political and technological structures (Harari, 2014), and in this ever-more globalized world multinational firms are trying more and more to seize the tremendous opportunity that the global markets represent. Thus, being able to evaluate the main forces and elements that shape the evolution of the firm's boundaries is today more relevant than ever, as the sheer volume of academic research confirms, and makes for a very interesting subject.

Figure 1: Historical M&A Data 1985-2018 (Projected), by Number and Value ($billions)



Source: Institute of Mergers, Acquisitions and Alliances (IMAA)

In this context, this work aims at representing an empirical attempt at comprehending mainly the economic and technological reasons that potentially have an impact on the firm's decision to conduct diversification.

The link between the economy and technology is nowadays becoming stronger and stronger, as firms of the globalized world are experiencing first hand the repercussions that the massive technological breakthroughs of recent decades have determined on their daily business operations as well as on their whole business models (United Nations Conference on Trade and Development, 2017). Therefore, it is important to understand the drivers and shapers of the current state of the art. To do so, I will examine a sample of Mergers and Acquisition (M&A) operations conducted by global multinational firms active in various sectors of the digital economy. In contrast to the plethora of related Corporate Strategy and diversification literature of the past and present century stands the paucity of digital M&A literature, especially in recent years, a void to which both this work and the global academic community is trying to fill with calls for papers on the new paradigm of the Digital Firm in the Digital Age (Cheseldine, 2018). Therefore, theoretical and empirical investigations in this area represent a yet fresh attempt at discovering new perspectives over the rationales that guide the new business models that have risen since the start of the last Technological Revolution, identified with the advent of Information Technology and Telecommunications (Makridakis, 1995). Past insights which derive from M&A literature will be applied and checked to verify the extent to which they are still applicable to the new digital firms; a prominent role of the this work will be dedicated to the innovative activities of the observed firms, which in recent years have come to represent the core purposes around which business success is created. With global R&D spend on the rise (Pilat,2007), innovation output and processes are more relevant than ever, and the implications on M&A operations cannot go unnoticed. My aim is to discover some of these interesting implications that technological and innovation activity bring to M&A deals, and to encourage additional investigative work directed to the interpretation of the impact that the ongoing development of the Information Revolution has and will have on Corporate Strategy decisions of the most relevant firms of the new digital economy.

1.2 M&A Literature Review: Classification and Empirical Performance Observations

At the core of M&A operations is the decision of expanding the corporate scope of the firm in order to achieve market success; for multi-business firms, which are active across different business sectors and/or markets, market success is measured on two different levels, the corporate level and the business unit level (Collis &

Montgomery, 1998). Corporate level market success allows for the creation of a *corporate advantage,* which is achieved when the entirety of the business units making up the overall corporation derives value from being embedded in the corporate structure, since either organizational, operational or financial synergies are created and spread throughout the corporate scheme so that all business units reap their benefits. This process is orchestrated at the corporate level through coordination and configuration of the multi-business firm's portfolio of resources, competences and businesses. Business unit level market success allows then for the creation of a *competitive advantage* (Porter, 1985), through which the individual business unit achieves and sustains above average profitability performance in regards to the industry in which it operates. In this regard, Porter identifies two diverse types of competitive advantage: cost leadership (in which the firm aims at operating at lower costs in relation to industry peers) and differentiation (in which the firm aims at bringing a unique value proposition to the market, that stands out in terms of some product/service feature, and that is thus recognized as unique by the customers).

Evaluating the presence or absence of both corporate and competitive advantages represents one of the major goals of Corporate Strategy literature and managers, as the evaluation of the multi-business firm's single business units and overall portfolio represents the fundamental basis on which all consequent decisions regarding the expansion of the corporate scope are taken. Corbetta & Morosetti, 2018, draw from recent and relevant literature (Invernizzi, 2012,2014 & 2017, Campbell et al, 2014, Coda et al, 2017, Puranam & Vanneste, 2016), and recap the three main perspectives under which the multi-business firm can evaluate each business unit in the bigger context of its corporate strategy; these are:

- *Business Logic*
- *Capital Markets Logic*
- *Added Value Logic*

The *Business Logic* operates a comparative observation of the positioning of each business unit, under two distinct lenses: the level of attractiveness of the business'unit industry, measured by the difference between the industry's average return on capital and the industry's weighted average cost of capital, and the business unit's competitive advantage (or disadvantage), measured by the difference between the business unit's return on capital and the industry's average return on capital. The two perspectives are then combined to relate the performance of the business unit to the performance of its industry.

The Capital Markets Logic instead takes a critical look at each business unit from a stock market perspective, combining together the market value of the business unit and the value in use, or fair market value, of the same business unit. The former is defined by the business valuation that potential acquirers of that business conduct and propose to the seller. Other valuation methods include using comparable valuations from similar business units and/or transactions, or simply the stock market capitalization of the business. The latter is the value at which two independent parts should be willing to conduct a trade regarding the business unit. This definition is in line with the concept of Net Present Value of the business unit's future stream of cash flows, and with the fair value matrix concept proposed by Campbell et al., 2014. A comparison of the two values can give indications on how to best make use of the business unit, and whether to pursue further growth of an undervalued business (Market Value < Fair Market Value) or whether to divest an overvalued one (Market Value > Fair Market Value) .

The *Added Value Logic* differs from the previous two in the sense that it also tries to capture the positive or negative contribution that the overall corporation (via the activities of the Corporate Headquarters, or CH) puts into place within the competitive strategy context of each individual business unit. The perspective then takes the form of a cost-benefit analysis, in which, for each individual business unit, the CH's positive and negative contribution are weighted against each other, to then develop an holistic view of which ties the business unit within the greater corporate scheme. The presented process is conducted by asking the following critical questions:

- Does the business unit create more value under a stand-alone scenario, or within the overall corporate scheme? (*better-off-test*)
- Does the business unit create more value under this overall corporate scheme or under other potential ones (e.g. the ones of relevant competitors)? (*best-alternative-test*)

A thoughtful answer to these two questions can lead to a correct evaluation of the contribution of the CH to the business unit under scrutiny, and can provide for the correct evaluation of the parenting strategy, which, if successful, leads to the establishment of the corporate advantage. Overall, these three different logics provide a great overview and evaluation methods for the management of the multi-business firm. The eventual gaps which originate from such analysis can then be potentially filled by adjusting the corporate scope. In the following section, I will focus on the expansion of this same scope.

Expansion of the corporate scope can be achieved either via organic growth or via M&A, and profound cost-benefit analysis is conducted by the firm, which in the end compares the two options and opts for one of the two (Morosetti, 2018). The latter option, M&A, is one of the most researched topics in financial and managerial literature, but the heterogeneity of its forms and shapes makes it hard to model such operations into precise classifications. Nonetheless, Bower, 2001, identifies five different categories that defines diverse strategic activities behind the undertaking of such operations by a firm:

- *The Overcapacity M&A*: this type of deal is typically conducted in saturated and capital intensive industry sectors and is guided by efficiency-related reasons, such as opportunities for elimination of cost and process redundancies, operational streamlining and maximization of production capacity, economies of scale.

- *The Geographical Roll-up M&A:* this type of deal is typically conducted for market-expansion reasons, by firms who see business opportunity and who create value via exposure to different markets, geographies and customers. They are more linked to business development on the market side than business efficiency reasons on the operational side. Given the international outlook of the deal, localization advantages accruing from local market presence are often main drivers of this type of operation.

- *The Product or market-extension M&A:* this type of deal is conducted with the main goal to gain access to new products, services and overall new businesses. Vertical integration deals are typical in this regard, and the creation of operational synergies (Morosetti, 2018) is the main value creation objective.

- *The R&D M&A:* this type of deal is conducted by the acquiring firm with the objective of acquiring relevant Technological and Intellectual Property (IP) know-how from the acquired (or target) firm; in the typical case, there is an incumbent firm which acquires a small start-up, who has developed in-house a new technology which shall grant future market success in a growing industry.

- *The Industry Convergence M&A*: this type of deal is typically conducted in order to gain access to a new strategic positioning in a potentially high-growth industry. The acquiring firm recognizes that current industry boundaries are changing under its feet and views M&A as the instrument through which effective industry repositioning can be achieved. Developing industry dynamics are therefore a major driver of this type of acquisitions.

Behind all of these classifications is the strategic need of the target firm to achieve better market performance. Another M&A strategic category, known as Inversion deals, is linked to tax optimization opportunities viewed by the bidder firm, which sets up the acquisition in order to benefit from legal schemes at the target's home-country or region. Other authors (Agrawal & Walkling, 1994, Sanders, 2001, Harford & Li, 2007, Roll, 1986) argue that strategic motives are not entirely sufficient as M&A drivers, and that managerial self-interest and sense of hubris creates room for a lot of opportunistic deals. According to these views, acquiring firms' managers undertake M&A to boost their "ego" and sense of power that comes with access to special deal grants and rewards (Stock options and other benefits), and not necessarily to boost their firms' bottom line performance.

Nonetheless, no matter the motivating reason, the ultimate goal of M&A research has been the one of understanding the performance implications of involved parties, and to observe whether these deals actually create or destroy value. The process of measuring M&A performance varies according to the focus of analysis. M&A performance can be observed using qualitative or quantitative approaches (Corbetta & Morosetti, 2018); qualitative approaches dive into the analysis of the synergy realization that the deals create, whereas quantitative approaches generally focus on accounting returns (ROE, ROIC, Turnover, etc..) or financial returns on the stock market. The time period of analysis also varies, from short-term to long term studies. Corbetta & Morosetti, 2018, and Haleblian, 2008, summarize the main general findings that result from relevant M&A performance research (Capron & Pistre, 2002, Puranam & Vanneste, 2016, Zollo & Meyer, 2008). These are the following:

- Organic growth and M&A have experienced similar success rates in terms of performance measures, so that one cannot say that there is one clear best way to conduct decisions of expansions of the firms' corporate scope

- M&A performance either creates or erodes value for acquiring firms; this has been observed both in studies which focus exclusively on acquiring firm returns (Chatterjee, 1992; D. K. Datta, Pinches, & Narayanan, 1992; King, Dalton, Daily, & Covin, 2004; Moeller, Schlingemann, & Stulz, 2003; Seth, Song, & Pettit, 2002) and in studies which focus on decomposition of total M&A value creation (given by the joint-returns of both bidder and target firms) (Bradley et al., 1988, Houston et al., 2001, Leeth & Borg, 2000).

- There is high variance in the distribution of M&A performance, both inter-firms and intra-firms.

- The majority of the target firm shareholders benefits from the acquisition. The average stock price increase for these firms is 30% given by the deal announcement. Acquirers thus pay considerable premiums to gain control of target firms.

- M&A deals generally create value if the performance metric observed is the combined market capitalization of bidder and target firms. The average increase in this regard revolves around 12%.

Such variability of M&A drivers and performance results is precisely one of the main reasons behind the great amount of literature trying to model such corporate decisions. With the progressive increase in total transaction volume and number of deals, further research efforts shall then result as fully justified and welcomed.

1.3 Introduction to High Technology Industries in the modern economy: trends and M&A activity

During the 2008-2018 years, the high tech industry, classified broadly as the union of different market segments (consumer electronics, semiconductors and solar, print and imaging, computer and peripherals, software) was able to withstand the global downturn caused by the massive credit crunch of 2008, thanks mainly to its global nature of operations, price erosion of mobile and smartphone sales, and the rise of Cloud and Software-as-a-Service (SaaS) business models. (Capgemini, 2011). Total high tech manufacturing output was already experiencing, from 1995 to 2007, higher growth rates, in terms of Gross Value Added (GVA). than total manufacturing output, spurred by the increasing demand for computers and electronic devices. In recent years, the pace of innovation and the shortening of product life cycles have gone hand-in-hand, with growth and innovation in the software-realm fostering additional growth for manufacturers of the electronic devices on which the software runs. Containing costs without sacrificing quality has become ever more essential for tech players, as the shift from product-based business model to services-based business models demands lighter asset structures, especially since the pace of innovation is able to determine rapid shifts in market dynamics. On the market side, more and more focus has been dedicated to customer service, as the rise of Big Data has allowed companies to provide targeted and personalized services to fit the peculiar needs of the different customer clusters in their user bases. At the same time, advancements in cognitive computing and machine learning are allowing companies to drive additional revenue. The centrality of customer's data and the mobile ecosystem is allowing firms to ride the trend of flexible consumption ("pay-as-you-go") users enjoy thanks to smartphone and smartphone applications (Deloitte, 2018). Meanwhile, matters of cybersecurity and data privacy will hold great weight in determining the fate of technology firms, no matter the size.

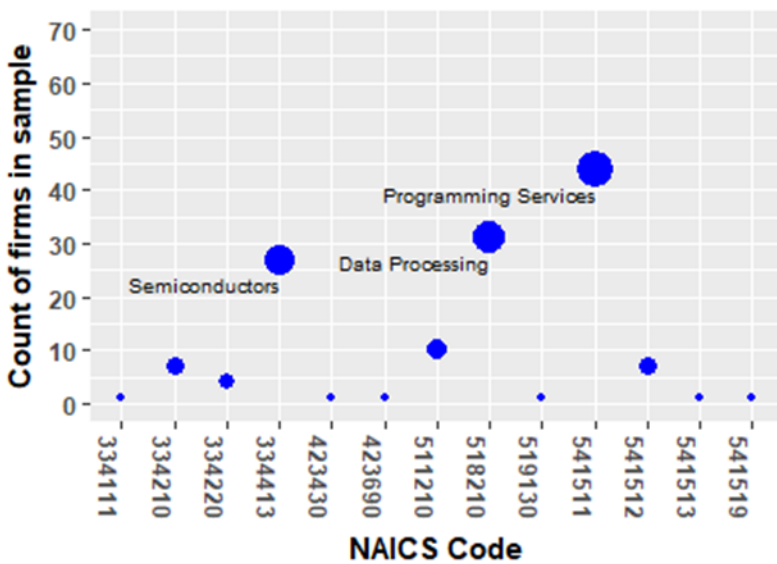
This scenario has determined great relevance for the tech M&A landscape, as short product life cycles determine new needs to quickly acquire capabilities that lack within the boundaries of each firm. Nowadays, one in every five M&A deals involves a tech target (BCG, 2017). Therefore, an M&A investigation such as this one occurs in a highly relevant period of time, in which technological and acquisition trends (abundance of investment funds from private equity players) are shaping overall activity.

2 Data

The data collection process used for the following investigation comprises different databases and sources used to gather the relevant data. In this section, I go over the different steps. First of all, a relevant sample of deals had to be constructed. M&A deal data was collected via the Zephyr Database. The deal search strategy looked for announced and completed deals of high-technology target firms listed on the NASDAQ National Market, from March of 2008 until March of 2018. The High Tech Sector and its subsectors were identified using the North American Industry Classification System (NAICS) codes, revised in 2017 and classified in the 2017 NAICS Manual. The list of subsectors characterized as "High-Tech", which make up the final sample utilized for the empirical analysis, is the following:

- 33411-Electronic Computer Manufacturing
- 334210 Telephone Apparatus Manufacturing
- 334220 Radio & TV Broadcasting and Wireless Communication Equipment Manufacturing
- 334413 Semiconductor and Related Device Manufacturing
- 423430 Computer, Peripheral Equipment and Software Merchant Wholesalers
- 423690 Other Electronic Parts and Equipment Merchant Wholesalers
- 511210 Software Publishers
- 518210 Data Processing, Hosting and Related Services
- 519130 Internet Publishing and Broadcasting and Web Search Portals
- 541511 Custom Computer Programming Services
- 541512 Computer Systems Design Services
- 541513 Computer Facilities Management Services
- 541519 Other Computer Related Services

Figure 2: Number of Firms per Industry Sub-sector in Final Sample



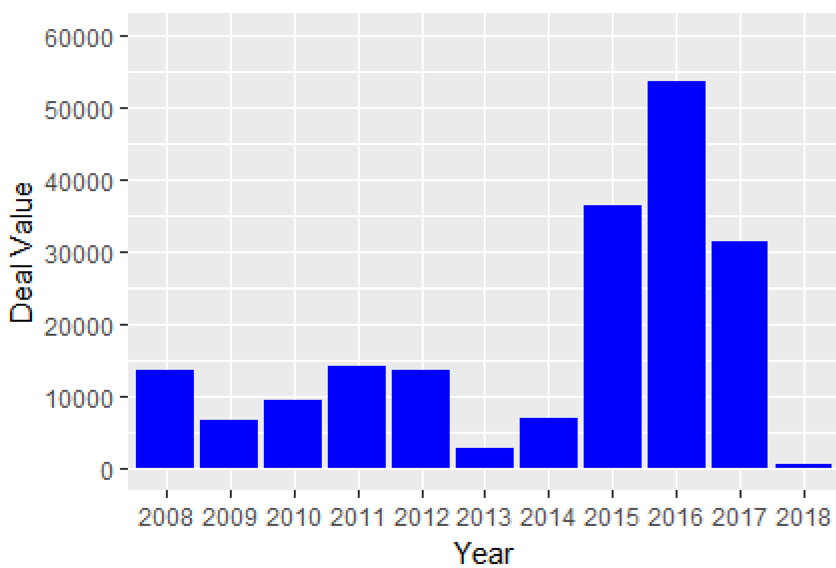
The data collection process highlights the three most represented Industry Sub-sectors, which are Custom Computer Programming Services (NAICS 541512, with 44 firms), Data Processing (NAICS 518210, with 31 firms) and Semiconductors (NAICS 334220, with 27 firms). Together, they account for 75% of total firms in my sample, and they will be the main reference for the subsectorial analysis that will follow in Section 4.

The original sample dataset contained 315 deals; deals with missing data on relevant variables, such as the announcement date, were eliminated; deals by the same acquiring company over the period were eliminated, in order to account for confounding effects on the stock price, and only the first deal was maintained. The final sample then consisted of 136 unique deals. For the first part of the analysis, daily financial data were collected via Bloomberg and Datastream databases. Via Bloomberg, time series data for the daily adjusted closing price of each of the target firms were obtained. The adjusted stock price is taken in order to account for the effect of stock splits, dividends'distributions and rights offering. Trading data were obtained from June of 2006 until of April 2018, to ensure sufficient trading volume for all firms included in the final sample. The relevant data for the sample's reference market Index (NASDAQ Composite, Ticker Symbol: ˆIXIC) were then obtained through Datastream. For the second part of the analysis, operating data were obtained through the Orbis Database; where data on key variables were missing, the firms'official annual reports were checked. Data on the each target company's number of patents were obtained via the Global Patent Index and cross-checked with data from the United States Patent and Trademark Office (USPTO).

Table 1: Final Sample Descriptive Statistics

n (Number of Firms)	136
Median Deal Value -$Million	440.4
Median Pre-Deal Target Revenue - $Million	203.2
Proportion of Cross-Border Deals (Acquirer's country code ≠US)	11,8%
Proportion of Cash Payments	88%

Figure 3: Total Deal Value ($billion) per Year, by Completed Date



3 Methodology

3.1 Methodology Overview

The empirical analysis is divided into two parts: first, an event study is conducted to address the impact of the M&A announcement on the stock returns of the target firm. In the second part, I investigate upon the impact of certain target firm characteristics on the target's returns. Consequent variables are introduced and tested primarily via the use of multiple regression analysis. The variables deal with the degree of innovativeness of the target firm (Innovation Increase, Innovation Intensity, Number of Active Patents), Industry related characteristics (Technological Subsector, divided in: Semiconductor, Data Processing Firms, Computer Programming Services Firms), nature of the deal (Deal Size, M&A Experience of the Acquiring Firm), level of financial Distress of the target firms and a timing variable, which controls for the effect of recent Merger Waves.

3.2 Event Study Methodology

3.2.1 Introduction, objectives and structure

The event study methodology was first introduced around 1970 (Fama et al., 1969), gained traction in the final decades of the century (Brown and Warner,1980, 1985, Peterson,1989,MacKinlay, 1997) and was later used widely in finance and management studies. An event study is an empirical approach which focuses on secondary data, that is data which is not directly collected by the researcher but which is publicly available through public and institutional databases. The core focus of an event study is to measure the valuation effects of a corporate event (M&A announcement, IPO, earnings announcements, corporate divestitures,etc..) by observing the reaction of the stock price in the time period surrounding the date of an event of interest. The valuation effects are measured by calculating the difference in returns between the returns effectively realized on the market by the security and the predicted returns, which are calculated based on the historical stock data along a previously-specified time window. This difference, categorized in many studies as "Abnormal Return", is then tested for statistical significance, in order to verify whether it can be actually inferred that there is an association between the event and the Abnormal Return. The statistical inference in most event studies is conducted starting from the following hyphothesis, where $H_0$and H_1represent the null and the alternative hypothesis:

H_0: The occurrence of the event has an impact on the stock price equal to 0 (Abnormal Returns = 0)

H_1 : The occurrence of the event has an impact on the stock price different from zero (Abnormal Returns $\neq$0)

Being a secondary data approach for conducting empirical analysis, the methodology has several advantages:

- *Time and Resource Efficiency*: The researcher collects data that has already being gathered by a third party (a research institute, or a database provider), thus avoiding the higher costs of data retrieval typically associated with experimental or survey research.

- *Data quality and Reliability:* The level of reliability of the data is usually high, and many database providers now provide real-time updates on many datasets and variables of interest; the data is usually very quantitative and thus very adept for conducting quantitative research.

- *Research Transparency*: The level of objectivity and accessibility of the data,as well as the methodology used by the researcher, allows for a thoroughly verifiable research output.

Combined with the advantages, it is also important to recognize some limitations of secondary data research, and thus of event studies:

- *Sample Complexity*: Depending on the research question addressed and the structure of the particular sample obtained, such method may not always be the best solution in order to investigate a particular topic; experimental and survey research may address the needs of the researcher better, and thus need to at least be considered over a secondary data approach.

- *Lack of familiarity with the collected variables:* in secondary data the researcher is heavily dependent on the gathered data's structure and assumptions, and this may cause interpretation problems once the analysis is conducted.

- *Absence of Key Variables:* the collected data may lack key information the researcher needs to address his/her own research question.

- *Potential presence of confounding effects not accounted for in the collected data:* this might limit the researcher's ability to correctly conduct appropriate statistical inference.

For the purpose of this study, as well as many others centered around financial and operating data of public companies, the degree of standardization and breadth of information concerning the variables usually available via third-party databases makes this approach particularly beneficial for the researcher interested in analyzing the impact of particular events on the stock returns, and it can be therefore safely concluded that the advantages outweigh the disadvantages.

Any event study can be broken down in several, consequential steps, that constitute the entire approach (referenced from Bromiley et al, 1988, Peterson,1989,MacKinlay, 1997). These are the following, and will be presented in the following, dedicated subsections. One brief note on the terminology used in the following paragraphs: in an Event Study, I will use the term "stock", or "firm" to refer to the same identical construct, or entity. The two terms are therefore interchangeable, as there is a 1-to-1 relationship between a public firm and its current stock. Thus, the expressions "the stock i" is identical to "the firm i".

1. Underlying assumptions
2. Event Definition
3. Definition of time Parameters: Event Windows
4. Estimation of Expected Stock Returns
5. Estimation of Excess Returns
6. Aggregation for a Group of Securities
7. Test for Statistical Significance

3.2.2 Underlying assumptions

The key assumption in conducting event studies is Capital Market Efficiency. This term implies that, in capital markets, stock prices quickly react to new information, and incorporate such information by adjusting the price level, which then reflects and incorporate all relevant information regarding the specific security.

Therefore, when an event involving the security occurs, the event's effect is readily absorbed in the stock price, which adjusts for the occurrence. Thus, this means that the change in the stock price brought about by the event is included in the new price level; this way, the effect of the event in the time period close to the occurrence can be analyzed by looking at the stock's movement in the relevant time-frame. If this assumption was not met, it would mean that the stock price would not account for the event's occurrence and therefore it would be impossible to link any movement in the stock price to the event.

Within the general definition of Capital Market Efficiency, three different levels,or forms, are distinguished:

- *Weak Form,* which implies that current stock prices reflect only historical information.
- *Semi-Strong Form*, which implies that current stock prices reflect not only historical information, but also all current publicly available information.
- *Strong Form*, which implies that current stock prices already reflect all current information of any kind (thus making it impossible for an investor to obtain above average returns).

For the event study approach to be properly applied, at least a Semi-Strong form is assumed. Other important assumptions behind the methodology are: the ability to identify the event's occurrence with precision, which implies attributing an exact event date to it. For corporate events, this is usually linked to the announcement date provided by the company, which uses various official sources (e.g. Investor Meeting, corporate website) to diffuse new information on to the markets; the absence of confounding events (e.g. a Downsizing announcement or CEO switch a few days following the M&A announcement), which may occur in the vicinity of the identified event date and could therefore fail to allow the researcher to correctly isolate the impact of the single event; the requirement of sufficient stock data availability (trading volume), which renders the methodology not applicable to private companies or recently-listed public companies; the absence of events happening on two dates too close in calendar time (the definition of close depends on the definition of time parameters, addressed in section 3.2.4), which then allows to assume that each event is independent of other events, and that the co-variances across securities is equal to zero, thus excluding the hypothesis of auto-correlation (MacKinlay, 1997). On a more subtle, but nonetheless very important note, the assumption which implies the theoretical relevancy of the studied event represents another key point of the methodology, and ensures that the findings are, in addition to being analytically correct, inherently interesting *per se.*

3.2.3 Event Definition

Each event study centers around the identification of a relevant date of interest in which the event occurs. In this study, as in many others in the financial and managerial literature, such event is the announcement of a M&A deal. When gathering sample data, it is important to assign each firm to an exact date in time in which the firm's relevant event occurs, called *event date, or* τ_0 *,* which represents the reference point for any firm included in the sample. In the databases utilized for this work, the downloaded deal data already references the identified event date (announcement date).

3.2.4 Definition of Time Parameters: Event Windows

Once the event date has been identified, two different time periods, or windows, are constructed:

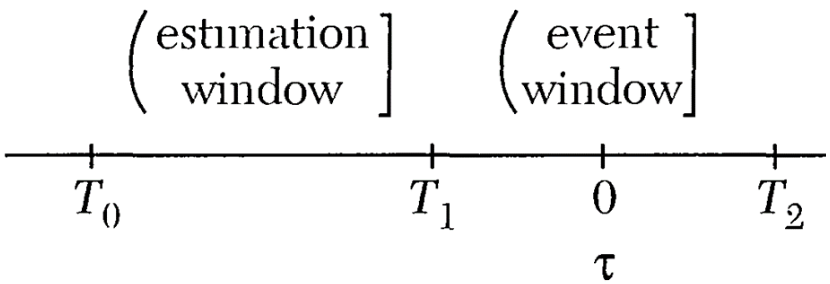
- *The Event Window*, which is a time period centered around the event date τ_0 and which stretches for a certain number of days prior to and following τ_0*;* the event window is used to observe the effective daily stock returns that occur on the day and in the days that immediately precede and follow the event. The length of the event window is usually set by the researcher, as there is no fixed number. Most event studies which use daily data usually consider event windows of from 21 to 121 days surrounding the event date (Peterson, 1989), and within a certain event window subsequent subsets of event windows are observed. In this event study, I utilized a 20 days event window (τ_0 *+ 10 days,* τ_0 *-10 days)* then subsetted into smaller event windows *(*τ_0 $\pm$*5,* τ_0 $\pm$*3,* τ_0 $\pm$*2,* τ_0 $\pm$*1).* I will also report data on the stock's movement on the actual Event Date τ_0 . The determination of an appropriate Event Window length refers back to the need of avoiding covariance between events. If, to avoid covariance, the Event Windows of two Events must not overlap, it is possible to calculate the maximum amount of non-overlapping events that can occur in one year; after doing so, we compare this number with the yearly number of events occurrences in a typical year, given by our sample events distribution. Assuming that the yearly distribution of the total number of Events analyzed (given by sample size, n, equal 136 in this work) is evenly spread, so as to have, within each year, around the same number of events, with an n of 136 and a total amount of years equal to 10, in each year, from 2008 to 2017, the average number of event occurrences should be 136/10 = 13,6, or 13 Events. Compared with the actual distribution, the number captures the average quite well. To instead calculate the maximum number of non-overlapping events that can happen in one year using a τ_0 $\pm$*10* Event Window*,* one divides the total amount of days in a year (365) by the total length, also in days, of the longest Event Window desired (20 days, in this case: the 10 days prior to the Event Date, plus the 10 days after the Event Date). The result, rounded to an integer, is 18. Given that 18 > 13, covariance can be theoretically avoided, as the threshold is not surpassed. Naturally, as the empirical sample of yearly distribution is actually different from 13, an appropriate check was conducted for my sample, to make sure that no more than 18 Events were happening within a single year; also; the actual Event Dates were also analyzed to make sure that, even if the yearly threshold was respected, Events' occurrences were not clustering together in a single month or period. I now go back to the general features of the Event Window*;* it is common practice to use an

event window which surrounds the event, and does not just include the days right *after* its occurrence; this is done as one aims at observing whether some stock volatility occurs in the day leading up to τ_0 , which might indicate some information leakages about the event itself. If a semi-strong form of Capital Market Efficiency holds, this should not happen, but it is a situation which is anyways controlled for.

- *The Estimation Window*, which is the time period which comprises historical trading data for the observed security and which is utilized for the Estimation of Expected Stock Returns. The length of this window is also decided freely by the researcher, with most event studies considering estimation windows ranging from 100 to 300 days prior to the event date (Peterson, 1989). For this study, I utilized an estimation window ranging fromτ_0 - *150* days to τ_0 - 21 days.

As anticipated, there is no clear-cut consensus over the choice of Time Parameters; it is important to note that the larger the windows considered, the harder it is for the researcher to exclude all potentially confounding events, whereas the larger the Estimation Window, the more accurate the Estimation of Expected Stock Returns, thus raising a trade-off issue in the methodology design. Also it is important that the two windows do not overlap, in order to ensure that the process of Estimation of the Expected Stock Returns is not influenced by the event itself.

Figure 4: Event Study Time Parameters (Adapted from MacKinlay, 1997)



For the purpose of this work, I will define L1 as the length, in days, of the Estimation Window (*T() - T1*) and L2 as the length, in days, of the event window (*T2-T1).* Note that the round and square bracket denote mathematical exclusion, or inclusion, of the T term in one of the two intervals. In the image above, the Event Window L2 includes all days between T1 and T2, not including T1 (the starting point is, therefore, T1+1, with 1 representing a single day); the Estimation Window L1 includes all days between T1 and T(), not including T()(the starting point is, therefore, T()+1). τ_0 is indicated in the figure as the event date, occurring at time 0. In the mathematical equations that will follow in the next paragraphs, when the following terms are introduced: $_{L1}\sum$, or $_{L2}\sum$, I intend to mean the sum of all referenced parameters included in the specified Event Window. As such, $_{L1}\sum$means "take the sum of all elements included in the L1 window (Estimation Window), which starts at T()+1 and ends at T1". When sample size, *n,* is used, $_n\sum$ means "take the sum of the referenced parameters included in sample n, from 1 to n".

3.2.5 Estimation of Expected Stock Returns

The first element needed for calculating Abnormal Returns is a measure of the expected return of the stock, that is, a prediction of what would have happened to the stock price, during the Event Window considered, if no event had occurred; this prediction is based on the historical trading data provided by the Estimation Window. A diverse number of approaches, or models, have been the subject of interest in the relevant literature. Referring to MacKinlay (1997), these are: Constant Mean Return Model, Market Model, Multi-Factor Models, Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT). The literature is strongly biased towards the use of the Market Model, as the other models, even when more complex, are reported by the author to add little predictive power in regards of such model. By looking at more recent literature (Sorokina et al, 2013), this methodological status quo seems to hold still, and therefore I will proceed by using the well-known and popular Market Model.

Such model , in order to compute the predicted, or expected, return of a certain security i over the relevant Event Window, utilizes OLS regression to regress daily stock returns against the daily market returns of the identified Estimation Window. The return R of stock, or a market index i during time period t, measured in discrete terms, is defined as follows, where P refers to the daily closing price of stock, or market index, i:

$$R_{it} = \frac{P_{it} - P_{i(t-1)}}{P_{i(t-1)}}$$

Therefore, the linear regression of the Market Model can be reported as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

$$\mathrm{E}(\varepsilon_{it}) = 0 \qquad \mathrm{var}(\varepsilon_{it}) = \sigma^2{}_{\varepsilon_{it}}$$

$$\sigma^2_{\varepsilon it} = \frac{1}{L1 - 2}\left[{}_{L1}\sum(R_{it} - \alpha_i - \beta_i R_{mt})\right]$$

where R_{it} is the stock return of security i at time t, R_{Mt} is the market's return at time t, and α_i, β_i and ε_{it} are the linear regression parameters (α_i being the intercept term, β_i being the regression coefficient, capturing the adjustment of the stock return given a certain level of R_{Mt}, and of the market model, and ε_{it} being the error term). All model parameters using the standard linear regression approach (Goldman et al, 1985, Zou et al, 2003) and can be therefore calculated as:

$$\alpha_i = \mu_i - \beta_i \mu_m$$

$$\beta_i = \frac{{}_{L1}\sum(R_{it} - \mu_i)(R_{mt} - \mu_m)}{{}_{L1}\sum(R_{Mt} - \mu_m)^2}$$

$$\mu_i = \frac{1}{L1}\left[{}_{L1}\sum R_{it}\right]$$

$$\mu_m = \frac{1}{L1}[_{L1}\sum R_{mt}]$$

By implementing the above-mentioned model, one can therefore find an estimated stock return for each stock, for each day of the Event Window considered.

3.2.6 Estimation of Excess Returns and

Given the application of the Market Model, the Excess, or Abnormal Returns, can be computed for each day of the Event Window, L2. The daily Abnormal Return at a certain day t within the Event Window is therefore computed as the difference between the actual return (noted as *R'*) of stock i on day t, and the estimated return predicted by the model parameters:

$$AR_{it} = R'_{it} - R_{it}$$

This way, any discrepancy between actual and predicted returns on a given trading day in the Event Window is captured via the Abnormal Return. Under the null hypothesis, H_0, the Event Window sample of Abnormal Returns will follow a normal distribution, with mean 0 (the expected value under the hyphothesis of no significant impact of the event on the stock price) and variance, noted as $\sigma^2(AR_i)$, which takes the following form:

$$\sigma^2(AR_i) = \sigma^2_{\varepsilon i} + \frac{1}{L1}\left[1 + \frac{(R_m - \mu_m)}{\sigma^2_m}\right]$$

The variance of the Abnormal Returns is therefore composes by the variance of the Market Model's error term and an additional variance term, which stems from the sampling error of the Model's parameters. The larger the Estimation Window L1, the smaller this second term becomes, approaching 0 and thus becoming negligible and leaving $\sigma^2_{\varepsilon i}$ as the main determinant of Abnormal Returns' variance. The normal distribution of AR_i is thus summarized:

$$AR_i \sim N(0, \sigma^2(AR_i))$$

The calculation of the daily Abnormal Return is completed for every firm considered. Every firm will then have its own Estimation and Event Window, and its own Market Model equation, from which AR_{it} will be computed. The next steps sees then the aggregation of several AR_{it} in order to derive an aggregate estimate, which serves as the reference measure for the entire sample considered in each event study.

3.2.7 Aggregation for a Group of Securities

The aggregation process needs to be achieved through all Event Window days, and across all sample stocks considered. Here, the process can take two different approaches, which nonetheless lead to the same result. On one hand, the AR_{it}can be summed across all Event Window days, and then averaged for the single firm, resulting in a Cumulative Abnormal Return for stock *i* (CAR_i). The process is then repeated for all firms in the sample stocks, whose respective CAR are then averaged, leading to the Cumulative Average Abnormal Return ($CAAR$) for the entire sample across the Event Window. On the other hand, the AR_t at time *t,* which represents a day within the Event Window, is computed first for all firms at day t, leading to an Average Abnormal Return at time t across all sample stocks (AAR_t);then, the AAR are summed across all Event Window days, leading to the $CAAR$ for the entire sample. Both aggregation methods equal as far as the identification of the final sample $CAAR$. In this analysis, I proceed with the illustrating the first approach, which is then used with the empirical data at hand. Starting from the aggregation of all AR_{it} for a single stock i, and two separate days $\tau_1$and τ_2(where T1 $<$ $\tau_1\leq$ τ_2 $\leq$ T2) in the Event Window L2, the Cumulative Abnormal Return ($CAR_i(\tau_1, \tau_2)$), is computed as:

$$CAR_i(\tau_1, \tau_2) =_{(\tau_1,\tau_2)} \sum AR_{it}$$

The variance of CAR_i takes the following form as the length of the estimation window L1 expands beyond a certain threshold:

$$\sigma^2(\tau_1, \tau_2) = (\tau_1 - \tau_2 + 1)\sigma^2_{\varepsilon i}$$

If, instead, L1 is not sufficiently large, the above variance must be adjusted for the second term that constitutes the variance of the error term in the Market Model:

$$\frac{1}{L1}\left[1 + \frac{(R_m - \mu_m)}{\sigma^2_m}\right]$$

Under the null hyphothesis H_0, the distribution of the $CAR_i(\tau_1, \tau_2)$ is Normal, with mean 0 and variance equal to $\sigma^2(\tau_1, \tau_2)$:

$$CAR_i(\tau_1, \tau_2) \sim N(0, \sigma^2(\tau_1, \tau_2))$$

As explained in the illustration of the aggregation method, each firm's CAR is then aggregated, and divided by the sample size, *n,* leading to the Cumulative Average Abnormal Return($CAAR$):

$$CAAR(\tau_1, \tau_2) = \frac{1}{n}[_n \sum CAR_i]$$

whose variance is equal to :

$$\sigma^2 CAAR(\tau_1, \tau_2) = \frac{1}{n^2} \sum \sigma^2(\tau_1, \tau_2))$$

Under the null hypothesis, H_0, the distribution of the sample's $CAAR(\tau_1, \tau_2)$ is Normal, with mean 0 and variance equal to $\sigma^2 CAAR(\tau_1, \tau_2)$:

$$CAAR(\tau_1, \tau_2) \sim N(0, \sigma^2 CAAR(\tau_1, \tau_2))$$

3.2.8 Test for Statistical Significance

Once a CAAR for the entire sample is calculated, a statistical test is conducted to determine whether to reject or not reject H_0 , the null hyphothesis. That is, it is important to determine whether the observed $CAAR$, is statistically significant from 0, the reference value under the null condition. The literature (Brown and Warner, 1980 and 1985, Patell,1976, Boehmer, Masumeci, and Poulsen, 1991,Corrado, 1989; Corrado and Zivney, 1992) has developed different statistical tests which start from a basic time-series t-test and cross-sectional t-test and introduce progressive adjustments that take care of different event study conditions which affect the distribution of the $CAAR$, and even departures from certain assumptions regarding the variables' distribution. The majority of these tests are however, parametric, therefore implying a certain distribution of the variable of interest. This work mainly refers and utilizes a parametric t-test to test the overall significance of the observed $CAAR$, whose results will be presented in the following section. Therefore, given the distribution of the $CAAR$, the test statistic T is calculated as follows:

$$T = \frac{CAAR(\tau_1, \tau_2)}{\sqrt{\sigma^2 CAAR(\tau_1, \tau_2))}} \sim N(0,1)$$

4 Empirical Analysis

4.1 Section Overview

Now that the methodological approach of the event study has been introduced, the present section will address the results of the empirical analysis applied and conducted on the presented sample of 136 unique M&A announcement deals in the High Technology Industry sectors, the data introduced in the Data section of this work. The first part of the analysis, concerning the application of the Event Study itself, is conducted on the Event Study Metrics Software. The successive statistical analysis is conducted using the R software. First, the results of the overall test for statistical significance on the $CAAR$ will be presented and commented; secondly, a detailed explanation of each individual moderating variable introduced in subsection 3.1 will be provided, combined with the development of hypothesis regarding its potential role in the present analysis, which will partially draw from both existing relevant literature and from personal expectations on the topic. In the last part, the presented variables' individual moderating influence on the $CAAR$ will be tested using multiple regression analysis. Finally, the observed results will be commented and possible explanations with the findings will be provided and confronted with the relevant literature.

4.2 Event Study Results

The relevant literature has generally identified a positive impact of M&A announcement events on the returns of target firms (Asquith & Kim, 1982; D. K. Datta et al., 1992; Hansen & Lott, 1996; Malatesta, 1983); the table below, reported and adapted from Deshmukh, 2012, summarizes the findings of other M&A announcement Event Studies focusing on the returns of acquired firms; following this, I provide a brief set of summary statistics on the key observed findings, also reported below in table 2b.

Table 2a: List of findings of Target Firm Returns' Event Studies (from Deshmukh, 2012)

Study	Sample Period	Sample Size	Event Window	CAAR
Langetieg (1978)	1929-1969	149	(-120,0)	+10.63%
Bradley, Desai, Kim (1988)	1964-1984	236	(-5,5)	31.77%
Dennis and McConnell (1986)	1962-1980	76	(-1,0)	+8.56%
Bannerjee and Owers (1992)	1978-1987	33	(-1,0)	N/A
Kaplan and Weisbach (1992)	1971-1982	209	(-5,5)	26.9%
Berkovitch and Narayanan (1993)	1963-1988	330	(-5,5)	N/A
Maquieira, Megginson, and Nail (1998)	1963-1996	55	(-60,60)	38.08%
Mulherin (2000)	1962-1997	202	(-1,0)	+10.14%
DeLong (2001)	1988-1995	280	(-10,1)	+16.61%

Table 2b: Summary of findings of Target Firm Returns' Event Studies

Mean Sample Size	Average Sample Period	CAAR Range (Min-Max)	Mean CAAR
174	22 years	(+8.56%, + 38.08%)	+15.85%

The overall trend denotes a significantly positive overall trend of the CAAR, across different sample sizes, years, and Event Window stretches. These studies are not necessarily sector-focused, but they give a general confirmation of the fact that M&A announcements tend to be positively affect the stock of the target firm. Looking at more industry-focused literature on Mergers and Acquisitions in the High Technology realm , for which a massive body of literature is currently lacking,(Kohers and Kohers, 2000, Deshmukh, 2012, Andre ́et al. 2004, Lusyana & Mohamed Sherif, 2016), the positive relationship between the event and the CAAR is also confirmed, although not all of these studies focus on target returns. Anyways, this generally positive direction is what I also expect to find going into the analysis. Out of the samples of High Tech studies presented, an especially interesting result comes from Lusyana & Mohamed Sherif, 2016, which report an increase in the CAAR's intensity for short-term and domestic (US) acquisitions from the 1997-2002 period, the years leading up to the "Dot Com Bubble", to the 2007-2014 period. Given the fact the my sample period overlaps for 6 years (2008-2014) with the one reported by the study, it will be interesting to see how the positive results compare,if they do, if not in direct comparison, as I only consider the 2008-2018 period, at least in the direction of the Abnormal Returns, taking also into account the general findings of previous Event Studies reported in the table above.

Looking now at the present sample of 136 deals, I report the event's studies results for the time-series T-test of statistical significance of the observed CAAR over the different Event Windows *(* $\tau_0 \pm$ *10* , τ_0 $\pm$*5,* τ_0 $\pm$*3,* τ_0 $\pm$*2,* τ_0 $\pm$*1,*), as well as the overall graphical trend of the CAAR for the $\tau_0 \pm 10$ Event Window:

Figure 5: Sample's CAAR trend for the (-10,10) Event Window

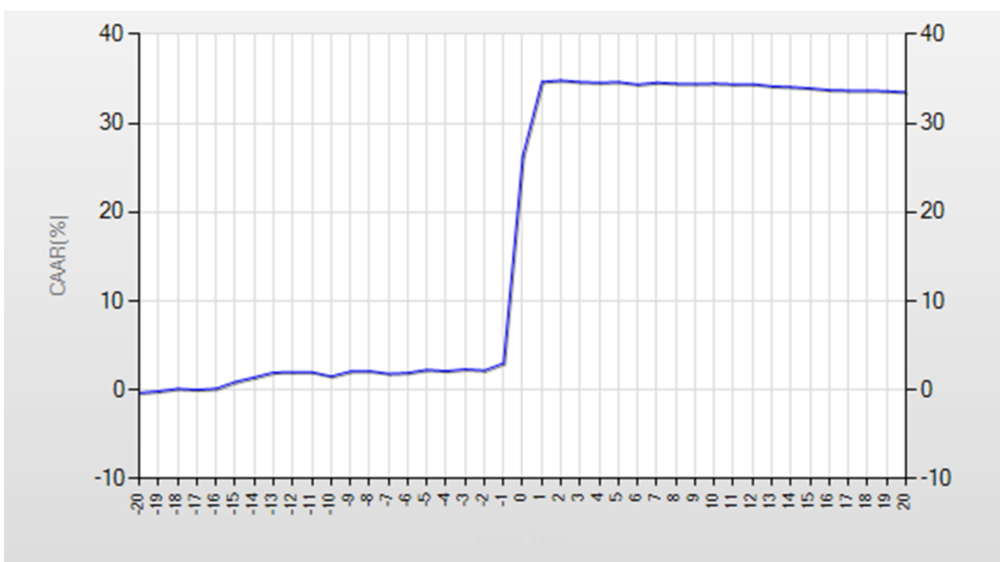


Table 3: CAAR's time series T-test for statistical Significance, results

Event Window	**Mean CAAR**	**Test Statistic**
(-10,10)	+32.47%	10.6507***
(-5,5)	+32.71%	11.1787***
(-3,3)	+32.52%	11.181***
(-2,2)	+32.48%	11.0778***
(-1,1)	+32.46%	11.2026***
Event date (τ_0)	+23,24%	7.9925*

**p-value <0.01*   *Proportion of firms with positive CAAR at* τ_0= 78.68%

The results highlight a Cumulative Average Abnormal Return (CAAR) of about 32% in the 20 days surrounding the event date (-10,+10) with respect to 0, identified as the event date for each firm. The majority (around 70% of the CAAR's magnitude, if we divide the CAAR generated at $\tau_{0,}$ = 23.24%, by the overall CAAR generated throughout the largest Event Window considered (+32.47%) of the abnormal return is generated at the Event Date. As reported, all subsets of Event Windows are significant at the 1% significance level, confirming the predominant direction of the literature and the main M&A financial performance findings reported by Corbetta & Morosetti, 2018. The mean CAAR is also included in the right end of the CAAR range reported in Table 2b (+8.56%, + 38.08%), thus confirming the view of the related studies. The fact that the CAAR falls in the right end of such interval, while being indeed greater than the Mean CAAR +15.85% of previous studies, may indicate partial alignment with the finding reported by Lusyana & Mohamed Sherif, 2016, in relation to the higher CAAR magnitude observed over the 2007-2014 years. Another interesting indicator of the alignment of such result with the related literature is given by looking at the proportion of sample firms for which the CAAR at the Event Date τ_0 is positive, in regards to the total of all firms in the sample. The firms analyzed in the studies reported in Table 2a report numbers in the interval (70%-95.8%), with a mean proportion of 84.4%. The sample this study refers to happens to have a Proportion of 78.68%, also in line with the presented interval.

In general, given what was already stated in the above-mentioned literature, the following results certainly provide a basis for confirmation of the positive stock returns typically enjoyed by target firms on the M&A

announcement date. The observed sample of High Tech companies also behaves in similar fashion to what recent and less recent literature experienced in their empirical results. Now that the effect of the the event has been determined, the critical observation of the relevant characteristics that play a moderating role in the analysis will follow. These features, of various nature, constitute the heart of the research interest that backed this work, and their role and observed moderating effect will be therefore illustrated next.

4.3 Moderating Factors: Variable introduction and hypothesis development

Once established the positive relationship between the Event and the target firm's Abnormal Returns, the overall aim of this work, as anticipated in the introduction to this work and in section 3.1, is to investigate upon the impact of certain target firm characteristics on the target's returns. Specifically, establishing a set of variables which try to capture the fundamental role that Innovation activities play in the High Technology Sectors of the economy is without question the most important objective of the present discussion, since the interpretation of the results may shed light on the relationship between the Innovation Management activities at the firm level, the Industrial context in which they are conducted, and the overall impact on the performance and corporate strategy decisions. These variables are primarily four, which will be shortly introduced in detail: Innovation Increase, Innovation Intensity, Number of Active Patents, and Technological Subsector. In addition to these variables, other interesting variables are also investigated. These variables are: Deal Size, M&A Experience of the Acquiring Firm, level of financial Distress of the target firms and a timing variable, which controls for the effect of recent Merger Waves. The rationale behind the use of some of these variables is two-fold: one hand, their role as moderating factors in M&A deals has been well documented in relevant M&A literature reviews (Haleblian et al, 2008). However, their effect in influencing these scenarios is not something the research still quite agrees upon on an absolute level, especially for something like M&A experience. Therefore, by using them as control variables in the following analysis, it will be interesting to observe the effect they individually and conjointly take, as well as the degree to which they overall apply to this particular sample of High Technology target firms. In the following paragraphs, each individual variable will be defined, matched against existing literature, and a final pre-analysis hypothesis will be developed to serve as the expected result, which will be then tested using the sample data at hand. Additional details will follow in the successive methodological section, in which the statistical tests and their results will be presented.

4.3.1 Innovation Intensity

Measuring Innovation at the corporate level has always been a great struggle for the academic and business world. The basic problem around this measurement obstacle is the fact that innovation is by nature risky and costly for the firm, and subject to a high degree of failure rates. A certain amount of input in dollars does not guarantee an ideal output. Yet, as most companies still struggle in trying to find effective ways to measure it, the amount of money spent on growth projects is still the most recognized and used "Innovation Metric" (BCG,2007), whereas there is still ground to be covered in the incentives area of innovation, especially related to key personnel with innovative potential (Staudt et al. 1991, BCG,2007). While the efficacy of metric has long been the subject of debate for the academic and professional practices related to Innovation, the role of Research & Development expenses as a proxy for the creation of innovation has been nothing but that of the main character of the story (Damodaran, 1999, Chan et al, 2001,Kaharan, 2015, Baumann & Kritikos, 2016). Therefore, R&D expenditures are a central focus of the current work, especially given the centrality of the metric within the highly technological nature of the observed industry sectors. Before moving forward, it is important to state what will be the definition of Innovation Intensity. In this work, I define Innovation Intensity of firm i in year t as the well-know ratio:

$$InnovationIntensity_{it} = \frac{R\&D\ Expenditures_{it}}{Total\ Revenue_{it}}$$

In a recent literary review of 17 studies more focused on the M&A impact of Research Intensity (Das et al, 2012) , the majority of results indicate a positive link between R&D Intensity and overall M&A performance, from an holistic, and not just necessarily from the point of view of either the acquirer or the target; 11 out of the 17 studies examined feature such finding. However, given the low sample size of studies reported by Das and the imperfect nature of the metric as a proxy for Innovation, my expectations going into the empirical analysis stand unbiased, and therefore do not significantly depart from the absence of a positive (or negative) moderating effect on target's firm CAR by the Research Intensity of the firm. In other words, it could very well be that, on one hand, the more money the High Tech target firm spends in R&D, the more positive the valuation on the stock market at the time of the M&A announcement deal, especially if this firm operates in high growth sectors whose future market sizes are projected to expand in future years. On the other hand, the acquiring firm really has no idea about the actual performance improvement that each incremental R&D dollar might bring to the benefit of the soon-to-be merged entity. Or if it does, having conducted prior due-diligence, it could also discover that the R&D activities of the firm are indeed burning cash with no real actual innovative outcome to be brought on the market in the near future, and this could negatively (or better, less positively) reflect on the target firm's shareholder at time time of the deal announcement, at least in relative terms. In the present text, I distinguish between High and Low Innovation Intensity, in order to be able to subset the sample accordingly. To determine the reference level which identifies the threshold between High and Low Innovation Intensity, I refer to the average value of the Innovation Intensity metric over time, across all NAICS industries here considered. R&D Data on 1011 publicly listed US firms was collected for the 2008-2017 period. This sample of 1011 firms represents the industry sample from which the threshold was determined. Industry data was averaged across firms for a single year, and then across years. The overall R&D-to-Sales sample median for the period at the specified industry level is 16.75%. In the empirical analysis, the Innovation Intensity metric was then obtained for the previous 4 years prior to the announcement date, and their average was compared to the industry's median level. A firm with a 4-year average R&D-to-Sales ratio equal to or above 16.75% was then characterized as High with regards to the Innovation Intensity metric, Low otherwise. In conclusion, I develop the following hyphothesis regarding the variable, called $H1$:

$H1$: *A high level of R&D Intensity of the target firm does not play a significant moderating effect on the target firms' CAAR in the Event Window considered.*

4.3.2 Innovation Increase

As a second variable focusing on the role of Innovation, I consider the Innovation Increase variable. The variable is still based on the R&D-to-Sales Ratio introduced at 4.3.1, but this time the focus is not on the absolute level of the metric, but on its direction. That is, observing not only the average level of the metric across years, but calculating its growth path might be a more effective indicator of the importance of Innovation practices for a technology firms in a certain period. If the target firm has increased its R&D efforts in the years prior to the announced merger or acquisition, it may be reasonable to imply that innovation is considered a priority for the company's market success, no matter the reference level of the metric in terms of the industry as a whole. After the merger, it is likely that the acquiring firm will inject additional financial resources in the R&D Department of the acquired in order to fulfill its growing innovation potential. Thus, from the perspective of the target's investors, the future acquisition is perceived as beneficial for the target company's future growth and for future market success of the innovative projects in current development. Another interpretation is suggested by Phillips et al.,2013, which states that in a favorable M&A market, prospective bidders may very well be receptive to Innovation trends of this sort, and thus this could lead target firms to strengthen their innovative efforts in order to play a signaling role and incentivize acquiring firms to bid for them, paying an acquisition premium to acquire the relevant know-how, and thus ultimately reward target shareholders. Before mentioning some additional literature on the topic, I now proceed to define the variable and the rationale for subsetting the sample according to it. As anticipated, the starting point is the Innovation Intensity variable, defined at 4.3.1. From that, the Innovation Intensity variable from the 4 years leading up to the Event Date is collected, and, to determine the direction of the R&D expenditures, so the Innovation Increase itself, the Cumulative Annual Growth Rate (CAGR) of the 4 year period is computed for each firm. Finally, the sample is divided between firms who experienced an Innovation Increase in the observed period (CAGR >0), and firms who did not experience it (CAGR$\leq$ 0). To sum what mentioned, the variable is defined as follows:

$$Innovation\,Increase = CAGR_{\tau_0-4}(Innovation\,Intensity_{\tau_0-4})$$

$$CAGR_{\tau_0-4}(Innovation\,Intensity_{\tau_0-4}) = (\frac{Innovation\,Intensity_{\tau-1}}{Innovation\,Intensity_{\tau-5}})^{0.25} - 1$$

where $(Innovation\,Intensity_{\tau_0-4})$ is the Innovation Intensity data for the 4 years leading up to τ_0, and $CAGR_{\tau_0-4}$ is the Cumulative Annual Growth Rate of the Innovation Intensity variable in the same period. In the literature, a positive relationship between R&D increases and abnormal returns has been observed on several occasions (Penman and Zhang 2002; Eberhart, Maxwell, and Siddique 2004; and Lev, Sougiannis, and Sarath 2005), and in this regard, the overall trend that emerges gathers more consensus if compared to the Innovation Increase Variable. Therefore, going into the analysis, I expect a positive moderating effect on the CAR by the Innovation Increase variable. This leads me to state H_2:

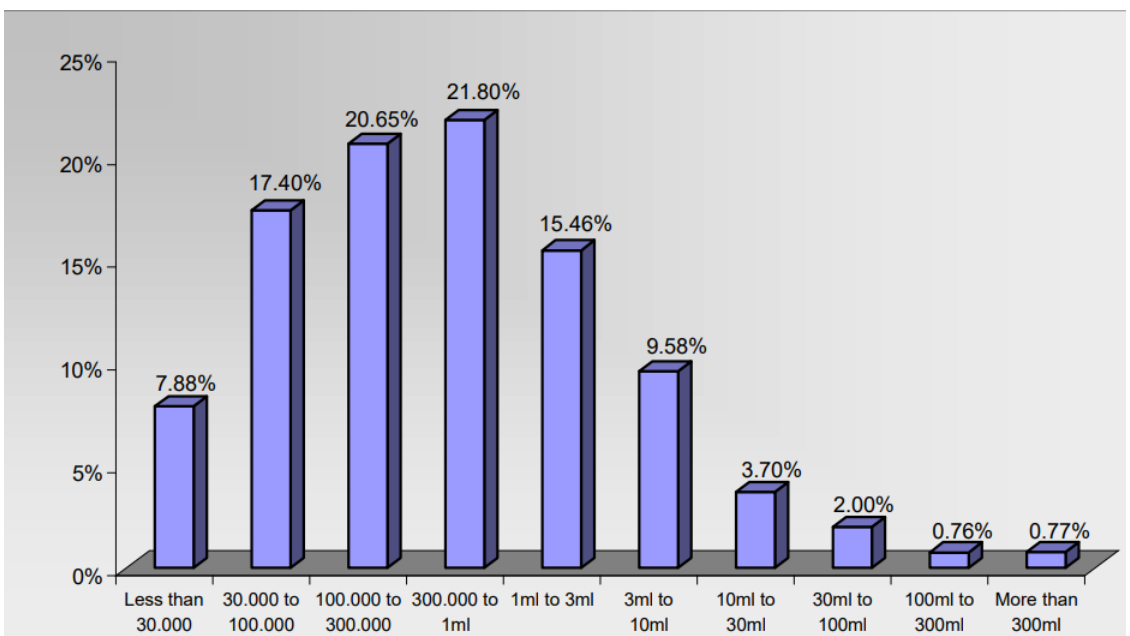
H2 : An Innovation Increase by the target firm does play a significant, and positive, moderating effect on the target firms' CAAR in the Event Window considered.

4.3.3 Patenting Activity

Another variable related to Innovation is the number of active Patents held by a firm (Kurtossy, 2004); in this case, the target firm. In addition to looking at the amount of money a firm spends, looking at the value and/or size of its Intellectual Property (IP) portfolio gives precious indications in terms of the level of innovativeness of a certain company competing in highly technological sectors, where the importance of intangible assets has kept growing (Orsenigo & Sterzi, 2010). From a theoretical perspective, patenting has represented a key tool for companies to compete in the innovation field, since it served multiple functions; on one hand, it served its classic purpose of incentivizing Innovative activity at the firm level by providing the innovator legal and economic protection against imitation processes; this allows the owner of the patent to effectively compete on the market and to raise the costs of competition for its rivals; the patent also serves, in this context, a powerful bargaining lever for cross-licensing agreements of many sorts, among firms which are looking to access new know-how and capabilities. At the industry level, patenting also serves a positive role; by applying for patents, the innovator discloses the nature of its invention, to a certain extent, and thus helps carry the overall state of the art of technology forward. In this context, patenting activity serves an important basis for future inventive efforts that build on past applications.

At the same time, the effect of these qualities has been found to be extremely dependent of contextual conditions. For example, Orsenigo & Sterzi, 2010 report that patent effectiveness is dependent on factors such as the type of innovation conducted (Product vs Process innovation,with the former being more positively related to Patenting Effectiveness; Radical vs Marginal Innovation, with the with the former being more positively related to Patenting Effectiveness), Firm Size, and Industrial context (where the authors report an effective role of Patenting only in certain industries such as Chemicals, Pharmaceuticals, Biotechnologies, and Energy). Micro and macro features surrounding the R&D process thus determine a variety of results regarding patent effectiveness, with the overall literature reporting a variety of conditional results. (Pammolli & Rossi, 2005, Arora & Ceccagnoli, 2006). Other studies have questioned the effectiveness of Patents in protecting Innovation. For instance, the Mannheim Innovation Panel (1993) and Kurtossy (2004) report that secrecy (the ability of a firm to maintain secrecy over the key innovative products, processes that foster current and potentially future competitive advantages), retention of key personnel (put in place through effective motivation, goal-setting, incentive systems and rewards) and complexity (the ability of a firm's innovative products and/or processes to result complex to stakeholders outside the firms; this inhibits imitation and copying patterns from competitors, who are then unable to easily reproduce the innovation and thus propose it on the market) are more effective than Patents in retaining proprietorship of product and process innovation. Therefore, firms with the greatest number of patents may not necessarily be the most innovative. Horstmann et al. (1985) argues that the economic and information costs (that come with disclosure) of patenting outweigh the potential gains for the investor. Another important distinction to make is between Number of Active patents and Patent Value. The two metrics do not necessarily go together (EPO Patent Survey, 2005), where it is shown that most Patent value is derived only by a small percentage of total patents examined (figure below).

Figure 6: Total Patent Value (x axis, €million) and sample frequency (y axis, in %); N = 9017



Source: EPO Patent Survey, 2005

In this literature context, I also looked at M&A studies in which the relevant variable was used in trying to observe value creation patterns, as Mergers and Acquisitions are often conducted for the sole purpose of acquiring IP and technological know-how (Bryer and Simensky, 2002). The most recent study investigated (Stenholm and Wallertoft, 2016), reports positive announcement returns for M&A acquirers of targets holding IP. Cited work is interesting since the database used for the number of patents metric, Global Patent Index, is the same used here. The announcement return of the target firm is not examined. It will therefore interesting to apply the same metric to a different sample and see the announcement behavior of the stock price on the part of the acquired patent holders.

All in all, the general view of the role of patenting in promoting innovation effectively is far from being an absolute and immutable finding. The conflicting findings and theories leave room for a lot of open discussions on the topic, and lead me to state a non-directional hyphothesis for the Patenting variable, labeled $H3$;

$H3$: *Patent possession by the target firm does not play a significant, and positive, moderating effect on the target firms' CAAR in the Event Window considered.*

The variable Patenting Activity will be codified as follows: the number of Active Patents for each firm in the sample is obtained from the Global Patent Index Database. Then, each firm was classified as either a company with Active Patents (Number of Patents > 0) or o company with no Active Patents (Number of Patents $= 0$)

4.3.4 Technological Subsector

The sample collected presents, at least on paper, significant categorical differences in terms of the Technological Subsector to which each target company in the sample is classified, according to the NAICS classification presented in the Data section. The most numerous sectors are: Custom Computer Programming Services (NAICS 541511, 44 firms), Data Processing Hosting and Related Services (NAICS 518210, 31 firms) and Semiconductors and Related Device Manufacturing (NAICS 334413, 27 firms). In order to extend the moderating analysis to the remaining 34 firms, belonging to adjacent but less well-represented subsectors in the sample, an aggregation procedure was conducted, based on the Subsector's degree of similarity, or relatedness, given by the NAICS Codes. Therefore, each of the remaining 34 firms was included in one of the three most numerous Sub-sectors; to conduct an accurate aggregation procedure, the first two digits of the NAICS code, which signal technological relatedness according to the 2017 manual, were examined for each firm; then, these first two digits were compared to each of the three main Sub-sectors, and thus each firm was put into the one Subsector sharing the same two digits of the NAICS Code. At the end of the procedure, the sample's Subsector Distribution was the following:

- Custom Computer Programming Services (NAICS 541511, 53 firms)
- Data Processing Hosting and Related Services (NAICS 518210, 42 firms)
- Semiconductors and Related Device Manufacturing (NAICS 334413, 41 firms)

From here onwards, such Industry-related variable is used to determine whether industry-characteristics determine a certain moderating effect on the target firm's announcement return. That is to ask, are there certain, sector-specific features, that have a role in explaining potential reactions on the stock price at the announcement date? First of all, it is important to look at way in which the identified NAICS Sub-sectors are defined. Each of the three main ones are presented as follows, according to the 2017 NAICS Manual:

- *Custom Computer Programming Services (541511): This industry comprises establishments primarily engaged in writing, modifying, testing, and supporting software to meet the needs of a particular customer*
- *Data Processing Hosting and Related Services (518210): This industry comprises establishments primarily engaged in providing infrastructure for hosting or data processing services. These establishments may provide specialized hosting activities, such as Web hosting, streaming services, or application hosting (except software publishing), or they may provide general time-share mainframe facilities to clients.*
- *Semiconductors and Related Device Manufacturing (334220): This industry comprises establishments primarily engaged in manufacturing semiconductors and related solid-state devices. Examples of products made by these establishments are integrated circuits, memory chips, microprocessors, diodes, transistors, solar cells and other optoelectronic devices.*

From the reported definitions, one major difference that emerges is that two (Custom Programming, Data Processing) out the three industries observed are more focused in developing software-centric solutions, products A previous short-term Tech M&A Event Study (Deshmukh, 2012) reports significant return differences in this context; the author observes that, *ceteris paribus*, acquirer and targets within software-centric industries experience higher Abnormal Returns than targets belonging to hardware-centric industries. This is reported by the author to be due to the difference in tangible capital intensity as a percentage of total assets, which commands smaller purchase price premiums compared to acquisition of software centric-targets.This view clashes with what reported by McKinsey, 2016, which identifies the Semiconductor Industry as historically subject to high deal-value, high purchase premiums and low deal volumes if compared to other high tech industry players; in most cases, the high premiums commanded by the Industry seem to be justified, as the opportunity for synergy creation is strong and sometimes overlooked by potential bidders. It may also be true that, if not properly conducted, the capital and asset intensity may render the complexity of the M&A integration process within the Semiconductor industry higher than for software-centric companies. S&P Global Ratings, for the period 2013-2017, signals higher revenue growth rates in the software realm, confirming the overall shift of software-focused solutions (cloud services, mobile spending, data analytics, security), gradually displacing hardware sales. Both software and hardware have been gaining as of 2017 (Nasdaq, 2017),with software companies ahead by about 3.2% in terms of stock-gains; a positive rebounding outlook, for 2018 and onwards, for the semiconductor subsector is mentioned (KPMG 2018), with Wireless Communications and Internet of Things as the top drivers for sectorial revenue growth. Diversification and M&A Activity are also expected to be represent top-strategic priorities for semiconductor players during the 2018-2021 window. If we look at a longer and perhaps more significant time window, (1990s-2017), one cannot fail to notice the tremendous growth of the Semiconductor sector on a global level (from $33 billions in 1990 to $412 billions in 2017, according to Statista and the WSTS), spurred by the ever-increasing used of electronic devices. Referring back to McKinsey, 2016, it emerges that M&A in the Semiconductor industry has picked up both in terms of value and volume since 2012, a feature quite well reflected in my sample.

So far, the only Tech M&A study reported a positive differential between software and hardware, whereas market news also tend to favor the software side. However, industrial M&A patterns in the Semiconductor market may seem to indicate that the reapable returns shall be particularly interesting for Semiconductor targets, especially from 2012 onwards, a window in which 25 out of the 41 deals in the sample's Subsector occur. The combination of capital requirements and industrial trends both seem to be reasonable factors for any potential CAAR difference to be found in the analysis; therefore, my starting point in terms of hypothesis development will be neutral. Given the reviewed sources and the extensive lack of specific literature on this topic, I thus state the following hypothesis for the examined High Tech subsector variable, H_4:

$H4$: *The target firm's subsector does not play a moderating effect on the target firms' CAAR in the Event Window considered.*

In the empirical analysis that follows, a dummy variable for each subsector was created, so that each firm is paired up to such a dummy, taking the value 1 if the firm belongs to the referenced subsector out of the three main ones considered, 0 otherwise.

4.3.5 Deal Size

Now that I have introduced all variables trying to capture the degree of innovativeness of the target firms considered, I will introduce other relevant variables as additional moderators; the first of these is Deal Size. The variable tries to capture the relative magnitude of the deal. It is constructed by comparing the target firms's Transaction Enterprise Value (which regularly includes the acquisition premium paid by the acquirer), in other words, the Deal Value, with the size of the acquired firm, measured by its Total Revenue (measured as the latest pre-deal yearly Revenue). For each firm, Deal Size is then:

$$Deal\,Size = \frac{Deal\,Value}{Total\,Revenue_{Target}}$$

With Total Revenue being the Yearly Total Revenue in the last Available Year prior to the deal announcement (e.g. if the deal is announced on March, 23rd, 2009, Total Revenue of FY2008 would serve as the reference for calculating Deal Size). Therefore I have an EV/Sales multiple, which gives an indication of the ratio of the Deal Value on the revenue of the target firm. This metric offers a perspective of how much an acquiring company is willing to pay a target company in relation to its revenue, and thus allows for proper comparison across my sample. This variable aims to be a proxy for the size of the deal in relation to the target's size, which has been a topic covered and examined in an extended way across the relevant literature (Haleblian et al, 2008). The effectiveness of large vs small M&A has to this day led to contrasting results and has being labeled of being a complex relationship (Healy et al., 1992, Cornett & Tehranian, 1992, Moeller et al., 2004, Hitt et al,2009); a strong driver of acquisition performance in large M&A is likely to result from developed integration capabilities, which help especially in the case of large acquisitions, in which a bigger target is better positioned to have an immediate impact on the overall performance of the acquiring firm (King et al, 2008). Other authors (Alexandridis et al, 2010) report a negative relationship between target size and acquisition premium, and more importantly value destruction for acquirers of larger targets, no matter the level of the paid premium. BCG (2017) reports negative average 1996-2016 CAR for deals with deals size greater than 1$ billion, positive CAR otherwise. A lot of these results is also dependent on the metric used for capturing the effect of size, which vary according to the author's preference (Market Capitalization ratios, Deal Value,Deal Value/EBIT,etc..), but that nonetheless all pretty much do a good job at capturing the construct. In recent years, just looking at the High Tech Sectors, big deals (Deal Value > 500$ million) drive a significant amount of the total tech deal value, as well as posting strong growth in terms of sheer number of deals (BCG, 2017). In my sample, deals of these characteristics are well represented (63 out of 136), and should provide for interesting analysis. In terms of the Deal Size multiple previously introduced, the 2017 BCG Technology Report indicates a yearly EV/Sales multiple for tech targets on the rise in the 2013-2016 period, from 2.1 in 2013 to 2.9 in 2016, with a 2.6 median for the whole period. Such increase is due to the significant marginality obtainable by software companies, which are able to keep cost of goods sold down thanks to the very marginal production and distribution costs.This has led to an increase in the acquisition premium required to acquire such targets. While trying to relate and speculate over the role of Deal Size on Tech M&A Announcement Returns beyond the grasp of the mentioned literature, it is important to remember that especially in this industry, an important portion of the deal value reflects not necessarily the target's ability to create value in the present environment, but the growth prospects of the target firm, which might not be immediately captured in the current level of total Revenue. There might be situations where a company has a low absolute Revenue level, weak marginality but strong growth prospects, thus resulting in a high level of the Deal Size multiple. It might also happen that a company with a high absolute Revenue level and marginality lacks significant growth prospects in the future; in this case, there might still be a high level of the Deal Size multiple occurring, as the acquiring company "honors" the current level of marginality and cash-generating ability of the target by paying a premium reflected in the Deal Value. In these situations, these two deal would be considered as "big", as reflected by the high level of the EV/Sales multiple, even though the underlying reasons that conducted to the multiple level are structurally different. Nonetheless, we see that the multiple metric does a good job in capturing these differences, and is therefore appropriate for the present analysis.

In this context, since I am using a Deal Value multiple and not a pure Deal Value, and following the indications from the researched literature, I develop a neutral pre-analysis view on the variable, summarized in $H5:$

$H5:$ *The level of the Deal Size multiple does not play a significant effect on the target firms' CAAR in the Event Window considered.*

In the empirical analysis, the firms in the sample were divided into two buckets via the use of a Dummy Variable, taking the value of 1 if the EV/Sales multiple is above the sample's median of 2.6 (which coincides with the 2013-2016 figures reported by BCG in their report), 0 if the EV/Sales multiple is equal or inferior to the sample's median of 2.6.

4.3.6 M&A Experience

Another variable that has been subject of M&A research is linked to the accumulation of M&A experience on the part of the acquiring firm. This differentiates between serial acquirers, that is, firms that, prior to the observed deal, have already completed other deals and have already dealt with the subsequent integration process, and first-timers, or firms that lack previous M&A experience, and which are thus approaching their first acquisition. Research efforts have gone a long way in trying to find structural differences between these two groups of acquirers, and their results are far from being unanimous, even though, from a theoretical perspective, the intuitive answer should lead to assume better M&A performance experienced by serial acquirers (Haleblian et 2008). Some studies (Haleblian and Finkelstein, 1999) find a non-linear relationship between M&A experience and post-acquisition performance, and identify the application of past experience to very different acquisition scenarios as one of the main drivers that lead to the departure from the linear assumption which states that more experience always increases acquisition performance. This is also confirmed by others (Zollo & Winter, 2002), who confirm the role of task heterogeneity as a main driver of performance variation. It then seems that pure accumulation of past experience does not help if an acquiring firm is not able to recognize which past learning experience to apply in which new context; in this sense, the activity of formalizing past experiences seems to be beneficial in applying said concept more effectively (Zollo & Singh, 2004). Laamanen & Keil, 2008, find a positive moderating effect played by acquirer's experience, whereas Haleblian & Finkelstein, 2002, confirms the finding but also, a bit counterintuitevely, identifies peak performance states in which the degree of similarity between past and current situations is not too high or too low. Zollo & al, 2002, confirm a U-shaped relationship between acquisition experience and performance. All these studies thus focus on "learning by doing" type of situations, in which the acquirer gathers experience by directly engaging in the acquisition. In contrast to this general approach stands an interesting study in the commercial banks sector (Delong and Deyoung, 2007), who show commercial banks learning not only by doing, but also via indirect observation of other banks's successes and failures. What transpires from of these scientific investigations is that there is a link between experience and performance, but that these links is deeply moderated by context and the ability of the firm to retain generated experience. Another lens under which the variable can be observed is time. According to the Boston Consulting Group, 2017 which again looks at Technology M&A, serial acquirers do not experience superior acquisition performance in the short term (they actually report worse performance than inexperienced buyers); in the medium term (1 year), they instead significantly outperform, perhaps showing that application of past experience is gradually shaped in the post-acquisition period, which coincides with the roll-out of the integration process.

The conclusions that I then derive for the present investigation are then multi-faceted. The link between experience and performance is definitely present, although the modalities under which it shows are highly context-related. The complex construct then seems to acquire more structure with time, and therefore a short-term and linear examination such as mine might not directly show any relationship at all. Another important consideration to make will be about the process with which, in my sample, serial acquirers will be identified and separated from first-timers. I will elaborate on this in more detail in the following section which deals with the linear regression methodology. For now, I conclude the paragraph by stating the neutral hyphothesis concerning M&A Experience's moderating role for the observed target firm, labelled $H6$:

$H6$: *The acquirer's level of M&A Experience does not play a significant effect on the target firms' CAAR in* *the Event Window considered.*

In terms of the variable's classification for the purpose of the analysis, I proceed as follows: I characterize a firm in my sample as a "Serial Acquirer" if, in the six years prior to the announcement date, it has completed at least a number of M&A operations greater than or equal to 8; otherwise, the firm will be considered as a "First-Timer". This number is derived from the literature (Haleblian & Finkelstein, 1999, Zollo & Leshchinskii,2004) which, in describing the previously introduced U-shaped relationship between organizational learning and performance, quantifies in about 8-9 the number of M&A operations necessary to start extracting a performance benefit. Therefore, this number represents the threshold level which will be used and tested.

4.3.7 Financial Distress

Financial Distress on the part of the acquired firm falls under the branch of several performance metrics that try to explain acquisition performance. Several studies (Bruner, 1988, Lang et al,1989,Servaes,1991, Rau & Vermaelen, 1998) focus on Tobin's Q (Market Value to Total Asset Value Ratio) to explain the direction of acquisition benefits. Their evidence suggests that overall acquisition performance increases when the acquired firm is in a state of distress, or low-performance. A major explanation of the phenomenon,given also by more and less recent literature (Chatterjee,1992, Houston et al., 2001, Lamaneen et. al, 2014, which by the way neatly focuses on the US software industry) is that low performing firms offer great restructuring upside and high margins for value creation to bidder firms, which therefore offer great turnaround opportunities and synergy creation potential. Haleblian, 2008 in his literature review, thus properly describes the presented mechanism by labelling the takeover market as a disciplinary mechanism in this sense. From the view of the target firm's shareholder, it should then make sense that a stronger (in relation to a healthy target) positive return should occur at the announcement date, since the event signals the potential occurrence of the business turnaround in the near term. Although this view is quite spread out among interested authors, others (Clark & Ofek,1994) do not come to the same conclusions. In their 1994 study, it is suggested that a sometimes neglected aspect might be represented by the inability of the acquired firm to successfully integrate the distressed target, which was increased exactly by the low-performance of the acquired firms. This is an interesting aspect to consider, even though the majority of the studies clearly point in the opposite direction.

Therefore, in terms of hypothesis development, I expect and intend to verify the following regarding Financial Distress; I then state $H7$:

$H7$: The target's level of Financial Distress does play a significant (positive) effect on the target firms' CAAR in the Event Window considered.

A relevant consideration to make in this paragraph relates to the classification of a Financially Distressed target; as mentioned, many studies among those mentioned look at Tobin's Q; the most recent of this pool (Lamaneen et. al, 2014), and perhaps the most directly comparable, as it also deals with the US Software Industry, characterizes Seller Distress as the Debt to Total Assets ratio, and also looks at whether Net Income and Return On Invested Capital have declined in two consecutive years prior to the announcement's year, drawing inspiration from Bruton et al., 1994. In the present work, I intend to depart from these measures; the reasons why are the following: first, an excessive reliance on Asset Value may not be the best indicator for performance in an Industry in which so much innovation, value and performance is created through the R&D practices, which do not end up in on the balance sheet, as they are treated as operating expenses. Secondly, simply looking at Net Income and ROIC's trend over a certain period might not tell the whole story about whether a certain firm is actually in a financially distressed situation (e.g. A tech company posting Yearly revenue of 5$ billion in 2008 then sees Revenues decline in the two following year, to 4.5$ billion in 2009 and to 4$ billion in 2010; according to Lamaneen, this may end up as being characterized as a financially distressed firm, even if its situation is far from being a liquidity crisis and its decline may be more related to environmental factors). In this study, I instead will use EBITDA (Earnings before Interest, Taxes, Depreciation and Amortization) as a relevant measure, and will classify a firm as Financially distressed if its EBIDTA is negative (<0) in the year prior to the announcement date. EBITDA has been utilized as a popular measure for financial distress in the literature (Yawson, 2009, Kang & Shivdasani, 1997, Asquith et al, 1994, Andrade & Kaplan, 1998, Eichner, 2008, Pindado et al, 2008) ; Asquith et al, 1994, in their debt restructuring research, define financial distress as the inability of the EBITDA to cover the period's interest expenses (Yawson, 2009, and Kang & Shivdasani, 1997, use the same measure in the opposite way, so as to identify positive coverage, and thus non-distressed situations); the authors also make an additional distinction within firms unable to achieve coverage; in fact, they do not take into empirical consideration firms who do cover between 80% and 100% of yearly interest expenses, as they deem those firms not yet willing to actively respond to the distress situation, as the negative performance would appear to be of moderate severity; Eichner, 2008, confirms this view, and also utilizes EBIDTA as the closes proxy for the firm's capacity to generate operating cash flow. This general approach is in line with the measure I utilize here. By considering only firms with negative EBITDA, the inability to repay financial expenses for the pre-deal year is already assumed (as the interest coverage ratio of EBIDTA/Interest would already be lower than 1, and, in fact, negative); in addition, my approach only considers firms with a recognized state of distress (given the above mentioned view presented by Asquith et al, 1994) and therefore these firms should be more actively aware and/or responsive in respect of the distressed situation; other and more recent efforts (Tinoco & Wilson, 2013, Schmuck, 2013, Gutierrez et al, 2015, Rezende et al, 2017) also make use of EBITDA in similar fashion. Schmuck, 2013, confirms the utility of EBITDA in serving as key metric for tracking distress; in particular, the author mentions two main advantages the metric provides in this regard: first, the independence from diverse amortization and depreciation practices, and secondly, the fact that EBITDA allows for a "cleaner" look at the company's ability to generate operating results, as it is devoid of non-recurring events which may greatly impact the balance sheet, such as extraordinary asset transactions. This view is confirmed by other studies on the topic (Lai, 1997, Whitaker, 1999, and Buschmann, 2006). In conclusion, as cash flow generation for firms with positive EBITDA is not automatically assumed, it is reasonable to conclude that a negative EBITDA represents even more of a negative indicator of financial distress and potential liquidity problems.

[1]

4.3.8 Merger Waves

This last variable is more linked to the overall market environment, and testes market reaction in relation to the time-frame in which the M&A deal happens. Historically, it is possible to identify different merger waves, that is, periods of time in which M&A volumes and overall activity levels, in terms of both transaction size and volumes, are particularly intense. Since 1985, year since which deal volumes and value have increased, four merger waves have been generally identified; they are briefly summarized (from Brauer, 2018 and Cordeiro,

[1] Eichner, 2008 and Lai, 1997, are referenced from Schmuck, 2013

2014) in the following lines; they are preceeded by other three significant merger wave periods, which started at the turn of the previous century:

- *4th Merger Wave (1981-1989)*: The main drivers of this period were the overall rise in global stock markets, the relative weakness of the U.S. dollar and a favorable regulatory environment which allowed progressive deregulation of certain industries. The under-performance of multinational conglomerate firms lead to their break-up, as firms pushed to re-gain monosectorial focus. In this context, the introduction of new take-over tools lead to more sophisticated deal-crafting across a wide range of targets. Financial restructuring options such as junk bond financing and leveraged buy-outs (LBOs) became widely used transaction schemes. This wave was terminated by the collapse of the junk bond market and the 1990 recession.

- Fifth Merger Wave (1992-2001): The main drivers of this period are the historically low interest rates, coupled with strong and long-running bull markets, which were fostered by the rise of Internet firms which were exploiting the massive technological advancements of the 1990s. These years are full of deals featuring strategic buyers who were willing to conduct mega-mergers using a lot of equity financing. Major industries involved in these deals were the banking, defense, healthcare and telecommunications. This wave was terminated by the burst of the “Dot Com Bubble” and economic recession.

- Sixth Merger Wave (2001-2008): The main drivers of this period are favorable financing conditions, the privatization of state-owned enterprises and the strong progression of the globalization trend. The increasing sinchrony of the world’s economies lead to an increase in cross-border transactions and participation of private equity firms. Emerging market companies also started to experience an uptick in activity. This wave was terminated by the economic crisis and global credit crunch of 2008, which resulted in a great loss of confidence in global capital markets.

- Seventh Merger Wave (2014-present): The main drivers of this period are the return of optimism in the market coupled with unprecedented levels of capital available for investments, especially on the part of private equity players. The managerial belief in the volatility of the markets in terms of overall growth has lead many managers to believe that it might be easier to buy growth externally rather than internally. This wave is still ongoing as reflected by recent transaction levels.

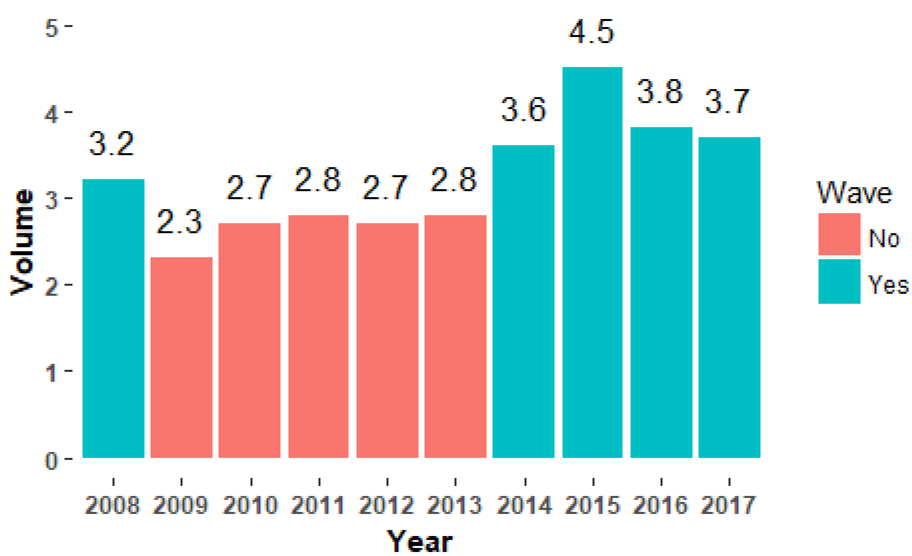
Merger waves have long been the subject of scrutiny by the literature. Some scholars (Banerjee & Eckard, 1998, Leeth & Borg, 2000, Matsusaka, 1993, Hubbard & Palia, 1999) chose to focus on the scientific examinations of single merger waves; the overall results are quite mixed. Banerjee and Eckard examine the first great merger wave period (1899-1901, according to Nelson, 1956) and reported significant value creation on the part of both bidder and target firms. Analyzing the 1920s merger wave, Leeth and Borg report gainings on the part of the targets but absence of any acquisition gain or lost by bidder firms. Matsusaka examines the 1960s and observes positive returns for acquiring firms willing to diversify while retaining target's management, and negative returns in the case of related acquisitions. Hubbard and Palia build on the previous finding and also suggest the importance of strategic focus in determining acquiring firm returns.

Other researchers focus on either between or within wave periods. A lot of the research focus is on the side of the acquiring firms (Carow et al.,2004,Moeller et al.,2004, McNamara et al., 2008,), where most authors find positive returns accruing to acquiring firms moving either at the very beginning or at the very end of wave periods. This view suggests that the market seems to punish firms adopting reactive behavior, by acquiring firm out of some type of overall market pressure while in the midst of the acquisition frenzy. Since a lot of the effort seems to be on the acquiring firms within single waves, an initially neutral view for the target firms in my sample is suggested, as I am not led to believe in positive returns accruing to target firms independently of the time period. Although a positive view on target firms' performance during high M&A activity period is confirmed by some studies (Jarrell and Poulsen, 1989, cite stronger competition for corporate ownership as the main driver of increased target returns, whereas Jarrell, Brickley and Netter, 1988, focus instead on changes in the regulatory environment that shift returns from acquiring to target firms), these studies do focus on very specific merger periods, characterized by singular economic and regulatory environment; therefore I adopt caution in extrapolating initial hypothesis from these research efforts. The sample period covered (2008-2017) spans over interesting years for M&A activity, as the economic crisis occurring in the first years of the window takes its toll on both M&A deal volumes and total value. 2008 coincides with the ending year of the sixth merger wave, while 2014 stands as the start of other positive years in terms of M&A activity (JP Morgan, Dealogic, 2018). Therefore, such overlap provides for a good look at the behavior of the High Tech target firms returns in such periods, and should possibly help in the investigation of time-related return differences in the examined years. Therefore, I develop the following hypothesis regarding the last variable examined, labelled $H8$:

$H8$: *Merger Wave years do not play a significant effect on the target firms' CAAR in the Event Window considered.*

In the ten-year period examined, there are then five years of relatively more intense M&A volumes (2008,2014-2017) and five years of relatively less intense M&A Volumes (2009-2013). In terms of sample classification, I then proceed as follows: I classify an event in my sample as either "In-Wave" , if the deal's announcement date falls in the 2008,2014-2017 years, "Out-of-Wave" otherwise.

Figure 7: Global M&A Volumes 2008-2017 ($tn)



Source: JP Morgan, Dealogic, 2018

4.4 Statistical Analysis: Tests

Now that the moderating variables have all been introduced, in this section I proceed to test the several hypothesis presented along section 4.3. The present section is structured in the following way; first, I consider only Technological Subsector divisions and test for CAAR differences among the three sub-samples identified via a modified ANOVA. Then, I consider all moderating variables together and build a multiple-regression model, with the moderating variables as the independent variables and the CAAR as the dependent variable. The results are presented across all Event Windows used and consequently illustrated.

4.4.1 Subsectorial Analysis of Variance

The reason for wanting to investigate Technological Subsector differences in the sample is two-fold: first, it is the only variable that can be subsetted into more than two categories, allowing therefore for different statistical tests if compared with the other moderating variables used. Secondly, I found it to be one of the most interesting variables from a research point of view. The lack of Tech M&A Event Studies which focus on industrial differences, as well as the high degree of current business relevance of these sectors, led me to wanting to dedicate special attention to this moderating construct.

The statistical test then used to test $H4$ (The target firm's subsector does play a significant, and positive, moderating effect on the firm's CAR in the Event Window considered) is a one-way ANOVA (Analysis of Variance); the basic idea of the one-way ANOVA is to test whether there are relevant differences in the mean measurement of one particular numerical variable (in this case, the CAAR) across certain groups (in this case, the different Technological Sub-sectors); if there are, the test then proceeds with an investigation of which group pairs display the most relevant differences between each other; therefore,each group-pair comparison is evaluated (in this case, the three comparison pairs are: a) Data Processing-Custom Computer Programming Services, b) Semiconductor-Custom Computer Programming Services c) Semiconductor-Data Processing) . The three groups considered here refer back to 4.3.4: Custom Computer Programming Services (NAICS 541511, 53 firms), Data Processing Hosting and Related Services (NAICS 518210, 42 firms) and Semiconductors and Related Device Manufacturing (NAICS 334413, 41 firms). The classical application of the ANOVA refers to common assumptions, some of which are not applicable here; the two relevant ones that are challenged here are the assumption of equal sample sizes and equal variances across groups. The former is given by the subsector distribution previously described and obtained at 4.3.4, the latter was empirically examined using Levene's test (Levene, 1960) which resulted in being significant at the 5% significance level. Therefore, to implement the ANOVA with the proper assumption adjustments, I refer to Welch,1951, which illustrates an alternative the robust approach to conduct the ANOVA under the modified assumptions. The test is then run across all Event Windows for the CAAR of the 3 groups, summarized in the following table:

Table 4: One-Way ANOVA (modified assumptions) Results Table

Event Window	F-Stat	P-Value
(-10,10)	4.061	2.11%**
(-5,5)	2.7675	6.9%*
(-3,3)	2.2397	11.34%
(-2,2)	2.1043	12.88%
(-1,1)	1.996	14.27%
Event date (τ_0)	0.40164	67.06%

**p-value <0.1*   ***p-value <0.05*

The CAAR difference of the three groups is statistically significant at the 5% and 10% level along the two longest Event Windows considered [(-10.10),(-5,5)]. This means that the null hypothesis of equal means across the Computer Programming (short-named *CP* in the test results table), Data Processing (*DP*) and Semiconductor (*SC*) Sub-sectors can be rejected, indicating that there is a least one subsector showing a CAAR significantly different from the others. To figure out which of the three groups shows the observed difference, a non-parametric post-hoc test is conducted using the introduced group comparison pairs. In this case, I use the Games-Howell Post-Hoc Test (Games & Howell, 1976), which also does not assume equal variances and sample sizes and thus fits the initial, modified, assumptions. The test is conducted across the above-mentioned significant Event Windows; as anticipated, applying post-hoc testing to the [(-3,3)(-2,2)(-1,1)] Event Windows would be useless, as the ANOVA results already suggest that the null hypothesis of equal means across the three Subsector groups cannot be rejected. The results are the following:

Table 5: Games-Howell Post-Hoc Test Results Table for (-10,10)

Subsector	n	CAAR	Variances	Pair	Mean Diff.	T-Stat	p-value
CP	53	24%	0.041	$DP-CP$	15%	1.7	22%
DP	42	39%	0.293	$SC-CP$	12%	2.58	3%**
SC	41	36%	0.057	$SC-DP$	-3%	0.32	95%

***p-value$<$ 0.05*

Table 6: Games-Howell Post-Hoc Test Results Table for (-5,5)

Subsector	n	CAAR	Variances	Pair	Mean Diff.	T-Stat	p-value
CP	53	26%	0.046	$DP-CP$	13.8%	1.64	24%
DP	42	39%	0.262	$SC-CP$	9.4%	2.03	11%
SC	41	35%	0.053	$SC-DP$	-4.4%	0.51	87%

The test results indicate, only for the (-10,10) Event Window, a positive and significant (at the 5% level) CAAR difference between the Semiconductors and Related Device Manufacturing (NAICS 334413, 41 firms), and the Custom Computer Programming Services (NAICS 541511, 53 firms). Such difference takes the value of 12%. The 9.4% difference for the same pair results in being non-significant at the 5% level for the smaller Event Window of (-5,5). The variance heterogeneity is relatively stable across all tables, with the Data Processing subsector showing a much higher level overall, whereas the two other subsectors are much more similar in this regard. Thus, in one case, we have a significant difference between hardware-centric and software centric business models. Referring back to the discussion in section 4.3.4, this result seems to validate the particularly positive M&A trends experienced by Seminconductor targets in recent years; these companies'shareholders may experience a superior CAAR at the Announcement Date as a result of the high industry premiums that come entailed with the final Deal Price (McKinsey,2016). These premiums may well be a reflection of both the peculiar M&A environment of the Semiconductor Industry, which, given the relatively low M&A volume, features fewer attractive targets to bid for, thus creating a bigger pool of bidders competing for a smaller pool of targets, and the structural characteristics of the acquired firms, which offer great synergy potential and value creation possibilities for the right acquirer willing to conduct deep integration processes featuring organizational, as well as strategic, restructuring measures.

In the next section, through multiple-regression analysis, the Technological Subsector variable analyzed until now will be combined with the other independent variables, and a more comprehensive view will be provided, The following section, in this context, will then serve as a way to test the robustness of the this ANOVA when other variables are thrown into the mix in trying to explain the overall variance of the sample's CAAR.

4.4.2 Multiple Regression Analysis

Regression analysis is applied to the sample's CAAR across different Event Windows, in order to test the conjoint impact of each of the presented variables on the dependent variable of the Abnormal Return at the announcement date. The regression is constructed in a gradual way (explained below), in order to perform sensitivity analysis on the single regression coefficients that relate to the moderating constructs related to the target firm's Innovation activities; this allows to gauge their level of robustness to the introduction of other independent variables (Deal Size, M&A Experience, Financial Distress and Merger Waves) as controls. In summary, the regression variables will be the following:

- **Dependent Variable:** the sample's CAAR for the 136 targets in the collected deal sample. The different Event Windows around the Event date (τ_0) are 5: *(τ_0 ± 10 , τ_0 ±5, τ_0 ±3, τ_0 ±2, τ_0 ±1)*

- **Independent Variables:** these are the 8 moderating constructs presented at 4.3: Innovation Intensity, Innovation Increase, Patenting Activity, Technological Subsector, Deal Size, M&A Experience, Financial Distress and Merger Waves. In order to be used in the regression, they are inserted as binary variables, taking a value of either 1 or 0 and quantified in the following manner:

1. *Innovation Intensity* is a dummy variable taking the value of 1 if the relative level, in respect of the High Tech Industry as a whole,of the median R&D to Sales Ratio in the 4 years leading up to the announcement is above the industry's median (in relation of an industry population data of 1011 firms for the 2008-2017 years,) of 16.75% , or 0 if below.

2. *Innovation Increase* is a dummy variable taking the value of 1 if the direction of the CAGR of the R&D

to Sales Ratio in the 4 years leading up to the announcement was positive, so with CAGR > 0, or 0, if CAGR <=0.

3. *Patenting Activity* is a dummy variable taking the value of 1 if the target firm holds active patents as the deal is announced, 0 otherwise.

4. *Semiconductors (SC)* is a dummy variable taking the value of 1 if the target firm is included in the Semiconductor Industry Subsector.

5. *Computer Programming (CP)* is a dummy variable taking the value of 1 if the target firm is included in the Computer Programming Services Industry Subsector.

6. *Deal Size* is a dummy variable taking the value of 1 is the EV/Sales acquisition multiple for that target firm is above the industry's recent years median of 2.6 (BCG Tech M&A Report, 2017), 0 if below.

7. *M&A Experience* is a dummy variable taking the value of 1 if the target firm is acquired by a firm with a number of previous acquisitions in the 6 years before the deal announcement greater than or equal to 8 (Haleblian & Finkelstein, 1999, Zollo & Leshchinskii,1999).

8. *Financial Distress* is a dummy variable taking the value of 1 if the firm's EBITDA in the last year prior to the deal announcement is negative, 0 if above.

9. *Merger Wave* is a dummy variable taking the value of 1 if the year in which the acquisition is announced has been characterized by high global M&A volumes (2018 JPMorgan Global M&A Outlook), 0 otherwise.

In order to conduct linear regression, I empirically checked for the validity of one is most important assumptions, the absence of heteroskedasticity (unequal variance of regression residuals); to perform the check I used the Breusch-Pagan Test (Breusch-Pagan,1979), under which the null hypothesis is the desired assumption of homoskedasticity. For my sample, the test results in being non-significant at the 5% level, validating the initial assumption of homoskedasticity. Now that the relevant variables are all recapped, I will explain how the regression model was built; as a first step, the variables related to the target firms's degree of innovativeness were introduced one by one in the following manner: first, the CAAR across different event windows (EW) was regressed against the Innovation Intensity variable ($IInt$) , resulting in:

$$CAAR_{EW} = \alpha + \beta IInt + \varepsilon$$

secondly, the Innovation Increase variable ($IInc$) was added, resulting in:

$$CAAR_{EW} = \alpha + \beta IInt + \gamma IInc + \varepsilon$$

third, Patenting activity (P) was added, resulting in:

$$CAAR_{EW} = \alpha + \beta IInc + \gamma IInt + \delta P + \varepsilon$$

fourth, dummies identifying the Semiconductor (SC) and Computer Programming (CP) subsectors were added, resulting in:

$$CAAR_{EW} = \alpha + \beta IInt + \gamma IInc + \delta P + \kappa SC + \lambda CP + \varepsilon$$

the process was then iterated to add the additional and above-presented variables as controls (second step), allowing to reason about the entity and significance of each individual variable in contrast with the overall model, which in the final step takes the following form:

$$CAAR_{EW} = \alpha + \beta IInt + \gamma IInc + \delta P + \kappa SC + \lambda CP + \rho Size + \varsigma Exp + \eta Dist + \phi W + \varepsilon$$

where $Size$, Exp, $Dist$, W are terms referring respectively to Deal Size, M&A Experience, Financial Distress and Merger Waves. For each event window, the two-step process was repeated, as 2 regressions were conducted. Across 5 Event Windows, that makes for 10 different regression models. The results are presented below. In the presentation of the results, it is important to relate back to the methodological approach to Event Studies (Peterson, 1989) and to keep in mind how to interpret the results across different lengths of Event Windows: an Event Window which is too short may fail to fully capture the full effects of the examined variables and constructs, as the stock price may take a longer period of time to adjust to the M&A deal announcement and thus fully incorporate all relevant information regarding the involved parties. On the contrary, an Event Window which is too large may result in causing an instability in the levels of the observed variables, as other factors not directly related to the Event may cause further stock price adjustments and thus be reflected with biased estimates. For these purposes, longer [(-10.10)] and shorter [(-1,1)] Event Windows may result in being less robust. Accordingly, the results for the [(-5,5),(-3,3)] shall be theoretically more stable. Nonetheless, all utilized Event Window regression results will be now presented. The tables below follow the logic introduced in the present section, starting from the Innovation variables regression (the sample's CAAR regressed against the Innovation Intensity Variable, the Innovation Increase Variable, the Patenting Activity and Technological Subsector dummies) and ending with the complete multiple regression model which includes all controls.

Table 7 : Regression Models for CAAR(-1,1)

	Dependent variable:	
	CAAR(-1,1)	
	(1)	(2)
Innovation Intensity	−0.006	−0.025
	(0.060)	(0.060)
Innovation Increase	0.177***	0.155***
	(0.058)	(0.058)
Patenting Activity	−0.177**	−0.162**
	(0.071)	(0.070)
Semiconductors	0.005	−0.014
	(0.077)	(0.079)
Computer Programming	−0.119*	−0.114
	(0.067)	(0.070)
Deal Size		−0.037
		(0.060)
Acquisition Experience		0.009
		(0.059)
Financial Distress		0.190***
		(0.063)
Merger Wave		−0.005
		(0.058)
Constant	0.414***	0.387***
	(0.065)	(0.082)
Observations	136	136
R^2	0.115	0.188
F Statistic	3.395*** (df = 5; 130)	3.233*** (df = 9; 126)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 8 : Regression Models for CAAR(-2,2)

	Dependent variable:	
	CAAR(-2,2)	
	(1)	(2)
Innovation Intensity	-0.009	-0.027
	(0.061)	(0.061)
Innovation Increase	0.179^{***}	0.158^{***}
	(0.059)	(0.059)
Patenting Activity	-0.170^{**}	-0.156^{**}
	(0.072)	(0.071)
Semiconductors	0.002	-0.017
	(0.078)	(0.080)
Computer Programming	-0.122^{*}	-0.118^{*}
	(0.068)	(0.071)
Deal Size		-0.039
		(0.061)
Acquisition Experience		0.009
		(0.060)
Financial Distress		0.177^{***}
		(0.065)
Merger Wave		-0.003
		(0.059)
Constant	0.412^{***}	0.389^{***}
	(0.066)	(0.084)
Observations	136	136
R^2	0.113	0.176
F Statistic	3.321^{***} (df = 5; 130)	2.993^{***} (df = 9; 126)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 9 : Regression Models for CAAR(-3,3)

	Dependent variable:	
	CAAR(-3,3)	
	(1)	(2)
Innovation Intensity	-0.014	-0.029
	(0.061)	(0.061)
Innovation Increase	0.168^{***}	0.147^{**}
	(0.059)	(0.059)
Patenting Activity	-0.171^{**}	-0.156^{**}
	(0.072)	(0.071)
Semiconductors	0.008	-0.015
	(0.078)	(0.080)
Computer Programming	-0.122^{*}	-0.123^{*}
	(0.067)	(0.071)
Deal Size		-0.054
		(0.061)
Acquisition Experience		0.013
		(0.060)
Financial Distress		0.158^{**}
		(0.065)
Merger Wave		0.004
		(0.059)
Constant	0.417^{***}	0.404^{***}
	(0.065)	(0.083)
Observations	136	136
R^2	0.109	0.166
F Statistic	3.195^{***} (df = 5; 130)	2.778^{***} (df = 9; 126)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 10: Regression Models for CAAR(-5,5)

	Dependent variable:	
	CAAR(-5,5)	
	(1)	(2)
Innovation Intensity	−0.016	−0.030
	(0.061)	(0.062)
Innovation Increase	0.150**	0.128**
	(0.059)	(0.060)
Patenting Activity	−0.158**	−0.143**
	(0.073)	(0.072)
Semiconductors	0.015	−0.011
	(0.079)	(0.081)
Computer Programming	−0.127*	−0.129*
	(0.068)	(0.072)
Deal Size		−0.063
		(0.062)
Acquisition Experience		0.011
		(0.060)
Financial Distress		0.153**
		(0.065)
Merger Wave		0.010
		(0.060)
Constant	0.419***	0.411***
	(0.066)	(0.085)
Observations	136	136
R^2	0.097	0.153
F Statistic	2.801** (df = 5; 130)	2.531** (df = 9; 126)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 11 : Regression Models for CAAR(-10,10)

Table 1:

	Dependent variable:	
	CAAR(-10,10)	
	(1)	(2)
Innovation Intensity	−0.045	−0.060
	(0.064)	(0.065)
Innovation Increase	0.157**	0.132**
	(0.062)	(0.063)
Patenting Activity	−0.156**	−0.146*
	(0.075)	(0.076)
Semiconductors	0.028	0.007
	(0.082)	(0.085)
Computer Programming	−0.138*	−0.135*
	(0.071)	(0.076)
Deal Size		−0.063
		(0.065)
Acquisition Experience		0.027
		(0.063)
Financial Distress		0.105
		(0.069)
Merger Wave		0.050
		(0.063)
Constant	0.425***	0.406***
	(0.068)	(0.089)
Observations	136	136
R^2	0.105	0.137
F Statistic	3.062** (df = 5; 130)	2.232** (df = 9; 126)
Note:		*p<0.1; **p<0.05; ***p<0.01

5 Analysis of Results

5.1 Regression Tables overview

The relevant literature has generally identified a positive impact of M&A announcement events on the returns of target firms, no matter the industry in which they operate (Asquith & Kim, 1982; D. K. Datta et al., 1992; Hansen & Lott, 1996; Malatesta, 1983), and this is also confirmed in my study, where 136 High Tech target firms enjoy a Cumulative Average Abnormal Return (CAAR) of about 32% in the 20 days surrounding the event date τ_0 (-10,+10), identified as the event date for each firm. A lot of this generated value is connected to various factors that deal with the rationale behind the acquisition, impacted both by the bidder (Operational Synergy and Value Creation opportunity that leads to an acquisition premium) and the target (market position and intention behind divestiture, financial performance and liquidity situation, possession of strategic know-how). In this work, total attention was turned to High Tech firms, and an Event Study with subsequent regression analysis was put in place to try to capture and motivate the peculiar reasons and factors behind target firms' shareholders's M&A value creation. In this context, the current relevance of these sectors within the global economy, as well as the disruptive potential that they hold in terms of ability to innovate, has led my desire to investigate the impact of certain variables I believed were deeply linked to the innovative activities of these companies, as well as other variables which have been the subject of a great amount of M&A research. A presentation and interpretation of the multiple regression tables now follows.

Interesting results are then observed within the analysis of the factors which impact the sample's CAAR the most across the different Event Windows [(-1,1),(-2,2),(-3,3),(-5,5),(-10,10)]. The regression models' F Statistics are all significant at the 5% level.The percentage of total variance explained by the model, and indicated by R^2, is quite low, going from around 10-11% to a maximum value of 19% across all regression models. As the core objective of this work is to reason about the association of the single variable's coefficients, as well as the interactions between them, the low predictive power of the model is acceptable. This is also reflected in the decision of focusing the interpretation of the results on the direction, rather than the numerical impact, of the single regression coefficients. Starting from the four measures used to capture the degree of innovativeness of the target firm, and by additionally inserting other control variables, I find (at the 5% significance level):

1. A statistically significant and positive association between the CAAR and the target firms' Innovation Increase variable.
2. No significant association between the CAAR and the target firms' Innovation Intensity variable.
3. A statistically significant and negative association between the CAAR and the target firms' Number of Active Patents.
4. No significant association between the CAAR and the target firms' Industry Subsector.
5. No significant association between the CAAR and the acquirer's prior acquisition experience.
6. No significant association between the CAAR and the target firms' Deal Size variable.
7. A statistically significant and positive association between the CAAR and the target firms' level of Financial Distress.
8. No significant association between the CAAR and the target firms' Merger Wave variable.

The direction and level of the results'coefficient are relatively stable across Event Windows. This holds true especially for the significant coefficients of the Innovation variables, which are regressed before and after the insertion of the other four control variables. As the main aim of this work is to identify key factors, related to Innovation practices, which have an impact on the acquired firms' stock returns, findings 1 through 4 are particularly interesting, especially considering the theoretical interrelations between them. In the following section, the impact on the CAAR indicated by these four variables are highlighted and explained, in terms of the relevant literature presented in section 4 and from a personal perspective.

The target firm shareholders benefit from a positive trend in Innovation expenditures, here proxied via the presented Innovation Increase variables, but not from high levels of innovation expenditures (Innovation Intensity) *per se*. In addition, holding Active Patents, no matter how many, seems to be detrimental to the target's shareholder. Finally, the Technological subsector variable is non-significant at the 5% level; if we compare this with the subsectorial analysis of CAAR's variance discussed at 4.4.1, we see that, once other variables are inserted in the analysis, the role of the Subsector in explaining the model's variance vanishes. Deal Size, M&A Experience and Merger Waves result in being non-significant in the present analysis, whereas as target firms experience Financial Distress, the CAAR increases. A detailed interpretation of each of these results and their potential interactions now follows.

5.2 The impact of Innovation

These findings indicate that firms with increasing R&D expenditure have a higher CAAR compared to the residual firms in the sample. This means that the market rewards those firms that increase their innovation efforts over time, and does not value absolute levels of R&D expenditures as much. In terms of mere results, this is in line with other relevant studies on the positive impact given by R&D increases on Abnormal Returns (Penman and Zhang 2002; Eberhart, Maxwell, and Siddique 2004; and Lev, Sougiannis, and Sarath 2005); a possible theory underlying the following result coincides with what I hypothesized in section 4.3.2, which is that an increasing R&D expenditure level in terms of Revenue may imply that significant growth projects and innovative activities, with potentially interesting returns on investment, are occurring at the said firm; they are deemed worthwhile projects in whose success the firm believes; this belief is signaled to the bidder market via the growing R&D-to-Sales ratio, and once a bidder interested in acquiring the firm appears, that bidder, *ceteris paribus*, will reward the shareholders of the R&D-increasing target firm more than another prospective target. Thus, a market-signaling role is played by firms who increase their innovative efforts over time, which are then rewarded by the market. In this regard, a similar signaling role is also mentioned by Phillips et al.,2013, who take a slightly different view and state that this trend is more reactive than proactive, in the sense that R&D increases are mere reactions put in place by target firms to appear as more appealing targets within a favorable M&A market, and are not necessarily genuinely backed by high potential projects within the firm's boundaries. In the Phillips et al.,2013 study, R&D increases are therefore more of a function of external industry conditions. My view is instead that constant R&D increases through time proactively imply, as well as signal, quality innovation activity in a more effective way than a high, but constant, R&D expenditure. They are thus undertaken based on the potential of the innovative projects at hand. The R&D increase thus signals to the prospective bidder that the projects are headed in the right direction, and that acquisition efforts, which will inject additional financial resources into the innovative activity, will be well justified and rewarded by a positive output and performance yield. Stable R&D Expenditures, no matter how high or low in terms of industry benchmarks, may not instead give as strong on an indication on the probability of a positive output of the innovative projects, and that is why bidder firms tend to reward and pay stronger acquisition premium to firms who increase R&D expenses over time. This trend is strictly related to the difficulty for the general stakeholders to determine efficient R&D spending. As innovation is risky, costly and subject to high-failure rates, the link between the money injected (input) and the performance obtained (output) is feeble. In this context, investors do not trust High R&D expenditures (as they have no certainty that high output will follow high input), as much as increasing R&D Expenditures, as the latter is more reassuring of a potentially good probability of a successful output.

Patent possession by the target company negatively affects the CAAR accruing to the shareholder. This sounds counter intuitive if we compare this finding with the great importance that acquisition of IP, technological know-how and related resources has for M&A activity, as it is one of the main rationales that currently pushes acquiring firms to integrate external knowledge rather than developing it in-house. In section 4.3.3, I have illustrated the many functions patent allow firms to achieve in this regard. At the same time, I have shown the great degree of context-dependence on which the ultimate success of patenting activities depends. In interpreting this results, this construct immediately comes to mind in trying to identify potential reasons and implications behind the result. It may be that, to a prospective bidder, the current patent portfolio may be outdated for its current strategic needs; the legal lifetime of a patent (20 years) far outruns the lifetime of the average product life-cycle, of business model, or the average company (U.S. Bureau of Labor Statistics, 2015) , especially in this day and age where digital and technological trends are shifting gears in terms of velocity of development and application. Therefore, acquiring a firm with a lot of patents may not directly imply acquisition of the proper know-how needed to successfully compete on the market at one particular moment in time. Additionally, the Pareto-Law which models the relationship between the number of patents and patent value may be applying here, so that bidder firms, once in midst of the due diligence process, evaluate total IP held by the target firm and eventually incorporate that into the final Deal Value. If we assume the cited relationship number of patents would not be reflected into a premium in such a situation.

Given the sample of firms at hand, a more punctual interpretation of the result builds on the role of context dependence for patenting activity (Orsenigo & Sterzi , 2010). If one looks at the industry trends that have taken the here analyzed High Tech Sectors by storm in recent years, one cannot miss the centrality that software-related applications and business models have come to take in the overall market scenario. More and more tech companies thrive on software, used for various realms of technological applications (Cloud services, Mobile E-commerce, Data analytics services, Cyber-security, Sharing Economy, Online Advertising, etc..). Even hardware companies are working to identify new strategies to penetrate the attractive software market, so that there is an entire industry dynamic taking place in this sense. As the role of software takes more and more of a central role in the High Tech industries, the impact on Intellectual Property rights, and on the right strategy to protect these rights, changes as well. Traditional ways of protecting intellectual property related to technical and industrial applications (patents) get replaced by more effective, and less costly, protective measures. Software is by regulation inserted into the sphere of copyright protection, as it is seen as more of a creative venture than a technical one. Copyright enjoys free, immediate and longer legal protection compared to patents, but it is not the only factor in potentially explaining the encountered relationship, in fact, it is only the tip of the iceberg. What the hardware-to-software shift means is that new ways of developing effective protection of a company's technology and innovative assets are being put in place, and have already started to be get noticed by research efforts a few years back (Mannheim Innovation Panel, 1993, Kurtossy 2004). These methods (secrecy, retention of key personnel and complexity) hold a key spot in this discussion, and they are swiftly applicable to software know-how and intellectual proprietorship. In addition, the present and relevant trend of Open Innovation, defined by Chesbrough, 2003), as " a paradigm that assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as the firm looks to advance their technology", implies that, in such an environment, the importance of effectively handling secrecy, complexity and key innovative personnel policies are more important than ever.

In light of these findings and industrial scenario, I explain the negative association between the target firm's number of patents and the CAAR in terms of the view of the bidder firm, which may see the patent portfolio of the target firm as either non-valuable and not relevant anymore. The over-reliance on an outdated or a non-relevant patent portfolio may then signal a weak competitive position in comparison to other firms, who may not be as rich in terms of patenting activity for all the right reasons mentioned in the above paragraph. The competitive lag then results in a relatively more negative Abnormal Return, as the bidder firms either finds no value in the patent portfolio or finds additional integration and restructuring measures to be put in place to complete the acquisition and to put the newly merged entity on a more successful market position. Therefore, the target firm's shareholders suffers a negative from a negative Abnormal Return at announcement date, potentially caused by the strategic irrelevance of the patent given current market conditions.

In this situation, belonging to a particular High Tech Subsector does not seem to be a significant factor for target firms in the sample. The Analysis of Variance illustrated at 3.4.1 does not hold anymore, as the majority of the CAAR's variance is explained by the other significant regression coefficients. In this regard, the lack of literature, paired with the growth trends seen across all major High Tech industries (refer back to section 4.3.4) does not allow to infer there is any disparity in the distribution of sectorial dynamics. In general, all three major subsectors analyzed enjoy positive Abnormal Returns at the M&A deal announcement date, and there is no good reason to believe that firms in one industry are reaping more benefits than others when all considered variables are taken together. The therefore positive momentum and centrality of High Tech firms for the current state of the economy is thus to be intended as something occurring throughout all technological subsectors; therefore, the CAAR differentials examined in this sample may be simply due to chance.

5.3 Control Variables

As mentioned, the effectiveness of large vs small M&A has to this day led to contrasting results and has being labelled of being a complex relationship (Healy et al., 1992, Cornett & Tehranian, 1992, Moeller et al., 2004, Hitt et al,2009); a strong driver of acquisition performance in large M&A is likely to result from developed integration capabilities, which help especially in the case of large acquisitions, in which a bigger target is better positioned to have an immediate impact on the overall performance of the acquiring firm (King et al, 2008). To test the effect of Deal Size on this relevant sample, a EV/Sales acquisition multiple was constructed, and the sample was divided according to median industry benchmark for High Tech firms (2.6). Regression results are non-significant for this multiple, no matter the Event Window examined. Whereas a definitive conclusion regarding the role of Deal Size does not transpire from this work (and even if it did, the conflicting findings of the literature suggest that more empirical investigations are required in this area), such a result may suggest that, independently of the size of any M&A deal, the integration capabilities of acquiring firms are what matters most. As any deal presents strongly diverse and unique characteristics, adapting to the individual case and knowing how to approach the integration process in the right way is, at least on the theoretical side of things, a more valuable asset that can be applied across industries, market contexts, and firm sizes. Under this perspective, perhaps the present results can be seen as more approachable.

Getting to the analysis of M&A experience, one of the most interesting variables in the present analysis, this work certainly provides room for additional research efforts, which stretch beyond past research activity, mainly by Zollo (and other, for references relate to the dedicated section 4.3.6). On a general note, there is a present understanding that the role of organizational learning in M&A situations is primary. The parts of the construct on which the literature lacks consensus are the forms and shapes of this role. Past studies show evidence of a non-linear relationship between M&A experience and performance, others discriminate between the learning experience and the effective codification of this learning within the firm boundaries (via the creation of the so-called M&A playbooks) which represents the firm's efforts in retaining the knowledge developed through past deals and integration processes. Another important dimension anticipated is the timing variable, which tries to consider how much time or how much M&A experience is necessary for a serial acquirer to constantly benefit from past situations, and whether the benefits appear in short rather than long-term. Task heterogeneity and degree of similarity analyzed by past literature also confirm the primary role of context in this analysis. Within the present work, I have tried to verify the impact of the acquiring firm's acquisition experience on the Abnormal Return generated on the announcement date. Acquiring firms were characterized experienced if, in the 6 years prior to the announcement date, they had completed at least a number of M&A operations greater than or equal to 8. The variable was then inserted into the linear model presented above. A perhaps hopeful hypothesis that could have been stated prior to the analysis was that target firms who are acquired by serial and experience bidders shall enjoy relatively stronger positive Abnormal Returns, as they benefit from the learning experience of the acquirer throughout the integration process and beyond. The non significant results of this study naturally depend on the methodology applied; the study is focuses on short-term returns and does not control for codification of learning; it may well be that a longer empirical investigation of the present sample may present different results. Nonetheless, what can be concluded is that M&A experience is certainly one of the most complicated constructs that researchers try to empirically codify, as it does not immediately show up in the balance sheet; for these reasons, it is exactly one of the most interesting concepts to reason about for interested scholars. Therefore, the non significant results of the present work should not turn off future empirical efforts.

The last significant finding is related to the target's level of financial distress. The announcement of the deal is in this regard seen positively by the market, more so than in better performing firms. The target's shareholders see the acquisition as a potential restructuring method for achieving a stronger level of operational efficiency, thanks to the integration of the target firm by the acquirer. This proves to be true especially for acquisitions within related sectors, which often involve a strategic buyer who pays a premium to acquire control of the target in spite of the difficult situation in which the target firm navigates. This is confirmed in my sample, in which 75% of firms who suffered financial distress (in the year prior to the announcement)t are indeed acquired by a firm within the same technological subsector. Firm similarity and relatedness implies additional bidding efforts by willing strategic buyers, which raise the acquisition premium in order to gather control of the restructuring opportunities. The present result is in this sense adherent to past literature on the topic, which is across diverse industry sectors. (Chatterjee,1992, Houston et al., 2001, Lamaneen et. al, 2014). A positive note that emerges from this work is that the metric used to capture Financial Distress (the target's level of EBITDA in the pre-announcement year) proves successful and valid if compared to the other distress metrics presented in section 4.3.7. In this regard, the literature observed (Damodaran, 2010, Nissim, 2017), as well as my general considerations provided, appear to be validated.

Table 12: Analysis of Financial Distress- Summary

	Mean CAAR (-5,5)
Financially Distressed Targets (n = 40 firms)	46.02%
Non-Distressed Targets (N= 96 firms)	27.17%
% of Strategic Buyer for Distressed targets ($NAICS_{Target}$= $NAICS_{Acquirer}$)	75%

As a last control variable, Merger Waves were taken into consideration; recapping from section 4.3.8 , within the-year period examined, there are then five years of relatively more intense M&A volumes (2008,2014-2017) and five years of relatively less intense M&A Volumes (2009-2013). In terms of sample classification, I proceeded as follows: I classify an event in my sample as either "In-Wave" , if the deal's announcement date falls in the 2008,2014-2017 years, "Out-of-Wave" otherwise. The relevant literature has recently seemed to find a consensus over the Merge Waves dynamics shaping the return of acquiring firms; for target firms, while the returns are found to positive within some studies, no particular role is yet identified, and this analysis is confirmatory in this regard. It may be that the seventh merger wave, identified from 2014 onwards, may structurally change in the near future, but for the present sample, any relevant result was not identified.

6 Conclusion

The research effort was particularly directed to the recognition of the impact of the Innovation factors, as well as other factors which have historically being the subject of M&A literature. Overall, it seems that R&D increases and Financial Distress generate stronger returns at announcement dates, whereas Patenting Activity has an impact in the opposite and negative direction. R&D intensity, technological subsector, size of the deal, acquisition experience and the year in which the deal is announced do not seem to significantly impact Abnormal Returns.

As the main objective of this work was to illustrate the contribution of certain innovative activities on M&A short-term performance, the present results combine for some interesting implications for high tech firms in the M&A literature. Due to the nature of innovation management processes at the firm level, R&D increases may play a stronger signaling role in identifying solid growth projects than the absolute level of R&D. This is an important consideration to make given the feeble relationship between innovation input and output. The relationship between stock returns and patenting activity is also very important to notice in the current days, as the technology industry's shifts from high value hardware to high value software-focused business models and applications implies necessary adjustments in innovation protection practices, as well as in the competitive strategy of firms willing to conduct innovation and build their competitive advantages in these new areas. Technological relatedness and financial distress, at last, confirm the importance of synergy creation strategies where core-competences can be leveraged.

As one of the few Event Study focusing on the target firm perspectives in the High Tech industry, I believe this empirical work contributes to the literature as in helping to explain the impact of the rise of new technological industries on the competitive strategy and portfolio restructuring implications. Target firms shareholders considering an M&A acquisition path from the seller perspective may benefit from the present results in their acquisition strategy development, no matter if composed by a single divestiture effort or more structured as a divestiture program. Following these insights may help in extracting more shareholder value from the planned M&A operations, as well as in setting the merged entity up for future business success in the technological business scenario. These shareholders may also derive some insight on the shifting innovation management practices, especially in terms of protection, as they move forward in the development of their growth projects. As it stands as quite unique in terms of the sample structure and years observed, my hope is that this work shall also represent a solid basis for future investigations on the role if innovation in M&A activities. At the same time, it is not free of limitations; the main ones are identified in the following lines:

- As mentioned, the identification of R&D expenditures as the "king" of all innovation metrics is not perfect, despite its widespread use, and there be other factors better-suited to act as a more useful proxy of a firm's innovation output. Other key variables (presence of certain Innovative thinkers and R&D labs, long-term innovative projects not yet launched and present on the balance sheet, open innovation activities) do not necessarily show up on the balance sheet, but might be just as important.

- The use of EBIDTA, although relatively precise (Damodaran, 2010, Nissim, 2017), is not here linked to the level of debt of the target firm. Accounting for this additional variable should provide a more accurate measure of distress, even though the relationship found here between this construct and the CAAR is solid and confirms the view of the literature.

- The complexity of M&A deals may go beyond the realms of linear models such as linear regression. Despite its aggressive use in the relevant literature, choosing alternative models may provide additional insights into how certain models capture the true role of certain moderating constructs. As exemplified by Zollo & Reuer, 2002, in their observation of the role of M&A experience, not all variables can be necessarily moderated in a linear way, and this should be accounted for.

At the same time, the present text should provide provide interesting perspectives for future research efforts. Two of these are provided here:

- Observing R&D increases not only from the perspective of the target firm but also from the one of the acquiring firm should shed additional light on the ultimate motivations that lead to the M&A deal. If the acquiring firm has lacking R&D activity, the acquisition may signal an attempt at internalizing external innovative knowledge, whereas if the opposite happens, it may be a sign of important growth areas on which future trends may be founded. Analyzing this relationship at the firm and also at the industrial level should provide for interesting insights.

- The true role of software-related innovation protection practices going forward is yet to be determined. As these years represent the midst of high-speed technological advantages, their true effects on the management of technological capital may not yet be in full force.One potential way to observe further trends would be to control for copyright ownership in M&A performance of High Tech firms, and not just for Patent ownership. This way, the value shift from technical innovation protection methods to creative innovation methods could be addressed even more directly. As It is yet to see whether software-focused business models will make patents cease their current industrial relevance, I invite and suggest on further empirical investigation.

Given the complexity of M&A deals , it is hard to identify immutable laws that shape firm performance. At the same time, more and more efforts in this research area shall result in providing interesting views on how the High Tech industry is moving forward, especially in these times where the global economy leans strongly on technological capital and innovation.

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A Appendix

A.1 Zephyr Database Search Criteria

As mentioned in section 2, the list of M&A deals was selected using the Zephyr Database;the original list of 315 downloaded deals was compiled according to the following specifications, attached below from the data export Excel file.

	Zephyr		
Update number	30		
Software version	30.0		
Data update	03/04/2018 (n° 30204116)		
Username	1712355		
Export date	04/04/2018		
Cut-off date	31/03		
		Step result	Search result
1.	All stock exchange: NASDAQ National Market (Target)	24,566	24,566
2.	Company type: Company (Target)	1,597,724	24,566
3.	Deal type: Acquisition, Merger	654,848	2,593
4.	Current deal status: Announced, Completed	1,494,569	1,589
5.	Time period: on and after 20/03/2008 and up to and including 20/03/2018 (completed-confirmed, completed-assumed, announced)	1,023,558	1,252
6.	NAICS 2017 (primary codes): 333295 333315 334111 334112 334113 334119 334210 334220 334413 334511 421430 421690 423430 423690 443120 511140 511210 514210 518210 519130 541330 541511 541512 541513 541519 541710 541711 541712 (Target)	264,993	315
	Boolean search: 1 And 2 And 3 And 4 And 5 And 6		
		TOTAL	315

A.2 Global Patent Index Search Criteria

When searching for patent data, I referred to the appendix section of Stenholm and Wallertoft, 2016; the SQL criteria utilised were the following:

- Applicant Name (APP): the target company name in my sample
- Applicant country of residence (APPC): US
- Publication country (PUC): US
- Publication kind (PUK): Granted patent (b1 or b2)
- Publication date (PUD): [Announcement day minus 20 years, Announcement day]
- Is granted (ISG): Yes

Quoting from the above-referenced authors:
"*APPC ensures that patents owned by a foreign company with the same name as the company of interest are not included in the count. PUC ensures that each patent is only counted once, regardless of how many countries it is published in. PUK and ISG ensures that patent applications which were denied or have not been completed are not included in the count. PUD ensures that the patents are still active, given a patent term of 20 years (USPTO Manual of Patent Examining Procedure - Section 2701, 2015).*"