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RELATEDNESS & EXPERIENCE IN TECHNOLOGY ACQUISITIONS: HOW THEY IMPACT THE PERFORMANCE OF TARGET INVENTORS

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ABSTRACT ENGLISH

M&A in high-tech sectors are vehicles of sourcing knowledge, technology and talents for more established companies. Despite of the prevalence of this practice, prior studies suggest that acquisition in this realm does not bring the desired outcome. This study aims to examine the factors that influence the outcome of the acquisition by looking at the performance of the target inventors in the post-acquisition period. In particular, it aims to measure how the innovation capacity of the various target inventors is influenced by the degree of overlap between the target and acquirer captured by two independent dimensions, namely **technology overlap** and **market relatedness**, as well as the capability of the acquirer in managing the acquisition captured by **experience** in acquisitions. The study involves the analysis of a sample of 469 inventors from 127 acquisitions, acquired between 2006 and 2015.

Keywords: Technology Acquisitions of Small High-tech Firms, Technology Overlap, Market Relatedness, Acquirer Experience, Innovative Performance, Patent Quality

ABSTRACT ITALIAN

Le M&A nei settori ad alta tecnologia sono veicoli di acquisizione di conoscenze, tecnologia e talenti per le aziende più affermate. Nonostante la prevalenza di questa pratica, studi precedenti suggeriscono che l'acquisizione in questo settore non porti al risultato desiderato. Questo studio mira ad esaminare i fattori che influenzano l'esito dell'acquisizione esaminando la performance degli inventori del target nel periodo post-acquisizione. In particolare, esso mira a misurare come la capacità di innovazione dei vari inventori del target sia influenzata dal grado di sovrapposizione tra il target e l'acquirente rilevato attraverso due dimensioni indipendenti, vale a dire la **sovrapposizione** di **tecnologia** e di **mercato**, nonché la capacità dell'acquirente di gestire l'acquisizione rilevata dall'**esperienza** nelle acquisizioni. Lo studio prevede l'analisi di un campione di 469 inventori di 127 acquisizioni, acquisite tra il 2006 e il 2015.

Parole Chiave: Acquisizioni Tecnologiche di Piccole Aziende High-tech, Sovrapposizione Tecnologica, Correlazione di mercato, Esperienza dell'Acquirente, Prestazioni Innovative, Qualità dei Brevetti

Index

Annexes 78

Appendixes 86

References 94

Index of Figures

Index of Tables

INTRODUCTION

The frequency and scale of global mergers and acquisitions (M&A) have increased significantly over the last twenty years, despite recurring reports of their high failure rates (Gomes et al., 2011). However, the growth of M&A activity, both in terms of volume of capital involved and popularity, is in stark contrast to the high failure rates. In addition, the meta-analysis conducted by King et al. (2004) concluded that none of the strategic and financial variables studied is significant to explain the variance in post-acquisition performance and, extending this vein, Weber et al. (2009) recommended that future research should pay more attention to non-financial variables. In addition, with regard to the broader M&A sector, previous research has also usefully investigated the evolution of both cross-border and domestic acquisitions by multinationals (Liu et al., 2014). However, while existing research has made progress on some aspects, there is little research that investigates the trend of cross-border or domestic acquisitions of high-tech companies, i.e. companies that invent and innovate technological products and services.

The purpose of the article is to investigate the factors that influence the overall performance of acquisitions of high-tech companies in US. In particular, the article aims to examine the impact of **Relatedness** (or **Overlap**) between the **high-tech** acquirer and target both in terms of technology as well as market, the **Experience** of the former in past transactions, and the effectiveness of applied post-acquisition integration on the overall performance of the acquiring enterprises.

It is argued that the potential for synergy between them and the effectiveness of the post-acquisition integration approach applied by the acquirer can significantly contribute to explaining the overall performance. Nonetheless, there is limited research that investigates the impact of synergy potential on M&A performance and, in particular, in high-tech contexts. Indeed, few documents have investigated the moderating and mediating effects of potential synergies of the post-acquisition integration approach in such a context (Weber et al., 1996). Within these broad debates, we believe that **Relatedness** (**Overlap**) **and Experience are key factors**.

We analyzed a series of **127** financial transactions in the **American high-tech industries** that took place in the period **2006 - 2015**, investigating the patenting activity of the inventors acquired before and after the completion of the operation, using multiple proxies to measure performance. Our results show the specific way in which **Relatedness** and **Experience** effects are particularly relevant in the context of M&A.

Therefore, having stated in what consist our thesis, we briefly present the main sections, which are organized as follows: **Chapter 1** starts with the review of the literature on M&A in the high-tech industry, followed by **Chapter 2** where we review the literature on synergistic potential and effectiveness of post-acquisition integration in M&A to develop our hypotheses. Subsequently, in **Chapter 3** we provide the basis on the reliability of patents as an effective measure of innovative performance, referring to the literature of the past; moreover, we qualitatively disclose some of the measures we used to define the value of patents. **Chapter 4** explains the research project that concludes with the statement of the three hypotheses**. Chapter 5** lays the foundations of the methodology, showing the primary and secondary sources that made the process of data collection possible. **Chapter 6** explains the methodology used to build the final database of patents and inventors, the set of variables considered, together with the main steps taken to structure them; then, the econometric model chosen to perform the statistics is presented. Finally, in **Chapters 7** and **8**, the results of the study are presented, and discussed, together with an indication of the theoretical linked implications.

Part One – Literature Review

CHAPTER ONE

THEORETICAL OVERVIEW

This first chapter aims to define M&A transactions and what are the main strengths and weaknesses observed. This theme will be discussed in section 1.1. Subsequently, the article will go deeper analyzing the concept of high-tech companies in the United States area, to understand what the drivers and reasons for these transactions are. First: What is the role of 'technological acquisitions'? Why is it so critical? And even more specifically, what is meant when talking about knowledge? The answers to these points are contained in section 1.2. To conclude, in 1.3 the concept of 'Relatedness' will be introduced, and it will be stated how it impacts the entire process of M&A.

1.1 M&A IN HIGH-TECH COMPANIES: OVERVIEW

What is the meaning of M&A (Merger & Acquisition)? Merger and Acquisition is a generic term used to describe the consolidation of companies or assets through various types of financial transactions, including mergers, acquisitions, consolidations, tender offers, purchase of assets and management acquisitions (Bruner, 2001). Particularly, this paper will focus on 'acquisition' and even more in detail, '**acquisitions' in the high-tech industry in the United States area**. When a company takes over another entity and establishes itself as the new owner, the purchase is called 'acquisition'. From a legal point of view, the target company ceases to exist, the acquirer absorbs the business, and the shares of the acquirer continue to be exchanged.

This financial concept has become even more crucial in the last years. The world is changing at an incredible pace due to several related factors and companies are struggling to remain in the market and make profits. As shown in the following graph, even though the trend of the number of M&A in the US is following subsequent peaks and nadirs, the average value is increasing over time demonstrating how companies believe in this method.

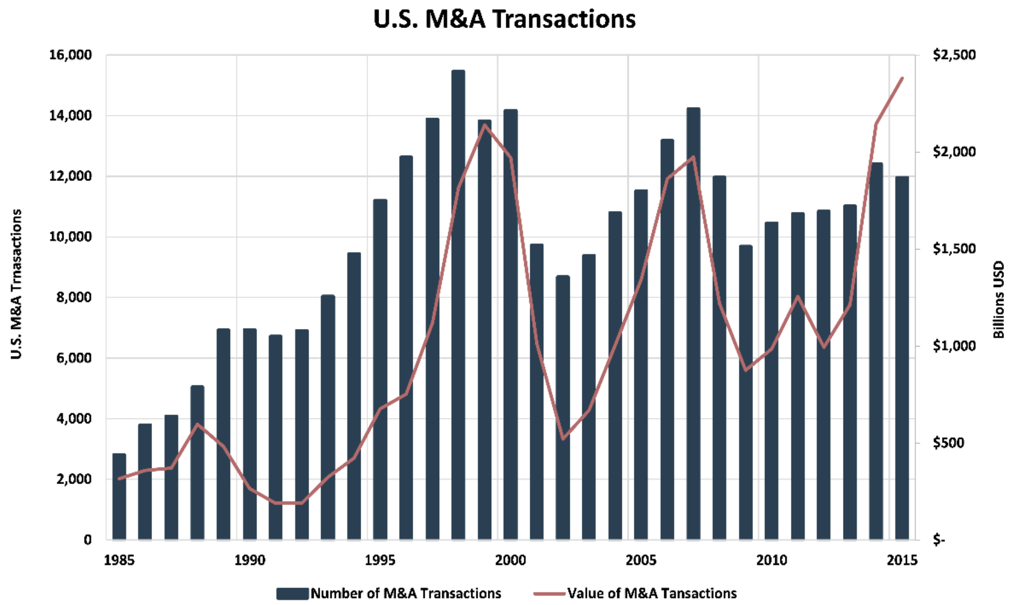

Figure 1 - M&A in US (Source: EdgePoint)

Successful companies know they consider these factors trying to leverage both internal and external resources to maximize the output (Cartwright et al., 2006). But which are these elements we are talking about? First, globalization. Basically, it entails that boarders around the world are becoming fuzzier, that distance is no more an issue, the market is no longer local, but includes the entire globe. It gives new opportunities to companies, but at the same time brings many threats, as competitors from other continents could enter the market (Bretos et al., 2017). Second, shorter product life cycles. It is not easy to keep up with the constant innovation of material, techniques, processes, especially in some high-tech industries. As soon as a new product is launched on the market, the next one should already be on the agenda (Coccia, 2016) and ready to be produced to defend the current market share from external attacks. Third, information is much more accessible, customers know which product has the best features according to their expectations. In addition, they are increasingly demanding, as basic needs in developed countries are already met and they are looking for new secondary ones. Many other factors could be mentioned, but the general concept is clear: firms must adapt to the changing environment as quickly as possible. This is one of the main reason why mergers and acquisitions are becoming so predominant in recent years. If conducted properly, the benefits could easily outweigh the negative consequences, making the financial transaction an incredible move against the competition (Bauer et al., 2017).

M&A, one of the most powerful external strategies a company could adopt (Hitt et al., 2000), may occur for several reasons, for example Lowering Costs or Growth. Entering a new geographical market, increasing the market share or getting technological assets (e.g. scientists, inventors, patents) are considered inside the 'Growth' domain (Gomes et al., 2012). In particular, getting technological asses can be expressed by the term 'Technology Acquisition' and this paper is mainly focused on this topic.

1.2 THE IMPORTANCE OF TECHNOLOGY ACQUISITIONS

Firms consider this process a key element in the M&A world. Why? Literature documents how it can strongly influence the outcome of the financial transaction itself as well as future positive (or negative) effects in the next months, years as stated by Miyazaki Hironobu in his paper 'An analysis of the relation between R&D and M&A in high-tech industries' (Hironobu, M., 2009). Moreover, it is considered crucially related to innovation (Pessoa, 2007); and innovation is essential to conquering the competitive advantage.

Focusing on R&D (Research & Development), it often refers to innovative activities undertaken by companies in developing new services/products or improving existing ones. The employee working in this area is commonly called 'Inventors' and their capability/ knowledge is at the base of the department. Acquirers are interested in others who have strong, capable inventors, able to produce many high-quality licenses. This concept is close to the core of the analysis of this paper: **how to successfully being able to enhance the performances of the acquired inventors or at least, keep the same track of positive performances**. Acquirers want to be sure that once the transaction is completed, the new inventors will continue to produce at the same pace, or even better, in the new workplace. Unfortunately, it is very difficult as it will be shown in the next chapters.

In support of what has been just written, a positive correlation has been found between R&D and the productivity of enterprises in all sectors, and it increases its intensity going from low-tech to high-tech companies (Ortega-Argilés et al., 2009);

exactly the latter is the one taken into consideration in the paper. In addition, high-tech enterprises where it's easier to accumulate and store knowledge, thus increasing the potential of the department, were found to have "virtuous" Matthew effects meaning that it's easier for them to innovate just because they continuously innovate, while low-tech enterprises exhibit the opposite: "vicious" Matthew effects (Antonelli et al, 2011).

1.2.1 THE ROLE OF KNOWLEDGE

Knowledge has several meanings. Regarding the scope of the dissertation, it can be defined as 'skill in, understanding of, or information about something, which a person gets by experience or study (Cambridge Dictionary) and store in his/her mind'. Knowledge could be created in many ways and Nonaka together with Takeuchi presented a model of how organizations dynamically do it. It is achieved through the recognition of the synergistic relationship between tacit and explicit knowledge in the organization, and through the design of social processes that create new knowledge by converting tacit knowledge into explicit knowledge. (Choo, 1996) Tacit knowledge is embedded in individuals and is difficult to formalize or to communicate with others. It consists of subjective know-how, insights and intuitions that derive from having been immersed in an activity for a prolonged period such as inside an R&D department. On the other hand, explicit knowledge is formal knowledge that is easy to transmit between individuals and groups. As suggested, tacit knowledge is complicated to obtain and represents a driver that guides firms in a financial transaction.

Going further in the literature, the Knowledge-Based View has to be mentioned in order to understand better the relative influence between technology acquisitions and knowledge of investors. It argues that knowledge is at the heart of competitive advantage, that it is an irreplaceable resource (Grant, 1996). The following figure will suggest visually how this concept works.

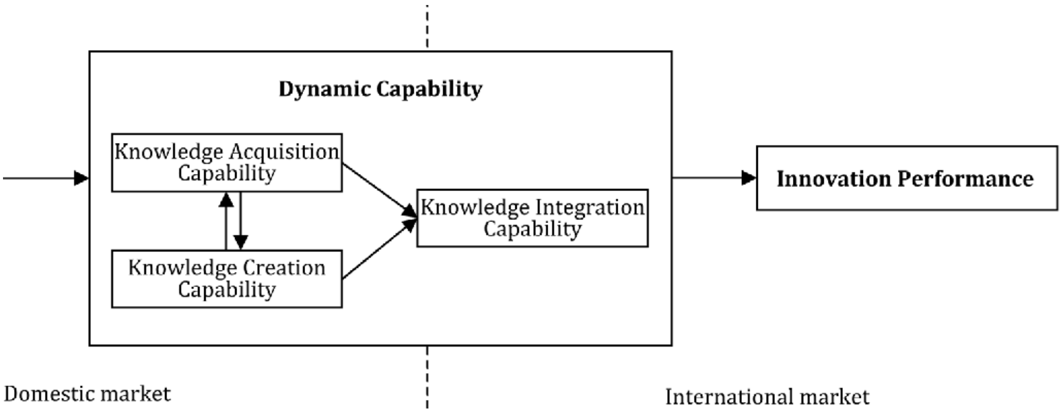

Figure 2 – How Knowledge-Based View works (Source: SemanticScholar)

The challenge lies in the fact that it is rather difficult to acquire and then master it. Through M&A acquirers provide stimuli, mindset and environment necessary to foster the integration of know-how and the creation of new skills inside the company transforming tacit knowledge rooted in inventors into explicit one (Kogut et al., 1992). In addition, M&A is essential for a complementary reason: the knowledge inside a single company is not sufficient to beat the market. There is the necessity of diversification, of heterogeneity that can come from these financial operations (Westa et al., 2014). Companies are moving towards a concept of Open Innovation summarized in Figure 3.

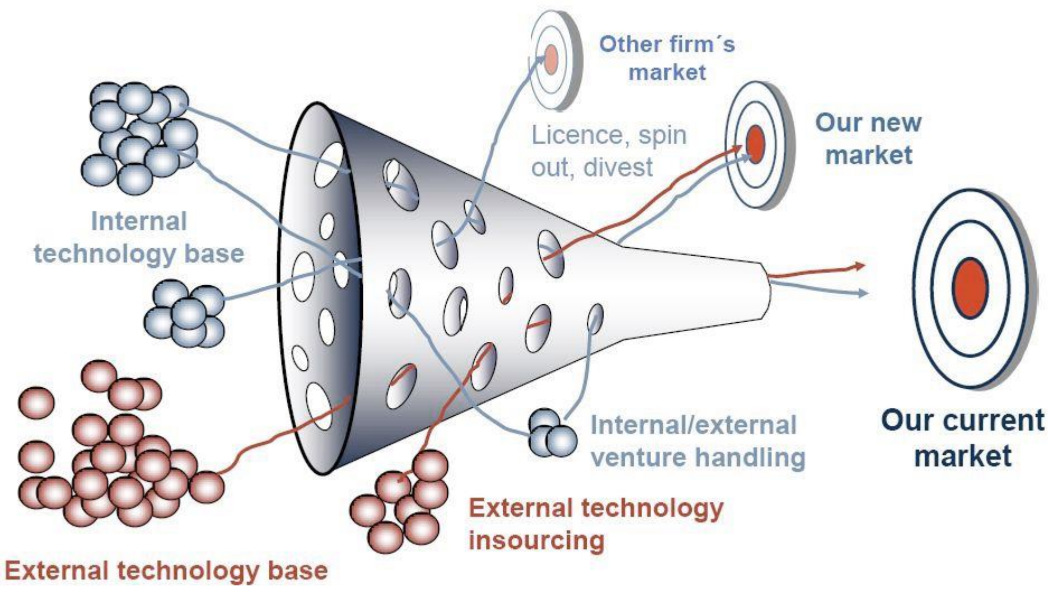

Figure 3 - Open innovation' scheme (Source: Fabbricafuturo 13/11/2013)

The paradigm of Open Innovation can be understood as opposite of the conventional model of vertical integration, considered a 'closed' innovation model, restricted to the perimeter of the company. On the contrary, putting the concept succinctly, Open Innovation is "the use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand the markets for external use of innovation, respectively" (Chesbrough, 2003). This variety of knowledge translates into as many ways as possible to combine new and in-house knowledge, and thus a greater likelihood of product innovation. Indeed, the easier the access to knowledge is, the simpler the company can combine the know-how transferred and the knowledge within the company, with a higher probability of success of product development. As mentioned before, access to knowledge beyond the firm's boundaries, and even within the firm, is typically difficult (Kogut t al., 1992); people need incentives, the right mindset, and a shared environment to facilitate knowledge transfer and this is exactly what M&A is meant for.

1.3 RELATEDNESS

Relatedness is defined as 'a particular manner of connectedness'**. It is a measure that captures similarities between two or more entities**, or in our case, companies. The concept of 'relatedness' becomes crucial in the paper, being able to open up new ways of analyzing the efficiency and efficacy of an Acquisition, providing new data considered complementary to the most used parameters. In the next pages we will answer questions such as: How relatedness determines the performances of technology acquisitions? How does it help to keep performance high?

It can be said that industries are connected to the extent that they use the same type of resources and we refer to "resources" in a very broad sense, ranging from tangible assets (for example, machinery and raw materials) to intangible assets (know-how, strong brands, etc.) (Neffke et al.,2009). In principle, each of these resources can be a source of relatedness if they can be used in more than one industry. If we think about all the different resources of a company, an important, if not the most important one, is **its employees and their skills**. Ultimately, people are the bearers of knowledge and the know-how of a company, and people are equipped with the necessary skills to transform other resources into valuable products. As a result, we focus on people and alternative uses of their skills such as resources to determine the correlation between industries. In particular, we study among which industries qualified inventors change jobs and how they react to it in terms of performance. We argue that if a qualified individual finds alternative employment in another industry, the production processes in its old and new industries draw on similar expertise and are in this sense related.

As stated also in the paper ‘Knowledge-relatedness in firm technological diversification’ (Breschi et al., 2001), the concept of knowledge-relatedness is very broad and includes different dimensions of knowledge. They can be grouped into three main categories: Proximity, Commonality and Complementarity. We are interested, thus we will further analyze, the last two: Commonality and Complementarity. First, Commonality refers to the situation in which a firm needs to develop the same piece of knowledge in several different technologies (Teece, 1982) and it relies on M&A to acquire new inventors to strengthen the know-how in that particular area. Second, Complementarity indicates that there is a need to use together two or more different technologies to create a single new product or process (Pavitt, 1998). In both cases, an overlap between inventors occurs and it can be seen as two-fold: Target overlap and Acquirer overlap (Sears et Al., 2012). Each one of them affects in a different way the value created by the technological capabilities of the companies due to factors such as absorption capacity, redundancy of knowledge and organizational disruptions.

What are the consequences of the overlap? How does relatedness determine the performances of technology acquisitions? Those questions and many others will be answered further in the dissertation.

The first chapter aimed to highlight the growing importance of technology acquisitions in high technology industries, driven mainly by the need to acquire knowledge in rapidly changing environments, in accordance with the company's Knowledge-Based View. In addition, we dwelt on the concept of 'Open Innovation' and how it is impacting the overall picture. To conclude the chapter, ‘Relatedness’ has been introduced. It will cover a predominant role in the next chapters, being central in the dissertation, with particular attention to the impact on inventors' performance.

CHAPTER TWO
POST-ACQUISITION OUTPUT

To begin with, post-acquisition integration is essential to reap the expected benefits of the deal, gather synergies and create value (Haspeslagh et al., 1991). Post-acquisition integration is an important process of organizational change that requires great effort and dedication of resources (Larsson et al., 1999) and can divert management's attention from core activities (Yu et al., 2005). A challenge for acquisition companies is therefore to face a difficult integration process while maintaining the focus on ongoing activities (Puranam et al., 2003). However, an integration process rarely takes place as a single initiative within an organization. Rather, organizations often achieve multiple and overlapping changes (Hafsi, 2001). Managers of acquiring companies therefore find themselves having to balance the integration between the focal acquisition and ongoing operations while simultaneously managing other change processes. Research on Mergers and Acquisitions (M&A) has often examined post-acquisition integration processes as isolated events (Laamanen et al., 2008). In this way, scholars focused on management decisions and the results of the focal integration process without recognizing the broader organizational context within which these decisions and results develop. This organizational context consists of strategic issues and change processes that, although exogenous to the focal acquisition, can significantly influence the integration process and its output.

2.1 FACTORS AFFECTING PERFORMANCES OF ACQUIRED INVENTORS

The literature covers this topic extensively. Acquisitions are necessary to make significant and social changes (Baumann et al., 1997) that inevitably lead to turmoil, potentially disrupting, in turn, the ability to create knowledge. This disruption has an impact on the productivity of inventors, both in terms of pure survival (or continuity of the patents) and on productivity with the acquirer. Moreover, it can be seen that while integration has a generally negative effect on the productivity of the inventors acquired, the effects are even more serious for some scientists than for others. In particular, those inventors who have lost most of their status and centrality due to the fact of being integrated, have suffered the most discomfort, or at least their technical productivity has decreased more (Paruchuri et al., 2006)

Over the years, many factors have been analyzed trying to understand which of them were the most significant, those that have most influenced the performance of acquired inventors. Two have been clearly distinguished: ‘mobility’ and the subsequent relationship between ‘mobility’ and ‘productivity’ (Gomes et al., 2012).

2.1.1 INVENTORS MOBILITY & INVENTORS MOBILITY RELATED TO PRODUCTIVITY

The involuntary departure of an inventor leads to an immediate loss of human capital. In most cases it is impossible to compensate for the loss of an experienced and competent worker because a suitable replacement may not be available, or at least it takes time for new employees to familiarize with the working and organizational environment of the new company and to have the same success as its predecessor (Cardarelli et al., 2019). Many companies seek the knowledge and skills acquired through mergers and acquisitions (M&A) at the company level (Cloodt et al., 2006). **However, the real actors of knowledge transfer from M&A are individuals rather than organizations** (Argote et al., 2000). Knowledge with the highest value is often tacit and sticky, embedded in individual research (Szulanski, 1996). Even within the same company, these workers have enormous differences in terms of embedded knowledge, knowledge about the network, hierarchical positions, and so on.

It is very common in the aftermath of the acquisition, the R&D personnel of the target move to the acquirer’s organization or unit. An inventor mobility allows knowledge transfer from the previous company while the inventor continues creating new knowledge through collaboration with employees of the new firm. It has been found that during an acquisition, target employees with knowledge in just the target sector (different from the acquirer one) may face issues to create new knowledge and performance may decrease (Paruchuri et al., 2006). Conversely, an employee who previously acquires knowledge and experience in both sectors (acquirer and target, if different), will be well prepared for the change given by the financial operations. Since it may have established channels of collaboration with workers in both companies, there is a high probability that new knowledge will be created (Marks, 2007). However, such knowledge creation may suffer from challenges such as individual learning ability, confidence level and change in the organizational identity after the M&A (Nonaka, 1994).

Knowledge creation requires a well-designed organizational environment to increase the motivation of R&D workers (Grant, 1996). However, companies may fail to plan a so productive organizational identity during the period of post-acquisition integration (Puranam et al., 2007). Consequently, the success of technology acquisitions depends crucially on effective post-merger integration (Paruchuri et al., 2006).

A first interpretation of the topic could come from the experiment done by Hoisl. Considering the individual level, Hoisl (2007) analyzed 15,595 patents. Based on a questionnaire sent to all inventors in the database, he assembled a sample of 3,049 completed questionnaires. Productivity was analyzed on the basis of 39,417 patent applications submitted by the inventors. He concluded that the mobility of inventors was positively correlated to productivity. Furthermore, while age and other demographic factors did not influence productivity, external sources of knowledge had a positive effect. However, the result is not shared by all the literature. Groysberg and Lee (2009) examined the exploratory and exploitative performance of mobile security analysts in investment banking at the corporate and individual level. Unlike other studies, they found that the performance of star inventors actually decreased after they moved to another company. This could be related to the fact that, because these workers had company-specific skills, they needed time to acquire new skills and adapt to the new environment.

In any case, it would be optimal for companies to keep information about the quality of the inventor’s secret, but this is not possible. Therefore, companies must make special efforts to keep inventors not only within boundaries, but also productive, for example, in an incentive-based vision (Kapoor et al., 2007). On the part of the national economy, this freedom of movement has the advantage of promoting labor mobility, leading to a better qualitative match between the worker and the new employer. A better quality of correspondence, in turn, leads to a greater innovative performance of employees and, consequently, to an increase in social welfare.

2.2 DETERMINANTS OF SUCCESS

The literature highlights many factors in the search for the 'determinants of success' of an M&A process, those that ultimately prove to be truly significant in understanding whether or not the financial transaction will be successful. Focusing on technology acquisitions in the US, three of these emerge with greater force: Absorptive Capacity, Relatedness and Experience. The first one will be analyzed in section 2.2.1 while in 2.2.2 will be the turn of 'Relatedness', a key concept of this paper. Last but not least, 2.2.3 introduces the concept of 'Experience', very helpful in assessing the success of acquisition as well.

2.2.1 ABSORPTIVE CAPACITY

The knowledge gained through external networking is widely accepted as one of the most important resources for a company to be innovative. The skills associated with the acquisition, assimilation and exploitation of external knowledge ("absorption capacity") are of primary importance in this field. While several studies highlight the importance of networked relationships for the acquisition of new knowledge, most remain vague in explaining their impact on the assimilation and exploitation of know-how. Models reveal that the quality of external relationships and the overall size of the network imply access to valuable knowledge and that they positively influence the organization's ability to assimilate and exploit it in the pursuit of innovation, thus providing a good starting point for successful M&A (Binder, 2018). The concept of Absorptive Capacity has been defined by Cohen and Levinthal (1990) as the firms' ''ability to recognize the value of new, external knowledge, assimilate it and apply it to commercial ends'' and it is exactly what we are referring to. It revels to be a crucial component in gaining a competitive advantage in the market. Further, they also showed how impactful it is though the model depicted in Figure 4.

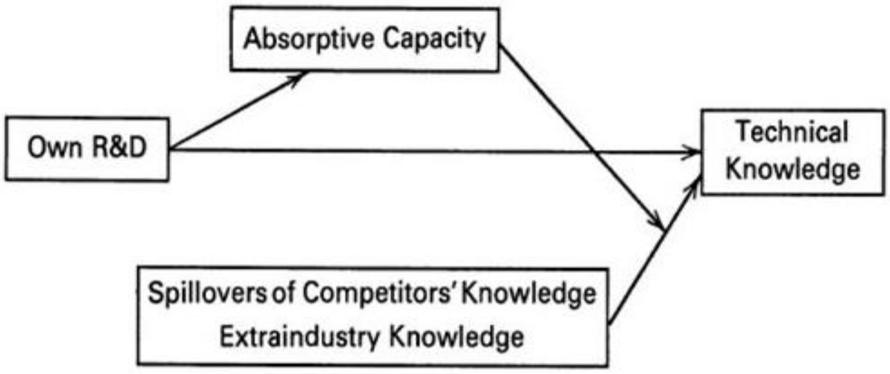

Figure 4 – Absorptive Capacity and sources of firm technical knowledge (Source: SlidePlayer)

The company generates new knowledge in two ways: directly through its research and development activities and, second, by drawing it from competitors and non-industrial sources such as government and university laboratories. A central feature depicted by the model is that the Absorptive Capacity of the company itself depends on its R&D. Because of this mediation function, the Absorptive Capacity influences the effects of appropriability and technological opportunity conditions on R&D (Hussinger, 2010). Therefore, the effects of these elements are not independent of the R&D itself. The interaction means that a company is not able to passively assimilate the know-how available to the external world. Rather, to exploit the R&D output of its competitors, the company invests in its Absorptive Capacity by conducting its own R&D. To sum up, this model implies that, as the ease of learning decreases, learning becomes more and more dependent on the company's R&D activities, the focus of our thesis.

2.2.2 DIFFERENT TYPES OF RELATEDNESS

In section 1.3 a general overview of 'Relatedness' has already been given. At this point, the focus will be on 2 common types of relatedness and how they influence the performances of a technology Acquisition.

- **TECHNOLOGY RELATEDNESS (OVERLAP)**

  In high-tech industries, companies are increasingly engaged in acquisitions to expand their technological capabilities and improve their innovation performance (Cassiman et al., 2005; Hagedoorn et al., 2012; Stiebale, 2013). Previous research on technological acquisitions has suggested that the correlation between the technological knowledge of the acquirer and of the target, i.e. the technological relatedness, is an **important predictive factor of post-acquisition innovation performance** (Cloodt et al., 2006; Ornaghi, 2009). The technological relatedness refers to the extent to which the target technologies overlap with those of the purchaser (Ahuja et al., 2001). A company strengthens its technological resources through technology-driven innovation, i.e. by incorporating its current technological resources into the innovation process for further progress along its technological trajectories (Dosi, 1982). The organizational process related to technology-driven innovation through acquisitions involves the integration and reallocation of the target's technological resources into the innovation process of the purchaser. Thus, unlike market-driven innovation, which requires a cross-functional interaction between R&D and marketing functions, technology-driven innovation requires an interaction mainly between the R&D functions of the two companies in the upstream phases of the value chain to pool their technological resources.

Although one would expect acquirers to choose targets that help them innovate and achieve synergies, this is not always the case for two related reasons.

- First, companies often neglect the main sources of synergy, pay attention to the wrong sources or fail to avoid the sources of synergy dilution (Rao et al., 2016).
- Second, buyers need to absorb new information on potential targets. The less a potential acquisition target is related to a company's existing portfolio of assets, the greater the complexity it adds to the decision to select information, and the more difficult it is to absorb new information about the potential target technology (Cohen et al., 1990).

Therefore, the decision to select a target in a technology acquisition depends not only on the characteristics of the acquiring or target companies, as has been suggested so far (Capron et al., 2007; Shen et al., 2005), but also on the ability of the buyers to meet the information associated with the technology assessment of the potential targets and their compatibility with the existing buyer's technologies.

- **MARKET RELATEDNESS**

Measured through product-market correlation based on target and buyer product market segments. A company's sales records in a product segment reflect the market knowledge the company has accumulated through experiences, such as customer needs, preferences and behaviours in that segment (e.g., Fang et al., 2011). Relying on four-digit SIC (Standard Industrial Classification) codes to identify product market segments, the proportion of the target's turnover that overlapped the buyer's turnover in terms of product market segments can be calculated. It represents one of the main ways Product Market Relatedness has been calculated in the past literature. Results are controversial as explained further. Nonetheless, Cassiman, Colombo, Garrone and Veugelers (2005) brought to light an interesting fact; significant differences emerge between rival and non-rival companies that share the same technologies once the acquisition has been made. First, rival firms show a greater reduction in R&D department performance after the agreement than non-rival firms. There are statistically significant differences between the two categories with regard to the frequency with which the companies have indicated that they have closed R&D facilities (38.9% for rival companies against 12.5% for non-rival) and have dismissed R&D personnel (44.4% for rivals against 18.8% for non-rival). In addition, M&A operations between direct competitors have rarely created companies that explore new technological fields and benefit from new external technological sources. The results highlight a lower propensity to patent, a lower speed in the introduction of new production processes and in the development of new technological knowledge and a lower ability to combine their skills with those of the partner to obtain synergistic gains.

Besides this cutaway on the difference between rival and non-rival companies, general results in literature show that the **acquisition of a target with a moderate level of correlation with the product market will**

lead to a higher performance of post-acquisition technological innovation compared to the acquisition of a target with a too low or too high level of correlation with the product market. A target with a moderate level of correlation with the product market will provide new market inputs for technological innovation without incurring a significant cost associated with cross-functional interactions (Lee et al., 2014).

2.2.3 EXPERIENCE

The organizational learning process produces new knowledge that in turn can lead to competitive advantage and improved business performance (Hitt et al., 2000). **Experience** in routines increases the effectiveness of using them in the future (Nelson et al., 1982); this is called experiential learning or "learning by doing" (Kolb, 1984). Experience within a particular field focuses attention on the field, making the acquisition and evaluation of environmental information more efficient, as well as the identification and exploitation of opportunities within familiar areas (Dutton et al., 1984). Therefore, the trend is to obtain localized feedback from experience to reduce the momentum towards exploring sectors that are too far away from the company focal one. In this way, behavior is directed by organizational routines that result from cumulative experiences, even in the presence of new opportunities (Starbuck, 1983). In this direction, Amburgey and Miner (1992) developed the concept of 'repetitive momentum', which occurs when an organization acquires experience by repeating a specific action. Over time, these routines occur with less conscious effort. In particular, companies engaged in M&A activities develop knowledge and skills in acquisition processes not just related to due diligence, negotiation of agreements, financing and integration (Hitt et al., 2001), but also pre-acquisition assessment and post-acquisition integration. In turn, M&A becomes more automatic in the sense that the learned behavior assumes a more central role in decision-making processes. **Past behaviors tend to be repeated because they are perceived as less risky and more rewarding than attempting new behaviors with which they have limited experience** (Levitt et al., 1988).

CHAPTER III

PATENTS AS A MEASURE OF INNOVATIVE PERFORMANCE

In a knowledge-based economy, innovative competence has been acknowledged as a prerequisite for sustainable growth (Capello et al., 2014). A source of growing innovative competence has been recognized as a concentration of knowledge that facilitates innovative activities such as research, absorption and recombination of information. In addition, the diffusion of knowledge, in particular tacit knowledge, can improve innovation performance as discussed in the previous chapters. Companies often make acquisitions to gain access to new knowledge, but they may differ significantly in the way they use the knowledge they have acquired. Choi & McNamara (2018) have demonstrated that the company's previous innovation models drive this choice. To explain it better: companies that have previously focused on incremental innovations internally tend to acquire new knowledge similar to the one already developed inside. In contrast, companies that previously focused on 'bold' innovations tend to leverage the knowledge gained mainly through new innovations. Thus, they show that companies use acquisitions as a means to extend their internal innovation models.

"How do we know if patent statistics measure anything interesting? (Griliches, 1990). This is a fundamental question that haunts any empirical researcher who uses patent statistics as a measure of innovation. If patents and innovations are closely related, we can continue to study the former as a good proxy for the latter; if not, we need to consider carefully to what extent patent data could be useful. Answering this question requires a direct measure of innovation, and measured innovation must be non-trivial, socially valid and based on technological progress. **Innovations in the high-tech industry offer precisely this empirical context.** We have chosen to study this field for three reasons:

- First, these product innovations require considerable engineering effort and often embody patentable inventions.
- Second, even if they are US-based companies, the industry has a global reach, with manufacturers of various sizes and organizational types, and from different countries. The availability of such patent data allows us to explore correlation patterns between patents and innovations with rich variations in cross-sections and time series. These features make the sector relevant and suitable.
- Third, the choice of the high-tech context is a conservative approach to assessing the usefulness of patent statistics. The technologies are complex and rapidly evolving.

It should be specified that a survey conducted by Cohen et al. (2000) on R&D found that companies in this industry rely quite heavily on trade secrets as the primary means of appropriating the results of their innovations. Therefore, finding a positive and statistically significant relationship between patents and innovations would be more challenging than in other areas where there is a clearer mapping between products, technologies and intellectual property (IP). In this regard, section 3.1 will introduce past searches that have relied on patents as statistical indicators to measure business performance, in particular focusing on their advantages/disadvantages; section 3.2 will explore indicators related to patents quality and section 3.3 will address the main limitations related to patent analysis.

3.1 CONSIDERING PATENTS AS STATISTICAL INDICATORS

A central issue in the innovation economy is how patents influence the incentives for innovation. In the standard static framework for a single innovation (e.g., Klemperer, 1990; Gallini, 1992), increased patent protection encourages innovation by protecting the innovator's profits from potential imitations. A key feature of innovation, however, is that it is cumulative. For example, current innovations in biotechnology and software can be used as a basis for future improvement (Scotchmer, 2004). This consideration has led to the examination of patent policy in a two-step innovation framework where a second innovation is based on the first (Scotchmer, 1996). This approach emphasizes the division of profit among innovators and argues that it is necessary to transfer profit from follow up to initial innovators to provide sufficient incentives for fundamental initial innovation.

It is important to note, however, that the effects of patents on innovation in a given industry are often determined jointly by several factors. For example, while stronger patents can stimulate R&D in innovative industries, the higher marginal cost of innovation and lower fixed cost of innovation can make patents weaker in a more innovation-friendly industry. To give even more meaning, we can rely on the study of Burk and Lemley (2009), concerning the pharmaceutical industry and the information technology industry, considered both highly dependent on innovation for growth. It has been found that patent protection is crucial for innovation in the former case, but not in the latter. The different nature of innovation costs in the two sectors could potentially explain the difference. Therefore, while different industries and/or countries may want a different patent strength to stimulate innovation, the correct formulation of patent policy will require careful consideration of multiple factors.

3.2 PATENT QUALITY: MAIN INDICATORS

The empirical literature on patent economics employs a wide range of patent-based measures to indicate economic characteristics such as "scientific basis", "importance" or "value" of patented inventions. Consequently, Hall (2004), states that patents measure something beyond R&D inputs since they define the company's knowledge base. In this sense, patent data play a much more comprehensive role in the analysis of innovation, so that **patent statistics are increasingly used as a measure of innovation performance**. In fact, patents should describe something new and not obvious: to be granted, an invention must include something not previously recognized in a previous publication (Walker, 1995), and provide new knowledge. It is considered necessary to add that although scholars have attempted to assess the validity of these proxies by relating them, for example, to inventor surveys, the appropriateness of these indicators is currently the subject of heated debate (e.g. Gambardella et al., 2008, Gittelman, 2008).

A list of the most commonly applied patent measures in the empirical literature on innovation are cited in the following pages and most of them will be further adopted in our analysis.

- **Forward citations** are defined as the number of all citations received by a given patent from subsequent patents. This measure is typically interpreted as the "importance", "quality" or "significance" of a patented invention. Previous studies have shown that forward citations are highly correlated with the social value (Trajtenberg, 1990) and the private value of the patented invention (Hall, 2004). The highly cited patents could be an indicator of the effects of "corporate reputation" that derive from the company's past competitive advantages because reputation is an intangible asset (Hall 1992) that can be counted among the resources that improve companies' performance (Barney 1991; Peteraf 1993); in fact, it has been linked to the superior financial performance of Roberts and Dowling (2002). In addition, forward citations reflect the economic and technological "importance" perceived by the inventors themselves (Jaffe et al., 2000) and by fellow technology experts (Albert et al., 1991).

- **Backward citations** determine the legal boundaries of an invention by defining a related corpus of the prior art. Empirical evidence shows a positive relationship between the number of backward quotations and the value of the patent (Harhoff et al., 2003). The number of cited patents reflects the extent of patenting in a given field of technology and thus the profitability of inventions in that field. They reveal the retrospective foundation on which an invention is made; they signal the importance of external knowledge for the company's ability to develop new technologies. That is, the higher the number of citations made, the more the firm appropriates the advantages of others' proprietary technologies. References to the knowledge contained in previous patents provide information about the nature and originality of the research that contributes to a patent (Jaffe et al., 2002; Trajtenberg et al., 1997). They are also positively linked to the value of a patent (Arts et al., 2013). In fact, Schoenmakers and Duysters (2010) demonstrate how backward citations can contribute to the radicality of technological inventions. The most creative inventions have been identified as the visualization of new combinations of subclasses or technological components at the patent level (Fleming et al., 2007).

- **Citations-Lag.** It is a proxy of the value of the patent defined as the time taken to be cited for the first time from the date of publication (Gay et al. 2005). These authors found that the previously cited patents are likely to receive more forward citations and a faster citation rate, which is the rate of time it takes to receive the next citation since the last received citation. The tendency to have a faster citation rate means that once a patent is first cited, its chance of receiving further citations in a relatively short period of time may be greater. Therefore, to emphasize short-term citations when evaluating recent patents that do not have sufficient forward citations, the first citation delay can be used as a proxy for the value of the patent. Moreover, patents covering more fundamental technologies are often cited later than applied patents because it takes longer for fundamental inventions to be understood and used by others (Sampat et al., 2003). To test this, it could be used the average citation delay.

- **Patent Renewal.** Studies in this field take advantage of the fact that it is expensive for patent holders to maintain patent protection for a further period of time and in other countries. Therefore, it is assumed that the value of maintaining patent protection over time and in different geographical regions are related to the economic importance of the invention (OECD, 2009). In most patent systems, patent holders have to pay a periodic fee to maintain their patents. Generally, the renewal fee increases over time and, at the end of each period, patent holders must decide whether to renew it or not. If they decide not to pay, the patent lapses and the invention becomes public knowledge. Observations on the percentage of patents that are renewed at different ages, together with the relevant renewal fee schedules, provide information on the distribution of the value of patents and the evolution of this distribution over the life of a patent (Griliches, 1990). The rationale behind this approach is based on economic criteria: patents are renewed only if the lifetime value of the patent is higher than the renewal cost of the patent; indeed, when the renewal fee is not paid, the patent has expected returns in future periods below the threshold. In any case, the approach to patent renewal has a number of limitations. For example, the abandonment of a patent may not be indicative of a low value, but of a change in a company's strategy, linked for example to an external shock. In rapidly evolving technologies, many inventions have a high value when introduced, but become obsolete shortly afterwards.

- **Patent Families' size.** The value of patents is also associated with the geographical scope of patent protection, i.e. the number of jurisdictions in which a patent has been applied for. The fact of applying for patent protection abroad is already a sign of economic value, as the decision reflects the owner's willingness to bear the costs of international patent protection. The motivation is closely linked to the decision to renew a patent; it is expensive to make a patent valid in more than one country and maintain protection (Putnam, 1996). The geographical scope of protection, as reflected in international patent concessions for a given invention, reflects the market coverage of an invention: the greater the number of countries where protection is sought, the greater the potential for commercialization and profit. For example, Lanjouw and Schankerman (2004) find a strong positive relationship between a patent quality index and family size. Harhoff et al. (2003) provide evidence that patents that are part of large international patent families are more strongly associated with economic value.

- **Number of Claims.** The purpose of a patent is an important determinant of its economic value, as it defines the legal dimensions of protection and therefore the extent of market power attributed to the patent. A wider scope of the application refers to a wider field of technology from which others are excluded. However, the "purpose" or "breadth" of a patent is difficult to measure. The scope is reflected in its claims, but also in combination with backward patent citations. Some economists have used the number of claims to indicate the legal scope of patents. It has been argued that because each individual patent represents a set of inventive components, the number of complaints may be indicative of the value of the entire patent. However, the tendency of some applicants to "inflate" the number of claims for strategic purposes makes it rather difficult to calculate the true relationship between scope and number of claims. The empirical analysis on this subject is poor but quite positive. In their patent quality factor model used to analyze research productivity in the United States, Lanjouw and Schankerman (2004) found that the number of claims is the most important indicator of patent quality in six of the seven technology areas studied.

3.3 PATENT-BASED INDICATOR: BENEFITS AND LIMITATIONS

While representing invention activity through patent-based indicators, it is worth noting the benefits, but also the disadvantages of such measures, as discussed in past literature. In light of past considerations, the benefits of patent analysis can be outlined as follows. First, patents cover a variety of technologies and provide a standardized ontology to identify them. This allows early recognition of technological changes and provides insights for the evaluation of M&A options related to technology (Ernst et Al. 2000). It also allows the performance of specific R&D units within large companies to be analyzed (Ernst, 1998) and companies that are not obliged to publish information about their R&D activity (Ernst H., 1999). Second, patents have a close link with the invention. Whether or not they are based on research and development, most eminent inventions are patented (OECD, 2009). Third, patents provide a link to the inventor, enabling the evaluation of individual performance and the identification of key inventors, a crucial aspect in the development of this dissertation. Last, patent documents contain much relevant information about the invention process: well-structured description of the invention, the field of technology, name and surname of the inventor, applicant, citations and claims. This allows both technical and economic analysis, evaluating the quality of the patent both in terms of financial performance and technological impact (Ernst, 2003).

However, as indicators of technological activity, patents have some non-negligible disadvantages. First, the distribution of the value of patents is strongly distorted (van Zeebroeck, 2011); in fact, only a few patents have a very high value for society, many of them have almost no application, which means that the related invention is useless or has been filed for purely strategic intentions. Such heterogeneity makes the simple counting of patents misleading for the analysis. Second, patent data are complex because they are created by complex legal and economic processes; therefore, to be analyzed effectively, they require specific knowledge. Third, the propensity to patent changes depending on the industry; for example, the relative effectiveness of a patent in discrete or simple technology products is greater than that of complex products that include many separately patentable components (Merges et al., 1990). This introduces a possible distortion in the multisectoral analysis of the inventive performance of companies. Fourth, the propensity to patent changes depending on the size of the companies, as larger companies can spread the fixed costs of patent applications over a large number of patents (Cohen et al., 2000). In addition, due to the considerable legal costs, a small company may find it difficult to enforce its patent rights. Fifth, the propensity to patent changes depending on the country (Cohen et al., 2002). Differences in laws and practices around the world limit the comparability of patent statistics between countries. It is therefore preferable to use patent data from the same patent office (Keller, 1994). Last but not least, not all patents generate innovation: "block patents" are defined as unused patents that a company does not intend to license, but keeps for strategic reasons (Motohashi, 2008).

While it is not possible to completely avoid all the limitations mentioned when performing an intercompany analysis, patent data represent the only alternative for objective measurement of individual performance. Therefore, the methodological section (Chapter 6) will address the main limitations encountered, together with the main solution identified by us and past searches.

CHAPTER IV

Research Question and Hypothesis

4.1 LITERATURE GAP AND RESEARCH QUESTION

According to the resource-based and knowledge-based view (Chapter 1) differences in innovative performance among enterprises are the result of different sources of knowledge (Bierly et al., 1996). Therefore, it is the firm's ability to acquire, transfer and integrate the knowledge base of the acquired firm into the knowledge base of the acquiring firm that creates a sustainable competitive advantage (Barney, 1986). However, it has been realized that not all acquisitions are made for technological reasons with the sole intention of learning (Hamel, 1991). Mergers and acquisitions may also be motivated by market-entry and market structure considerations, or by the desire to expand the company's product range internationally (Hagedoorn et al., 1999). These considerations motivate companies to undertake non-technological acquisitions that are less likely to provide technological knowledge to the acquiring company. However, companies operating in **high-tech** sectors, such as biotechnology, electronics, software, and hardware, are forced to manage their assets aggressively to keep pace with technological change. Mergers and acquisitions allow high-tech companies to build core competencies, enlarge existing business lines and even expand geographically. According to McKinsey, financial transactions can often fill gaps in a product line, open new markets and create new capabilities in less time than it takes to build companies internally. These moves can be a prerequisite for achieving a dominant position and the best guarantee of survival. Technological ends are unique because they have a large proportion of intangible assets that have no value. Market participants may not fully understand the proprietary technologies to which the firm is committed, because technologies often involve highly specialized knowledge. Success in technology firms depends strongly on intangible assets that are highly illiquid and difficult to replace, such as internal culture. All these conditions cause a high degree of information asymmetry. To add on top, the uncertainty surrounding the value of high technology activities is even more accentuated in the global context because there may be limited information that are disclosed about activities. Because foreign activities are geographically distant, the target may be more expensive to evaluate and more difficult to monitor than a national target. From the perspective of a U.S. parent company that can acquire foreign high-tech assets, there is uncertainty about the potential integration of these assets with existing assets because it may involve the cooperation of different national cultures and regulations. In addition, cultural differences between the acquirer and the target may obscure the value of the assets under consideration and the former's ability to manage the foreign workforce.

As it could be noticed in this dissertation up to this point, there is still much to investigate. In our opinion, the concept of '**Relatedness**' declined in its major forms (**Technology** and **Market**) represents a relevant foundation on which this dissertation should be built as it manages to cover under its umbrella a multitude of aspects not easily connected in other ways. In fact, summarizing what has been said so far, scientific research of the past has written about this concept always taking some portions of it. Consequently, no evidence has yet been provided of the impact of these factors simultaneously on the post-acquisition performance of the acquired inventors. Focusing on **Technology Relatedness** (or **Overlap**), although the flow of literature regarding the post-acquisition performance of inventors has received increasing attention in recent years, all studies have considered mainly independent static variables at the enterprise level (e.g., size). As a result, they have not examined the impact that decisions made after the completion of the acquisition could have on the productivity of the acquired inventors. On the other side, also the concept of '**Experience'** in acquisitions referred to the acquirer must be included. As stated in Chapter 2, it is considered a very helpful element in assessing the success of the financial operation. Even in this case, not many past studies have paid attention on the latter and this makes it even more interesting for us, being a useful element of diversification.

Our research question goes in this direction and can be defined as follows:

How do Technology Overlap, Market Relatedness and Experience of the acquirer influence the innovative performance of target inventors in the post-acquisition period?

4.2 HYPOTHESIS DEFINITION

- **TECHNOLOGY OVERLAP**

Target selection is the result of a research process in which an acquirer selects the target company that best fits his acquisition objectives, compared to the alternatives (Chakrabarti et al., 2013). Since an important objective in technology acquisitions is the improvement of technological skills, this research focuses on potential targets with technological knowledge that allow acquirers to achieve the desired innovation results. This process requires acquirers to identify and assess the potential value of the technological skills of alternative targets. Making sense of external technological knowledge and understanding its potential to recombine with internal knowledge requires a certain level of familiarity with the associated technological area, or technological relationship (Lane et al., 1998). Technological relatedness can be assessed along the dimensions of technological 'Similarity' and 'Complementarity' (Cassiman et al., 2005). Technological similarity refers to the extent to which the technological capabilities of two companies focus on the same strictly defined areas. In other words, it determines the degree to which the skills of two companies in the same sector are shared. Consequently, the acquisition of similar capabilities allows buyers to increase their existing technological capabilities (Berchicci et al., 2012). Technological complementarity, on the other hand, refers to the extent to which technological capabilities are concentrated on different strictly defined areas within the same widely defined area (Makri et al., 2010). It determines the degree of their skills in distinct but related areas and, following an acquisition, allows them to experiment a new recombination between existing and newly acquired capabilities (Rhodes-Kropf et al., 2008).

Focusing on the former, the technological similarity between an acquirer and a potential target increases the accuracy of the assessment of the technological capabilities, increasing the acquirer's ability to recognize, evaluate and internalize external knowledge, i.e. the absorption capacity (Schildt et al., 2012). A high degree of technological similarity allows the acquirer to better understand the assumptions that shape the target's technology (Lane et al., 1998) and the possible technological problems that may arise when using this technology (Makri et al., 2010). Thus, the buyer can more easily assess the technological and commercial value of the target's expertise as the technological relatedness between a buyer and a potential target increases. This implies that, in screening potential targets for acquisition, targets with similar technological capabilities to those of the acquirer result in lower research costs than targets with unrelated technological capabilities (Chondrakis, 2016). Therefore, we assume the following:

Hypothesis 1

The Technology Overlap between the acquirer and the target has a positive impact on the patenting activities of the target inventors after the acquisition.

- **MARKET RELATEDNESS**

Our second hypothesis is based on the observation that the high-tech industry is characterized by a specific "industrial culture" that differs from other industries. Even if in conditions of absolute homogeneity cultural differences within an industry have been observed (Schreyoegg, 2005), we argue that a common basic "culture" can still be expected. In this sector, companies have developed their own entrepreneurial, creative and risk-taking culture and are organized into flexible, interdisciplinary project teams with usually low levels of hierarchy, open communication and informal organizational structures, thus creating dynamic, lean and effective organizations that promote innovation (Powell, 1996). In addition, they are trained in a very similar way and follow the same important goal of generating innovation by focusing on R&D activities. Considering Schweizer (2005) and the fact that the high-tech industry is a global industry (Van Brunt, 2000), it can be concluded that there is a specific culture. Therefore, the culture of a company can be considered an important part of its capabilities and not only a precondition to avoid integration problems. It is therefore assumed that a goal of the same industry sector, for example, within the high-tech industry, will facilitate post-acquisition integration through a more fluid acculturation process, given similar cultural and organizational characteristics. Furthermore, we assume the existence of a sector-specific absorption capacity (Cohen & Levinthal, 1990) as mentioned in Chapter 1. From a learning perspective, an acquisition has the advantage that the acquirer draws on industry-specific experience. This is in line with the argument of Hagedoorn and Duysters (2002) that sectoral differences are important in the context of M&A and the results of Porter's research (1987) suggest that an acquisition strategy should be directed towards related activities. Their results suggest that industry relatedness has a positive effect on the success of an acquisition. Moreover, they indicate the need to combine strategic, organizational and cultural factors to achieve synergies and knowledge transfer. The similarity of management style facilitates post-acquisition integration and knowledge transfer even if there is no acquisition experience and direct contact between the acquirer and the target. Given that the characteristics of the core business and the mindset of management and employees are very similar, most high-tech companies follow the same dominant logic (Prahalad & Bettis, 1986). Most of them pursue the same business model that focuses on research and development activities in order to generate innovations.

With the acquisition of other high-tech companies, not only do they remain in the same industrial sector and follow the same dominant logic, but they are also able to strengthen their core business and their core competencies by rapidly integrating the acquired company and, therefore, favouring innovation due to the reduction of organizational, human and cultural issues. We state therefore:

Hypothesis 2

The Market Relatedness between the acquirer and the target has a positive impact on the patenting activities of the target inventors after the acquisition.

- **PREVIOUS ACQUISITION' EXPERIENCE OF THE BUYER**

The desire to obtain valuable resources, including the know-how, technologies and skills possessed by the target companies has been one of the main reasons that drive the most recent wave of acquisitions (King et al., 2003). The number of acquisitions has increased significantly in high technology sectors (Inkpen et al., 2000), indicating that these companies are gaining more and more experience in making acquisitions. Frequent buyers are more likely to make subsequent acquisitions because they have the opportunity to learn from their past ones (Haleblian, Kim, & Rajagopalan, 2006) and to develop routines. Very and Schweiger (2001) identified an "experience accumulation process" that acquirers have developed to improve their management of future transactions, supporting the idea that the acquisition experience has a positive impact on acquisition performance. Even if the majority of past researches that discussed this topic adopt the implicit belief that familiarity within acquisitions always shows positive consequences; Husted, Gammelgaard and Michailova (2005) argue that capturing synergies from know-how sharing in the post-acquisition integration process is a multifaceted and complex process that often proves problematic. However, the results of Haleblian and Finkelstein (1999) clearly indicate that more experienced buyers are able to differentiate between the challenges of different types of acquisitions, while inexperienced buyers tend to generalize inappropriately from their limited experience. The authors argue that the routines and practices that are accumulated in previous acquisitions can be transferred to subsequent acquisitions.

It is assumed that the more a company acquires, the more it will develop screening skills (Vermeulen and Barkema, 2001), and will acquire knowledge about the right level of integration (Pablo, 1994). In addition, it will improve its ability to transfer and integrate knowledge during the post-acquisition phase. Therefore, we assume that experienced high-tech companies are able to successfully transfer and integrate the acquired knowledge, thus increasing their innovation speed (Nelson & Winter, 1982).

Hypothesis 3

The Acquirer's Acquisition Experience has a positive impact on the patenting activities of the target inventors after the acquisition.

Part Two – Empirical Analysis

CHAPTER FIVE

DATA COLLECTION

How Relatedness and Experience in technological acquisitions impacts the performance of the inventors acquired. This is our research question and to test it, we analyzed a sample of **127** acquisitions that took place in A**merican high-tech industries** over the period of time **between 2006 and 2015**. All buyers are large, well-established companies, while the target companies are small and medium-sized enterprises with less than 500 employees.

The performance analysis will focus on the target inventors, whose productivity will most likely be affected to a greater extent than that of the acquirer: they could improve it or vice versa no longer produce patents. To build the sample we have based on several public databases such as the United States Patent and Trademark Office (USPTO), the European Patent and Trademark Office Database (EPO) and the Japanese Patent and Trademark Office Database (JPO), defined by the Organization for Economic Cooperation and Development (OECD) as triadic patent offices (Hicks et al., 2001). Patent data are stored in those well-structured databases that give access to data to the public, allowing quantitative analysis of technological innovations through patents as indicators of innovation (Chen et al., 2012). Open source databases differ in their geographical coverage and in the extent of the processing phases to which they have been submitted. Among these, the USPTO is the easiest to use and the one with the most freely available processed data.

Data related to this thesis were collected by 'Patentsview' and the 'PATSTAT' database. The first is based on data from the United Stated Patent and Trademark Office (USPTO), while the other one provides a more complete overview of patent activity worldwide.

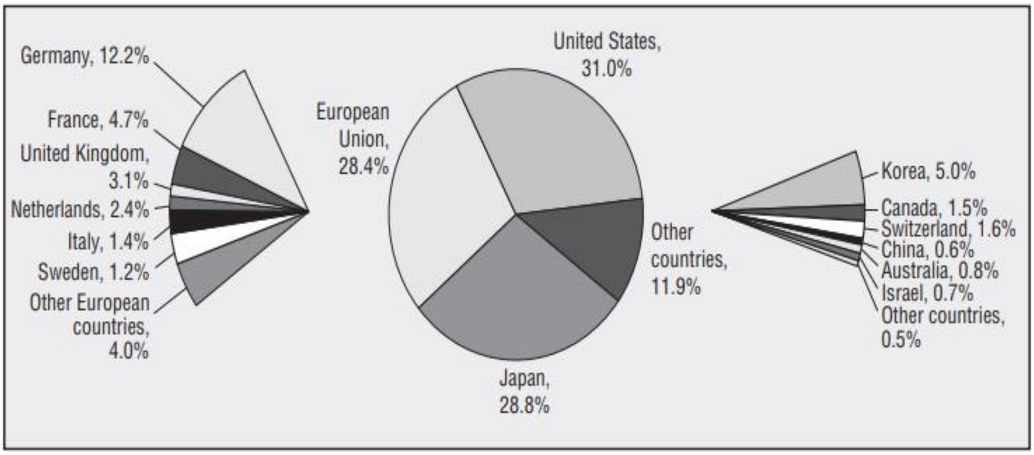

Figure 5 - Share of countries in total triadic patent families (Source: OECD) [1]

Figure 5 gives a view of how countries could be subdivided into the aforementioned triadic patent offices: USPTO, EPO and JPO.

The next chapter (5.1) illustrates which methodological assumptions have been made to make data statistically meaningful while collecting and defining patent-based indicators. Meanwhile, sections 5.2 and 5.3 provide an overview of primary and secondary data sources.

5.1 METHODOLOGICAL ASSUMPTIONS

What are the most common methodological assumptions used when analyzing patents? Usually, they are three: **Country of attribution**, **Reference Date**, and **Patent family**. In the following section, each of them will be defined and examined in detail.

It is crucial to select the right ones; in fact, patent statistics can only be interpreted significantly if an adequate knowledge of the criteria and methodologies used to compile them is applied. Indeed, these elements have a crucial influence on the outcome of the research.

[1]Patent counts are based on the first priority date, the country of residence of the inventor and fractional counts.

5.1.1 COUNTRY OF ATTRIBUTION

This information can be found in patent documents that list inventors from different countries. But why is so fundamental? Coming from recent trends including globalization and digitization (Chapter 1), there is an increasing multiplication of synergies between inventors living in different countries. This is also due to the growth of increasingly large and multinational companies, which give their inventors the opportunity to move between countries during their careers. When talking about 'Country of attribution', 3 are the key items that can be found within the individual patent: information about the '**country of the applicant'**, the '**country of the inventor'** and the '**country of priority'** where the first filing was made.

With regard to the first, the country of residence of the applicant designates the ownership or control of the invention. Through it, significant insights into how a particular country positions itself vis-à-vis others, for example under the voice 'innovation', can be found. The second instead, takes into account the inventiveness of local laboratories and the workforce in a particular country. Usually, the inventor's place of work is indicated under this parameter. As the third and last one, we find the counting of patents for priority office. This parameter can help to understand how the various offices within countries are considered by inventors/companies: some may be chosen because they guarantee better conditions (e.g. protection or costs) or because they represent a strategic country for the company.

Following the OECD guidelines (2009), the '**country of residence of the inventor**' is considered the best way to analyze the 'country of attribution' of a patent, as it has been historically proven that the results are more reliable. Nevertheless, several pitfalls are hidden within this category. Often the data are not reliable because different indications of location from the true ones could be entered for various reasons (e.g. tax). That is why robust control tests must be and have been, carried out in this regard.

5.1.2 REFERENCE DATE

A patent can be characterized by 4 main dates:

- The **priority date** (first date of filing a patent application, anywhere in the world, to protect an invention) is the oldest and therefore can be considered the closest to the date of the invention. There are various ways to file a patent application: the process of patent protection begins with a first filing, a first patent application before each subsequent filing to extend protection to other countries.
- The **date of application** is the date on which a patent is filed with a specific patent office. There is a delay of 12 months between residents and foreigners for traditional direct procedures. Usually, the applicant files an application with the national office (this generates the priority date) and then extends the application to other countries by applying directly with the relevant patent offices (this generates usually an application date with a maximum gap of 12-16 months with the priority date).
- The **date of publication** reflects the time when information about the invention is disclosed to the public and made available to statisticians. In general, 18-24 months from the priority date.
- The **grant date** is the date on which the patent rights are conferred to the applicant by the authorized body.

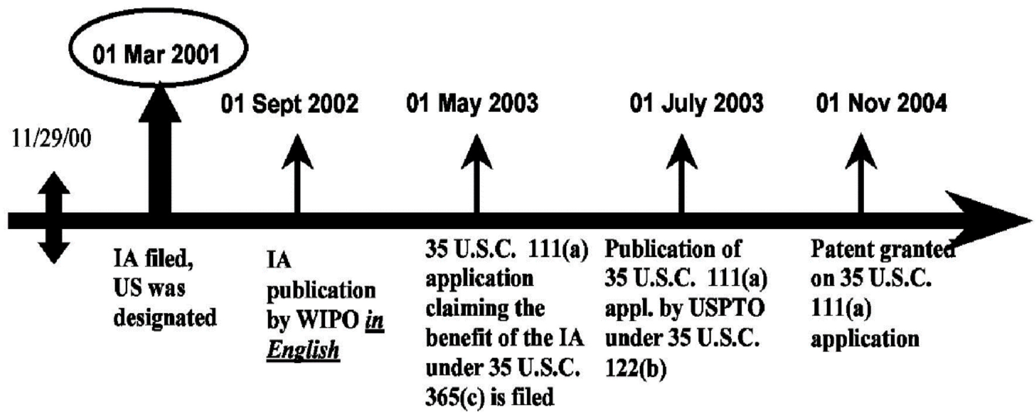

Figure 6- Patent Timeline, USPTO

In order to facilitate the comprehension of the concept, Figure 6 shows a timeline followed by a patent in the USPTO office: from the priority date on 01/03/2001, to the grant date on 01/11/2004. In this case, the whole process took around 3.5 years.

Moving now to indicators related to the reference date, the most technologically or economically significant one is the **priority date**. It is the closest to the date of the invention as already mentioned. There is evidence that companies that choose to patent an innovation, do so at the beginning of the process so that they have the option to withdraw the filing at a later date if the invention proves disappointing. Therefore, in order to reflect the performance of the invention, it is recommended to use the priority date to compile patent statistics. Vice versa, dates based on the date of application and/or grant suffer from a number of biases associated with the patenting process. The data depend on various administrative delays (e.g. the examination process) and the strategic behavior of the patent holder. Moreover, information is not comparable between countries because the gap between the priority date and the application (or grant) date varies from country to country: e.g. In the US, the applications are filed with the US patent office immediately after the invention occurs, while foreigners file the application one year later (priority year). This can introduce bias in times of rapid technological change or for countries where technology is growing rapidly.

5.1.3 PATENT FAMILIES

5.1.3.1 SEVERAL DEFINITIONS

Several definitions characterize this terminology. The wide range of possible uses of patent family data is growing and awareness of the consequences of choosing one patent family definition over another is becoming increasingly important. Broader definitions of families may be preferred when exploring patent filing strategies to ensure that all possible links between patent filings are included. On the other hand, restricted definitions are preferred to broad definitions when comparing the outcomes of litigation in different jurisdictions, as this ensures the comparison between patents that protect exactly the same invention. This section presents **four** of the most widely used definitions of patent families. The first three correspond to families built using only priority links registered in patent databases. These are ‘equivalent’ families, ‘extended’ families and families ‘based on the first filing’. The fourth definition refers to families whose composition is ‘validated by experts'. We will refer to the latter type as families based on new technical content. All these families are briefly described below.

- First, **patent equivalents** are generally considered the best way to identify patents that protect the same invention. They are defined as applications that have exactly the same priority or a combination of priorities.
- Second, **extended families** aim to capture all possible links between two given patent applications. Figure 7 is a classic example of this structure.

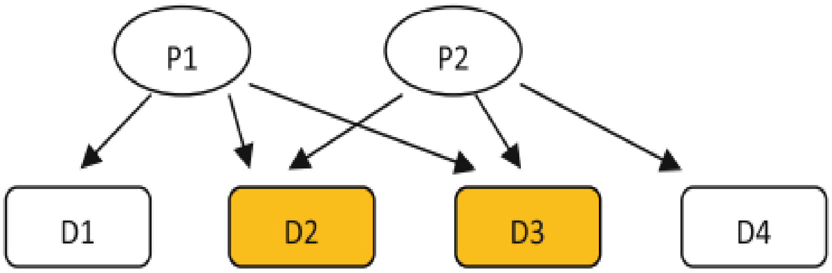

Figure 7 - Extended Family Structure (Source: Martinez, C., 2010)

  However, they are sometimes criticized because the first filing may end up not protecting exactly the same invention as the last filing. Extended families are built by consolidating both direct and indirect priority links between patent applications within families. As a result, it is possible to find two patent documents without common priorities, but which are indirectly linked because both share at least one priority with a third application.
- Third, **families based on the first filing** (or families with the oldest priority) are families in which each first filing forms a family together with subsequent filings claiming it as a priority. An important difference between this type of families and others is that they are not mutually exclusive when, for example, the first two applications lead to a single subsequent application. In this case, each subsequent filing will belong to two different families (each defined by one of the first two priority filings) and will therefore be counted twice in the overall household count. This is the methodology chosen by the World Intellectual Property Organization (WIPO) to build the patent families it publishes annually in its patent statistics report. These types of structures are also used by the EPO to

forecast future deposits and to report statistics on first deposits by country of priority and deposit flows between the different geographical blocks on the Trilateral website.

- Finally, the **expert validated families**, based on innovative technical content, differ from the previous definitions in that the expert control is used to validate the composition of the patent families. They are based on the principle that a family must be composed of patent documents that protect the same technical content. The experts examine new applications and certify whether or not their technical content corresponds to that of the existing families.

To see more information about different patent family’s definitions, see Annex 2.

5.1.3.2 SIMPLE VS COMPLEX PATENT FAMILIES

Family structures are often classified as simple or complex. Martinez C. (2010) considered all structures with a first filing followed by one or more subsequent direct filings as **simple**. the rest of the structures are considered **complex**. It was found that around 75% of all extended families filed in the 1990s are characterized as simple. The finding that such a large proportion of families are developed in simple structures has important consequences for the comparison of results between the different methods of building a family. Simple structures mostly reflect a filing strategy that consists of requesting coverage for an invention in one country, probably the applicant's country of origin, followed by a series of equivalent international filings that aim to obtain protection for that same invention in other countries. When working with such data, attention must be paid. Data must be treated with caution, as the families can only be as valid as the raw data: Martinez C. (2010) found that the distribution of families with different structures is not statistically independent from other patent dimensions. In addition, different family definitions may have a greater impact on some family compositions than others. For example, the definition of equivalents may be more restrictive and lead to smaller families than the definition of extended families. This may be crucial in some contexts, such as econometric studies that use family size as a proxy for patent value. Researchers should be aware of these aspects in order to **choose the definition of family that best fits their specific research purposes**.

5.2 PRIMARY SOURCES – OFFLINE DATABASES

The data used for this study are extracted from 2 main sources: PATSTAT, which is based on OECD bulk data, and PatentsView, which is based on USPTO. Although online databases offer real-time and up-to-date information, studies are more based on off-line databases, which makes it easier to produce and analyze innovation indicators for statistical purposes. In addition, ex-post scalability and compatibility with other sources of information are significantly higher.

5.2.1 PATSTAT

Patent data have been widely used by scholars for empirical research in the economic and social sciences, in particular for research related to innovation and technology. The technology itself described in the patent document is the most important information for engineers. On the other hand, information is more relevant for social scientists, for whom the most important information can be found as soon as a patent is viewed. Annex 3 gives a clear example of how a patent looks like. Those types of patents can be found inside PATSTAT, a worldwide patent database created by the European Patent Office (EPO) at the request of a task force led by the Organization for Economic Cooperation and Development (OECD). The OECD leads the Patent Statistics Task Force, whose members are the World Intellectual Property Organization (WIPO), the EPO, the Japanese Patent Office (JPO), the Korean Intellectual Property Office (KIPO), the US Patent and Trademark Office (USPTO), the US National Science Foundation (NSF) and the European Commission (EC). PATSTAT is a raw patent database whose data are textual information extracted from patent documents. Most of the raw data are obtained from the EPO's main bibliographic database, called DOCDB, which includes data from over 90 patent authorities worldwide. PATSTAT contains information on applications, publications, inventors, citations, patent families, technology categories, priorities and so on. In summary, the database consists of a set of 15 tables that follow a relational database schema (see Figure 8) in which the tables can be linked together using a relevant insertion key. For each application (APPLN_ID), the application date and priority date (APPLN_DATE and

PRIOR_DATE), the name of the applicant (PERSON_NAME and DOC_STD_NAME), the address (PERSON_ADDRESS) and the IPC class (IPC_CLASS_SYMBOL) are retrieved.

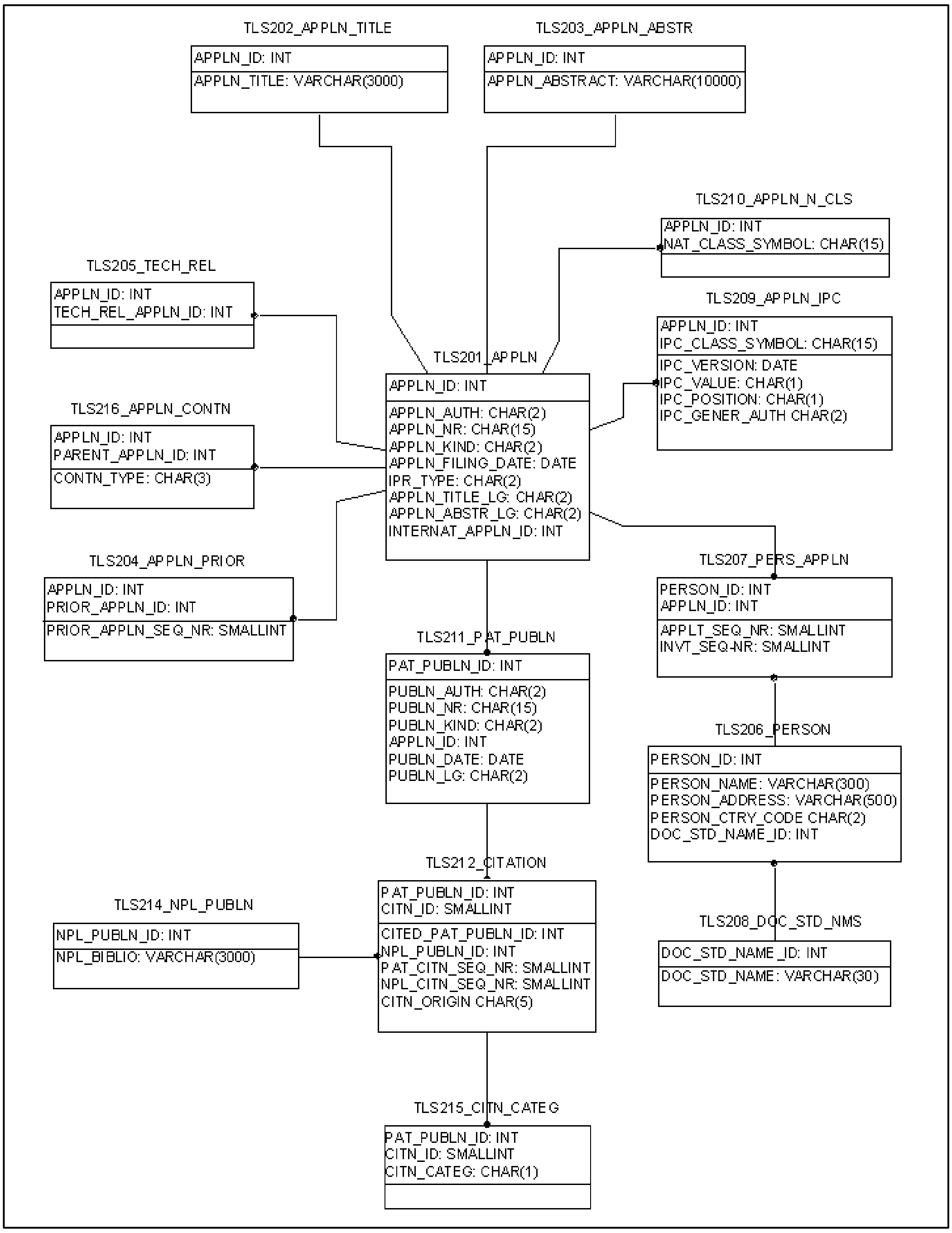

Figure 8 - PATSTAT Table Scheme (Source:EPO)

5.2.2 PATENTSVIEW

PatentsView is based on the data set of the United States Patent and Trademark Office (USPTO) and collects the complete text information of patents granted since 1976. It is the result of the campaign supported by USPTO as an invitation to new and innovative approaches to disambiguate the names of inventors (Han, et. al, 2019). The platform longitudinally links the inventors, their organizations, locations and overall patent activity. The original database is composed of 55 different mass files, which can be raw (version 1) or processed (version 2). The first shows the information as it appears in the source text and XML files of the U.S. patent application, while the latter represent disambiguated values that have undergone previous data processing.

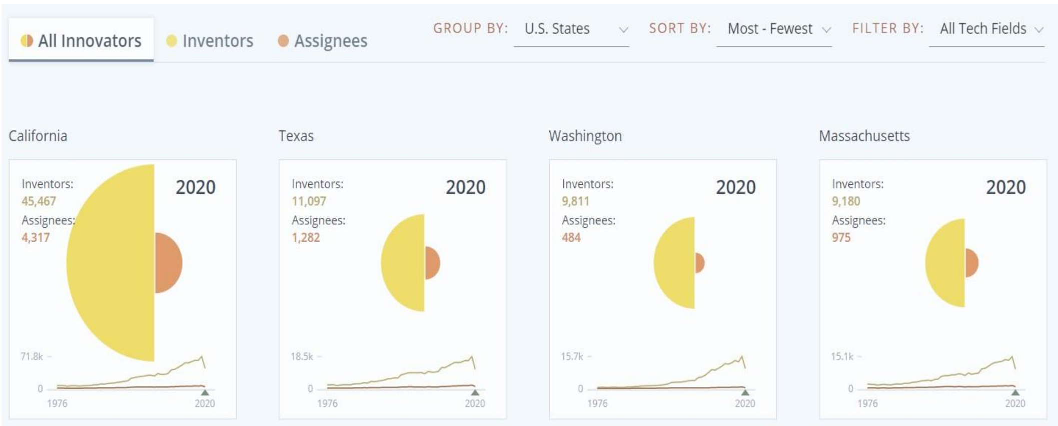

Figure 9 - PatentsView Home Screen (Source: PatentsView)

Figure 9 gives a clear and simple example of some data that could be easily viewed from this database. In the home screen there is the possibility to select Inventors, assignees, or both at the same time; and data can be analyzed by choosing the adequate mix between several options. In any case, we need to consider they may not be 100% correct even if disambiguated, therefore a cleanup of the raw files was required to increase the completeness of the sample. Being fairly recent, Patentsview still seems to be quietly unexplored in the literature of the past. However, from our analysis and for the companies involved in the sample, Patentsview proved to be a very reliable database in terms of completeness and consistency of data. However, its main limitation derives from the lack of information related to patent families, a key indicator of patent quality. Moreover, the absence of data on the original priority date and the identity of the family of each patent does not allow to classify patents neither as first filings nor as family patents.

5.3 SECONDARY SOURCES – PATSTAT ONLINE

PATSTAT Online is the online database used in this study. It is an online database for patents, therefore easily accessible from local networks or the Internet. The advantage is that it is updated more frequently, and this has proven to be useful for spot-checking purposes. To be precise, PATSTAT Online is the online interface for PATSTAT mass data. Unlike the Offline version, which requires a paid subscription, it is freely accessible. It requires an understanding of the SQL language, requiring SQL queries for data recovery (see Annex 4 and 5 to have a real example applied for this study). The disadvantage is related to the limitations of the service. In fact, it sets a limit to the computing power required to run the query and imposes a maximum number of rows of data that can be downloaded, which results in many hours of work that could be easily avoided. These restrictions make this tool a limited utility for checking and verifying robustness.

CHAPTER SIX
METHODOLOGY

This chapter will show the mathematical/econometric procedure followed in this dissertation. Section 6.1 consists of the disclosure of the steps through which we have built the two databases, one at the company level and one at the inventor level, concluding with the definition of the final database. The variables instead will be listed in the following section (6.2), while in section 6.3 we will examine the model specifications.

6.1 SAMPLE PREPARATION

As previously described in Chapter 5, two were the databases combined together in this study: **Patentsview** (55 bulk data files) and **PATSTAT**, which together represent several gigabytes of raw data analyzed. Integration between files of the same dataset and between different dataset files is made possible thanks to freely available patent link tables, condensable through keywords as seen in Figure 8 (Chapter 5). Each file is built on a specific observation unit, which can be the firm, the inventor or the individual patent. The more the level of observation goes from the company to the patents, the higher the level of granularity and completeness of the data provided by the patent databases. In fact, most of the data is dedicated to patents giving information such as backward citations, forward citations, number of claims, family identification, filing date, making it possible to calculate performance indicators related to both the quality and quantity of patents generated by each inventor under observation. For this thesis, the set of initial data of interest are represented by those inventors who have filed patents with the target firm at any time before or after the acquisition. From this data pool, more importance is subsequently given to those patents filed not before and not after than 5 years from the date of completion of the financial transaction. Therefore, as described in the following sections, the available datasets have been progressively restructured and aggregated to be more functional to the analysis, moving from the observation unit of the company to that of the inventor.

6.1.1 SAMPLE DESCRIPTION

6.1.1.1 FIRM LEVEL

In order to analyze the impact of the acquisition on the patent activity of the acquired companies, data have been collected according to specific criteria using patents as a basis. A first criterion followed was the selection of **only American companies** operating in **high technology** industries: therefore, all the inventors considered work in this type of sector. Which, as already seen at the beginning of this dissertation, has a high percentage of patents compared to other less 'fast-changing' industries. Second, only **successful patent applications** (i.e. patents granted) have been considered and non-US transactions have been eliminated because due to the greater gap between the geographical, institutional and cultural dimensions, these companies present a number of different challenges to complete the transaction. The reference date taken into consideration is the **first filing date** (or the first priority date) of the simple family of each patent. In parallel, all patents filed were initially considered, and in a second step **only those between - 5 years and + 5 years from the date of completion of the acquisition.**

The productivity of each inventor has been calculated using patent data, which have been used in several studies to measure the production of innovation (e.g., Ahuja et al., 2001), as already mentioned in Chapter 3. We collected information for each company on the nature of the business that was involved before the acquisition, on the stake of the small target company acquired during the acquisition (that must be **higher than 50%**) and on the main financial data. Our main source is the starting database (Thompson + Zephyr – see annex 1) provided by Prof. Aghasi (Cambridge University) and obtained by merging 2 documents called in fact ‘Zephyr’ and ‘Thompson’. After identifying the companies involved in the sample, we measured their patenting activities in order to identify the active inventors to be considered. The actual starting number of acquisitions identified was equal to 319, from where we carried several skimming levels reaching the final value of **127** operations analyzed. It emerged that 39 out of 319 did not present any kind of patent both on the acquirer and target side from the databases used. At this point, of the remaining 280, another 129 were eliminated because the target firm did not present patents. It is supposed to be ordinary as we are considering small companies, often startups, that usually do not have enough cash available to finance patents' applications in well-recognized offices. To conclude other 24 transactions have been removed reaching the final figure of **127** because there were no patents filled by the incumbents in any database used by us. Each of these steps has been accurately doublechecked.

6.1.1.2 INVENTOR LEVEL

469 inventor_id represents the final number of inventors used as a sample in this study, they are therefore referred to as the 127 transactions analyzed. Below we will explain the steps and the main assumptions that led us to this value.

To begin with, an inventor was included when, prior to the year of acquisition, he made at least one successful first deposit with the target company. In addition, we considered as **year 0 the year of completion of the acquisition**, and not the year of the announcement, according to the methodology of Kapoor et al. (2007). Since patents require a variable but relevant time to be developed, the year of the acquisition was considered as part of the **pre-acquisition time window**, consistent with past literature. Using the announcement date, in fact, the probability of innovations that would have been mistakenly counted before the acquisition as part of a post-acquisition result would have increased. By collecting the names of these inventors, we finally investigated the patent history of each of them, with particular attention to the different companies where they worked. As confirmed by previous studies, the analysis of data from different sources is commonly a problem of applied economics, which requires significant time and effort to perform tasks not directly related to the research itself. These inconsistencies can lead to measurement errors, missing values, and small samples, reducing the reliability of any estimate. To create a clean sub-sample with U.S. patent data produced by the target companies and target inventors, we have processed and integrated the previously mentioned data sets using PostgreSQL, an open-source relational database management system (Annex 8). For these reasons, we have relied on PatentsView and PATSTAT jointly to overcome their individual limitations. Later, since some of the companies were missing in all 2 databases, we manually retrieved the information from online sources to check if the missing companies were actually missing.

Further in the dissertation, we will provide more details on how patent data was collected and assembled, pointing out the main obstacles to collecting data from patent databases.

6.1.2 COMPANY DATABASE

To define the patent activity of the target inventors, we first had to identify the names of the target companies. This operation is particularly delicate, due to the lack of standardization of the assignee's name. In order to reduce the impact of word dissimilarities caused by acronyms, names and spelling errors, previous literature has defined well established name harmonization techniques at the assignee level. In recent years, in fact, there has been a growing activity on the problem of ambiguity of names in bibliographic documents (Smalheiser et al., 2009).

6.1.2.1 THE ISSUE OF COMPANY’ NAMES HARMONIZATION

As already mentioned, patent data are collected from patent databases without specific methodological requirements, resulting in a lack of standardization with regard to patent applicants, inventors and metadata (Lotti et al., 2013). The literature of the past has tried to quantify the occurrence of spelling mistakes and the impact on patent research. Harmonization is usually followed by a process of disambiguation, with the aim of facilitating the analysis at patent level. The quality and usefulness of the harmonization procedure is measured in terms of ‘completeness’ and ‘accuracy’. The first refers to the extent to which the name harmonization’ procedure is able to capture all the name variants of the same holder; the second refers to the ability to assign the name variants to a single harmonized name of the patent holder. Due to the limited availability and lack of standardization of applicants' metadata, it is more difficult to distinguish between the repetition of names of the same organization and the presence of different entities with the same name. Of particular importance, and strong motivation for the disambiguation procedures carried out, is the study conducted by Stein and Hoppe (2012), which measured the impact of spelling errors on patent research, pointing out, for example, that 98% of a sample of patents taken from the USPTO database contains errors, most of which are spelling errors. This is largely due to the fact that the names of applicants are filed in accordance with various conventions without checking previous submissions. This generates several problems for statistical analysis, whose determinants can be summarized in 3 macro areas: 'Lack of a unique identifier for applicants and inventors'; 'typing errors in text fields', and 'numerous observations with missing information'.

Special attention should also be paid to mergers and/or acquisitions, name changes and subsidiaries. For example, when aiming at the harmonization of legal entities, all patents held by subsidiaries could be considered as belonging to one legal entity, the holding company. Therefore, when harmonizing legal entities, each patent holder's name must be verified against historical information on naming practices and ownership in order to address these issues. In light of these considerations, the risk of losing relevant information in our sample due to the lack of name standardization was considerably high. As suggested by Thomas et Al. (2010), we relied on more than one patent database to minimize the risk of data loss.

6.1.2.1.1 APPROACH FOLLOWED

The way information is stored, managed, displayed, and searched has become increasingly important. How to deal with it? The Recognition of Named Entities (NER), initially applied in biotechnology, has become a crucial means of extracting information of great value most of the times difficult to find. The NER approach has the potential for interesting applications in economics and management science, especially in the field of data integration at the company level. A simplified but still effective branch of this methodology is the one we have applied: the **dictionary - based approach**. It is based on the collection of great datasets of names and variants of names. Dictionaries are essentially large collections of names, which serve as examples for a specific entity class. The correspondence of dictionary entries with the text analyzed is, as mentioned, a simple and very precise NER method. It can be also used to approximate matching techniques by automatically generating typical spelling variants for each entry. The extended dictionary is then used to obtain exact matches with the text. To be precise, 2 main consequent steps have been followed: **Data Pre-processing** and **Name Clearing:**

- In the **pre-processing phases** (or **characters cleaning**), the data is prepared for processing in order to facilitate the effective cleaning and harmonization of names. Several steps are followed: the individual impact of each step is limited but makes it easier to progress through consecutive steps and significantly increases the overall result. Data preprocessing is highly dependent on the content of the underlying data. Consequently, extensive changes or adaptations may be necessary when processing names from a different data source. Depending on the data source, non-letter characters (A to Z) and non-characters (0 to 9) can be encoded or represented in various ways, inducing further name changes. Generally, character cleaning removes different types of character representations and formatting codes or converts them to standard ASCII characters. For example:
    - HTML formatting codes such as "" are removed or replaced by spaces when possible.
    - Characters accented as "É" are replaced with their non-accented ASCII equivalents.
    - Names may contain not only letters and digits, but also characters such as ",", ";", and "-", used to separate words or to indicate abbreviations and combinations. These characters can complicate the separation or analysis of names into single words, which is necessary for further cleaning steps.

  The purpose of punctuation cleaning is to harmonize all these punctuation characters and thus facilitate the analysis of names into individual words at a later stage. A common process from which we drew inspiration is the following:

    1. Double spaces are replaced by single spaces.
    2. Quotation marks followed by a space that appears at the beginning of a name or preceded by a space that appears at the end of a name, are replaced by a quotation mark without a drag space.

3. Quotation marks are removed from names that have only quotation marks at the beginning and end of the name.
4. Names are scanned for non-alphanumeric characters at the beginning and end of the name, and these characters are removed if necessary.
5. Comma and period irregularities are harmonized so that commas are not preceded by spaces but followed by a space and periods are preceded only by letters or digits.

- During the second phase (or **name cleaning)**, the name is cleaned and harmonized. As mentioned above, our approach takes into account the content of the data; more extensive improvements or adaptations may be necessary when processing names from a different data source. Many patent holder names contain a kind of indication of legal form (e.g. "INC.", "LTD."). These legal form indications are responsible for a considerable number of name variations due to the variety of abbreviations and spellings used. At this stage, the legal form entries are harmonized and moved to a separate section, thus considerably reducing name changes. Legal form indications are separated as they do not constitute a distinctive part of the name; this logic also applies to other words. Especially in the case of companies, additional words such as "CORPORATION" and "COMPANY" do not add anything to the distinctive character of a company name. When two names are found to be identical, except for the presence of such words, the name of the patent holder will be considered as referring to one and the same organization. An example is “IBM” and “IBM CORPORATION”.

  Typographical and spelling errors are responsible for considerable variations in the name. These types of errors can be identified by evaluating word similarities. While this type of analysis is simple for common English words, proper names usually require a manual validation effort to ensure accuracy. For example, "AMTECH" and "IMTECH" differ only by a single character, but it would be wrong to automatically assume that the names refer to the same patent holder. For frequent words and language variations can be observed without ambiguity and thus harmonized effortlessly. The harmonization of spelling variations replaces all common word variants with a harmonized variant that can be used to match name variants. Significant name variations are also caused by word separation, punctuation and non-alphanumeric characters, which clearly have no relevance in identifying the distinctive features of a name (e.g. "IBM" and "I-B-M"). Condensation removes all non-alphanumeric characters so that a harmonized variant can be used to match names.

This approach has been successfully applied to all company names. Then, to finalize the database, for each company we have defined all the other relevant data. Special importance has been put in the respective technological profile based on the **IPC** codes associated with their patents, and **SIC** codes associated with the industry, useful to define the **Technology Overlap** and the **Market Relatedness** between the acquirer and the target, respectively. In addition, SIC codes were also crucial in determining the **Experience of the Acquirer.**

Note: ‘Experience of the Acquirer’ has been incorporated in the database after the merge with the database 'Merge_Thompson_Zephyr' discussed in the next section (6.1.2.2)

6.1.2.2 MERGE THOMPSON – ZEPHYR

Once all the 127 core transactions were correctly identified, they were used as a starting point for a more in-depth study related to the 'Experience' variable. In particular, Professor Keivan provided us with the same two initial databases of the research (Thompson and Zephyr), but this time containing not only the transactions of our interest but also all the other acquisitions made by the aquirors in object in the **5 years preceding our base sample**. This means that since our base sample is composed by transactions made from 2006 to 2015, the new transactions considered will vary **between 2001 and 2014**.

In order to obtain this result, it was necessary to implement a merge between the two databases, by standardizing the columns with different names according to the selected one. The final result was the 'Merge_Thompson_Zephyr' database (see attachment 7), composed of 44 columns + 3 related to experience indicators: 'General Experience in acquisitions', 'Experience in High-Tech acquisitions' and 'Experience in Similar acquisitions' (see Section 6.2.2 for more details). The former is precisely one of the three independent variable of our research

To conclude, the file ‘Merge_Thompson_Zephyr’ has been combined with the previous Firm level, enriching it not only with columns on the ‘Experience’ variable but also with many other complementary data related to the focal transactions or to the specific acquirer/target in object (see annex 7).

6.1.3 INVENTORS DATABASE

The inventors' dataset was built as follows. Starting from the list of successful patent applications generated by the company in the years before the acquisition, we have retrieved the related "patent_id". A methodological question was related to which patent to consider; as mentioned in chapter 5, the concept of "family" affects many patent searches and there are various definitions of how to link different patents into "families". Past studies are mainly based on the DOCDB patent family (i.e. simple families), defined as the set of applications that share the same priorities. These families aggregate patents that claim exactly the same priorities. However, it can happen that an inventor starts working on a development project for the continuation of a patent, which would not represent a first filing. In fact, the continuation of a patent is defined as patents filed by an applicant who wants to pursue further steps in an invention disclosed in a previous application. In the application for a continuous, the invention must include at least one inventor named in the previously filed application (USPTO Manual, 2019). Therefore, when reference is made to the performance of inventors, considering only the first filing of DOCDB families, there is a risk of negatively affecting the productivity of the inventor, not considering the incremental effort of active inventors in the continuation of the patent. In other words, for each inventor we counted one patent per family, taking the oldest one, regardless of its nature of first filing. To carry out this analysis we based on PATSTAT data, and in particular on 4 tables, as did Cardanelli, A. et al. (2019): TLS204_APPLN_PRIOR, TLS216_APPLN_CONTN, TLS205_TECH_REL, TLS201_APPLN. Therefore, to be included in our sample of inventors**, an inventor must have been the applicant for one or more of these patents**, which we will call key patents.

6.1.3.1 APPROACH FOLLOWED

In order to effectively outline the patenting activity of the target inventors during their career, a singular identifier should be applied to each of them. However, the unique identification of inventors presents significant challenges: the USPTO does not require inventors to have unique and consistent identifiers. When talking about 'consistent', **four** distinct issues need to be overcome according to Smalheiser et al. (2009). First, a person can publish under several names; second, many individuals have an equivalent name; third, the metadata needed to differentiate between individuals is often incomplete or completely missing; and finally, not only is the share of multi-author scientific articles increasing, but also multidisciplinary and multi-institutional efforts.

This lack of standardization makes it more difficult to identify inventors, especially identical names could also be mentioned different inventors and inventors with common surnames may result in possible underestimation of patents. In addition, incomplete data on female inventors who have changed their names due to marriage may also cause mismatches (Hoisl, 2007b). To address this problem, PatentsView relied on Lai et Al. and past literature on the disambiguation of inventors (Raffo et al. 2009; Carayol et al., 2009) (Introduced in Chapter 5) to develop an algorithm that was integrated into the PatentsView data platform in March 2016. The algorithm uses hierarchical discriminating coreference as a replacement approach to extend the PatentsView data standard and was developed by the research team led by A. McCallum and N. Monath. In particular, it disambiguates the inventors by looking: First name, surname; Similarity in patent title / Abstract; Common Position; and other entries.

After retrieving each inventor's patent portfolio, we examined the inventors' mobility and omitted those inventors who patented outside the target company before the acquisition date. Consistent with previous studies (Kapoor et al., 2007), inventors who patent elsewhere after the acquisition date are considered within the analysis and classified as "leavers". In addition, inventors who no longer patented after the acquisition are considered as part of the sample, since their removal could have affected our study. However, in line with previous studies (e.g. Kapoor et al. 2007) and our research demand, **our interest is linked to those active inventors** whose performance is often addressed through patent analysis.

Another point to mention, is that patent data can also lead to an overestimation of inventors' mobility. The fact that inventors have filed a patent with a special company does not automatically mean that the inventor has changed jobs. For example, a strategic alliance between two companies may be a possible explanation for 2 different applicants. It is essential to pay close attention to the succession of patents of an equivalent inventor. To give an example, in case an inventor initially registers a patent with a company X, in the following year with Y, then again with X, we do not consider moving the inventor because it is assumed that he worked on the project with Y in conjunction, without leaving X. A second case, similar the previous one, is where an inventor shows simultaneously an equivalent ID_PATENT with an equivalent date in 2 different companies. Probably a partnership has occurred between the two, so it is not considered a possible shift.

The final sample consists of the results of an aggregation activity carried out on three different databases: company level, inventor level and then the database provided by Aghasi 'Thompson + Zephyr'. As always with the help of SQL Postgres, we were ready to build the database used in the econometric model. The database was built in such a way that each column represents an explanatory variable (which will be explained in the next section). Then, once linked for each inventor the patents he has made in his career (i.e. PATENT_ID), we were ready to attach several quality indicators to each patent. So, by dividing patents into pre- and post-acquisition we determined the typical value per indicator within the time windows (+/- 5 years), thus having average quality values per inventor. Below, we are going to show the variables that are able to make the econometric model work. We have three dependent variables and for each of them we would like to search the relationships with the independent variables.

6.2 VARIABLES

6.2.1 DEPENDENT VARIABLES

Three dependent variables are presented below, one measures the variation in productivity, while the other two are variables that seek variations in patent quality. The objective is to measure not only the variation in terms of the number of patents filed, but also how the quality of these patents has changed since pre-purchase.

- **Change Inventor Productivity**

  The variable represents the difference between the number of patents generated by the inventor in the five-year window after the acquisition and five years before the acquisition.

  $$\Delta \textit{ Patents productivity} = \#\textit{Patents } (0; +5) - \#\textit{Patents } (-5; 0)$$

  The productivity of each inventor before and after the acquisition of the patent has been measured, considering in both cases a time window of five years.

- **Change Inventor Patent Breadth**

  In 1994, Lerner proposed an index that determines the extent of the patent in terms of the number of different 4-digit subclasses of the International Patent Classification (IPC). The index is described as (Squicciarini et al., 2013):

  $$SCOPE_P = n_p \; ; \; n \in \{IPC_1^4; \dots; IPC_i^4; IPC_j^4; \dots; IPC_n^4\} \; \& \; IPC_i^4 \neq \; IPC_j^4$$

  Where, n_p is the number of different 4-digit IPC subclasses. Thus, as the number of distinct 4-digit IPC classes increases, the broader the index and the higher the technological and market value of the patent. He also noted that the breadth of patents in the company's portfolio significantly affects the value of the company and that patents with a significant breadth are more attractive when many potential replacements are admissible. A few years later, Matutes et al., (1996) examined patent focusing on duration and scope and proposed that the scope of the patent should be used to encourage early disclosure of basic inventions. The "**Change Inventor**

Patent Breadth" draws its origins from these theories and today it is measured and defined as the difference between the average breadth of patents generated by the inventor in the five-year window after acquisition and five years before acquisition.

$$\Delta \textit{ Breadth} = \textit{Average Breadth } (0; +5) - \textit{Average Breadth } (-5; 0)$$

- **Change Inventor Patent Quality Index 4**
  Previous studies have developed several patent indicators with the aim of capturing not only the technological but also the economic value of innovation. The Change Inventor Patent Quality Index 4 is a composite indicator based on four dimensions of basic patent quality: **forward citations, size of the patent family, number of claims, backward citations**. It is determined as the difference between the average quality of patents generated by the inventor in the five-year window after the acquisition and the five-years window before.

$$\Delta \textit{Quality index} = \textit{Average quality index } (0; +5) - \textit{Average quality index } (-5; 0)$$

It should be noted that the original formulation of Lanjouw and Schankerman (2004) assumes that all components play an equally important role (same weights). This has been decided since the exploratory analysis showed that the weights differ between the various technological fields and depend on the time span considered and the OECD has therefore decided to give equal importance to all components, leaving to future researchers the task of identifying the coefficients that best reflect the relative importance of the various quality factors. Clearly, although the OECD indicator tries to summarize a complex and multidimensional issue such as the quality of patents, it nevertheless suffers from the usual limitations of all composite metrics, and therefore must be carefully analyzed.

6.2.2 INDEPENDENT VARIABLES

- **TECHNOLOGY OVERLAP**

  The International Patent Classification (**IPC**) is used to define the distribution of target and acquirer patents in different technology sectors and captures the extent to which two companies develop technology in the same classes. Grimpe and Hussinger (2014), based on recent literature, used the three-digit IPC level (Makri et al., 2010) and generates a measure of patent stock for each three-digit IPC class. The researchers defined the technological relatedness as the angular separation of the distribution vectors of the patent class F of the acquirer j and the target company i. The technology vectors F for each target i and buyer j can be interpreted as their technology portfolio. These vectors are used as a percentage of the total patent stock in order to disregard the differences in patent portfolio size between the patent portfolio of the target and that of the acquirer. In technical terms, the T correlation measure is equal to the normalized scalar product of these vectors. The formula is the following:

$$\boldsymbol{T_{ij}} = \frac{\boldsymbol{F_i \cdot F_j}}{\sqrt{(\boldsymbol{F_i' \cdot F_i})(\boldsymbol{F_j' \cdot F_j})}} \qquad \boldsymbol{0 \leq T_{ij} \leq 1}$$

  where 0 represents the absence of correlation of the patent portfolios of companies, while a higher value indicates the correlation. Of course, 1 means complete correlation.

- **MARKET RELATEDNESS**

  The same concept of Technology Overlap has been subsequently elaborated also at **SIC level**, where it has been taken into consideration no longer the technological sectors of the single patents, but the industrial sectors in which acquirers and targets operate. To be precise, it represents the relatedness between the target and acquirer based on the number of unique common 3-digit SIC codes between them divided by the unique total number of target 3-digit SIC codes.

- **ACQUIRER EXPERIENCE (LOG)**

  Given a financial transaction X between an acquirer and a target, it indicates the sum of all acquisitions made by the former in the 5 years prior to acquisition X. Each acquisition has an identical weight equal to '1'; the result will therefore be a positive integer ranging between 0 and +∞. The formula is the following:

  $$\sum_{i=1}^{5} A_{yearX-i} \; ; \; A = 1$$

  Where 'yearX' indicates the year of the focal acquisition X.

  For example, if X happened in 2012, all acquisitions made by the acquirer between 2007 and 2011 would be taken in consideration, each of them weighted as '1'.

  In the model it will be used the natural log transformation of the variable.

6.2.3 CONTROL VARIABLES

Concerning the inventor level, **five** control variables are used: Number of Patents, Patents Breadth, Patents Quality, Inventor Female and Inventor Tenure. They are calculated in the pre-acquisition period. When analyzing companies instead, **seven** were selected: Relative size, Target VC-backed, Target Age, Target Listed, Target Size, Industry Factors and Year Factors. While the inventor level data were based on our database, the variables at the company level were collected with the help of Prof. Aghasi.

1. **Number of Patents Before Acquisition for each Inventor**

   We checked for inventors' productivity before the acquisition by obtaining the number of patents assigned to each inventor in the five years preceding the acquisition. Ahuja and Katila (2001) also used a five-year pre-acquisition window because, as Griliches (1979) said, technological knowledge depreciates rapidly and loses most of its value during that period.

2. Inventor Breadth of the Patents Before the Acquisition

Similarly, the previous variable is determined as the average breadth of patents generated by the inventor in a window of five years before the acquisition.

3. Quality Index (4) of Patents Before Acquisition

It refers to the quality index expressed in the control variables. Also in this case, it is an average quality of the patents generated by the inventor in a window of five years before the acquisition.

4. Inventor Male

This variable simply indicates whether the inventor is "Female" or “male”: it is equal to 1 if the inventor is male and 0 if female. In our sample, the numbers for males are much higher than those for females (about 90% to be precise).

5. Inventor Tenure (log)

The last control variable of the Inventor level is calculated as the number of years between the date the inventor filed his first patent with the target company and the year of completion of the acquisition. It is used to take into account changes in an inventor's productivity during the working period in the target company. In the model, we use the natural logarithmic transformation.

6. Relative size

We determined the relative size as Kapoor and Lim (2007) did, dividing the number of inventors of the target by the number of inventors of the acquirer in the year of acquisition. We assume that the higher their number, the bigger the company they work for. In our opinion, it is necessary to check the relative size of the companies as they can influence both the propensity to acquire or not a potential target and guide the preference for a full or partial integration. On the one hand, the larger the target, the greater the likelihood that it will require greater post-acquisition autonomy (Ranft et al., 2002); on the other hand, as the size decreases, integration tends to be more complete because the acquirer can exert greater influence through greater decision-making power (Pablo, 1994).

7. Target VC – Backed

This variable is equal to 1 if the target is supported by VC before the acquisition and 0 otherwise.

8. Target Age

This variable indicates the age in years of the target firm at the time of acquisition. It is the difference between the acquisition year in object with the foundation year of the target.

9. Target Listed

Dummy variable equal to 1 if the target was a listed company before the acquisition date, 0 if not.

10. Target Size

This variable expresses the most updated number of employees in the target company before the acquisition date.

11. Industrial Factors

We have used a dummy variable to monitor the Industrial Factors. We have classified the acquirer by sub-sectors using the SIC codes. In this way, since our sample includes acquired companies operating in five sectors (Pharmaceuticals, Electrical and Electronic Equipment, Office and Computer Equipment, Computer Programming and Aerospace) we can control the heterogeneity of the sub-sector taking into account possible different attitudes towards post-acquisition integration that could characterize each of them.

12. Year Factors

As in the previous case, we have used a fictious variables. To be precise, 10 dummy variables, one for each year in which the acquisition was completed, keeping the others at zero. In doing so, we considered the possible impact of an acquisition made in different years. In fact, depending on the specific year, different macroeconomics factors could impact heavily on results.

6.3 MODEL SPECIFICATION

We estimate the effect that **Technological Overlap, Market Relatedness** and **Experience of the Acquirer** have on the innovative performance of the acquired inventors, measured by observing their patent production, USPTO patents by application date in a time window ranging from -5 and +5 compared to the year of completion of the acquisition. We use 2 different model specifications to study the three dependent variables: a Tobit model and an OLS (Ordinary Least Squares) model.

1. The Tobit model specification assumes a Gaussian linear regression model for the latent variable Y*, expressed as:

$$y_i^* = x_i' \beta + u_i$$

Assuming:

- Independent X and u
- $u \sim N(0, \sigma^2)$

Where the observed value y is defined as $y_i = \begin{cases} y^* & \text{if } y^* > 0 \\ 0 & y^* \leq 0 \end{cases}$

It is used for the conditioned average of a variable Y given a regressor vector X. In particular, when the Y variable is a censored or truncated version of a Y* variable that cannot be directly observed.

2. The OLS (Ordinary Least Squares) model specification is expressed by the following formula:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + u \quad n = 1, \ldots, 15$$

Assuming:

- Mean Zero. $\mathbb{E}(u) = 0$
- Common Variance. $Var(u) = \sigma^2$
- $u \sim N(0, \sigma^2)$

In this way it is assumed that a set of explanatory variables, collected in an X vector, can explain the impact on innovative performance. The set of coefficients β reflects the effects that the variations of X have on y. The u coefficient contains all the other factors that influence y, except for X.

6.3.1 MODELS

To test the hypothesis made in Chapter 4, we use two **Tobit** models together with an **Ordinary Least Squares** model. In each model the dependent variable changes as we are interested in investigating the impact of several explanatory variables on the innovative performance of the inventors.

As far as the control variables are concerned, **in every model all of them are applied** (both inventors and companies).

- **Model I (Tobit)**: The dependent variable is the *Change in Inventor Productivity*
    - Technology Overlap
    - Market Relatedness
    - Acquirer Experience (Log)
    - Nr Patent Inventor (Pre-acq)
    - Patent Breadth Inventor (Pre-acq)
    - Quality 4 Index Patent (Pre-acq)
    - Inventor Female

    - Inventor Tenure (Log)
    - Relative Size
    - Target VC-backed
    - Target Age
    - Target Listed
    - Target Size
    - Industrial Factors
    - Annual Factors

- **Model II (Tobit):** The dependent variable is the *Patent Breadth Inventor*
- **Model III (OLS):** The dependent variable is the *Patent Quality Index*.

Tobit is recognized to be a better estimator when the dependent variable is a count data as is the case for the dependent variables in Model I and II, this is the reason why it has been chosen.

CHAPTER SEVEN

EMPIRICAL RESULTS

7.1 DESCRIPTIVE STATISTICS AND CORRELATION ANALYSIS

	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Change inventor productivity	-1.424	16.875	-107	91	1														
2. Change inventor patent breadth	-10.207	80.199	-554	559	0.85	1													
3. Change inventor patent quality	-9.882	10.663	-70.14	33.08	0.09	0.06	1												
4. Technology overlap	0.788	0.203	0	1	0.07	-0.02	0.12	1											
5. Market relatedness	0.59	0.306	0	1	-0.1	-0.06	-0.03	0.28	1										
6. Acquirer exp (log)	1.874	0.674	0.693	4.007	0.24	0.27	0.02	-0.09	-0.26	1									
7. Inventor Nr patent (preacq)	7.397	12.907	1	117	-0.79	-0.63	-0.09	-0.06	0.11	-0.07	1								
8. Inventor breadth patent (preacq)	30.874	62.329	1	578	-0.7	-0.81	-0.1	0.02	0.09	-0.13	0.83	1							
9. Inventor quality index (preacq)	17.436	11.467	1	77	0.11	0.1	-0.64	-0.09	-0.08	0.27	0.03	-0.01	1						
10. Inventor female	0.183	0.387	0	1	-0.12	-0.13	0.01	0.12	0.07	-0.17	0.02	0.07	-0.16	1					
11. Inventor tenure (log)	1.494	0.642	1	2.485	-0.14	-0.13	-0.06	-0.08	0.02	0.13	0.33	0.29	0.11	0.01	1				
12. Relative size (inventor)	0.202	0.36	0.001	3	0.03	-0.03	-0.08	-0.22	-0.02	-0.01	0.02	0.04	0.01	-0.08	0.14	1			
13. Target age	20.388	9.705	5	54	-0.28	-0.28	-0.08	0.04	0.08	-0.5	0.11	0.19	-0.38	0.26	-0.01	-0.05	1		
14. Target VC-backed	0.82	0.17	0	1	-0.03	-0.04	-0.2	0.08	0.07	-0.14	0.04	0.05	0.09	-0.01	-0.08	0.05	-0.13	1	
15. Target listed	0.68	0.467	0	1	-0.13	-0.18	-0.23	-0.07	-0.17	-0.23	0.06	0.15	-0.05	0.1	0.05	0.22	0.43	0.23	1
16. Target size (employee)	243.819	130.385	2	496	-0.16	-0.12	-0.21	-0.2	-0.25	-0.1	0.08	0.08	-0.09	0.07	0.11	0.05	0.39	0.02	0.44

Table 1 - Descriptive Statistic & Correlation Matrix

Table n. 1 provides descriptive statistics and correlations for the variables used in the analysis. As shown, observing the dependent variables, together with the control variables at the inventor level, it can easily be verified that the sample of 469 inventors has suffered an overall drop in innovative performance. In fact, patent productivity during the post-acquisition period has experienced an average decrease of 1,424 patents per inventor. This result shows a percentage reduction of **19.25%**, considering that the average number of patents per inventor in the pre-acquisition window is about 7.4. Observing now what happened to the breadth of patents, also in this case a decrease has been recorded, specifically the patents filed by inventors had a decline in the number of 4-digits IPC codes registered of about 10.2 per patent (**33.06%** of the pre-integration value). Finally, moving on to the variable that looks at quality changes, the quality index (4) has decreased by almost **57%**, from 17,436 to 7,554.

At this point, we focus on the independent variables that are the focus of our analysis. With regard to the Technological Overlap between target and acquirer, the average value stands at around **0.788**. While it can be noted that the Market Relatedness is lower (**0.59**), although still high. This suggests that even if companies are not always in the same specific sub-sector (inside the high-tech world), they will tend to generate similar patents at the IPC level. The third and last independent variable in object is the Experience of the Acquirer in logarithmic scale equal to **1,874** acquisitions on average. It can be verified how the minimum value is still positive (0.674), a figure that shows that all the acquirers taken into consideration were already 'trained' with previous acquisitions before completing one of the 127 focal ones and, according to past literature, it has almost certainly contributed positively to the final figures.

Moving on the relationships between control variables, it is interesting to note the negative correlation (- 0.38) between the average age of a target company at the time of acquisition and the quality of the patents of the inventors inside, to mean that the more the company is young and therefore close to the start-up world, the higher could be the quality of the patents produced inside. This is probably due to the greater flexibility and propensity to experiment in order to diversify from incumbents already in the market. To add another point, the 82% of the targets are supported by VC at the date of the acquisition, which leads to the conclusion that there is a strong propensity of small and young companies in high-tech sectors to allow the entry of risk capital funds in their business. On the other hand, it is shown how it is less likely that VCs make investment decisions towards target companies with a high relative size (only 2%). The correlation matrix reveals also that the highest relation between two variables is between the size of the target expressed in number of employees and whether it is listed or not, which is 0.44. This value was to some extent expected, since a listed company is supposed to be quite developed, hence have a high number of employees on average. In the same way, a similar correlation of 0.43 between 'target listed' and 'target age' can be noted, because it is assumed that the longer (in years) it operates, the higher the chances to be listed.

Last, a good level of correlation, 0.33, links inventors' number of patents filed in the pre-acquisition phase and their tenure. In fact, the higher the time between the first filling and the acquisition date (tenure), the longer the time available to the inventor to patent new inventions compared to others.

Four other correlations catch our attention, all negatives:

- Technology Overlap and Relative Size (Inventor): - 0,22
- Market Relatedness and Target Size (Employees): - 0,25
- Acquirer Experience (Log) and Inventor quality index (pre-acq.): - 0.27
- Acquirer Experience (Log) and Target Listed: - 0.23

In conclusion, it is interesting to note that there is a very low correlation (3%) between quality indicators and the number of patents. If fact, we have highlighted an average reduction of 19.25% in productivity and, at the same time, a – 57% in quality (more than double). This aspect further confirms the importance of considering quality measures to evaluate inventors' performance and to effectively distinguish between high and low performance indicators.

In light of the above considerations, even if some of the variables have proven to be partially correlated, the results are such that no further correction is required.

7.2 RESULTS

VARIABLES	Model I	Model II	Model III
Technology overlap	6.805***	19.62***	4.094**
	(2.067)	(6.229)	(1.989)
Market relatedness	5.835***	18.45***	0.717
	(1.605)	(4.821)	(1.575)
Acquirer exp (log)	1.568**	5.258**	1.331*
	(0.730)	(2.196)	(0.714)
Inventor Nr patent (preacq)	-0.620***	0.777***	0.0204
	(0.101)	(0.173)	(0.0475)
Inventor breadth patent (preacq)	-0.0854***	-1.113***	-0.00309
	(0.0188)	(0.0620)	(0.00956)
Inventor quality index (preacq)	0.0142	0.00173	-0.702***
	(0.0355)	(0.106)	(0.0344)
Inventor female	-1.397	-3.567	-0.226
	(0.896)	(2.719)	(0.848)
Inventor tenure (log)	2.150***	5.984***	0.363
	(0.597)	(1.774)	(0.568)
Relative size (inventor)	4.440***	16.30***	-3.164***
	(1.405)	(4.476)	(1.152)
Target age	-0.0626	0.152	-0.283***
	(0.0603)	(0.182)	(0.0588)
Target VC-backed	0.113	-0.426	-9.121***
	(3.433)	(10.30)	(3.386)
Target listed	-1.901	-10.00**	2.822**
	(1.390)	(4.201)	(1.357)
Target size (employee)	-0.00457	-0.0327*	-0.00308
	(0.00603)	(0.0183)	(0.00576)
Time & Industry dummies	Yes	Yes	Yes
Constant	-7.271	-25.87*	7.731*
	(4.691)	(14.08)	(4.608)
Observations	469	469	469
R-squared	0.183	0.180	0.578
LR	541.16***	698.40***	
F statistic			25.07***

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

Since we used the same explanatory variables for each dependent variable, we decided to explain our estimates by analysing the results by variables and not by models, focusing on those relationships that are particularly significant. First, looking at the R-Squared values, it indicates that among our models, the one that explains most variations in innovative performance is the third (OLS), with a percentage close to 58%. At first glance, it seems that several coefficients are statistically significant, and among them in each model we have the three independent variables to support our assumptions. We are pleased to see that **all hypothesis has been verified** as it will be explained in the following lines.

Starting from the first variable, we can understand that there is a positive relationship between Technology Overlap and post-acquisition innovative performance of the inventors. The model III presents in fact a significant value ($p < 0.05$), and the data is even reinforced by the other two models where $p < 0.01$. This is in line with the hypotheses and with what has been said in the previous chapters, a Technological Overlap between 2 companies favours the performance of the inventors after the acquisition. The concept is perfectly in line with Kapoor et Lim. (2007), where they have verified how the overlap of competences (measured as the degree of relatedness between the granted and cited patents of an acquired company and those of the acquiring company before the acquisition) has a positive effect on the post-acquisition productivity of the acquired inventors. In fact, this allows a smoother integration, blocking in advance the emergence of further barriers to innovation.

In the same way, there is a strong relationship between performance and Market Relatedness. Also in this case, we refer to a positive correlation where the significance remains very high in the first two models ($p < 0.01$); but decreases in model 3. These results are in line with the second hypothesis, concluding that the greater the correlation at market level, the greater the probability that it leads to synergies and consequent increase in innovative performance.

The third and final independent variable is the Acquirer Experience. Like the two previous ones, it is positively correlated with the post-acquisition performance, exactly in line with hypothesis 3. The significance is high for models I and II where $p < 0.05$ while it is lower, but still noteworthy, in model III ($p < 0.1$). It is assumed that an acquirer with previous experience in terms of acquisitions has already absorbed a certain methodology in making them. We refer to the concept of 'learning by doing' which explains how a company learns from its past actions (usually mistakes) in order not to repeat them in the future if negative, going to improve the general performance.

Noteworthy is the variable 'relative size' that proves to be very significant in all three models ($p < 0.01$). It is clearly seen how it goes from positive for the first two models to negative in model III, when the variation in quality as a dependent variable is taken into account. This means that a high number of inventors in the target compared to the acquirer leads to an increase in productivity post-acquisition but to a decline in the average quality of individual patents, probably due to the fact that it is not possible to integrate all of them successfully in a short period of time. Similarly, also the number of patents filed by inventors in the pre-acquisition window is negative in the first model, while it goes positive in the following ones, maintaining a very high significance at $p < 0.01$ in the first two. This suggests that, since the number of patents before acquisition is high, there are greater chances of seeing a decrease in post-acquisition productivity; however, when moving towards quality variation, the relationship is reversed.

7.3 ROBUSTNESS CHECK

Although the estimates have successfully confirmed all our assumptions, we have decided to test the robustness of our results again by repeating the analysis in a narrower time window. In particular, in **the time frame -3 years / + 3 years from the date of acquisition**. Exactly as before, we based ourselves on a Tobit model for the first two dependent variables (productivity and breadth) and on an OLS model for the last one (quality). Table 1 shows the new results obtained.
Taking in consideration the R-Squared values, we can easily verify that also in this case the model VI is definitely the one with the highest value (about 56%), followed by the model V and the model IV with values between them very close. This means that the independent variables explain quite well most of the variations of the innovative performances.

VARIABLES	Model IV	Model V	Model VI
Technology overlap	2.761*	4.405	3.811*
	(1.436)	(2.696)	(2.162)
Market relatedness	5.938***	8.199***	4.665***
	(1.129)	(2.148)	(1.726)
Acquirer exp (log)	2.169***	4.734***	0.368
	(0.520)	(0.987)	(0.792)
Inventor Nr patent (preacq)	-0.793***	0.200**	0.110*
	(0.0732)	(0.0874)	(0.0584)
Inventor breadth patent (preacq)	-0.0740***	-1.074***	-0.0382*
	(0.0263)	(0.0432)	(0.0223)
Inventor quality index (preacq)	0.00881	-0.00114	-0.801***
	(0.0316)	(0.0605)	(0.0478)
Inventor female	-0.724	-1.140	-0.0598
	(0.626)	(1.191)	(0.928)
Inventor tenure (log)	1.064**	2.382***	0.550
	(0.428)	(0.797)	(0.630)
Relative size (inventor)	2.271***	2.657*	-0.247
	(0.852)	(1.557)	(1.252)
Target age	-0.146***	-0.0561	-0.473***
	(0.0421)	(0.0806)	(0.0644)
Target VC-backed	3.128	6.914	-14.26***
	(2.365)	(4.535)	(3.648)
Target listed	-2.911***	-7.914***	2.774*
	(0.968)	(1.854)	(1.473)
Target size (employee)	0.00267	-0.00442	0.00232
	(0.00450)	(0.00859)	(0.00683)
Time & Industry dummies	Yes	Yes	Yes
Constant	-2.177	-9.726	16.12***
	(3.301)	(6.317)	(5.066)
Observations	496	496	496
R-squared	0.267	0.286	0.564
LR	755.97***	1057.13***	
F statistic			22.81***

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

Table 3- Robustness Test

All in all, the results confirm our thesis on the positive impact that the Technological Overlap, the Market Relatedness and the Experience of the Acquirers exert on the performance of the inventors in the post-acquisition period. As expected, therefore, the results are robust when the time window is reduced. Observing the number of observations of this robustness check, it can be seen that it has increased compared to previous results (496 vs. 469). This occurred because, as we have already indicated, we want to measure only those inventors who remained in the targets and/or acquirers, to measure their change in performance. So, by narrowing the time window to (-3; +3) the number of people leaving the company in 3 years is lower than the number of those who left in 5. This difference is exactly equal to 27 people, which leads to a value of 496 inventors.

Part Three – Conclusions

CHAPTER EIGHT

CONCLUSIONS

8.1 DISCUSSION AND IMPLICATIONS

This thesis contributes to the development of post-acquisition performance studies, shedding light on key variables that can affect the general performance of acquired inventors; we add to the debate that sees inventors as the main drivers of competitive advantage and as determining factors for the success of acquisitions in high technology sectors. Indeed, in the context analyzed, consisting of technology acquisitions made between 2006 and 2015, the key assets of the organization have been identified in the technological expertise rooted in the knowledge of its highly qualified inventors (Grant 1996).

Taking companies only as reference units, in fact, we could run the risk of neglecting aspects such as the social context, overlapping skills and cultural compatibility that have proved fundamental to implement effective decisions. In this regard, this research has explored the micro-foundations of previous studies at the company level, providing a basis for their arguments. Going into the details of the dissertation, our results show how ex-ante conditions can strongly influence the outcome of acquisition of small high-tech companies, leading to its potential failure or success. In fact, **we argue that (i) Technological Overlap, (ii) Market Relatedness and (iii) Experience of Acquirers reduce the possibility of potential organizational trauma that may occur as a result of an acquisition, positively influencing the performance of inventors**. Indeed, in Chapter 7, we have empirically demonstrated that the innovative performance of the inventors is positively correlated with the degree of Technological Overlap between the acquirer and the target (ex-ante), with the degree of Market Relatedness between the acquirer and the target (ex-ante) and with the Experience in previous acquisitions of the acquirer.

In a Knowledge-Based View perspective (Chapter 1), we consider the delta in performance of the acquired inventors as a key factor for the acquisition success. Always following this line of reasoning, we believe that the Technological Overlap has positive effects on coordination, knowledge sharing, interaction and communication between inventors as well as on their monitoring and evaluation. In fact, there is an agreement in the previous literature that in highly specialized sectors, familiarity with procedures is crucial to effectively monitor employees' performance. On the other hand, when there is a mismatch between the skills of the acquirer and those of the target company, it becomes difficult to monitor and incentivize employee activity, with negative consequences in terms of general performance.

As already mentioned, there is evidence that technology acquisitions have above-average failure rates, with most of them failing due to dysfunctions in the social and organizational context (Paruchuri et al. 2006). Our study confirms these hypotheses (see results on Dependent Variables) and adds to the research flow that aims to identify the relevant factors that most influence the behaviours of inventors in post-acquisition cases. In particular, we have drawn inspiration by 2 fundamental studies in line our main results, but at the same time we have introduced important methodological measures that have increased the completeness of the research:

- The first study in question is the one of Kapoor et Lim. (2007), in which they took into account both the above mentioned KBV and the Incentive-Based View and showed how these two theories complement each other in explaining the decline in inventors' post-acquisition performance when there is a low level of knowledge overlap between acquirer and target. Although our first discovery may seem very similar to Kapoor and Lim (2007), the empirical analysis changes widely. Their study, in fact, focuses only on the high-tech industry and considers as a dependent variable **just the productivity of inventors**, measured through their patents. However, this approach may be misleading in effectively assessing inventors' performance, especially when referring to small high-tech acquisitions. As mentioned in Chapter 1, the rationale behind small firms' technology acquisitions is often linked to the need to introduce radical innovations within the firm. However, considering patents as a measure of just inventors' productivity, there would be the risk of overestimating the impact that complementary assets could have on inventors' performance by not effectively measuring the innovative contribution of the acquired inventors. In fact, it could be highly possible that the acquired inventors do not reduce their production of patents, in terms of number of patents, but instead **reduce the quality of their production** after entering the acquiring company. The patent indicators considered by us aim to overcome this problem by including in the model information on the scope and quality of the patent (indicator composed of forward and backward citations, number of claims, family size). This is confirmed by the result of our model, according to which among the 304 inventors who have increased their patent productivity (number of patents) at the acquiring firm, more than 56% (174) have experienced a reduction in patent quality.

- The second main theory taken into consideration by us is the one explored by Ernst and Vitt (2000), who identified the size of the acquired company (used as a control variable in our model), cultural differences and technological correlations as determining factors in the organizational breakdown and departure of inventors. Also in this case, similarly to the theory of Kapoor et Lim (2007), the argument and the dependent variable are partially analogous to the ones inside our thesis. The big change is within the **observation unit**. We have analyzed not only key inventors, but a broader range. In fact, they focused their analysis just on the former, running the risk of distorting the estimate downwards by **not measuring the potential of other inventors**, who could increase their performance once they arrived at the acquired organization.

In summary, past research has investigated the key management decisions that led to successful post-acquisition implementation; however, in the majority of cases, it has not taken the inventor as the main unit of analysis, remaining at a higher level of aggregation (i.e. company). Currently, this type of detail-oriented approach is gaining more and more ground in the literature; having said that, just the surface has been scratched by now. Our research looks precisely in this direction and highlights the fact that this fine-grained approach is definitely worth exploring. In fact, important findings have been discovered:

- The decline in performance of the target inventors in the post-acquisition period is in line with previous studies, but our results show that the performance of the inventors depends **heavily on technological overlap and market relatedness** between the acquirer and the target company. Acquisitions characterized by higher levels of overlap have seen a **lower reduction in the performance of the target inventors, which in some cases were even better than ex-ante**: the results show that the overlaps allow the target inventors to **maintain or improve not only productivity, but also the breadth and quality of their patents**.
- Similarly, our study shows that the **acquirer experience** has a direct impact on both the **breadth and quality of patents**, as well as **productivity**. Experienced acquirers can more effectively **support the capabilities of target inventors**.

In conclusion, this dissertation offers several contributions to the literature. First, it provides methodological evidence of an alternative, not yet widely explored in the literature, to measure acquisition success. In fact, we propose a methodology not previously explored by scholars due to the high number of patents under examination needed to complete the study. In fact, not only considering the first filings, but also the continuation of patents, we argue that it is possible to better estimate the actual performance of inventors, without neglecting the incremental efforts of employees acquired. Subsequently, through extensive use of quality indicators, we have provided a fine-grained analysis of the inventive step of a relatively large sample of inventors, providing a higher level of detail than previous studies dealing with the same topic.

We would like to conclude highlighting again that our analysis provides evidence of 3 key variables that studies should mandatorily take into account when implementing an acquisition: **Technological Overlap**, **Market Relatedness** and Preacquisition **Acquirer Experience**.

8.2 LIMITATIONS AND FUTURE RESEARCH

In light of the process followed during this dissertation, we believe that the results achieved are robust in showing the interaction between Technology Overlap, Market Relatedness and Acquirer Experience compared to the inventors' post-acquisition performance. That said, we believe that other factors could help future studies to continue this research and hopefully confirm what has been found.

- First of all, in this dissertation, target companies with up to 500 employees at the time of acquisition were considered. It would be interesting to see what would have happen to the final results if larger firms were considered; or even acquisitions between two incumbents.
- Second, our sample is limited to the U.S. region, and it might be interesting to investigate other countries as well to see whether the trend is repeating or not. If so, the analysis should conduct appropriate considerations about different patent cultures, standards and jurisdictions, which could affect the general performance.
- Third, as already demonstrated, established companies that need to make technology acquisitions should know that the lower the technological overlap they have with the target, the greater the effort required to preserve the performance of the acquired inventors. In this regard, further research could investigate possible alternative activities that companies could carry out to reduce potential post-acquisition issues.
- Fourth, a further point refers to the inherent limitations of patent data as a measure of performance. Indeed, it may be that acquiring firms are able to capture the value of acquisitions through other non-patent channels, or that they strategically prefer secrecy to patent publication.
- In conclusion, we propose a further consideration not present in our thesis, nor investigated by previous research. Several scholars have

argued the fundamental importance of inventors' personal relationships as key factors of individual innovative performance. However, no particular attention has been paid to the size of the team, whose change of components after acquisition could be a possible disruptive factor. In this regard, we believe that patent data allows for a detailed analysis, which could extend the completeness of the research by introducing this new observation unit.

The empirical results of this study bring to light important key points to evaluate when trying to identify a potential target in a high-tech acquisition process. Our analysis, in fact, provides detailed evidence of the relevance of both **overlap at the technology level**, where it suggests an effective tool to measure the separation between the technology portfolios of the acquirer and the target, and at the **market level**, demonstrating the correlation with the performance of inventors; in addition, an acquirer should seek to gain as much **experience** as possible, probably with firms even smaller than those in question, before venturing into larger acquisitions. As a general guideline, acquiros should seek to foster knowledge-sharing routines, facilitating the transmission of data and information on the one hand, and facilitating inter-organizational interaction in order to nurture and build social bonds between individuals on the other.

Annexes

ANNEX 1. STARTING DATABASE 'THOMPSON + ZEPHYR'

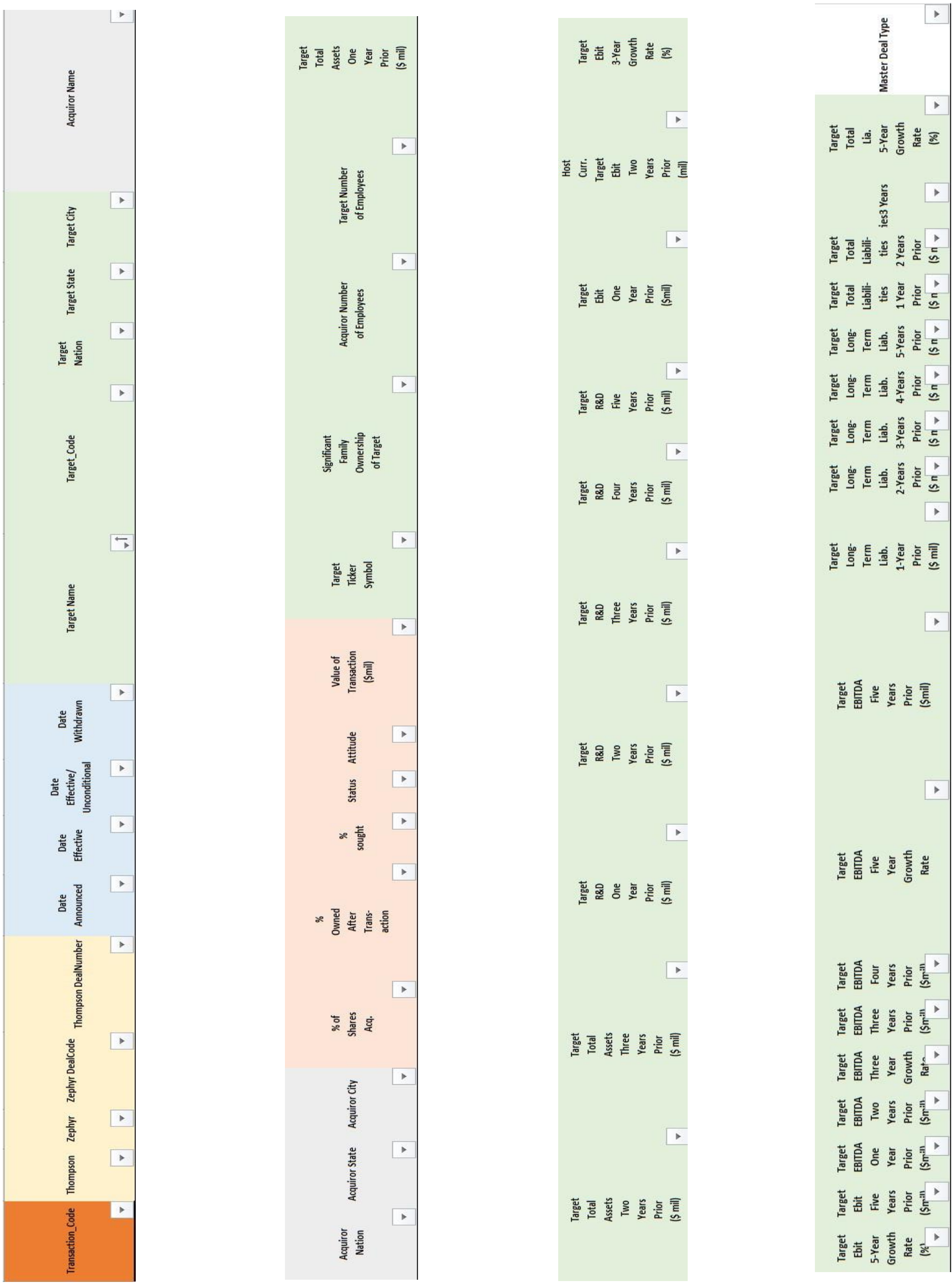

Figure 10 - Starting database 'Thompson + Zephyr'

ANNEX 2. MOST WIDELY USED PATENT FAMILY DEFINITIONS

Type	Interpretation	Uses	Definition	Expert quality control of patent linkages	Data availability
Equivalents	Patents that most likely protect SAME inventions.	Analysis of citations received, procedural history and legal differences of patent documents protecting the same inventions in different jurisdictions.	Applications having exactly the same priority or combination of priorities.	NO	**EPO - Esp@cenet equivalents** (www.espacenet.com) **Inno-tec equivalents** (www.inno-tec.bwl.uni-muenchen.de/personen/professoren/harhoff)
Extended families	Patents protecting SAME OR RELATED inventions.	Analysis of applicant strategies to extend patent protection over time and in different countries, as well as cumulativeness of inventions and patent thickets. Basis for the application of filters (specific offices, number of offices) to set economic thresholds on patent indicators.	Applications directly or indirectly linked through priorities.	NO	**EPO - INPADOC extended patent** (www.espacenet.com and PATSTAT September 2008 table TLS219_INPADOC_FAM) **OECD Triadic Patent Families** (www.oecd.org/sti/ipr-statistics)
Single priority families	Each first filing is treated individually, as the ORIGIN of a different family.	Statistical analysis of patent filing flows between priority countries and offices of subsequent filings to forecast patent office workloads.	Applications originating from a single priority. In the case of multiple priorities, a given subsequent filing is assigned to multiple single-priority families.	NO	**EPO - PRI system** (see trilateral statistics reports at www.trilateral.net/tsr) **WIPO families** (see world patents report at www.wipo.int/ipstats/en/statistics/patents)
Examiners technology-based families	Patent documents protecting SAME TECHNICAL CONTENT.	Primarily constructed by and for patent examiners to optimise their work.	Applications with exactly the same "active" priorities, understood as those adding new technical content.	YES	**EPO - DOCDB simple patent family** (DOCDB and PATSTAT September 2008 table TLS218_DOCDB_FAM)
Commercial novelty-based families	Patent documents protecting NEW TECHNICAL CONTENT.	Commercial databases, mainly addressed to help businesses make informed decisions, gain competitive intelligence and monitor industry trends.	Applications with technical content matching existing records. Based on the novelty principle.	YES	**Derwent World Patent Index (DWPI)** (www.thomsonreuters.com/products_services/scientific/DWPI)

Table 4 - Patent Families (Source: Martinez, C., 2010)

ANNEX 3. HOW A PATENT LOOKS LIKE

US 20120082102A1

(19) **United States**

(12) **Patent Application Publication** (10) **Pub. No.: US 2012/0082102 A1**

Kang et al. (43) **Pub. Date: Apr. 5, 2012**

(54) **METHOD FOR INDICATING PRECODING MATRIX INDICATOR IN UPLINK MIMO SYSTEM WITH BASED ON SC-FDMA**

(75) Inventors: **Byeong Woo Kang**, Anyang-si (KR); **Joon Kui Ahn**, Anyang-si (KR); **Dong Youn Seo**, Anyang-si (KR); **Jung Hoon Lee**, Anyang-si (KR); **Yu Jin Noh**, Anyang-si (KR); **Byoung Hoon Kim**, Anyang-si (KR); **Suck Chel Yang**, Anyang-si (KR); **Bong Hoe Kim**, Anyang-si (KR); **Dae Won Lee**, Anyang-si (KR)

(73) Assignee: **LG ELECTRONICS INC.**, Seoul (KR)

(21) Appl. No.: **13/148,886**

(22) PCT Filed: **Feb. 19, 2010**

(86) PCT No.: **PCT/KR2010/001039**

§ 371 (c)(1), (2), (4) Date: **Nov. 14, 2011**

Related U.S. Application Data

(60) Provisional application No. 61/161,049, filed on Mar. 17, 2009, provisional application No. 61/157,206, filed on Mar. 4, 2009, provisional application No. 61/153,974, filed on Feb. 20, 2009.

(30) **Foreign Application Priority Data**

Jul. 7, 2009 (KR) 10-2009-0061699

Publication Classification

(51) **Int. Cl.**
H04W 74/04 (2009.01)
H04W 72/04 (2009.01)

(52) **U.S. Cl.** **370/329**

(57) **ABSTRACT**

A method of transmitting PMI (precoding matrix indicator) information in an uplink MIMO system is disclosed. The present invention includes the steps of receiving channel information from a user equipment and transmitting information on a resource allocated to the user equipment in uplink transmission and PMI information indicating a precoding matrix to apply to a region of the resource among a plurality of precoding matrices to the user equipment based on the received channel information, wherein the resource allocated to the user equipment is allocated by a bundle unit of a prescribed number of subcarriers, wherein each of a plurality of the precoding matrices are applied to regions generated from dividing a whole frequency band into a prescribed number of regions, respectively, and wherein the precoding matrix applied to the resource among a plurality of the precoding matrices has a maximum area resulting from overlapping a frequency band occupied by the allocated resource with a frequency band having the precoding matrix applied thereto.

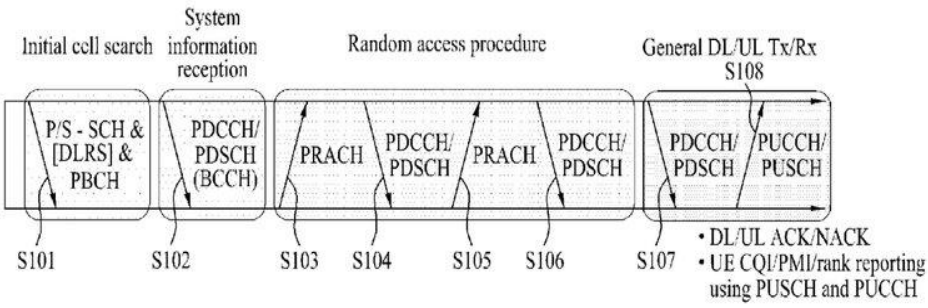

Figure 11 - How a Patent looks Like

ANNEX 4. EXAMPLE OF SQL CODE ON PATSTAT ONLINE

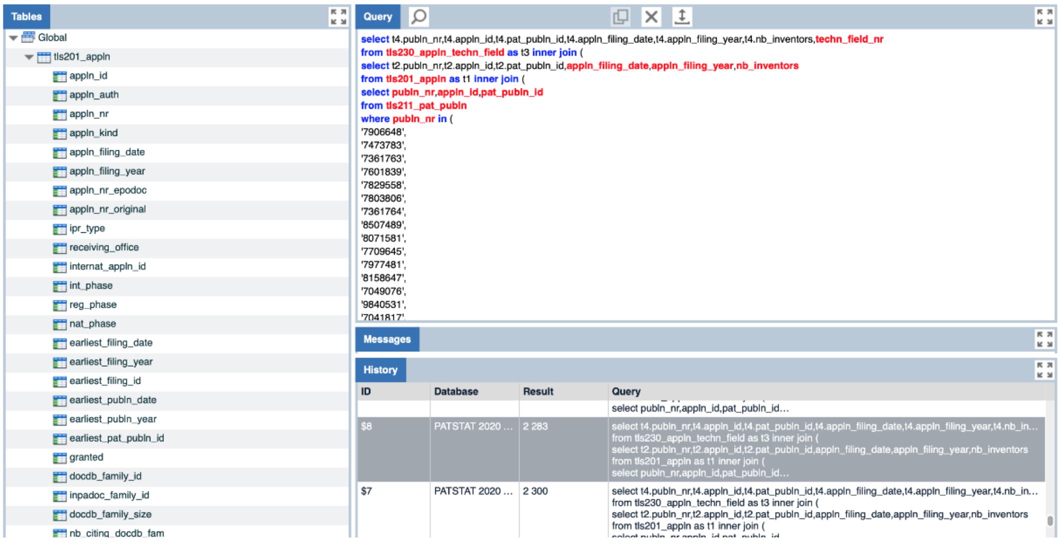

Figure 12 - MySQL code

ANNEX 5. EXAMPLE OF SQL CODE ON PgAdmin - PostgreSQL

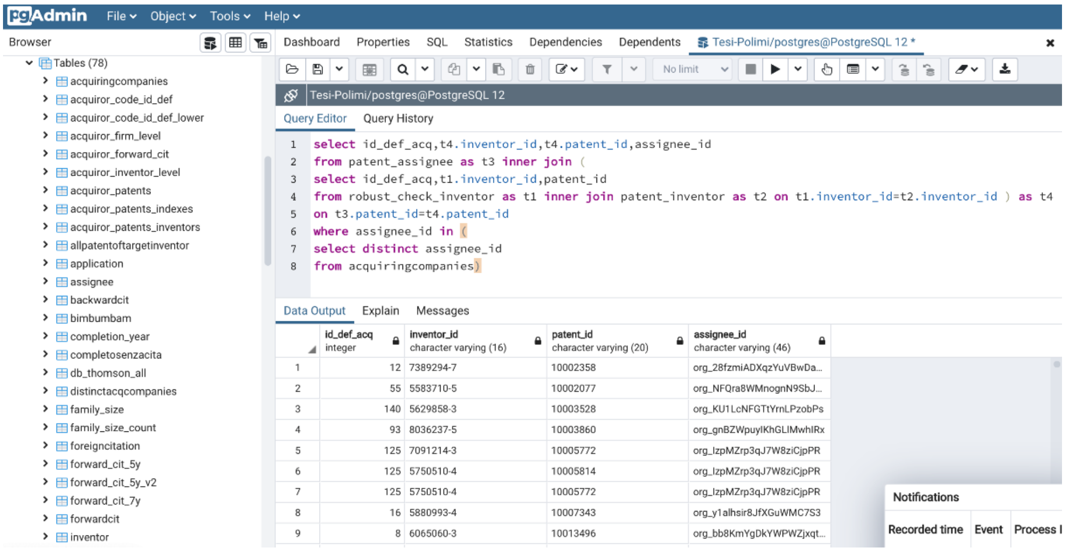

Figure 13 – SQL Code on PgAdmin - PostgreSQL

ANNEX 6. MERGE_THOMPSON_ZEPHY ON EXPERIENCE VARIABLES

2020_Merge_Thompson_Zephyr		
Variables	**Definition**	**Origin**
Transaction_Code	A unique identifeir given to the transaction	Starting DB
Transaction_date	Year of completion of the acquisition	Starting DB
Target_Name	The name of the target firm	Starting DB
Target_Code	A unique numerical identifier to the target firm	Starting DB
Id_Target_Def	A unique identifier given to the target firm	Starting DB
Date_Announced	Year of announcement of the 'sub' acquisition	Starting DB
Date_Effective	Year of completion of the 'sub' acquisition	Starting DB
Target_Name_"New"	The name of the 'sub' target firm	Starting DB
Target_Cusip	A unique numerical identifier to the 'sub' target firm	Starting DB
Target_Nation	Nation of the 'sub' target firm	Starting DB
Target_State	State of the 'sub' target firm	Starting DB
Target_City	City of the 'sub' target firm	Starting DB
Acquiror_Name	The name of the acquiror	Starting DB
Acquiror_Cusip	A unique numerical identifier to the acquiror	Starting DB
Acquiror_Nation	Nation of the acquiror	Starting DB
Acquiror_State	State of the acquiror	Starting DB
Acquiror_City	City of the acquiror	Starting DB
Perc_Share_Acq	Percentage owned before the acquisition	Starting DB
Perc_Owned_After_Transaction	Percentage owned after the acquisition by the acquiror	Starting DB
Acquiror_Nr_Employees	Number of acquiror employees	Starting DB
Target_Nr_Employees	Number of target employees	Starting DB
Acquiror_Primary_SIC_Code	Acquiror primary SIC Code	Starting DB
Target_Primary_SIC_Code	Target primary SIC Code	Starting DB
Other_Acquiror_SIC_Codes	Others acquiror primary SIC Code	Starting DB
Other_Target_SIC_Codes	Others target primary SIC Code	Starting DB
Acq_Total_EXPERIENCE	Total number of acquisitions made by the acquiror in the 5 years before the representative ac	Defined by us (patentsview and Patstat)
Acq_High_Tech_EXPERIENCE	Total number of acquisitions made by the acquiror in the high-tech sector in the 5 years befor	Defined by us (patentsview and Patstat)
Acq_EXPERIENCE_Similar	Total number of similar acquisitions made by the acquiror in the 5 years before the represent	Defined by us (patentsview and Patstat)

Table 5 - CodeBook Merge_Thompson_Zephyr

ANNEX 7. 2020_FIRM_LEVEL

2020_FIRM_LEVEL	
Variables	Definition
Transaction_Code	A unique identifeir given to the transaction
Thompson	Dummy: 1 = transaction present in Thompson; 0 = else
Zephyr	Dummy: 1 = transaction present in Zephyr; 0 = else
Thompson DealNumber	A unique identifeir given to the transaction in the Thompson database
Zephyr DealCode	A unique identifeir given to the transaction in the Zaphyr database
DateAnnounced	Date of announcement of the transaction
Completion_Year	Year of completion of the acquisition
perc_share_acq	Percentage of share
perc_owned_after_transaction	Percentage of share owned after the transaction
Acquiror_Name	The name of the acquiror
ID_Def_Acq	A unique identifeir given to the acquiror
Count_Of_Acq_Inventor_ID	Sum of acquiror inventors
Count_Of_Acq_Patent_ID	Sum of acquiror patents
Acquiror_State	State of the acquiror
Acquiror_City	City of the acquiror
Acquiror_Nr_Employees	Number of employees of the acquiror the closest possible to the transaction
Sum_Of_Num_Claims	Sum of acquiror number of claims
Sum_Of_Backward_Citations	Sum of acquiror bacward citations
Sum_Of_NPL_Backward_Cit	Sum of acquiror NPL backward citations
Sum_Of_Forward_Cit_5y	Sum of the acquiror forward citations
Sum_Of_Renewal	Sum of the acquiror renewal
Average_Of_Quality_Index_4	Average of acquiror quality index 4 taken at inventor level (forward citations, backward citations, patent family size, number of claims)
Average_Of_Quality_Index_5	Average of acquiror quality index 5 taken at inventor level (forward citations, backward citations, patent family size, number of claims, grant lag)
IPC_Acquiror	Number of acquiror IPCs assigned to each patent
Target_Name	The name of the target
ID_Def_Target	A unique identifier given to the target
Count_Of_Target_Inventor_ID	Sum of target inventors
Count_Of_Target_Patent_ID	Sum of target patents
Target_State	State of the target
Target_City	City of the target
Target_Nr_Employees	Number of employees of the target the closest possible to the transaction
Target_Sum_Of_Num_Claims	Sum of target number of claims
Target_Sum_Of_Backward_Citations	Sum of target bacward citations
Target_Sum_Of_NPL_Backward_Cit	Sum of target NPL backward citations
Target_Sum_Of_Forward_Cit_5y	Sum of target forward citations
Target_Sum_Of_Renewal	Sum of target renewal
Target_Average_Of_Quality_Index_4	Average of target quality index 4 taken at inventor level (forward citations, backward citations, patent family size, number of claims)
Target_Average_Of_Quality_Index_5	Average of target quality index 5 taken at inventor level (forward citations, backward citations, patent family size, number of claims, grant lag)
IPC_Acquiror	All acquiror IPCs assigned to each patent
IPC_Target	All target IPCs assigned to each patent
Acquiror_Primary_SIC_Code	Primary SIC code of the acquiror
All_Acquiror_SIC_Codes	All SIC codes of the acquiror (including the Primary)
Primary_Target_SIC_Code	Primary SIC code of the target
All_Target_SIC_Codes	All SIC codes of the target (including the Primary)
Acq_Total_EXPERIENCE	Total Experience of the acquiror in acquisitions from 1 to 5 years prior the focal one
Acq_High_Tech_EXPERIENCE	Experience of the acquiror in acquisitions in the high_tech sector from 1 to 5 years prior the focal one
Acq_EXPERIENCE_Similar	Experience of the acquiror in acquisitons in similar sectors from 1 to 5 years prior the focal one
SIC_Technology_Relatedness	Relation between the technology portfolio of target and acquiring firm at SIC level - Grimpe, et Al. (2013)
IPC_Technology_Relatedness	Relation between the technology portfolio of target and acquiring firm at IPC level - Grimpe, et Al. (2013)

Table 6 - CodeBook 2020_FIRM_LEVEL

ANNEX 8. 2020_INVENTOR_LEVEL

2020_INVENTOR_LEVEL	
Variables	**Definition**
Transaction_Code	A unique identifeir given to the transaction
Core	Dummy: 1 if the transaction belongs to the core ones; 0 else
Acquiring_Name	A unique identifeir given to the acquiror firm
Target_Name	A unique identifeir given to the target firm
Completion_Year	Year of completion of the acquisition
Inventor_ID	A unique identifeir given to the inventor
Name_First_PatentsView	First name of the inventor, as expressed on Patentsview
Name_Last_PatentsView	Last name of the inventor, as expressed on Patentsview
Male	Dummy: 1 if male; 0 if female
count_of_patent_id	Number of patents generated in the time interval considered.
sum_of_num_claims	The number and content of the claims thus determine the breadth of the rights conferred by a patent (OECD, 2009)
sum_of_backward_citations	Sum of number of backward citations.
sum_of_forward_cit_5y	Sum of number of citations received in the 5-years after the patent pubblication (patent grant date for USPTO)
sum_of_npl_backward_cit	Sum of number of Non-Patent Literature citations
sum_of_renewal	Sum of number of years during which the patent has been kept alive, starting from application date.
sum_of_patent_scope	Sum of Number of IPC
average_of_quality_index_4	Average of indicators: forward citations, patent family size, number of claims, backward citations
average_of_quality_index_5	Average of indicators: forward citations, patent family size, number of claims, backward citations, lag index
Year_Enter	Year in which the inventor filed the first patent at the target company
Year_leave	Year in which the inventor filed the last patent at the target (or acquiring) company
count_of_patent_id_POST	Sum of number of patents generated by the target inventor inside the acquiring firm in the time interval considered
sum_of_num_claims_POST	The Number and content of the claims thus determine the breadth of the rights conferred by a patent (OECD, 2009), post acquisition in the acquiring firm
sum_of_backward_citations_POST	Sum of number of backward citations, post acquisition in the acquiring firm
sum_of_forward_cit_5y_POST	Sum of number of citations received in the 5-years after the patent pubblication (patent grant date for USPTO), post acquisition in the acquiring firm
sum_of_npl_backward_cit_POST	Sum of number of Non-Patent Literature citations, post acquisition in the acquiring firm
sum_of_renewal_POST	Sum of number of years during which the patent has been kept alive, starting from application date, post acquisition in the acquiring firm.
sum_of_patent_scope_POST	Sum of Number of IPC, post acquisition in the acquiring firm
average_of_quality_index_4_POST	Average of indicators: forward citations, patent family size, number of claims, backward citations (post acquisition in the acquiring firm)
average_of_quality_index_5_POST	Average of indicators: forward citations, patent family size, number of claims, backward citations, lag index (post acquisition in the acquiring firm)

Table 7 - CodeBook 2020_INVENTOR_LEVEL

APPENDIX

APPENDIX 1. MAIN INDICATORS OF PATENT VALUE DISCUSSED IN LITERATURE

Indicator	Rationale	Main limitations
Granted	Limited legal protection if not granted; check by examiners.	Not very informative (large share: about 60% of patent applications are granted); USPTO: 95% of patents are granted.
Forward citations	Technological importance of inventions; impact on further technology developments.	Timeliness (availability over time), interpretation.
Family size (number of jurisdictions)	Costly to have protection in different jurisdictions; sign of market potential of an invention.	Representativeness issues; large share of patent applications are international.
Number of inventors	Proxy the cost of an invention (cost of research).	Rough measure which treats inventors equally; need for complementary information on the inventors (*e.g.* careers, patenting, etc.).
Renewals	Cost of maintaining a patent; renewal rates allow estimation of the distribution of value.	Timeliness, influence of technology life cycles, renewal rates different across technologies (different value).
Opposition	Market value of a patent. Costs and risks associated with legal disputes.	Timeliness, very small share (about 5% in EPO); how to detect mutual settlements.
Litigation	Costs and risks associated with legal disputes.	Timeliness, very small share, friendly settlements are frequent, data availability.
Firm market value, spin-offs, etc.	Patent value embedded as intangible asset.	Selected type of companies (stock markets, etc.).
Surveyed economic value	Patent value known by inventors or managers.	Subjectivity, selection issues, limited samples.

Table 8 - Main indicators of patent value discussed in literature (Source: Van Zeebroeck, 2007)

APPENDIX 2. OTHER PATENT BASED INDICATORS

1. Generality

Forward patent citations can be used to assess the range of subsequent generations of inventions that have benefited from a patent by measuring the range of technological fields (and consequently industries) that cite the patent (Bresnahan et al., 1995). The patent generality index has been used in a number of studies aimed, for example, at identifying technologies of general use (Hall et al., 2004); investigating the role of universities as sources of commercial technologies (Henderson et al., 1998); studying participation in studies and rent sharing in patent pools (Layne-Farrar et al., 2011); and understanding the functioning of the innovation market and how patent rights are enforced (Galasso et al., 2011). The patent generality index proposed here is based on a modification of the Hirschman-Herfindahl Index (HHI) and is based on information regarding the number and distribution of **forward citations** and the technology classes (CPI) of patents from which these citations originate. Unlike the way the generality has been calculated in previous studies, we consider all CPI classes contained in the patent citation documents and take into account the number and distribution of the 4-digit and n-digit CPI technology classes contained in the citation patents, where n refers to the highest possible level of disaggregation. The citation measures are based on EPO patents and the patent equivalents have been consolidated. The forward citations cover all citation categories and are limited to a citation window of 5 years. The formula is the following:

$$\mathbf{1 - \sum_{j} s_{PJ}^{2}}$$

S_{pj} the share of forward cites to patent p from class j out of n_p 4-digits IPC tech classes.

The proposed generality index is defined between zero and one, and the measure is high if a patent is cited by subsequent patents belonging to a wide range of fields - i.e. the invention considered has been relevant to a number of subsequent inventions, and not only in its technological class. On the contrary, if most citations are concentrated in a few fields, the generality index is low, i.e. close to zero. As suggested by Hall et al. (2001a), the measure of generality can be distorted when the number of patents on which it is based is small. Generality measurements depend strongly on the patent classification scheme used: the finer the classification level, the higher the measurements. In addition, the generality index treats technologies that are closely related but are not in the same class in the same way as they treat very distant technological fields. This may lead to overestimate or underestimate the generality of patents (Hall et al., 2004).

2. Originality

The originality of the patent refers to the breadth of the technological fields on which a patent is based. The measure of patent originality, proposed for the first time by Trajtenberg et al. (1997), makes this concept of diversification of knowledge and its importance for innovation operational: inventions that are based on a large number of different sources of knowledge should lead to original results. The originality of patents has been used in a wide range of studies, e.g. on the creation of start-ups with business support (Gompers et al., 2005) or on the value of post-merger versus pre-merger patents (Stahl, 2010). Based on Hall at al. (2001b), we define the originality indicator as:

$$\mathbf{1-\sum\nolimits_{j} s_{PJ}^{2}}$$

where s_{pj} is the percentage of citations made by a patent p to a class j patent compared to the 4-digit patent codes of the CPI n_p contained in the patents cited by patent p.

The citation measures are based on the EPO patents and take into account the patent equivalents. The construction of the originality indicator of patents follows a logic very similar to that used to build the generality index, with the main difference that the generality measures are based on term citations, while originality is based on **backward citations**. Unlike Hall at al. (2001b), it is based on all the CPI classes contained in the patent documents that the focal patent cites to minimize the prejudices that typically arise when the number of citations is small.

3. Radicalness

An index of patent radicality was proposed by Shane (2001), where the radicality of a patent is measured as an invariant count over time of the number of CPI technology classes in which the patents cited by the given patent are located, but in which the patent itself is not classified. He argues that the more a patent mentions previous patents in classes other than those in which it is found, the more the invention should be considered radical, as it is based on paradigms different from the one to which it is applied. This definition has been adapted in this work to take into account the relative weight of each 4-digit technology class contained in the cited patents. The indicator has been further normalized with respect to the total number of CPI classes listed in the backward citations, so that its value goes from zero to one. This means that the total number of citations corresponds to the citation count at the most disaggregated level available. The numerator instead reflects the number of 4-digit CPI classes contained in the cited documents, weighted for the times these classes appear at the most disaggregated level. The OECD radicality indicator is then compiled as follows:

$$\sum_{\mathbf{j}}^{\mathbf{np}} \frac{\mathbf{CTj}}{\mathbf{np}}; \quad \mathbf{IPCpj} \neq \mathbf{IPCp}$$

where CT_j denotes the count of the 4-digit ICP_{pj} codes of patent j cited in patent p which is not assigned to patent p, on n ICP classes in the backward citations counted at the most disaggregated level available. The higher the ratio, the more diverse the range of technologies on which the patent is based. The indicator proposed by Shane (2001) is fundamentally **backward in nature** as it captures the radicality of a patent in terms of difference from the predecessors on which it is based. Dahlin and Behrens (2005) propose instead a definition of radicality that is based on novelty, uniqueness and impact on future technological developments that patented inventions could have. They analyze the citation patterns observed before, during and after the filing of a patent, in order to assess whether it can be considered a radical invention. However, the indicator they propose is binary in nature, i.e. a patent is considered radical or not, and does not assess the degree of radicality of an invention. Continuous rather than discreet indicators are however extremely useful to evaluate, among other things, the quality and overall value of patent portfolios, as well as the innovative activity and production of companies over time. The OECD is currently working with external experts to propose and make operational a definition of radicality that is based on the work of Dahlin and Behrens and takes into account radicality with respect to previous, contemporary and future developments. The ultimate goal is to build a continuous radicality indicator that can be calculated for all patents.

APPENDIX 3. INTERNATIONAL PATENT CLASSIFICATION (IPC)

(Source: WIPO)

The International Patent Classification (IPC) was established in 1971 by the Strasbourg Agreement to provide a harmonized, language-independent, hierarchical system for the classification of technologies incorporated in patents. It divides technology into eight sections with about 70,000 subdivisions. Each subdivision has a symbol consisting of Arabic numerals and letters of the Latin alphabet. To be precise: eight sections, 128 classes, about 650 subclasses, about 6,800 main groups and more than 65,000 subgroups. For a practical vision see the following Figure 14.

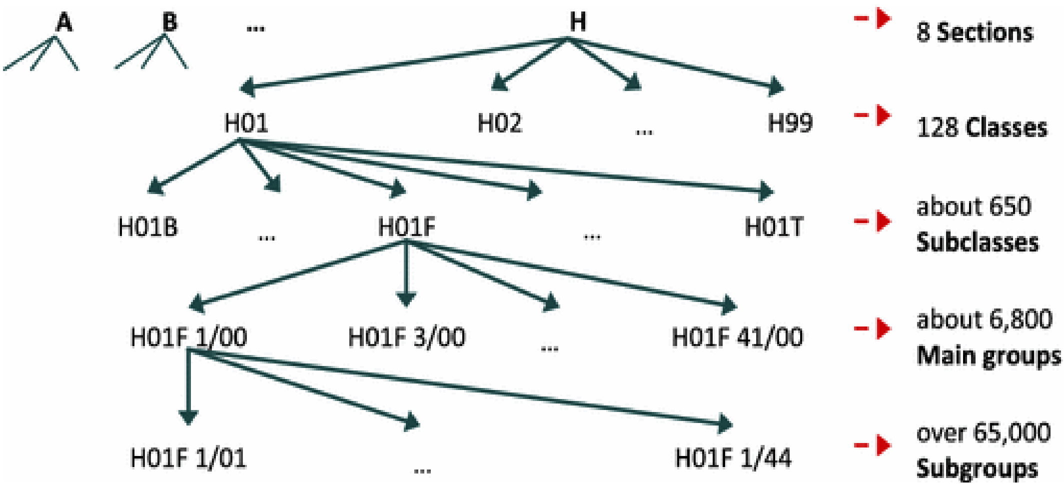

Figure 14 - IPC Classification (Source: WIPO)

To illustrate the structure of the IPC, consider the example of the "subgroup" IPC B64C 11/18, which covers "Aerodynamic characteristics of propellers used in aircraft". This group number is composed by section B ("Execution of operations; Transport"), class B64 ("Aircraft; Aviation; Cosmonautics"), subclass B64C ("Aircraft; Helicopters"), main group B64C 11/00 ("Propellers"), and subgroup B64C 11/18. When multiple inventive features are evident in an invention, examiners often cross-patent multiple CPIs. The appropriate IPC symbols are indicated on each patent document, of which more than 1,000,000 have been granted each year for the last 10 years. They are assigned by the national or regional industrial property office that publishes the patent document. The classification is indispensable for the retrieval of patent documents in the 'prior art' search. This retrieval is necessary for patent granting authorities, potential inventors, research and development units and other parties interested in the application or development of technology.

In order to keep the IPC up to date, it shall be subject to continuous review and a new version shall be published regularly. Translations of the IPC are prepared and published in many languages such as Chinese, Czech, Dutch, German, Japanese, Polish, Portuguese (Brazil), Russian, Serbian, Slovak, Spanish, Ukrainian. The revision of IPC is carried out by the IPC Committee of Experts.

APPENDIX 4. STANDARD INDUSTRIAL CLASSIFICATION (SIC)

(Source: CorporateFinanceInstitute)

The Standard Industrial Classification (SIC) is a system to classify industrial sectors with a four-digit code. Established in the United States in 1937, it is used by government agencies around the world to classify industrial areas. It has a top-down, hierarchical structure that starts with general characteristics and narrows down to specifications. The first two digits of the code represent the main industry sector to which a company belongs. The third and fourth digits describe the sub-classification of the group of companies and the specialization, respectively. For example, "36" refers to a company that deals with "Electronic and other equipment". The addition of "7" as the third digit to get "367" indicates that the business operates in "Electronics, Components and Accessories". The fourth digit distinguishes the specific industry sector, therefore a code of "3672" indicates that the company deals with "Printed Circuits". It should be noted that in the United States the SIC code was replaced by the NAICS code, which was issued in 1997 but not adopted by each institution. In fact, in some U.S. government departments and offices, such as the U.S. Securities and Exchange Commission (SEC), which continued to use SIC codes until at least 2019.

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