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M&A, DIVERSIFICATION, AND PATENT ANALYSIS: MEASURING INNOVATION PERFORMANCE

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Contents

Introduction

Focusing on the context of mergers and acquisitions (M&A), the objective of this Ph.D. thesis is threefold. First, it aims at highlighting the importance of innovation on the firm's growth and success; a special attention is given not only to the mere quantity of the invention process output but especially to its quality that is conceived in terms of an invention's technological *impact*, *originality* of its synthesized knowledge streams, and *generality* of its applicability in the technological space. Second, it aims at deepening our knowledge on the key drivers of innovation performance with a particular emphasis on the salient role of the firm's diversification of resources and its knowledge recombination capabilities. Third, by pointing out the shortfalls of the above-mentioned measures of innovation performance and innovation quality, it aims at building a multidimensional ex-ante measure able to capture in one indicator different and complementary aspects of a patented invention.

This Ph.D. thesis includes three essays that lay at the intersection of innovation and M&A literature. The first chapter investigates the directionality of the relationship between the quantity and the quality of innovation after an M&A and questions *how* the acceleration of the inventive process output affects the multifaceted features of the inventive quality (*i.e.* Ahuja & Katila, 2001; De Man & Duysters, 2005; Cassiman, Colombo, Garrone, & Veugelers, 2005; Cloodt, Hagedoorn, & Van Kranenburg, 2006; Makri, Hitt, & Lane, 2010; Valentini, 2012;

Harrigan, Di Guardo, Marku, & Velez, 2017; Harrigan, Di Guardo, & Marku, 2018). Interestingly, the results show a negative relationship, shedding new light on the dynamics that may affect the post-acquisition innovation performance and contributes in this way to the innovation and M&A literature.

The second study tries to go further by analyzing the underlying mechanism that can clarify *whether* the diversification of resources via M&A enhances or impoverishes the acquirer's post-acquisition innovation performance and *when* acquirers can leverage this strategy. Using the lenses of the resource-based view and the dynamic capability view (*i.e.* Barney, 1991; Peteraf, 1993; Helfat, 1997; Teece, Pisano, & Shuen, 1997; Zollo & Winter, 2002; Hoopes, Madsen, & Walker, 2003; Teece, 2007) this study advances the innovation strategy literature by answering how the access to valuable external resources goes through a process in which the dynamic capabilities play an important role and by showing the existence of complementarities between the acquisition of external resources and the acquirer's knowledge recombination capabilities that affect the innovation performance.

The third study proposes a novel patent measure able to capture three dimensions of a patented invention: the technological *diversity*, the technological *distance* from patent antecedents, and the degree of *novelty*. This measure can help both researchers and practitioners as it can be used as an effective proxy for the assessment of the firm's knowledge recombination capabilities, the detection of breakthrough inventions, as well as the identification of the firm's technological search strategies. In so doing, it advances the technology and patent literature (*i.e.*

Trajtenberg, Henderson, & Jaffe, 1997; Hall, Jaffe, & Trajtenberg, 2001; Verhoeven, Bakker, & Veugelers, 2016).

CHAPTER I

QUANTITY AT EXPENSE OF QUALITY?

MEASURING THE EFFECTS OF "SUCCESSFUL" M&A

ON INNOVATION PERFORMANCE

1. Abstract

Extant research suggests that a key driver of successful mergers and acquisitions (M&A) is the transfer of new technological knowledge, expertise, and capabilities which—if exploited effectively by the acquirer—can lead to an increase of innovation outputs (*e.g.*, number of patents). By segregating our sample of acquiring firms according to success in increasing their number of post-acquisition patents, we investigate additional post-acquisition effects on innovation quality which include the invention's technological *impact*, the *originality* of its synthesized knowledge streams, and the *generality* of its applicability on subsequent inventions. Using the matching estimators and propensity score methods in order to take into consideration the sample selection bias, results show that firms which completed successful acquisitions actually decreased the average quality of those innovation outputs. Our findings offer new insights concerning the innovation dynamics that may affect firms' inventive performance after experiencing an organizational change related to the M&A transaction.

2. Introduction

In a world of greater globalization, firms must have the capability to generate innovations continually in order to gain and sustain a competitive advantage that allows them to achieve success (Ranft & Lord, 2002; Crossan & Apaydin, 2010; Aharonson & Schilling, 2016). The lack of internal technological alternatives—which often hinders to keeping up with the pace of technology and to competing successfully (Teece *et al.*, 1997; Vasudeva & Anand, 2011)—may push firms to choose mergers and acquisitions (M&A) as an effective instrument to enlarge and enrich the scope of these potential combinations, and therefore accelerate the inventive process by gaining necessary technical knowledge and expertise (Chakrabarti, Hauschildt, & Süverkrüp, 1994; Ahuja & Katila, 2001; Cloodt *et al.*, 2006; Barkema & Schijven, 2008). The unprecedented increase in global M&A volume, 3.5 trillion U.S. dollars in 2014[1] alone and 47% higher than comparable 2013, confirms the great popularity of this growth strategy.

The success of M&A, according to strategic literature, is determined by several performance measurements (Bauer & Matzler, 2014), most notably when assessing innovation success, by a post-acquisition increase in the number of patents produced (Ahuja & Katila, 2001; De Man & Duysters, 2005; Ahuja, Coff, & Lee, 2005; Cloodt *et al*., 2006). Patent counts have long been accepted as a reliable indicator of R&D success and are one of the most direct measures of innovation

[1] Announced global volume of M&A, source Thomson Reuters.

output available (Scherer, 1965; Pakes & Griliches, 1980; Hitt, Hoskisson, Ireland, & Harrison, 1991). More specifically, while the pre-acquisition number of patents is a measure of the acquirer's knowledge stock, those granted after the transaction represent incremental knowledge stock created through successful inventive activity (Henderson & Cockburn, 1994; Ahuja & Lampert, 2001; Puranam & Srinkath, 2007). On the contrary, recent studies highlight the need to depart from considering the mere quantity of the inventive outputs and to focus on other dimensions of the innovation performance especially those reflecting the nature of knowledge in terms of quality (*i.e.* Makri *et al.,* 2010; Valentini, 2012; Di Guardo & Harrigan, 2016; Harrigan, Di Guardo, Marku, & Velez, 2017; Harrigan *et al.*, 2018).

The present study takes this latest challenge and attempts to answer the following questions. If, as extant research suggests, successful acquisitions transfer new technological knowledge, expertise, and capabilities which—if exploited effectively by the acquiring firm—can increase post-acquisition innovation outputs (*e.g.,* the number of patents), what is their effect on innovation quality? M&A may foster the innovation process, but how the acceleration of output production does influence the multiple dimensions of innovation quality? Basically, is there an increase of quantity at the expense of quality?

To achieve our aims, we analyze the quality of innovation of the firms operating in the U.S. communication services sector that engaged in M&A over the period 1998-2005. Using the traditional success metric based on changes in patent counts, it was possible to segregate M&A transactions which led to an increase of post-acquisition innovation outputs from the other contemporary deals occurring in the industry. Furthermore, by applying the matching estimators and propensity score methods, we better assessed the effects of successful M&A on three indicators of patent quality: invention's technological *impact*, *originality* of its synthesized knowledge streams, and *generality* of its applicability in the technological space.

In so doing, this chapter contributes to the existing literature in several ways. First, it sheds new light on the dynamics that may affect the post-acquisition innovation performance and further explains changes in the quality of the inventive activity. Second, it extends the M&A literature which primarily compares firms that made acquisitions to firms that did not, by investigating a deeper understanding of the performance variance between firms that chose this type of transaction. Third, this empirical work addresses the endogeneity issues raised by previous literature (Maddala, 1986; Shaver, 1998; Rodríguez-Duarte, Sandulli, Minguela-Rata, & López-Sánchez, 2007) through the adoption of the matching estimators and propensity score methods (Abadie & Imbens, 2002; Villalonga, 2004; Valentini, 2012; Chang, Chung, & Moon, 2013).

3. Literature review

The strategic management literature, while recognizes the important role of M&A in the firm's innovation strategy (Bettis & Hitt, 1995; King, Covin, & Hegarty, 2003; Harrigan & Di Guardo, 2017), it still shows inconclusive results about the directionality of M&A effects on innovation performance. A positive relationship has been found for technological acquisitions by Ahuja and Katila (2001) and by Cloodt *et al*. (2006). A negative relationship was reported by Hall (1990), Hitt *et al*. (1991), Hitt *et al*. (1996), and Ornaghi (2009), while other studies showed even neutral effects (Healy, Palepu, & Ruback, 1992; Prabhu, Chandy, & Ellis, 2005; Danzon, Epstein, & Nicholson, 2007).

M&A are expected to create additive synergies if they exploit economies of scale and scope by combining inventive organizations (Henderson & Cockburn, 1996; Cassiman *et al*., 2005; Chiu, Lai, Lee, & Liaw, 2008; Harrigan & Di Guardo, 2017; Harrigan, Di Guardo, & Cowgill, 2017). In particular, successful post-transaction integration can reduce R&D intensity, lower innovation risks (Hitt *et al.*, 1991), and improve a deficient organization's inability to innovate organically (Zhao, 2009). These types of benefits can hence offset the typical problems associated with the process of doing mergers and acquisitions: *e.g.* absorption of managers' time and energy (Hitt, Hoskisson, Johnson, & Moesel, 1996), creation of a short-term organizational focus which may negatively affect the firm innovativeness (Hall, 1990; Hitt *et al*., 1991), departure of key inventors or decreases of their productivity (Ernst & Vitt, 2000; Stuart & Sorenson, 2003; Kapoor & Lim, 2007). Although successful integration of the R&D function within acquisitions can be undermined by internal performance problems elsewhere that may distract the organization's attention (De Man & Duysters, 2005), failure in M&A made for technological motives generally occurs when the combined organizations do not succeed in achieving their desired technological objectives.

Therefore, it is important to better understand the dynamics that may affect the M&A innovation success by first defining how to gauge it. Existing literature firmly points out that the number of innovation outputs (*e.g.* patents) is a meaningful indicator of potential success, especially in fast-moving economies (Ahuja & Katila, 2001; De Man & Duysters, 2005; Ahuja *et al.*, 2005; Cloodt *et al*., 2006). However, taking into consideration that the distribution of the patents' value is highly skewed and that not all patents embody breakthrough innovations, it is relevant to account additional characteristics of the firm's knowledge and capabilities which may have a great influence on firm survival: the quality of innovation (*i.e.* Makri *et al*., 2010; Valentini, 2012; Di Guardo & Harrigan, 2016; Harrigan *et al.*, 2017; Harrigan *et al.*, 2018).

While increases in innovation outputs are simply observable by counting the number of patents, their respective quality is more complex. Scholars have suggested many innovation quality indicators but building upon the contributions of Trajtenberg *et al.* (1997) and Hall *et al.* (2001), we explore three different and complementary features of patent quality which include the technological *impact*, *originality*, and *generality* of an invention. More specifically, the technological *impact* reflects the technological influence and importance of the focal patent on subsequent inventions, and it signals its economic value (Hall *et al.*, 2001; Lanjouw & Schankerman, 2004). Impact measures highlight the extent to which the particular knowledge embodied in a patented invention has stimulated subsequent works of other inventors (Barberá-Tomás, Jiménez-Sáez, & Castelló-Molina, 2011). Patent quality can be indicated by the *originality* of the technology streams that were synthesized to create the focal patent and denotes the breadth of the multifaceted domains of the firm's knowledge base (Bierly & Chakrabarti, 1996; Hall *et al*., 2001; Argyres & Silverman, 2004; Valentini, 2012; Di Guardo & Harrigan, 2016). Finally, patent quality also considers the *generality* of applicability of the focal patent on further inventions emphasizing the breadth of variety of technological areas (Valentini, 2012; Di Guardo & Harrigan, 2016). In summary, we inquire how innovation quality may differ for the relatively successful M&A (as evidenced by increases in patent counts) compared with the other acquisitions occurring in the same time period in the sector under examination.

4. Theory and hypotheses

In the fast-paced knowledge economy, firms choose to engage in M&A for several motives such as entering desirable markets (Chevalier, 2004; Cassiman *et al.,* 2005; Brakman, Garretsen, Van Marrewijk, & Van Witteloostuijn, 2013), improving internal processes by integrating vertically and horizontally (De Man & Duysters, 2005), and especially by the rapid acquisition of new and diverse technological knowledge and capabilities (Link, 1988; Granstrand, Bohlin, Oskarsson, & Sjöberg, 1992; Chakrabarti *et al.,* 1994; Ahuja & Katila, 2001; Cloodt *et al.,* 2006). Zhao (2009) showed that technology-motivated M&A have become a widespread phenomenon in the U.S. economy, as they are effective means to gain competitive advantages while responding to acquirer's need to increase innovation outputs (Ahuja & Katila, 2001; Bower, 2001; Ranft & Lord, 2002; Cloodt *et al.*, 2006).

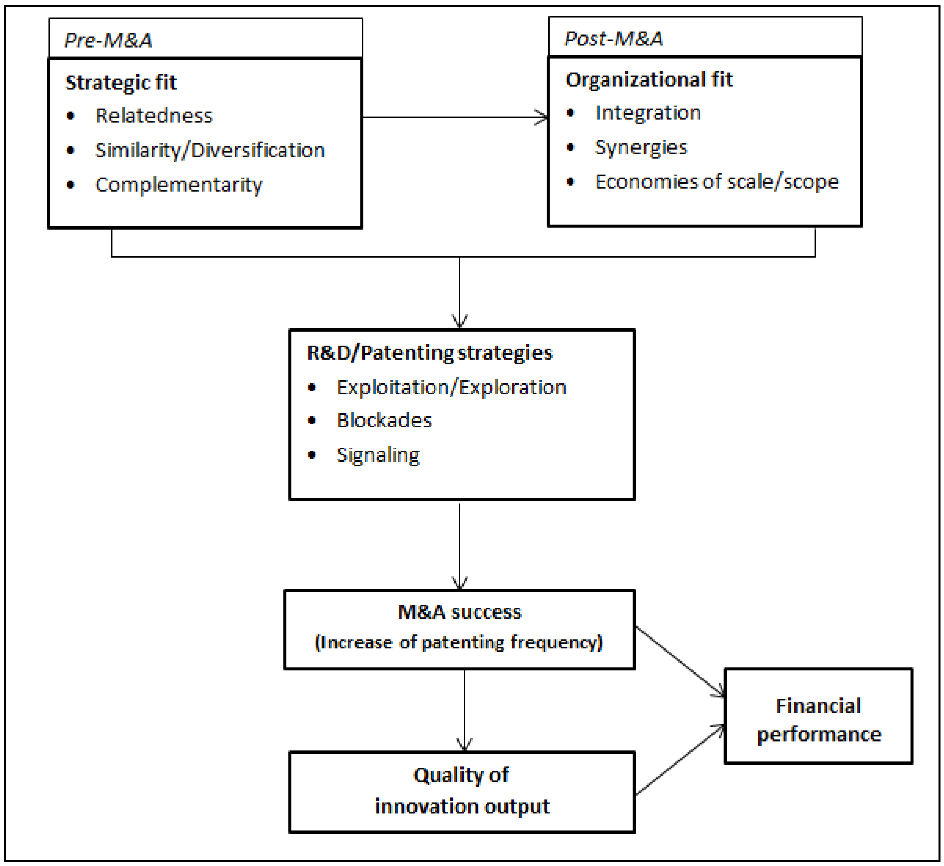


Figure 1.1 Antecedents of M&A success on innovation performance

In addition to financial and market penetration goals, acquiring firms measure their M&A success in terms of innovation improvements. Figure 1.1 depicts a synthesis of the M&A literature as it pertains to transactions undertaken for technology acquisition and the innovation outputs which are an expression of the M&A success. Our contribution is to clarify the effect of an acceleration in patenting frequency (which is evidence of M&A success) on the three patent quality indicators. In Figure 1.1. acquisition candidates are chosen according to strategic fit criteria characterized as the situation in which all of the internal and external elements relevant for a company are in line with each other and with its corporate strategy (Scholz, 1987; Hagedoorn & Duysters, 2002; Cassiman *et al.*, 2005; Cloodt *et al.*, 2006; Makri *et al.*, 2010; Dibiaggio, Nasiriyar, & Nesta, 2014).

The post-acquisition integration process (Figure 1.1.) is successful according to organizational fit criteria which influences the ease with which two organizations can be assimilated after an acquisition, particularly to exploit scale and scope economies and build effective synergies (Datta, 1991; Ranft & Lord, 2002; Schweizer, 2005; Puranam, Singh, & Zollo, 2006; Harrigan, Di Guardo, & Cowgill, 2017). The combined organization pursues its chosen R&D and patenting strategy that will, in turn, affect both patent quantity and quality. More specifically, acquirers will manage all the pre- and post-acquisition phases accordingly to two different types of purposes: (1) increase in the innovation outputs, or (2) increases in their quality.

Acquirers may adopt strategies aiming at increasing the quantity of innovation outputs to respond to significant pressures for immediate tangible results (Hall, 1990; Hitt *et al.*, 1991; Valentini, 2012). This behavior has taken hold as M&A become a popular growth strategy in the U.S. during the excitement generated by commercialization of the internet. In fact, acquirers try to boost their patent portfolio in order to signal to potential investors about the achievement of the innovation success, thereby increasing the firm's market value (Bloom & Van Reenen, 2002; Long, 2002; Hsu & Ziedonis, 2013; Haeussler, Harhoff, & Mueller, 2014). If this is the case, R&D exploitation is a fast way to accelerate innovation output production by leveraging in-house established knowledge and acquiring targets with closely related technologies (Seth, 1990; Anand & Singh, 1997; Haleblian & Finkelstein, 1999; Ahuja & Katila, 2001; Vermeulen & Barkema, 2001; Stettner & Lavie, 2014). Similarity and relatedness between target and acquirer's knowledge bases increase the speed of absorption of the new technological knowledge and the consequent commercial exploitation (Cohen & Levinthal, 1990; Mowery, Oxley, & Silverman, 1996; Lane & Lubatkin, 1998; Makri *et al*., 2010).

However, the aim of the acquirer may be also the exploration and absorption of novel and diverse external technological knowledge in order to stimulate the generation of hybrid and breakthrough innovations (Ahuja & Katila, 2001; Rosenkopf & Nerkar, 2001; Almeida & Phene, 2004; Phene, Fladmoe-Lindquist, & Marsh 2006; Phene & Almeida, 2008; Bapuji, Loree, & Crossan, 2011). When this goal is successfully achieved—although it often requires much time and a higher absorptive capacity—prior studies suggest that acquirers experience an emergent need to increase additional protection for these high value and strategic inventions. Strategic literature refers to them as the so-called "*defensive blockades"* which are adopted by firms to enlarge their manoeuvring space in order to avoid litigation (Kingston, 2001; Cohen, Goto, Nagata, Nelson, & Walsh, 2002; Blind, Edler, Frietsch, & Schmoch, 2006; Blind, Cremers, & Mueller, 2009; Andries & Faems, 2013; Mihm, Sting, & Wang, 2015). Although in origin the purpose of the acquirer was the increase of the patent quality, blockades may simultaneously increase patent quantity.

How these dynamics that continually involve acquirers, can affect the post-acquisition average quality of their patent portfolio? First, as inventions are primarily built in pre-existing technological trajectories, R&D exploitation will lead to relatively little improvements of the firm's existing knowledge base (Benner & Tushman, 2003; Phene, Tallman, & Almeida, 2012), therefore, it will negatively affect the technological *impact* which is particularly sensitive to radical innovations. In fact, signaling pursuits generate useless noise because acquirers inflate instrumentally their portfolio without making significant innovation improvements, impoverishing in this way the post-deal average technological *impact*. Although R&D exploration may generate (sporadic) breakthrough innovations which are expected to have a high *impact* on subsequent inventions, the presence of blockades aimed to strengthen the acquirer's invention protection, will increase the size of the patent portfolio and consequently decrease its average technological *impact.*

> *Hypothesis 1*: *Successful M&A (defined in terms of increases of innovation outputs) have a negative effect on the average technological impact of post-acquisition patents.*

The *originality* of knowledge streams that are synthetized in an invention is influenced by the degree of diversity of the technological knowledge used. Blockades foster the concentration of the newly granted patents on similar technological domains, around those of the post-deal breakthrough innovations. The same effect will be produced in the case of R&D exploitation and signaling. All these strategies are expected to influence negatively the average *breadth* of synthetized technology streams of the acquirer's patents.

> *Hypothesis 2: Successful M&A (defined in terms of increases of innovation outputs) have a negative effect on the average originality of backward-citation antecedents synthesized in their post-acquisition patents.*

The breadth of backward citation, namely *originality*, and the *generality* of applicability are highly related (Rosenkopf & Nerkar, 2001, Banerjee & Cole, 2010; Barirani, Beaudry, & Agard, 2015). More specifically, inventions that build upon a broader range of knowledge streams synthetized in them are expected to enjoy a higher number of technological alternatives (Lerner, 1994; Gambardella, Giuri, & Luzzi, 2007; Messeni Petruzzelli, Natalicchio, & Garavelli, 2015) that can inspire subsequent inventions in a broader technological space (Nerkar & Shane, 2007; Messeni Petruzzelli, Natalicchio, & Garavelli, 2015, Novelli, 2015; Kaplan & Vakili, 2015). This relationship is even stronger when referring to private firms (Barirani *et al.*, 2015).

Hypothesis 3: Successful M&A (defined in terms of increases of innovation outputs) have a negative effect on the average generality of the post-acquisition patents.

Although it has long been argued that there is a strong relationship between patent value and patent quality (Harhoff, Narin, Scherer, & Vopel, 1999; Lee, Lee, Song, & Lee, 2007; Fischer & Leidinger, 2014), there are few precedents for expecting a negative relationship between patent quantity and quality. Lanjouw and Schankerman (2004) used several indicators of patent quality and found evidence of a negative relationship between R&D productivity and patent quality at the firm level; Mariani and Romanelli (2007) replicated their negative findings at the inventor level. Also, Gambardella, Harhoff, and Verspagen (2011) showed a negative relationship between the quantity of inventions produced and the average value of the patent portfolio in their analysis at the inventor level. Valentini's (2012) M&A study found that firms improved their performance in term of quantity of innovation outputs whilst decreased their patent average quality and De Rassenfosse (2013) concluded that firms consciously made trade-offs between higher quantities of inventions versus lower average quality.

In summary, according to the existing literature we expect that *successful* M&A will experience a decrease in post-acquisition patent quality due to the R&D and patenting strategies they have adopted. Instead, the other deals, not being affected by these dynamics are expected to show no changes or even an improvement of the quality of their patented inventions.

> *Hypothesis 4*: S*uccessful M&A (defined in terms of increases of innovation outputs) have a lower average post-acquisition patent quality in comparison to other contemporary acquisitions.*

5. Method

In our examination of the directionality of the relationship between the quantity and the quality of innovation output in the M&A context, we address the endogeneity issues raised by Shaver (1998) and Rodríguez-Duarte *et al.,* (2007) by using the matching estimators and the propensity score matching methods combined with a difference-in-differences approach (Villalonga, 2004; Chang *et al.,* 2013). Indeed, the propensity scores which are calculated using a logistic regression reduce the selection bias of the observed data, and consequently the difference between treated and control groups. The difference-in-differences procedure eliminates unobservable factors and time trends that might be affecting the outcome of each firm present in our sample. In so doing, the pre-acquisition outcome represents our benchmark while the post-acquisition outcome represents the component of the difference that can be attributed to the acceleration of the inventive activity. More specifically, using a formal formulation for the propensity score method:

$$y^*_{i,t0} = \beta X_{i,t0-k} + \varepsilon_{i,t0} = F(y^*_{i,t0} > 0) \qquad (1.1)$$

$$P(y_{i,t0}=1| X_{i,t0-k}) = P(y^*_{i,t0} >0| X_{i,t0-k}) = P(\varepsilon_{i,t0} > -\beta X_{i,t0-k}) = 1- \Omega(-\beta X_{i,t0-k}) = \Omega(\beta X_{i,t0-k}) \tag{1.2}$$

The propensity scores generated represent the likelihood $y^*_{i,t0}$ of firm$_i$ to be treated at time t_0 (where t_0 identifies the year of the deal) conditional to an observable vector of covariates $X_{i,t0-k}$; this likelihood, of course, cannot be directly observed. In addition, $y_{i,t0}$ is a dummy variable that assumes two different values: "1" if the observation received the treatment at time t_0, and "0" without receiving the treatment, $\varepsilon_{i,t0}$ represent the error term while $\Omega(\cdot)$ represents the cumulative distribution function and assumes values from "0" to "1".

The predicted probabilities allow us to match each treated unit to its control "twin" on the unidimensional metric of the propensity score vector. In this study, we chose to apply the nearest-neighboring method with replacement and 5:1 comparisons (Rubin, 1973; Heckman & Navarro-Lozano, 2004). This method adopts a non-parametric matching procedure based on Mahalanobis distance and it is particularly suitable when the functional form is not properly specified as in this case the estimators that rely on propensity scores lose their efficiency (Leuven & Sianesi, 2015). Once the treated and control units are matched, it is possible to estimate the *average treatment effects on the treated* (ATT). To explain this latter estimand let specify that each observation has two potential outcomes:

$$\begin{cases} Y_i(0) \;|\; D=0 \\ Y_i(1) \;|\; D=1 \end{cases} \tag{1.3}$$

where $Y_i(0)$ represents the potential outcome of firm$i$ that did not diversify while $Y_i(1)$ if they did. (Abadie & Imbens, 2002; Abadie, Drukker, Herr, & Imbens, 2004). The treatment D is a dummy variable that is equal to "1" if the observation received the treatment, and "0" otherwise. We are interested to estimate the difference between these two potential outcomes $Y_i(1)$- $Y_i(0)$ and the average treatment effects on the treated which should be denoted as:

$$\tau_{ATT} = E(\tau|D=1) = E\,[Y_i(1)|D=1] - E[Y_i(0)|D=1] \tag{1.4}$$

that represents the difference between the expected value of $Y_i(1)$ if the firm$_i$ received the treatment and the expected value of $Y_i(0)$ if the same firm did not receive the treatment. The main point is that these outcomes cannot be jointly observed, because there is only one observable counterfactual outcome $Y_i(1)$ when D=1, meanwhile $E[Y(0)|D=1]$ is impossible to estimate. Hence, there is a need to construct two similar groups (treated and control) in order to allow comparisons between them. Therefore, the average treatment on the treated in the formulation below, can be specified as the difference between the outcomes of the treated and control group, and N represents the number of matches (Leuven & Sianesi, 2003):

$$\tau_{ATT} = \frac{1}{N} \sum_{i:D=1} (Y_{i,}(1) - \hat{Y}_i(0) \tag{1.5}$$

In order to leverage the matching outcomes, the procedure is repeated on 1,000 bootstrap samples. Bootstrapping is highly recommended because—unlike the standard test—the bootstrapped Kolmogorov-Smirnov test provides correct coverage even when there are point masses in the distributions being compared (Abadie, 2002).

To observe the effects of the M&A, consistently with prior research, we apply a 4-year window before and after the event (Sampson, 2007). Firms are treated if they experienced "successful" M&A that is indicated by increases in post-acquisition patent outputs.

Moreover, we apply matching with replacement in the estimation of the average treatment effect. Results of computations run on different settings show that matching each treatment unit with the four closest controls allows us to balance the bias such that we make variance trade-offs induced by the possible increase in bias obtained when selecting multiple controls for each treated individual versus the possible decrease in variance deriving from larger matched sample size.

Last, our hypotheses are tested using an alternative of the parametric t-test, the nonparametric Wilcoxon Signed Ranks Test (Corder & Foreman, 2009). This test pertains to the comparison of two samples which are paired, or related (Wilcoxon, 1945) and is indicated to be used in statistics when (for a given event) the assumptions of the paired t-test concerning a normal distribution of interval data are not met by the sample's data.

5.1. Data source

The U.S. communications services sector has experienced several M&A waves due to both technology shocks and deregulation (Harford, 2005; Gantumur & Stephan, 2011). We chose this industry for several reasons. First, the popularity of M&A as a means for firms to grow as demonstrated by a high number of M&A transactions

(Thomson Reuters, 2013; Thomson One's Mergers & Acquisitions, 2013; SDC Platinum Database, 2013). Second, this sector experienced increasing demand for the new technologies that made older technologies face declining demand (Christensen, 1997; Harrigan, 2003). Third, investor exuberance encouraged greater protection of intellectual property and spurred an era of high-density patenting activity (Hall & Ziedonis, 2001; Ziedonis, 2004). Fourth, competitive frenzy spurred constant innovation increases via M&A due to fears of survival (Danguy, De Rassenfosse, & de la Potterie, 2013). These particular features make the communications services sector highly suitable for analyzing the effects of successful M&A for technology acquisition on subsequent patent quality.

We focused on M&A in the U.S. communications services sector over the period from 1998 to 2005. Over this period there were 2,028 separate deals for majority-ownership control involving 928 different U.S. communications services companies but COMPUSTAT data (Standard & Poor's, 2013) was not available for all of them and some of these acquisitions did not involve firms having patents. For this reason, our sample consists of 675 M&A. It should be noted that as many acquirers engaged in more than one M&A in a single year, we pooled those transactions and considered them as one data transforming our dataset under the form acquirer-year of transaction/s. The final sample included 330 unit of analysis. For the measurement of the innovation quality indicators, we used information pertaining to 120,588 U.S. patents granted over the period from 1995 to 2009 that was obtained from their 3,686,084 citations. Patent citation information was retrieved from the Derwent Innovation Index database (2013).

Following Sampson (2007) we counted the number of patents that firms produced for the four-year period before and after a particular acquisition was consummated (where the transaction year was included in our pre-acquisition counts). Because Hall, Jaffe, & Trajtenberg, (2005) and Mehta, Rysman, & Simcoe, (2010) have pointed out that it takes time before a new patent can be built upon, our count of forward citations extended to 2012 for patents that were granted four years after an acquisition was made (making the forward-citation count for acquisitions consummated in 2005 the most forward-truncated).

5.2. Matching variables

The matching estimator method requires several control variables for a better matching of the treated firms with their "twins" in the non-treated group in order to provide a more reliable measure of the effects of the treatment (which consists in post-acquisition increases in patent outputs). Our tests examine whether the group that received the treatment experiences a better or a worse outcome in terms of the patent quality measures.

The covariates are consistent with those tested in previous studies (*i.e.* Valentini & Di Guardo, 2012; Di Guardo & Harrigan, 2016) and include firm-specific characteristics connected with size, productivity capabilities, leverage, intangible assets, etc. In Table 1.1, we report a summary of the key variables of interest.

	Variable	Description
1	Size	Asset-per-employee ratio.
2	Log Assets	Natural logarithm of total assets.
4	Productivity	Sales-per-employee ratio.
5	Leverage	Ratio of long-term debt to total assets.
6	Intangible assets	Ratio of balance sheet intangibles to total assets.
8	Number of M&A in the same year	Number of M&A completed in the same year.
9	Year dummy ‘98	Dummy variable to capture annual exogenous shocks and time effects for each year where the base case equals ‘1998’.
10	Year dummy ‘99	Dummy variable to capture annual exogenous shocks and time effects for each year where the base case equals ‘1998’.
11	Year dummy ‘00	Dummy variable to capture annual exogenous shocks and time effects for each year where the base case equals ‘1998’.
12	Year dummy ‘01	Dummy variable to capture annual exogenous shocks and time effects for each year where the base case equals ‘1998’.
13	Year dummy ‘02	Dummy variable to capture annual exogenous shocks and time effects for each year where the base case equals ‘1998’.
14	Year dummy ‘03	Dummy variable to capture annual exogenous shocks and time effects for each year where the base case equals ‘1998’.
13	Year dummy ‘04	Dummy variable to capture annual exogenous shocks and time effects for each year where the base case equals ‘1998’.
14	Year dummy ‘05	Dummy variable to capture annual exogenous shocks and time effects for each year where the base case equals ‘1998’.

Table 1.1 Summary of the variables.

5.3. Dependent variables

The innovation literature suggests several innovation performance measures based on both R&D input and output. De Man and Duysters (2005) in their review pointed out that input indicators may produce misleading results as decreases in R&D expenditure reductions (*e.g.* due to the removal of redundancies) not necessarily impoverish the firm innovativeness. Mainly for this reason, output indicators have been highly favored by scholars, and innovation performance has been measured by using patents as proxies for the fruits of firms' R&D outlays and inventive activity. Analyses of patent content—insights that capture both the depth and the breadth of engendered technological knowledge (Moorthy & Polley, 2010)—have been used as a reliable measure of firms' innovative performance and quality (Trajtenberg, 1990; Ahuja & Lampert, 2001; Fleming, 2001; Hall *et al.*, 2001; Rosenkopf & Nerkar, 2001; Nerkar, 2003; Hagedoorn & Cloodt, 2003; Miller, Fern, & Cardinal, 2007; Di Guardo & Harrigan, 2016).

The *prior art* cited in a patent document reflects the firms' inventive capabilities. Patents provide useful information about the antecedents of an invention (Belenzon & Patacconi, 2013; Karim & Kaul, 2015) which facilitate a better understanding of the core technologies of a firm (Wu, Chen, & Lee, 2010). In addition, a high number of forward citations means that the patent has greatly contributed to further inventions which are built upon. Last, in order to fully appreciate the post-acquisition innovation quality, we examine changes in three citation-based indicators: technological *impact*, *originality*, and *generality*.

5.3.1. Technological impact

The variable of technological *impact* reflects the technological influence of the focal patent on further inventions and it is measured according to the number of citations it receives from subsequent patents which build upon it. Forward citations are an indication of an invention's importance (Lanjouw & Schankerman, 2004) and the higher the number of citations, the higher its technological *impact* on subsequent innovations is believed to be (Hall *et al*., 2001). Hence, our measure of technological *impact* is assessed using the total number of forward citations, that refer to those received by each patent. Patent indicators based on forward citations are highly influenced by time: if two patents have identical features but different application dates, the more recent patent has a lower probability of being cited. For this reason, we normalized our measure of technological *impact* in order to allow the comparison between time periods, in so doing, we used the average value of the measure itself (calculated over all the patents in the same focal technological category whose application was filed in the same year).

5.3.2. Originality of the synthesized knowledge streams

Our *originality* measure of synthesized technology streams captures the breadth of the technological knowledge bases that have been synthetized in the focal patent and captures the antecedent technology embodied in each patent. This indicator is based on the *originality* measure of Trajtenberg *et al*. (1997) and Hall *et al*. (2001) and uses their classification codes for backward citations. It is expressed as follows:

$$Originality_i = 1 - \sum_{j=1}^{n_i} s_{ij}^2 \tag{1.6}$$

where s_{ij} represents the backward citations of patent *i* (expressed in percentage terms) that have class code *j*, out of n_i different patent technology classes during the four-year, pre-acquisition and post-acquisition windows, respectively. Where the *originality* of a patent's synthesized technology streams builds on many different technologies, it is considered to be more original than those which build upon a single technology and the *originality* of a patent's synthesized technology streams rises as the number of technological classification codes included is larger. Since the *originality* of a patent's synthesized technology streams is not affected by time, the measure did not require normalization.

5.3.3. Generality of applicability

For the measurement of our measure of *generality* of applicability of a focal patent in subsequent inventions, we followed the Trajtenberg *et al.*'s (1997) as operationalized by Hall *et al*., 2001. A high breadth of applicability of patent *impact* suggests that a patent has influenced subsequent innovations in a widespread variety of technological fields. It is calculated using the classification codes of the forward citations and can be represented as follows:

$$Generality_i = 1 - \sum_{j=1}^{n_i} t_{ij}^2 \qquad (1.7)$$

where t_{ij} indicates the forward citations of $patent_i$ that belong to the $class_j$, out of n_i patent technological classes during the four-year, pre-acquisition and post-acquisition windows, respectively. When the forward citations of $patent_i$ are from several different technology classifications, the *breadth* of patent *impact* measure will be high; otherwise, the measure's value will be low (or will equal zero in the case in which all the citing patents share the same classification code). Our breadth of patent *impact* was normalized by the average value of the measure itself (which was calculated over all the patents in the same focal technological category whose applications were filed in the same year).

6. Results

Table 1.2 includes the descriptive statistics of the treatment and the firm-specific variables used in the matching procedure. The pair-wise correlation matrix depicted in Table 1.3 show a low magnitude of correlation between the variables of interest, suggesting that multicollinearity is not an issue for our analysis.

	Variable	**Mean**	**Std. Dev.**
1	Treatment	0.551	0.498
2	Size	10.181	39.992
3	Log Assets	3.553	1.129
4	Productivity	0.453	0.999
5	Leverage	0.262	0.250
6	Intangible Assets	0.244	0.205
7	Dummy ‘99	0.154	0.362
8	Dummy ‘00	0.163	0.370
9	Dummy ‘01	0.154	0.362
10	Dummy ‘02	0.106	0.308
11	Dummy ‘03	0.093	0.292
12	Dummy ‘04	0.096	0.296
13	Dummy ‘05	0.090	0.287

Table1.2 Descriptive statistics of the variables

Table 1.4 reports the post-acquisition *impact* on the average quality of the innovation outputs for both *successful* M&A (in terms of innovation) and the other deals.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Treatment	1.000												
2	Size	-0.097	1.000											
		[0.096]												
3	Log Assets	0.193	0.070	1.000										
		[0.000]	[0.229]											
4	Productivity	0.061	0.099	0.005	1.000									
		[0.293]	[0.089]	[0.931]										
5	Leverage	-0.003	-0.149	0.148	0.103	1.000								
		[0.948]	[0.013]	[0.012]	[0.089]									
6	Intangible Assets	0.209	-0.163	0.158	0.041	0.171	1.000							
		[0.000]	[0.006]	[0.007]	[0.488]	[0.005]								
7	Dummy '99	-0.019	0.030	0.033	-0.056	0.020	-0.139	1.000						
		[0.730]	[0.600]	[0.550]	[0.330]	[0.727]	[0.018]							
8	Dummy '00	0.036	-0.022	0.013	-0.042	0.027	-0.049	-0.189	1.000					
		[0.508]	[0.698]	[0.805]	[0.466]	[0.643]	[0.400]	[0.000]						
9	Dummy '01	0.014	-0.036	-0.082	-0.019	-0.043	0.016	-0.182	-0.189	1.000				
		[0.790]	[0.533]	[0.143]	[0.740]	[0.468]	[0.784]	[0.000]	[0.000]					
10	Dummy '02	0.033	-0.072	-0.076	-0.000	-0.037	0.027	-0.147	-0.152	-0.147	1.000			
		[0.543]	[0.216]	[0.177]	[0.997]	[0.529]	[0.645]	[0.007]	[0.005]	[0.007]				
11	Dummy '03	-0.064	-0.005	0.054	-0.011	-0.004	0.162	-0.137	-0.142	-0.137	-0.110	1.000		
		[0.241]	[0.921]	[0.332]	[0.849]	[0.943]	[0.005]	[0.012]	[0.009]	[0.012]	[0.044]			
12	Dummy '04	-0.033	0.029	0.000	0.168	-0.022	-0.010	-0.140	-0.144	-0.140	-0.112	-0.105	1.000	
		[0.538]	[0.610]	[0.993]	[0.003]	[0.702]	[0.865]	[0.010]	[0.008]	[0.010]	[0.040]	[0.055]		
13	Dummy '05	0.009	0.040	0.103	0.085	0.031	0.133	-0.135	-0.139	-0.135	-0.108	-0.101	-0.103	1.000
		[0.861]	[0.489]	[0.066]	[0.145]	[0.600]	[0.024]	[0.014]	[0.011]	[0.014]	[0.048]	[0.064]	[0.060]	

Table 1.3 Correlation matrix, p-values in parentheses.

As expected, the signs of all quality indicators are negative for *successful* M&A, suggesting that the post-acquisition acceleration of the patenting frequency is done at the expense of quality. In particular, the sign of the patent *impact*—which captures the technological importance and influence of the focal patent in subsequent inventions—is negative and statistically significant. This finding shows how post-acquisition increases in the number of innovation outputs, actually decrease the average number of forward citations that each acquirer's focal patent receives, confirming our Hypothesis 1.

The post-acquisition *originality* of a patent's synthesized technology streams is negative and statistically significant, highlighting that the dispersion of technological antecedents is narrower when post-acquisition innovation output increases. Results suggest that post-acquisition R&D activities focus on a smaller range of technological domains due to *e.g.* pursuits of R&D exploitation, signaling, and blockades which erode their patent's innovation quality, consistently with Hypothesis 2. Moreover, we checked for the eventual adoption of signaling strategies by measuring the effects of both successful M&A and the other deals on a common market performance measure, namely Tobin's *q*; this indicator reflects the investors' expectations regarding the future cash flows that would be generated as well as the market's expectation about intangible assets (Hall *et al*., 2005; Patel & Ward, 2011; Sandner & Block, 2011).

Innovation Quality	Successful M&A	Other M&A
Technological impact	-0.33*	-0.16*
Originality	-0.01***	0.03***
Generality	-0.03†	0.01†

***p<0.01   **p<0.05   *p<0.10 †p>0.10

Table 1.4 Effects on post-acquisition patent quality.

Findings reported in Table 1.5 show that Tobin’s *q* improved for firms that increased their innovation output production. This means that when the R&D activities are driven by strategies of output increases, the market overestimates the acquirer’s innovation potential and expects higher future rent extraction. In so doing, the market does not seem to be able to fully appreciate the quality of the acquirer’s portfolio.

Tobin’s q	t_1	t_2	t_3	t_4
Successful M&A	1.63***	1.30**	1.33†	1.46***
Other M&A	1.21***	1.18**	1.54†	1.29***

Table 1. 5 Effects on Tobin’s q bifurcated by increases in innovation outputs.

In addition, our Hypothesis 3 finds confirmation, although it is very weak from a statistical point of view as it loses its statistical significance. However, the negative sign of this indicator suggests that higher increases in post-acquisition patents are less appealing to broader technological domains. All the listed results confirmed that *successful* M&A while increases the quantity of the innovation outputs, it impoverishes the average quality of the acquirer's portfolio. By contrast, the firms involved in other deals which experienced no increase of innovation outputs (or even a decrease), performed better in terms of average patent quality: *impact, originality* of their patents' synthesized technology streams and *generality* of applicability in other technological domains. These results are statistically significant and confirmed our Hypothesis 4.

7. Discussion and conclusion

The results obtained in the previous section allow us to take the debate on the relationship between M&A and innovation performance and to contribute to the existing literature in multiple ways. First, this chapter extends prior studies on innovation quantity and quality, by showing that their relationship in the specific case of M&A is negative. This result is consistent with the work of Valentini (2012) who observed that the patenting activity of the firms involved in M&A in the U.S medical devices and photographic equipment industry—in comparison to firms that preferred other R&D stimuli *e.g.* organic innovation, strategic alliances—was characterized by increases in the average quantity of innovation outputs and decreases their average quality. Similarly, the firms in our sample seem to have the same behavior: "*quantity at the expense of quality*". Therefore, it is possible to point out that increases in the patent quantity and their simultaneous quality impoverishment cannot be led to the occurrence of the M&A per se (as the engagement in at least one deal was an explicit sampling criterion) but it is attributed to the R&D and patenting strategies adopted by the acquirer: specifically, R&D exploitation, blockades, and signaling activities. In fact, our results can be hardly influenced by an eventual lack of the strategic and organization fit between target and acquirer, because in this case, it would be difficult to observe accelerations of the patenting frequency. Second, we enter into the so long discussed debate about the innovation performance measurement. The review of De Man and Duysters (2005) highlighted that the inconclusive results about the directionality of the M&A effects on innovation performance may be due to the different indicators used to assess it: input-based (*e.g.* R&D expenditure) or output-based (*e.g.* patents). In the light of our results, we add the reflection that these inconsistencies may be further caused by the choice of the patent quality approach rather than the well-established patent quantity methodology. Furthermore, the negative relationship between post-acquisition patent quantity and quality calls into question many prior studies which focused on the mere quantity of the innovation outputs. Third, we addressed the sample endogeneity issues raised by prior studies (Maddala, 1986; Shaver, 1998; Rodríguez-Duarte *et al.,* 2007) by using the matching estimator and propensity score methods (Rosenbaum & Rubin, 1983, 1984).

The managerial implication suggested by the present study can be summarized as follows: managers who choose to use M&A as a strategic means to acquire new technical knowledge, expertise, and capabilities, should not focus on short-term period, seeking immediate innovation output results, but they should adopt farsighted strategies aiming to the improvement of the quality of the patenting activity, however without "abusing" of blockades. Investors and market in general, should be more aware of the acquirers' post-acquisition innovation quality and not passively observe their granting activities.

This chapter presents several limitations that warrant attention. Our study focused on a single sector while it may be extended to multiple industries with similar or different structure. Moreover, we examined the changes in the quality of the innovation outputs only by assessing the patent dimension. Finally, in this work we used the Hall *et at.* (2001) quality indicators which are based on the US classification codes which are going to be obsolete as the U.S. Patent Office is exclusively adopting the Cooperative Patent Classification, a new patent classification shared with European Patent Office; this means that there urges the need to build new and as hoped better patent indicators. Further research might focus on the construction of novel and more dynamic indicators, *e.g.* those proposed by Harrigan *et al.,* (2017) which are based on Derwent Patent Classification.

CHAPTER II

THE COMPLEMENTARITY EFFECTS OF M&A DIVERSIFICATION AND KNOWLEDGE RECOMBINATION ON INNOVATION PERFORMANCE

8. Abstract

The aim of this chapter is to increase our understanding of *whether* the diversification of resources via mergers and acquisitions (M&A) enhances or impoverishes the acquirer's post-acquisition innovation performance and *when* acquirers can leverage this strategy. By focusing on the role of the acquirer's capabilities to recombine distant knowledge, we attempt to find a new explanation of the heterogeneity between firms' innovation performance. This study uses a sample of M&A transactions completed in the U.S. communication services industry between 1998 and 2005 and accounts for the possibility of unobserved self-selection into diversified acquisitions by using a quasi-experimental approach. Findings show that resource diversification positively affects the acquirer's innovation performance, and more interestingly, those acquirers that diversified and further developed high recombinant knowledge capabilities enjoyed a complementarity effect on their post-acquisition innovation performance.

9. Introduction

The diversification of resources (including technology) is of central concern to strategy scholars as it is a vehicle for organizational growth and an important source of competitive advantage (Miller, 2006; Ahuja & Novelli, 2016). The combination of multiple strands of knowledge, expertise, and capabilities is essential to face the increase of product complexity and succeed in competitive environments (Breschi, Lissoni, & Malerba, 2003; Suzuki & Kodama, 2004). Firms that are more diversified can have certain advantages in the competitive market since they can exploit a higher complementarity between different, although related technologies (Suzuki & Kodama 2004) and also since they can take advantage of unrelated technologies that take place in the firm. However, the wide plethora of resources required by the innovation activity is frequently difficult to be generated organically due to the lack of time related to the process of organizational learning (Teece, 1987; Granstrand, 1998), therefore, firms may choose to span their boundaries and diversify via mergers and acquisitions (M&A) in order to fill rapidly the gap between the resources already possessed and those necessary for sustaining the innovation process and keeping up with the pace of technology (Hitt *et al.*, 1996; Ahuja & Katila, 2001; Graebner, 2004; Cassiman *et al*., 2005; Cloodt *et al.*, 2006; Makri *et al.*, 2010).

Although M&A are often used as an effective means for diversifying resources (Ahuja & Katila, 2001; Cassiman *et al*., 2005; Cloodt *et al.*, 2006; Colombo, Grilli, & Piva, 2006), the acquirer may show different capabilities to absorb and recombine the target's knowledge, especially when it is diverse and distant from its own one (Ranft & Lord, 2002; Paruchuri, Nerkar, & Hambrick, 2006; Puranam *et al*., 2006; Puranam & Srikanth, 2007; Puranam, Singh, & Chaudhuri, 2009; Makri *et al.*, 2010).

Indeed, extant research on diversification has shown inconclusive and contrasting results regarding the directionality of the relationship with innovation performance. On one hand, studies have shown a positive influence thanks to the exploitation of existing resources and the development of new capabilities (Miller *et al*., 2007; Wan, Hoskisson, Short, & Yiu, 2011; Kim, Arthurs, Sahaym, & Cullen, 2013), on the other hand, studies have evidenced a negative effect due to the loss of the firms' ability to leverage their core competencies (Baysinger & Hoskisson, 1989; Hitt, Hoskisson, & Ireland, 1996). Instead, less is being known about how the capabilities of the acquirer to recombine a wide range of technological knowledge may trigger changes in the patterns of innovation and whether there are synergetic effects between M&A diversification and knowledge recombination.

Based on the Resource-Based View (RBV) and the Dynamic Capability View (DCV), the present study aims to investigate the effect of M&A diversification and the role of the acquirer's capabilities to recombine diverse knowledge on its post-acquisition innovation performance. Moreover, we explore the complementarity effect between M&A diversification and knowledge recombination on the acquirer's post-acquisition innovation performance. In doing so, we attempt to find an explanation of the heterogeneity on innovation performance between firms that are engaged in M&A transactions and further address the inconsistencies observed by prior research.

This chapter advances the RBV and DCV by answering how the access to valuable external resources goes through a process in which the dynamic capabilities play a role and the possible complementarities between M&A diversification and knowledge recombination capabilities in their effects on acquirer's post-acquisition innovation. We examine the U.S. communication services industry and test our hypotheses on a sample of M&A transactions completed between 1998 and 2005. We collected 120,588 U.S. granted patents and their 3,686,084 backward and forward citations. Differently, from other studies, we treat diversification *endogenously*, as firms choose to diversify according to their strategy in terms of technology acquisition/deployment, market position, perceived potential synergies, etc. (Campa & Kedia, 2002; Zhou, 2011). We account for the possibility of unobserved self-selection into M&A diversification by using a quasi-experimental approach and employing the endogenous treatment effects method.

10. Theoretical background

Explaining the performance differences between firms and identifying the determinants of a sustained competitive advantage, is a key issue for strategy scholars. The existing literature provides different approaches for a better understanding of the dynamics that allow firms to outperform their rivals. According to the RBV, competitive advantage is strongly related to the heterogeneity of the firm's resources (Barney, 1991; Peteraf, 1993; Hoopes *et al.,* 2003) and more recently, the DCV stresses the importance of the firm's capabilities to transform and reconfigure resources into an advantaged firm performance, especially in dynamic markets (*i.e.* Helfat, 1997; Teece *et al.*, 1997; Zollo & Winter, 2002). In addition, Eisenhardt and Martin (2000) argued that the combination of valuable, rare, imperfectly imitable, and non-substitutable resources and capabilities, is a source of competitive advantage, while, Teece (2007) identified the fundamental components of the dynamic capabilities focusing on the firm's capacities to sense opportunities and threads, to seize opportunities, and to transform and reconfigure resources (both tangible and intangible) in order to maintain the competitiveness. From this perspective, building successful innovation strategies means for firms the combining of a bundle of *unique* heterogeneous resources and the developing of the necessary dynamic capabilities to leverage them.

Technological diversification is an acknowledged way commonly used by firms to foster the innovation process by enhancing the cross-fertilization between different streams of technological knowledge (Miller, 2006). The achievement of this strategy can follow a dual-path, either by the increase of the R&D investments or by external technology sourcing. Organic growth, as suggested by RBV, has the advantage to avoid the potential copy from competitors that may reduce in part or totally the competitive advantage gained (Love, Roper & Vahter, 2014), nevertheless, it presents several disadvantages connected to the risks of the internal R&D projects, the path dependency and the *familiarity trap* (Patel & Pavitt, 1997; Ahuja & Lampert, 2001; Sydow, Schreyögg, & Koch, 2009), as well as, a certain time needed for the organizational learning (Teece, 1987; Granstrand, 1998;). In particular, the speed of innovation and the rise of product complexity may lead firms to undertake external routes in order to insert rapidly in the innovation process those capabilities that are difficult to be built internally (Nelson & Winter, 1982; Granstrand, Patel, & Pavitt, 1997; Gambardella & Torrisi, 1998; Suzuki & Kodama, 2004).

In this context, M&A are effective means to fill the gap between the technological resources already possessed and those necessary for keeping up with the pace of technology (Ahuja & Katila, 2001; Cassiman et al., 2005; Cloodt *et al.,* 2006). Mainly for this motive, M&A have become a popular and widespread strategy for many firms (Makri *et al*, 2010), particularly in high-tech industries (Link, 1988; Lee & Kim, 2016;). The innovation process, as argued previously, is the result of both resources and capabilities to combine different knowledge in a novel way (Kogut & Zander, 1992; Bogner & Bansal, 2007; Teece, 2007), therefore, acquirers need to recombine successfully the internal and external knowledge bases in order to push up the generation of new inventions (Schumpeter, 1934). As the acquisition of new and diverse technological knowledge is expected to enhance the acquirer's search capabilities (Cassiman *et al.,* 2005; Garcia-Vega, 2006; Quintana-Garcìa & Benavides-Velasco, 2008; Kim, Lee, & Cho, 2016), and absorptive capacity (Cohen & Levinthal, 1990; Zahra & George, 2002), firms that diversified their technology by extramural knowledge and further developed capabilities to recombine it efficiently, may benefit multiplicative and complementarity effects. Last, if these resources and their related activity systems have complementarities, the potential to create sustained competitive advantage is enhanced (Milgrom, Qian, & Roberts, 1991; Porter, 1996; Eisenhard & Martin, 2000; Colombo *et al*., 2006; Ennen & Richter, 2010).

11. Hypotheses

The firm innovation process is affected by both the uniqueness of resources possessed, as well as, the dynamic capabilities able to transform those resources into a durable competitive advantage. Our study focuses on the impact of M&A diversification and knowledge recombination on innovation performance from a dual approach, RBV and DCV. In our research framework (Figure 2.1), M&A specialization and diversification are two ends of a continuum, firms choose the degree of diversification according to their specific strategy: enlarge the heterogeneity of resources to be employed in the innovation process or specialize in their familiar resources to sustain extant core competencies.

The RBV literature suggests that diversification strategies are beneficial for firms when there is an excess of resources left idle from the firm's activity that allows the achievement of economies of scope (Panzar & Willig, 1981; Teece, 1982; Miller, 2006). In this approach, resources or capabilities can create value when shared across businesses (Markides & Williamson, 1994), therefore, more innovative firms may develop greater capabilities (Dierickx & Cool, 1989), which could be used by the firms to enter new markets (Cohen & Levinthal, 1990; March, 1991; Nonaka & Takeuchi, 1995; Teece *et al.*, 1997). However, Hall (1990) demonstrated that firms with lower levels of R&D investment were more likely to diversify than more innovative firms. When firms grow via M&A, they often seek capabilities and knowledge that are difficult to develop organically (Nelson & Winter, 1982).

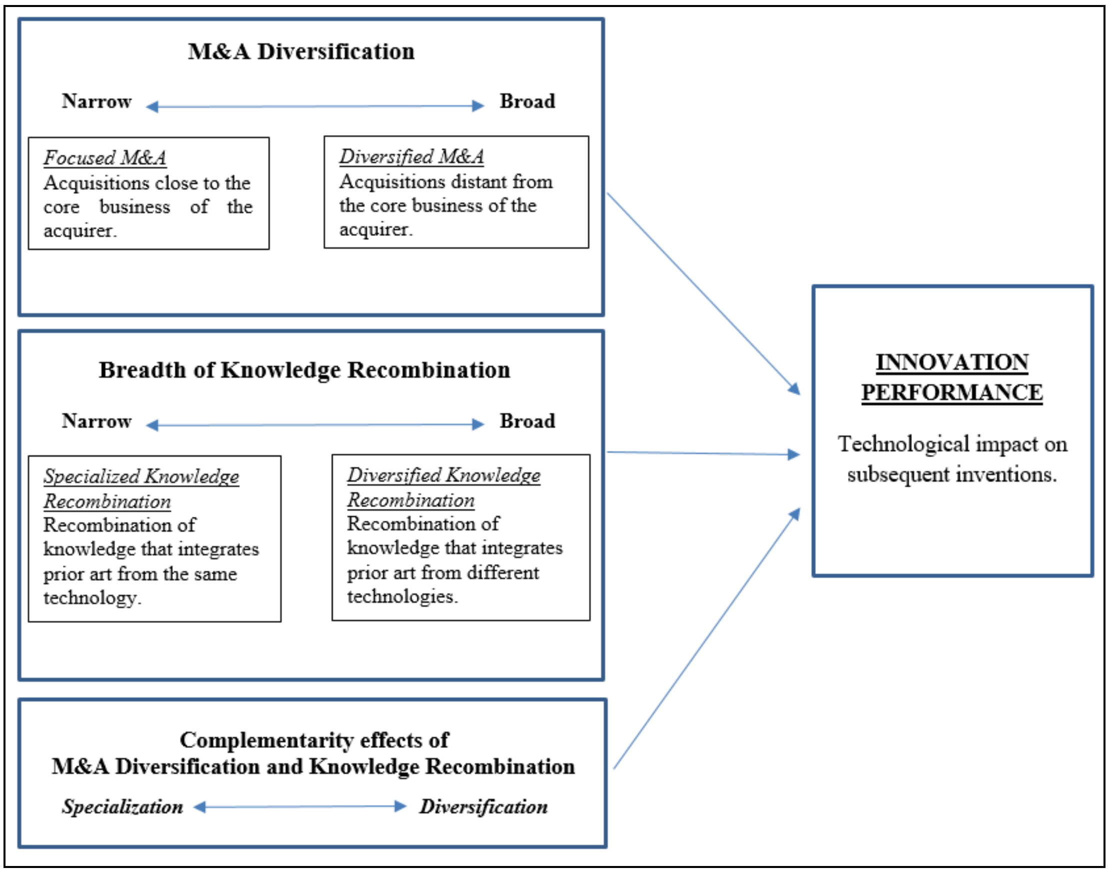


Figure 2.1 Research framework

Many studies have highlighted the importance of the technological-knowledge diversity as a potent source of a firm's inventive performance (Henderson &

Cockburn, 1996; Nesta & Saviotti, 2005; Garcia-Vega, 2006; Quintana-Garcìa, & Benavides-Velasco, 2008; Dibiaggio *et al.,* 2014). Firms that diversify, are expected to take advantage of broader tangible and intangible resources that in turn allow them to perform better than firms that did not choose this strategy (Palich, Cardinal, & Miller, 2000; Miller, 2006).

More specifically, the acquisition of businesses units (and their related technological assets) that are distant from the core business of the acquirer, increases the acquirer's breadth of search creating new opportunities (Granstrand *et al*.,1997; Patel & Pavit, 1997) fostering the generation of breakthrough innovations (Schumpeter, 1934; McEvily & Zaheer, 1999; Ahuja & Lampert, 2001; Lee & Kim, 2016). On the contrary, similarities and overlap between acquirer and target do not provide enough differences to enrich the invention capabilities and therefore they are less likely to be valuable (Kim & Finkelstein 2009; Makri *et al*., 2010). In fact, the exposure of the acquirer to new and diverse knowledge provides opportunities for organizational learning (Ghoshal, 1987; Hitt *et al.*, 1996) and the recombination of existing and new knowledge enable firms to produce path-breaking innovations (Schumpeter, 1934; Nelson & Winter, 1982; Fleming, 2001; Nerkar & Roberts, 2004; Miller, 2006; Teece, 2007), as well as to shift to new technological paradigms (*i.e.* Abernathy & Utterback, 1978). Those dynamics are expected to exert a positive impact on innovation performance in terms of technological impact on subsequent innovations.

Hypothesis 1: *A higher degree of diversification via M&A has a positive effect on the acquirer's post-acquisition innovation performance.*

The efficiency of the recombination process that involves distant knowledge is a determinant of the acquirer's performance (Ahuja & Katila, 2001; Teece, 2007) and it can be hardly imitated by competitors. Kogut and Zander (1992) introduced the concept of *"combinative capabilities"* referring to the organizational processes through which the firm exploits its knowledge (internal and acquired) and the unexplored technology potential to generate new inventions. Therefore, the firm's capabilities to recombine knowledge elements can be considered as a dynamic capability that it is expected to reward firms with higher innovation performance.

We conceive the knowledge recombination capabilities focusing on the diversity of the knowledge components. More specifically, the recombination of broad knowledge refers to the extent to which firms recombine knowledge from distinct and multiple technological domains, meanwhile, the recombination of narrow knowledge concerns the level of knowledge complexity in specific fields (Bierly & Chakrabarti, 1996). The ensemble of all these specific recombination capabilities can be hardly duplicated by rival firms and it is expected to have a positive effect on innovation performance. In summary, firms that are not able to identify, assimilate, and apply new external knowledge, will enjoy low benefits in terms of innovation performance (Cohen & Levinthal, 1990).

A challenge for firms is not only the identification of valuable external resources required by the R&D activity but also the “higher-order” capabilities that allow the enhancement of the acquirer’s innovation performance (Figure 2.1). In particular, technological diversification is a determinant for the enhancement of the firm’s absorptive capacity (Cohen & Levinthal, 1990; Garcia-Vega, 2006; Quintana-Garcìa & Benavides-Velasco, 2008; Kim *et al*., 2016;). Zahra and George (2002:186) defined absorptive capacity as a “set of organizational routines and processes by which firms acquire, assimilate, transform, and exploit knowledge to produce a dynamic organizational capability”. Firms with higher absorptive capacity have been argued to outperform their competitors (Barney, 1991; Zollo & Winter, 2002).

Moreover, the literature has long emphasized the role of complementarities and synergies when pursuing diversification strategies (Teece, Rumelt, Dosi, & Winter, 1994; Grant, 1996; Kim & Kogut, 1996; Ennen & Richter, 2010) and how these complementarities may shape the directionality of the firm’s innovation activities (Helfat, 1997). We expect that a firm’s broad knowledge acquisition fosters the generation of synergies among different technological components involved in the innovation process, making firms to leverage diversification (Dibiaggio *et al.*, 2014). Diversified M&A may help acquirers to enhance the firm-specific capability to assimilate extramural knowledge (Cohen & Levinthal, 1990; Garcia-Vega, 2006; Quintana-Garcìa & Benavides-Velasco, 2008). Firms may also benefit learning externalities if they develop specific tools to ease the development of different knowledge combinations (Dibiaggio *et al.*, 2014).

Acquirers that developed dynamic capabilities able to better leverage the breadth of the resources acquired are expected to have higher innovation performance. These dynamic capabilities are accumulative thanks to the firm's absorptive capacity and are expected to generate a complementarity effect with the resources employed in the innovation process. Hence, acquirers that diversify and develop dynamic capabilities able to recombine diverse, novel, and distant knowledge are expected to have higher innovation performance.

Hypothesis 2: *There is a complementarity effect between a higher degree of M&A diversification and knowledge recombination on the acquirer's post-acquisition innovation performance.*

12. Method

The present study examines the effects of M&A diversification and knowledge recombination, as well as, their conjoint impact, on the acquirer's innovation performance. Diversification has long been argued to be a strategic decision for firms and as such, it is a function of managers attempting to improve the outcome. The claim of causality, therefore, requires taking into account the endogeneity issues that may arise: *i.e.* the self-selection into diversified acquisitions. Self-selection is an important threat for our analysis as it can lead to erroneous empirical results and consequently to incorrect conclusions (*i.e.* Shaver, 1998; Hamilton & Nickerson, 2003; Clougherty, Duso, & Muck, 2016).

In order to mitigate the above-mentioned criticisms and account for unobserved factors that may influence our results, we apply the endogenous treatment effect method with maximum likelihood estimators (Terza, 1998; Terza, Kenkel, Lin, & Sakata, 2008). This method allows overcoming the issue of the treatment when is not randomly assigned. Endogenous treatment makes the untreated observations of the control group, not adequate counterfactual representatives of the treated group: the treated and control groups may differ from each other not only in terms of observable factors but also in terms of unobservable ones (Clougherty *et al*., 2016). We measure the effects of the treatment on the outcome in two different moments, before and after the M&A transaction.

More specifically, we apply the endogenous treatment-regression model[2] that uses a linear model for the outcome and a normal distribution to model the treatment assignment. This method is similar to the Heckman procedure (Heckman, 1976, 1978) and consists of two equations, one for the outcome and another for the endogenous treatment. To test our hypotheses, we use the following model:

$$INN_{i,t0+k=} f\,(DIV_{i,t0};\ RECOMB._{\ i,t0+k};\ DIV_{i,t0}{*}RECOMB._{\ i,t0+k}). \qquad (2.1)$$

The innovation performance of firm$_i$ in the time interval t_{0+k} is a function of the degree of M&A diversification, knowledge recombination, and their interaction effect. The specification of our model is the following:

[2] We performed the model by using the “etregress” STATA command.

$$\Delta INN_i = \alpha_0 + \alpha_1\, \Delta\, DIV_i + \alpha_2\, \Delta\, RECOMB_i + \alpha_3\, \Delta\, DIV_i * \Delta\, RECOMB_i + \boldsymbol{X_{c,i}}\, \boldsymbol{B_c} + \varepsilon_i. \tag{2.2}$$

where ΔINN_i captures the change in the innovation performance of firm$_i$. Our model considers two main effects $\Delta\ DIV_i$ and $\Delta\ RECOMB_i$ that represent respectively changes in the diversification degree of the firm$_i$ (attributed to the acquisition) and changes in its knowledge recombination capabilities. Of particular interest for our research questions is the interaction term used to test the complementarity effects on innovation performance. $\boldsymbol{X_{c,i}}\ \boldsymbol{B_c}$ is a vector of control variables, meanwhile, ε_i represents the error term that is assumed to be normally distributed.

In our model (2), $\Delta\ DIV_i$ represents the endogenous treatment. We segregated our sample into the treated group if the observed units were above the mean value of the $\Delta\ DIV$ variable and controls if they were below or equal to it. In particular,

$$\Delta\ DIV_i = \beta_0 + \beta_1\ \text{INSTRUMENT} + \boldsymbol{Z_{c,i}}\, \boldsymbol{C_c} + w_i \tag{2.3}$$

where $\Delta\ DIV_i$ is a binary variable that assumes a value equal to 1 if the firm engaged in diversified acquisitions and value equal to zero if it did not. We introduce a new instrument that uses the number of M&A transactions made by the firm in a single year. If M&A, as argued previously, is a means that allow firms to grow and diversify their technological resources, a high number of M&A transactions in a specific interval can be considered as a manifestation of the diversification strategy. Often, firms engage in M&A to influence their innovation performance, and our argument is that these changes in the innovation patterns are due to changes in the diversification degree. $\boldsymbol{Z_{c,i}}\ \boldsymbol{C_c}$ is a vector of covariates and w_i is the error term that is assumed to be normally distributed. ε_i and w_i bivariate normal with mean zero and covariance matrix

$$\begin{bmatrix} \sigma 2 & \rho\sigma \\ \rho\sigma & 1 \end{bmatrix} \tag{2.4}$$

We then estimate the maximum likelihood function (Maddala, 1986).

12.1. Sample and data

The present study focuses on the U.S. communication services sector, mainly for the essential role played by technology in allowing firms to gaining and sustaining a competitive advantage and the importance of the intellectual property protection (as demonstrated by many patent applications granted each year by the U.S. Patent Office). Our investigation of the conjoint effects of M&A diversification and knowledge recombination on innovation performance, required information regarding: (1) the M&A transactions for the sample selection, (2) the business industry classification for building our diversification scores, (3) the acquirer's patent documents for the proxies of the innovation performance and knowledge recombination, and (4) the financial data for the control variables.

Thomson One's Mergers & Acquisitions database (2013) provided details about the M&A transactions completed during the time interval 1998-2005 with the U.S. targets specialized in communications services. Those targets were identified by means of their primary industry NAICS codes[3]. Subsequently, financial and patent data were collected from 1992 to 2012 using respectively the *OSIRIS* (2015) and Derwent Innovation Index databases (2013). Consistently with prior studies, we applied a 4-year window before and after the deal (8 years in total) as this time period is considered appropriate for an invention to be generated and patented (Sampson, 2007). For additional analysis, we applied also a 5-, 6-, and 7-year windows. The pre-acquisition window includes the year in which the transaction took place. Our dataset has the form of firm-year of the deal observations with 330 units of analysis. It should be specified that as we are looking at changes between two time-windows (before and after the M&A transaction), we excluded from the sample those observations that had no granted patents in the post-acquisition window. In this case, the procedure would show an impoverishment of the innovation performance that cannot be attributed to the engagement in diversified acquisitions or the firm's recombination capabilities, but it is simply driven by the absence of patent data. For this reason, our final sample consists of 280 unit of analysis.

12.1. Dependent variable

For the assessment of the acquirer's innovation performance, we used an output measure commonly identified as the technological *impact* or usefulness of a patented invention. This popular proxy is calculated using the number of citations per year that

[3] The NAICS (North American Industrial Classification System) code of the target included: semiconductors; electronic storage; communication equipment; computing equipment; and software and IT technology services, among others.

the focal patent receives by subsequent inventions which are built upon (Trajtenberg, 1990; Trajtenberg *et al.*, 1997; Hall *et al.*, 2001; Ahuja & Lampert, 2001; Fleming, 2001; Rosenkopf & Nerkar, 2001; Hagedoorn & Cloodt, 2003; Nerkar, 2003; Miller *et al.*, 2007). According to the extant literature, the technological *impact* is able to capture both the patent technological importance as well as its economic value (Harhoff *et al*., 1999; Kaplan & Vakili, 2015). In particular, a high number of forward citations indicates that the invention has served as a platform for further technological advancements, distinguishing it as disruptive or breakthrough innovation.

For the technological *impact* measure, we used the forward citations of patents granted four years before and after the deal. Patent forward citations are sensitive to time, this means that if two highly similar patents are granted in different moments, the most recent one is more likely to receive fewer citations. In order to allow comparison between time intervals, we truncated the citation data as suggested by Hall *et al.* (2001) and normalized them using average values calculated over all the patents in the same focal technological category whose application was filed in the same year.

12.2. Independent variables

12.2.1. Diversification scores

In this chapter, we introduce a concentric measure of diversification based on 6-digit NAICS[4] codes (The NAICS was adopted in 1997 as an enhancement of the SIC[5] system to permit a higher comparability between the North American businesses, at establishment level). The NAICS allowed overcoming many SIC system inconsistencies, *i.e.* dissimilarity within the same 4-digit code or similarity between businesses categorized in different classes simply because they were not foreseen at the time when the SIC system was created. Moreover, the six-digit NAICS codes provide more detailed information useful to building a more precise diversification indicator (Wang & Zajac, 2007).

Referring to the model (2) explained in the method section, we are interested in finding out changes in the diversification scores attributed to the acquisition:

$$\Delta\, DIV_i = DIV_C - DIV_A \tag{2.5}$$

which is represented by the difference between the diversification degree of the combined firm after the acquisition (DIV_C) and that of the acquirer before the transaction took place (DIV_A). To capture this change, we use a measure of diversification based on the distance between the core business of the acquirer

[4] The primary NAICS (North American Industry Classification System) is production oriented as it categorizes businesses with similar methods of production. NAICS codes are self-reported by firms (acquirers and targets).

[5] Standard Industrial Classification.

identified by its primary NAICS code (APRIMENAICS) and the NAICS codes of the target(s) (TNAICS) [6] (Figure 2.2):

$$\Delta\, DIV_i = \left(\sum_1^n |APRIMENAICS - TNAICS_x|\right)/APRIMENAICS \tag{2.6}$$

where $x = 1, 2, 3 \ldots., n$ and the maximum value of n was 27 different $TNAICS_x$ industry codes (Figure 2.2 shows an example of calculation). This indicator is similar to the measure of technology breadth used by Harrigan, Di Guardo, & Cowgill (2017) or Miller (2004); both used concentric measures of technology distance.

The choice to take into consideration only the acquirer's primary NAICS code aims to account for: (1) the different integration costs faced by the acquirer for acquisitions that go far from its core business, (2) the different time needed by the acquirer to absorb non-core technologies, and (3) the different search opportunities given by non-core diversification (Seru, 2014; Kim *et al*., 2016). By construction, this indicator assumes only positive values starting from zero, where zero represents a perfect overlap between the APRIMENAICS codes and the TNAICS codes; on the contrary, a higher value indicates a greater distance between them.

[6] If an acquirer was involved in several M&A transactions, we considered all the NAICS codes of all the targets.

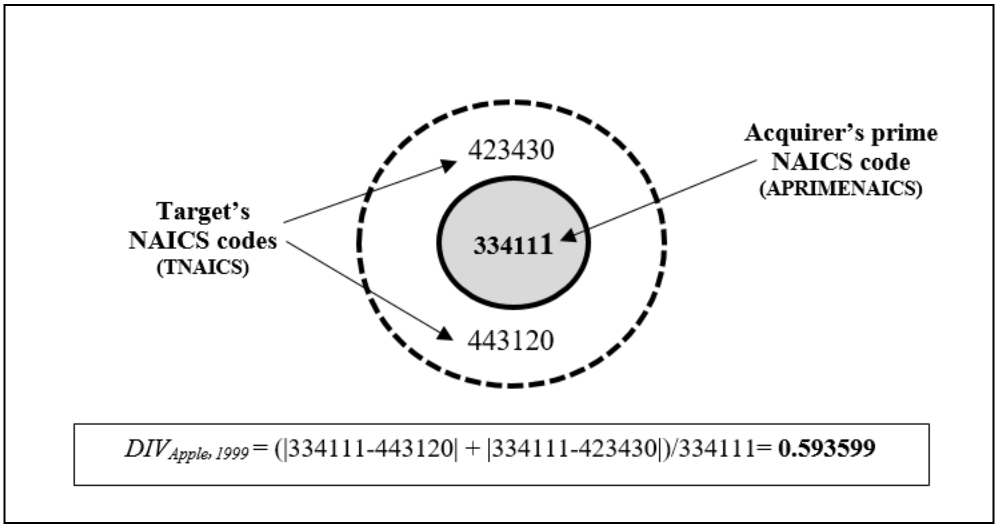


Figure 2.2 Example of calculation of the diversification score

12.2.2. Knowledge Recombination

Our measure of knowledge recombination focuses on the breadth of technological knowledge bases that were synthesized in a granted patent. It was assessed following the originality measure introduced by Trajtenberg *et al.* (1997) and subsequently operationalized by Hall and colleagues (2001):

$$Originality_i = 1 - \sum_{j=1}^{n_i} s_{ij}^2 \tag{2.7}$$

where s_{ij} indicated the proportion of the citations *made* by firm's patent$_i$ to preceding patents that belonged to various technological classes$_j$ out of n_i patent technological classes. The *originality* was calculated such that if a particular patent$_i$ cited mostly antecedent patents that belonged to a narrow set of technological classes, patent$_i$'s originality score would be low; if a patent$_i$ cited precedent patents from several different technological classes, patent$_i$'s originality score would be higher. Hall et al. (2001)'s adaptations of the technological classifications of the U.S. Patent and Trademark Office were used to obtain a manageable number of categories for comparisons across technology classes. Two measures of *originality*—for pre- and post-acquisition innovation activity, respectively—were calculated in order to reflect any differences that might have existed in the originality of patent applications made before and after an acquisition occurred.

12.2.3. Control variables

Firms' innovative performance may be explained by additional factors that were included as control variables: number of patents per year granted in each 4-year window, size, intangible assets, number of M&A transactions per year, and year dummies. We, hence, included the mean of the number of patents per year as a measure of the patenting activity and R&D efforts. Firms with a higher rate of patent productivity are expected to receive a higher number of citations with respect to a smaller one. The logarithm of total assets and was included as an indicator of the critical organizational mass that would be needed to realize scale economies when pursuing innovation activities. The intangibles variable (the ratio of intangible assets to total assets) was specified as a control variable to represent the potential existence of extant intellectual property. We chose to exclude the research and development expenditures because of the strong correlation with the number of patents (Ahuja &

Lampert, 2001; Fleming, 2001; Eggers & Kaul, 2018). Finally, we included the number of M&A transactions per year as an instrument for our diversification measure.

13. Results

Table 2.1 reports the descriptive statistics of the variables used in our analysis (year dummies are not reported), whilst the pair-wise correlations are included in Table 2.2; among the statistically significant relationships to note, the number of patents per year is negatively related to M&A diversification and the number of M&A transactions completed by the firm. In addition, this latter variable is positively related to our measure of diversification. All variables have a low correlation between each other ensuring the avoidance of multicollinearity issues that may raise.

	Variable	Mean	St. Dev.
1	Δ M&A Diversification	0.268	0.444
2	Δ Knowledge Recombination	0.074	0.214
3	Δ Number of patents	2.497	96.541
4	Intangible Assets $_{t0}$	0.192	0.208
5	Logarithm of total assets $_{t0}$	8.172	6.257
6	Number of deals $_{t0}$	2.236	2.255

Table 2.1 Descriptive statistics.

	Variable	1	2	3	4	5	6	7
1	Δ M&A Diversification	1.000						
2	Δ Knowledge Recombination	0.055	1.000					
		[0.359]						
3	Δ Number of patents	-0.183	-0.000	1.000				
		[0.002]	[0.990]					
4	Intangible Assets $_{t0}$	-0.167	0.082	0.051	1.000			
		[0.024]	[0.276]	[0.490]				
5	Logarithm of total assets $_{t0}$	-0.081	0.205	0.042	-0.070	0.408	1.000	
		[0.223]	[0.002]	[0.525]	[0.348]	[0.000]		
6	Number of deals $_{t0}$	0.173	0.035	-0.223	0.079	-0.018	0.011	1.000
		[0.003]	[0.560]	[0.000]	[0.289]	[0.790]	[0.862]	

Table 2.2 Correlation matrix.

Table 2.3 depicts the results obtained by the estimation of the endogenous treatment effects using the maximum likelihood estimator. We report changes between the post- and pre-event data. We included year dummies and firm controls. Our model shows a positive effect of the two main effects and the interaction term on innovation performance. M&A diversification (β=1.086, p=0.034), knowledge recombination (β=1.457, p=0.043), and their complementarity effect on innovation performance (β=3.829, p=0.000) are statistically significant. These results support all our hypotheses. The Wald test is highly significant, showing a good model fit. The estimate of the correlation of the treatment-assignment errors for the control group (ρ) is negative, this indicates that unobservables that increase diversification tend to occur with unobservables that decrease innovation performance.

Innovation Performance	Endogenous Treatment Effects with Maximum Likelihood Estimator			
	4-Year window	5-Year window	6-Year window	7-Year window
M&A Diversification	1.086	1.000	0.961	1.066
	[0.513]	[0.529]	[0.522]	[0.493]
Knowledge recombination	1.457	1.975	2.042	2.179
	[0.718]	[0.733]	[0.643]	[0.625]
Diversification*Knowledge Recombination	3.829	3.708	3.811	2.921
	[1.039]	[1.030]	[0.997]	[0.993]
Firm controls	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included
Constant	Included	Included	Included	Included
Rho	-0.556	-0.438	-0.359	-0.372
	[0.150]	[0.172]	[0.180]	[0.171]
Sigma	1510	1477	1440	1405
	[0.117]	[0.104]	[0.092]	[0.090]
Prob>χ^2	**0.000**	**0.000**	**0.000**	**0.000**

Table 2.3 Results for the endogenous treatment estimation using the full maximum likelihood estimator. Robust standard errors in parentheses.

Table 2.3 also reports results for a 5-, 6-, and 7-year windows for additional robustness check. While the effect of the M&A diversification tends to decrease using a more extended time-window, the knowledge recombination increases its significance in statistical terms, highlighting the cumulative nature of the knowledge itself. The complementarity effect remains highly significant (p-value = 0.000) for the 4-, 5-, and 6-year window while it decreases (p-value = 0.003) in the 7-year time frame.

14. Discussion and conclusion

The present study explores the effects of resource diversification via M&A on innovation performance by focusing on the role of the acquirer's knowledge recombination. Our results show that the acquisition of broad external resources fosters the opportunities for the acquirer to increase its competitive advantage over competitors in terms of inventive *impact* and usefulness. The RBV argument regarding the gaining of a competitive advantage through the heterogeneity of resources holds for our sample, as M&A diversification awards the innovation performance of those acquirers that add resources which are different from their core activities. In addition, the development of dynamic capabilities able to recombine distant knowledge, even if there is no change in the diversification degree, is beneficial for acquirers.

The focal result of this study consists in providing evidence of the existence of a multiplicative complementarity effect between the resources acquired by means of M&A and the "high-order" dynamic capabilities developed by the acquirer. Our examination shows that when firms diversified and further developed efficient knowledge recombination capabilities, they gained a synergic effect on innovation performance.

This study contributes to the existing literature in several ways. It advances the RBV and DCV by answering how the access to valuable external resources goes through a process in which the dynamic capabilities play an important role and showing the existence of complementarities between the acquisition of external resources and the acquirer's knowledge recombination capabilities, that affect the innovation performance. It contributes to the strategy literature by explaining the differences between firms' innovation performance due to inconsistency between the diversification strategy and the development of capabilities able exploit the new resources efficiently. The main managerial implication concerns the importance of an additional managerial effort in fostering the cross-fertilization between the target and the acquirer when engaged in diversified acquisitions.

Despite the above-mentioned contributions, this study presents several limitations. Our study focuses on a single sector while it may be extended to multiple industries with similar or different structure. Another limitation concerns the use of patents as a measure of the innovation performance, it has been long argued that some inventions are not patented in order to keep a certain outcome of organizational learning secret.

CHAPTER III

TECHNOLOGICAL DIVERSITY, TECHNOLOGICAL DISTANCE, AND INVENTION NOVELTY: BUILDING A MULTIDIMENSIONAL MEASURE[7]

[7] An improved version of this chapter has been published as: Harrigan K.R., Di Guardo M.C., Marku E., & Velez B.N. (2017). Using a Distance Measure to Operationalise Patent Originality. *Technology Analysis & Strategic Management*, 29(9), 988-1001. DOI: 10.1080/09537325.2016.1260106

15. Abstract

This chapter aims at providing a comprehensive ex-ante measure of the firms' technological knowledge and capabilities. Departing far from the Trajtenberg *et al.* (1997) *originality* construct, the present study applies a distance-measure methodology for building a multidimensional measure able to capture three different and complementary aspects of a patented invention: (1) technological diversity, (2) technological distance from patent antecedents, and (3) degree of novelty. This indicator exploits the information provided by the *Derwent World Patent Index* system allowing in this way the overcoming of inconsistencies between authorities and easing the comparison between firms operating in different countries. The measure proposed can be of help for both researchers and practitioners as it can be used as an effective proxy for the detection of breakthrough inventions, the identification of the firm's technological search strategies, the assessment of the firm's knowledge recombination capabilities, as well as the unveiling of the firm's exploitation/exploration dynamics. Results add important insights to innovation management and patent literature.

16. Introduction

Innovation is widely recognized as one of the most important drivers of the firm growth and success. A considerable and fast-growing body of empirical research has shown that the firms' technological capabilities are at the heart of competitive advantage since they significantly constrain the direction of corporate R&D and the ability to exploit opportunities (Birkinshaw, Hamel, & Mol, 2008; Kelley, Ali, & Zahra, 2013; Ardito, Messeni Petruzzelli & Panniello, 2016). In this perspective, detecting the specific characteristics of those capabilities and measuring them, is increasingly becoming important in both innovation and technology studies, attracting the attention of researchers and consultants (Messeni Petruzzelli, Rotolo, & Albino, 2015; Aharonson & Schilling, 2016).

The empirical literature on technology and innovation increasingly relies on measures based on patent citation, but they generally analyze the ex-post innovation patterns based on the information provided by forward citations (Ahuja & Lampert, 2001; Schoenmaker & Dusters, 2010). This requires a long time to be detected, therefore, it clearly emerges the need to build indicators able to analyze patent patterns and their technology characteristics at the time when the invention is granted. Some attempts have been done in this direction (*i.e.* Fleming, 2001; Strumsky & Lobo, 2015; Kaplan & Vakili, 2015; Verhoeven *et al.*, 2016), however, most scholars have considered several patent dimensions separately (*i.e.*, Aharonson & Schilling, 2016). Departing far from prior research, this chapter introduces an updated operationalization of Trajtenberg *et al*. (1997)'s *originality* construct (the *V-score*) and proposes a novel and more comprehensive measure able to capture three different and complementary aspects of a patented invention, namely the technological diversity, the technological distance from patent antecedents, and the degree of novelty. The V-score method considers the effect of having multiple technological classes in a patent's grant when producing scores that identify inventions with broad (or narrow) search processes. Then it compares the new measure's efficacy with the Hall *et al*., (2001)'s operationalization of *originality*. The chapter concludes by showing how the *V-score* method of measuring technological content is useful to managers of research organizations when evaluating the potential value of a patent's provenance or a firm's trajectory. Last, this study aims at contributing to the technology and patent literature by providing a novel approach to assessing the firm's technology capabilities, by going beyond the simple count-based measures and combining it with the distance-measure approach.

17. Literature review

The possession of intangible resources able to enhance the firm's capability differentials is essential to the gaining and sustaining of an advantage over competitors (Hall, 1990). The assessment of these capabilities, including those in the technology field, has become an increasingly important topic in both strategy and innovation studies. For this purpose, scholars have used survey data (Dewar &

Dutton, 1986; Acs & Audretsch, 1990; Chandy & Tellis, 2000) or the information extracted from patent documents. Most widely, researchers use patents as an effective measure of technological capabilities, especially in sectors with a high density of patenting activity (Ahuja & Katila, 2001; Fleming, 2001; Hall *et al.*, 2001; Hall & Ziedonis, 2001; Ziedonis, 2004). In fact, patents are the "earliest" record that reflects the firms' knowledge of technology domains (Wuyts & Dutta, 2014).

When a patent is granted, the Patent Office verifies the applicants' technological claims of novelty by searching through germane antecedent patents for evidence of intellectual origins; examiners may list patents from their searches to reflect the cumulative process by which knowledge is built (Alcácer & Gittelman, 2006; Alcácer, Gittelman, & Sampat, 2009). Their resulting patent-examiner's report can be used to characterize a focal-patent's reliance on diverse scientific sources and reflect its closeness to their innovational paths. In particular, the body of patent literature follows two main streams while building patent indicators of the firm's technological capabilities: ex-post (information available a certain time after the application date) and ex-ante (information available at the moment of the application) measures.

The ex-post information primarily refers to forward citations in terms of technological *impact* or their technological classification. The number of citations received by the focal patent has been widely used to measure the technological importance and impact, as well as economic value (Trajtenberg, 1990; Harhoff *et al*., 1999; Fleming, 2001; Ahuja & Lampert, 2001; Hagedoorn & Cloodt, 2003; Dahlin &

Behrens, 2005; Hall *et al.,* 2005; Nemet & Johnson, 2012; Messeni Petruzzelli, Rotolo, & Albino, 2015; Keijl, Gilsing, Knoben, & Duysters, 2016). Although forward citations provide useful information especially about the rent appropriation of the invention (Corredoira & Banerjee, 2015), they present some limitations. A patent in order to be cited requires a certain horizon of time (it might even never be cited), consider that for example, the patenting process requires around three years. In addition, the impact measure is the bias connected with the success of the invention per se (Verhoeven *et al.,* 2016), indeed, a specific invention might be served as the basis for an impactful/successful invention.

A recent body of literature attempted to capture the firm technological capabilities ex-ante (Verhoeven *et al*., 2016). The value of analyzing the content of patents' backward citations was suggested by Trajtenberg *et al.* (1997) and has been shown to be useful by several others as evidence of organizational learning and technological diffusion (Fleming, 2001; Fleming & Sorenson, 2001; Hall *et al.*, 2001; Dahlin & Behrens, 2005). The recentness of a patent's prior-art citations (Sørensen & Stuart, 2000; Hirschey, Richardson, & Scholz, 2001) and ownership dispersion of backward-cited patents (Ziedonis, 2004) have also been analyzed to obtain insights concerning patent value as a strategic asset. Corredoira and Banerjee (2015) analyzed the effects of the recombination of new knowledge as an antecedent of the influence on technological evolution. For the authors, the citations included in a patent are a reliable measure of the ability of the firm to recombine knowledge and a way to identify its knowledge base. In the same line of reasoning, Keijl *et al.,* 2016 by weighting the number of backward citations with their relative distance from the focal domain, proposed a raw measure able to capture counting and distance approach. Di Guardo and Harrigan (2016) used backward citations as a proxy of patent quality and shed some new light on one understudied alliances outcome like inventing performance. A recent stream of literature attempts to identify patent outliers, those that exert a stronger influence on the subsequent inventions by investigation on the determinants of patent citations. Messeni Petruzzelli, Rotolo, and Albino (2015) identified six key drivers: the use of scientific knowledge, the breadth of the technological base, the existence of collaboration in patent development, the number of claims, the scope, and the novelty.

Patent-content scores describe the range of technological streams that were synthesized in order for a focal patent to be granted its claims. Content scores characterize the dispersion (or variance) of diverse technologies that were built upon in each focal patent and indicate relative novelty of various inputs (where it occurs). Patent-content scores can position the focal patent's scope within inventive space (Novelli, 2015) by indicating the nearness of prior patent claims. Patent-content scores indicate whether a patent builds incrementally on prior knowledge or builds upon less-obvious technological antecedents. As such, patent-content scores are useful for characterizing the content of a firm's technological strategy over time.

The *originality* indicator proposed by Trajtenberg *et al.* (1997)—and operationalized in the NBER database by Hall *et al* (2001)— is similar to a Herfindahl-Hirschman index (Herfindahl, 1950; Greenberg, 1956; Hirschman, 1945;

1964; Rosenbluth, 1955) and it uses a counting methodology that can be specified as follows:

$$Originality_i = 1 - \sum_{j=1}^{n_i} s_{ij}^2 \qquad (3.1)$$

where s_{ij} indicated the number of backward citations of a firm's $patent_i$ that belong to the technological classification $code_j$ out of n_i patent technological classes. This operationalization although contributed to making research that uses patents more manageable and easier, it presents several shortfalls. First, the counting methodology proposed by Hall and colleagues (2001) grouped technologies into six subjective categories (with ninety-six sub-categories) to classify patents based on technology-class codes. Those classifications did not include newer technologies where much innovation occurred after 2001 (*e.g.*, biotechnology, nanotechnology, robotics, *et cetera*). Second, patents were sorted according to only one technology-class code (the bold-faced code contained in USPTO patent applications), even where a patent was granted claims in many diverse technologies. Third, counting methodology uses sub-category counts to provide weightings for squared and summed raw scores used to produce ultimate scores. Figure 3.1 shows this important aspect, indeed, weightings based on these arithmetic frequencies result in Patent A (having prior-art citations from *four* technology-class code classifications) having the same *originality* score as Patent B (having prior-art citations from *ten* different classifications). Fourth, the counting methodology does not distinguish effects from–distance among the focal patent's technology-class codes (its *claims*) and those of antecedent patents. For example, Patent B in Figure 3.1 has many antecedents with claims in "*T*" and "*W*" technology classes that are the same as Patent B's claims. Fifth, the counting method is not able to capture any degree of novelty for backward-cited patents to reflect the rate at which technological change is occurring—a rate that has accelerated over time within many industries and may augment or mitigate the relative "newness" of a focal-patent's claims. The above-mentioned considerations strongly highlight the need for a more comprehensive measure able to capture fully the detailed information provided by the patent document, taking also into account the parsimony.

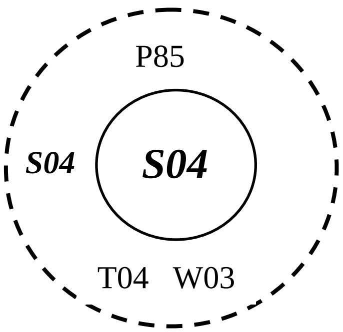
18. Development of a multidimensional measure

In this chapter, we propose a more comprehensive ex-ante measure to operationalize patent *originality*. Our *V-scores* are able to characterize differences in the technology-class code patterns that are contained in a patent-examiner's report—with a particular interest in those technology-class codes that are different from those of the focal-patent's grant. Using an approach suggested by Vanhaverbeke, Gilsing, Beerkens, and Duysters (2009) and Bapuji *et al.* (2011), technology-class codes of the focal-patent's grant are *core* (or central) in the Euclidian distance measures.

How Core and Non-Core Technology-Class Codes Affect Content Scores

Patent A:
US6238084-B1

Core 25.0 + Non-Core 3.0 = Raw Score = 28.0143
Three non-core/ One core code = multiplier of 3
***V-Score* = 84.0429**



P85	(1)
S04	(1)
T04	(1)
W03	(1)

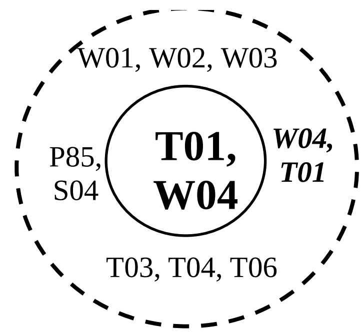
Hall *et al.* (2001) score = 0.75000

P85 = Cryptography
S04 = Clocks and Timers
T01 = Digital Computers
T03 = Data Recording
T04 = Computer Peripherals
T06 = Process Controls
U21 = Logic Circuits
W01 = Voice and Data Transmission
W02 = Broadcasting, Line Transmission
W03 = TV, Broadcast Radio Receivers
W04 = Audio/ Video Recording Systems

Key: **Boldfaced** codes represent technology-class codes of claims awarded to patent in its grant (its *core*) Codes outside the bold-faced circle represent technology-class codes of prior-art patents reported in patent-examiner's report to indicate the range of technological areas which were synthesized in order to create the focal patent. Lists show counts of technology-class codes representing the grants of prior-art patents. Coding is from *Derwent World Patents Index.*

Patent B:
US6026232-A

Core 38.1 + Non-Core 3.5 = Raw Score = 41.6301
Fifteen non-core/ Twenty-five core codes = multiplier of 0.6
V-Score = 19.3282



W04	(17)
T01	(8)
W02	(5)
T03	(2)
W01	(2)
W03	(2)
P85	(1)
S04	(1)
T04	(1)
T06	(1)

Hall *et al.* (2001) score = 0.75375

Figure 3.1 Core and non-core technology classification codes

Technology-class codes of backward-cited patents' grants are treated as *non-core* if they differ from the codes of the focal patent, as Figure 3.1 illustrates. Our measure benefits from the information provided by patent backward citations[8] and especially their technological classification. Differently, from prior contributions that used the three-digit classification codes (assigned by the U.S. Patent office) or the Hall *et al.* (2001) methodology, we choose the Thomson's *Derwent World Patent Index* (DWPI) classification codes. The *Derwent* classification system categorized each patent according to a consistent system of related technology classes that took into account all granted claims of each focal patent. The 289 *Derwent* technology classes are more parsimonious than the International Patent Classification (IPC) codes. Moreover, one of the characteristics of the *Derwent* classification system consists in the assignment of one or several manual codes to a single patent document, aimed at covering all the relevant aspects of the invention offering greater granularity than the Hall *et al.* (2001) 96-category schema. This multiplicity of technological domains allows a better assessment of broad and, particularly, narrow technological changes which are more difficult to be captured.

Our distance-score methodology relates a focal patent's granted claims and their respective relatedness to the content of backward-cited patents' claims in a way that suggests its patent's positioning in a stream of ongoing innovation (Novelli, 2015). The *V-score* examines patterns of relatedness among a patent's claims and those of antecedent patents in a way that does not treat their technology-class codes

[8] This method can be also applied to forward citations.

as though they were fungible. The distance-measure methodology accounts for similarities within technology-classification systems and weights the dyads of each respective combination of technology-class code according to its likelihood of occurrence.

For Patent A (US6238084-B1) in Figure 3.1, claims in code *S04* were granted to Patent A and one of the antecedent patents; code *S04* is *in-the-core* while codes *P85*, *T04* and *W03* are *outside-the-core* (or *non-core*). Similarly, for Patent B (US6026232-A), claims in codes *T01* and *W04* were granted to Patent B (and to 17 antecedent patents listed in the patent-examiner's report). Codes *T01* and *W04* are treated as *core* in calculating Patent B's *V-score* while the other technology-class codes are *non-core*. Frequency counts are the first step in calculating each type of content score. The Hall *et al.* (2001) counting methodology produces very similar content scores for both patents in Figure 1 while the *V-score* yields different scores for each example patent.

19. Operationalization of the distance-score measure

Construction of *V-scores* uses all of the technology-class codes representing claims that were granted to the focal patent as well as claims granted to its backward-cited antecedents. It may be expressed as follows:

$$V = \left[\left[\sum_{k=1}^{n_i} f_i\right] + \left[\sum_{k=1}^{m_o} f_o\right]\right] \times \left[\left[\sum_{j=1}^{n_i} p_{ij} / i_n\right] + \left[\sum_{j=1}^{m_o} p_{oj} / o_m\right]\right] \times \left[\sum_{o=1}^{m} f_o / \sum_{i=1}^{n} fi\right] \tag{3.2}$$

The three terms correspond to measures of (1) technological diversity, (2) technology distance from patent antecedents, and (3) degree of novelty per each patented innovation. Frequency counts are the first step in calculating each type of content score.

Figure 3.2 depicts a spreadsheet matrix of calculations used to build each patent's *V-score*. Its components are (a) *core* score $\sum W_i$, which represents the configuration of "grant" technologies with each other, (b) *non-core* score $\sum W_o$, which represents technologies of prior-art patents that are different than the 'grant' technologies, (c) raw score $\sum W_k$, which is the sum of the *core* and *non-core* scores, and (d) multiplier $\sum f_o / \sum f_i$, which weights the proportion of *non-core* to *core* technology-class codes and modifies the raw score's value. In Figure 3.2., the first left-hand column lists the technology-class codes from antecedent patents that are treated as *core* i_n (within the shaded box listing the focal patent's grant-codes) and *non-core* o_m to the focal patent (those outside the shaded area), depending upon the patent's claims. All frequency counts in the second left-hand column of Figure 2 refer to counts of codes for the antecedent patents (the f_k for i_n and o_m, respectively). If the codes of antecedent patents are the same as those of the focal patent, there is less "distance" between them (and the resulting *V-score* will be lower). Subsequent columns are used to record dyad probabilities, frequency factors, average *core*

Σf_i Σf_o $F = \Sigma f_k$ $\Sigma f_o / \Sigma f_i$ i_n f_k ff_k a_i, a_o W_k ΣW_i ΣW_o o_m p_j

BACKWARD		Citations Inside the Core					Citations Outside the Core	Total Codes Cited (Total DC)	Outside/ Inside Innovation Factor
DERWENT CODES AND FREQUENCY		30.00					23.00	53.00	0.77
A23| A32									
DC Codes	**DC Frequency**	**A23**	**A32**	**A85**	**L03**	**T03**	**Frequency Factor**	**Average Core Probability**	**Weight Percentage**
A23	15	100.00%	5.84%	6.90%	1.27%	1.53%	0.283018868	23.11%	6.540067925
A32	1	9.07%	100.00%	8.04%	1.52%	1.12%	0.018867925	23.95%	0.451872453
A85	5	12.81%	9.62%	100.00%	17.53%	3.22%	0.094339623	28.64%	2.701618868
L03	5	10.13%	7.80%	75.35%	100.00%	13.24%	0.094339623	41.30%	3.896458491
T03	4	4.51%	2.13%	[illegible]	4.89%	100.00%	0.075471698	23.33%	1.760803019
A89	5	11.64%	7.54%	[illegible]	6.03%	2.83%	0.094339623	6.05%	0.570584906
W04	3	0.66%	0.60%	1.32%	1.03%	16.01%	0.056603774	3.92%	0.222069057
P73	2	18.79%	13.80%	10.01%	4.24%	2.29%	0.037735849	9.83%	0.370796981
A12	1	1.21%	0.22%	1.02%	0.25%	0.05%	0.018867925	0.55%	0.010388679
A41	1	0.79%	0.01%	0.32%	0.25%	0.02%	0.018867925	0.28%	0.00525434
A60	1	1.48%	0.24%	0.66%	0.33%	0.06%	0.018867925	0.55%	0.010418868
A95	1	6.20%	8.76%	2.43%	0.09%	0.03%	0.018867925	3.50%	0.066072075
E14	1	2.01%	0.12%	1.17%	1.47%	0.17%	0.018867925	0.99%	0.01865434
P81	1	3.24%	4.55%	6.02%	7.49%	4.79%	0.018867925	5.22%	0.098444151
Q71	1	0.22%	0.27%	0.53%	0.27%	0.07%	0.018867925	0.27%	0.005132075
U23	1	0.00%	0.00%	0.08%	0.08%	0.45%	0.018867925	0.12%	0.002298868
V04	1	3.98%	3.00%	21.64%	8.16%	1.87%	0.018867925	7.73%	0.14583283
W01	1	0.27%	0.65%	2.11%	1.02%	1.29%	0.018867925	1.07%	0.020148679
W02	1	0.26%	0.38%	1.69%	1.08%	1.28%	0.018867925	0.94%	0.01770717
W03	1	0.26%	0.09%	0.56%	0.30%	0.85%	0.018867925	0.41%	0.007775849
X12	1	4.77%	1.72%	19.94%	5.29%	0.34%	0.018867925	6.41%	0.121009811
Raw Innovation Score		17.04340943							
V-Innovation Score (Using In/Out Factor)		13.0666139							

Figure 3.2 Spreadsheet for calculating V-scores

probabilities, and weighted-percentage contribution so the raw innovation score (for each technology-class code). The *non-core* portion of the *V-score* will typically be smaller than the *core* portion of the score because high *non-core* scores would suggest that a patent has synthesized seemingly-unrelated ideas that may be improbable to appear together. Unlikely scores would appear as *non-core* primarily during the period when the innovative precedent was being diffused; combinations of the unlikely technology-class codes would subsequently appear as *core* claims as inventors built upon the once-unlikely patterns of technological relatedness and subsequently asserted them in their own respective claims.

Core i_n and *non-core* o_m technology-class codes are counted to produce code frequencies, added to create sums of frequencies, and divided by sums to generate frequency factors. The weightings assigned to each respective technology-class code in calculating the patent-citation content score are the product of frequency factors and average *core* probabilities. The sum of the technology-class code counts $\sum f_k$ provides the denominator for calculating each respective code's *frequency factor* ff_k, which is multiplied times the average *core* probability to generate each weighted percentage that contributes to the raw innovation score. Average probabilities are calculated relative to *core* technology-class codes by averaging each row of probabilities p_j. Assessing the "nearness" of technology-class codes to each other is important for gauging how far-reaching a firm's patent may be in its innovative content. Nearness of technology-class codes can also be observed by noting which gestalts of technology-class codes patent examiners typically cite together (Alcácer & Gittelman, 2006; Benner & Waldfogel, 2008; Alcácer *et al*., 2009).

V-scores assess nearness of technology-class codes *pj* from Reference Table comparisons of all possible combinations of technology-class codes occurring for all patents granted in a particular year. These are calculated from *Web of Science* (Thomson Reuters, 2016). In Figure 3.2, the intersecting columns of *core* technology-class codes i_n with rows of *non-core* codes o_m, respectively, represent nearness dyads p_j, and these are two-way probabilities. Thus, for a patent application filed in 2001, the probability p_j of the technology-class code *T01* (for digital computers) occurring with *W01* (telephone and data transmission systems) was 14.1 percent. The probability p_j of technology-class code *W01* occurring with *T01* was 24.7 percent for that same year. Probabilities p_j changed from year to year as technology evolved and converged.

Average probabilities a_i,a_o were calculated by averaging each row's probability dyads p_j. Weightings W_k were calculated by multiplying each row's average probability a_i,a_o by its frequency factor ff_k; each W_k was scaled by a factor of 100 for analytical modeling. The *Raw Innovation Score R,* which is the sum of all weightings, can be decomposed into the sum of *core* technology-class code weightings ΣW_i (*Core Score C*) and the sum of *non-core* weightings ΣW_o (*Non-Core Score N). Core* and *non-core* effects can be analyzed for their respective impact on spawning subsequent inventions as they illustrate a patent's incremental novelty.

Content analysis of *core* (and *non-core*) scores indicates when formerly-*non-core* technology-class codes have entered the inventors' *core.* Using all of the technology-class codes of antecedent-patents' claims is useful in documenting a firm's cumulative process of building upon new technologies and isolating the incremental novelty of each patent in a thicket of claims.

To emphasize the effects of the *non-core* technology that may have informed an invention, a further adjustment is made to the *Raw Innovation Score R* that emphasizes more heavily the effect of having mostly *non-core* technology-class codes (or mostly *core* technology-class codes) in a patent's backward-dispersion pattern. The count of *non-core* codes Σf_o is divided by the count of *core* codes Σf_i to create the *Outside/ Inside Innovation Factor.* The correction factor $[\Sigma f_o/\Sigma f_i]$ is multiplied times the *Raw Innovation Score R* to produce the *V-score*.

V-scores are higher when antecedent patents have more *non-core* technology-class codes than *core* codes. *V-scores* are lower when patents draw largely upon technology that is already included in their focal-patent claims. As with the Trajtenberg *et al.* (1997)'s construct and Hall *et al.* (2001)'s *originality* score measure, low scores suggest that the focal patent has not synthesized very diverse technological roots in its invention. Conversely, if scores are high, the focal patent synthesizes substantially-different technology-class codes. High content scores suggest that the antecedents of the focal-patent are far from the inventors' technological “comfort zone” of knowledge or inventors were exposed to highly-diverse intellectual stimuli (Leonard-Barton, 1992).

20. Method

In order to compare both types of patent-content scores—*V-scores* and Hall *et al.* (2001)’s *originality*—we tested them as predictors of a common measure of firm performance like the return on assets (ROA). Our dataset is presented in a panel form and includes 171 communications-service providers whose performance measures were tracked for twelve years, 1994 through 2012, where data were available. Patent-content scores were calculated for 113,029 patents. Sample firms were identified using their North American Industrial Classification System (*NAICS*) codes (obtained from Thomson One’s SDC Platinum Database). Firms entered the communications-services industry as it became possible to digitize and transmit voice, data and video over one network; some of these firms had been acquired by 2012 (making financial data unavailable for the entire time span).

Web of Science contained both *USPTO* and *Derwent* patent classifications. The *Derwent* classification system categorized each patent according to a consistent system of related technology classes that took into account all granted claims of each focal patent (and that of its antecedents). Patent report information was provided by Thomson Reuters (Scientific), which retrieves data by *families* of related patents (PAN series) as well as by *individual* patent numbers (PN series). *Web of Science* also contains the required patent reports. The PN series was used to calculate *V-scores* herein. Financial information was obtained from *OSIRIS* (2015).

In addition to the V-scores and the *originality* measure, we included in our analysis other two variables: the technological *impact* measured as the total number of forward citations and the Hall *et al.,* (2001) measure of *generality* following the same procedure of the *originality* measure but using the forward citations instead. These additional variables have been found to be correlated with the measure of *originality*. Indeed, Serrano (2010) found that the most "original" of a firm's focal patents tended to be cited by the broadest range of subsequent users (a characteristic that Trajtenberg *et al.* (1997) called "generality"), but Nemet and Johnson (2012) disagreed—finding that citations to external prior art were significantly *less* important to predicting future prior-art citations than were backward citations that were made in the same technology class as the focal-patents' class—a finding which would indicate that investors value exploitation of extant knowledge and local search more highly than exploration activity (March, 1991; Rosenkopf, & Nerkar, 2001; Lavie & Rosenkopf, 2006).

Two sets of models were tested (3-year and 4-year lag comparisons) for 44 communications firms having long enough run of longitudinal data for analysis. A Davidson–Mackinnon *J* test (1981) compared results from OLS analysis. The Davidson–Mackinnon *J* test can be inconclusive where comparisons of Model 1 versus Model 2 (when reversed) provide inconsistent results (Greene 2012).

21. Results

Table 3.1 and Table 3.2 provide descriptive statistics for our panel dataset. Variables show a low correlation confirming that no multicollinearity issues are affecting our specification.

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6
1. ROA_t	4.19	13.42	-95.13	57.17	1.00					
2. V-score$_{t-3}$	35.69	21.04	.05	321.32	0.10	1.00				
3. Originality $_{t-3}$	28.93	12.24	0	62.5	-0.02	0.22	1.00			
4. Generality $_{t-3}$	0.98	0.59	0	8.19	-0.01	0.15	0.34	1.00		
5. Impact per pat $_{t-3}$	1.74	4.75	0	71.21	0.01	0.03	-0.03	0.05	1.00	
6. LogAssets $_t$	6.13	1.56	2.31	8.47	0.10	-0.08	-0.16	-0.06	-0.11	1.00

Table 3.1 Descriptive Statistics Using 3-Year Lag

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6
1. ROA_t	4.19	13.42	-95.13	57.17	1.00					
2. V-score $_{t-4}$	35.85	21.15	0.05	321.32	0.13	1.00				
3. Originality $_{t-4}$	29.04	12.14	0	62.5	0.05	0.22	1.00			
4. Generality $_{t-4}$	0.97	0.58	0	8.19	0.03	0.15	0.33	1.00		
5. Impact per pat $_{t-4}$	1.74	4.77	0	71.21	0.01	0.04	-0.03	0.04	1.00	
6. LogAssets$_t$	6.13	1.56	2.31	8.47	0.12	-0.08	-0.16	-0.05	-0.10	1.00

Table 3.2 Descriptive Statistics Using 4-Year Lag

In the results shown in Table 3.4 for the 3-year lag analysis and Table 3.5. for the 4-year lag analysis, the fitted values of the V-score regression model (Models 1 and 3, respectively) maintained explanatory power when included in the Hall *et al*. (2001) regression model (Models 2 and 4, respectively) while the fitted values of the Hall *et al*. (2001)'s regression model had no explanatory power when included in the V-score regression model (Models 1 and 3, respectively). Hence, it is shown evidence that the V-score is a stronger measure than the Hall *et al*. (2001)'s *originality* measure.

Return on Assets	**Using 3-year lag**		**Davidson-MacKinnon *J* Test**	
	Model 1	Model 2	Model 1 vs. Model 2	
V-score$_{t-3}$	0.049*	--	No. obs.	506
Originality$_{t-3}$	--	-0.019†	Coefficient	1.738
Generality$_{t-3}$	-1.849	-1.822	*p*-value	0.627
Impact per Patent$_{t-3}$	-0.320	-0.289	*F*-Test	10.79
Log Assets$_t$	-1.222	-1.534		
Firm Fixed Effects	Yes	Yes	Model 2 vs. Model 1	
Year Fixed Effects	Yes	Yes	No. obs.	506
Constant	-25.948*	-21.688*	Coefficient	1.003
No. observations	515	508	*p*-value	0.012
R^2	0.5251	0.5250	*F*-Test	10.79
†p<0.10 *p<0.05 **p<0.01 ***p<0.001				

Table 3.3 ROA predicted by *V-score* versus Hall *et al.* (2001)'s *originality* measure, 4-lag specification models

Return on Assets	**Using 4-year lag**		**Davidson-MacKinnon *J* Test**	
	Model 3	Model 4	Model 3 vs. Model 4	
V-score$_{t-3}$	0.062**	--	No. obs.	504
Originality$_{t-3}$	--	-0.124†	Coefficient	0.871
Generality$_{t-3}$	-1.125	-1.408	p-value	0.125
Impact per Patent$_{t-3}$	-0.228	-0.216	F-Test	10.46
Log Assets$_t$	-1.222	-1.534		
Firm Fixed Effects	Yes	Yes	Model 4 vs. Model 3	
Year Fixed Effects	Yes	Yes	No. obs.	504
Constant	-32.859***	-33.707***	Coefficient	0.923
No. observations	515	506	*p*-value	0.004
R^2	0.5525	0.5519	*F*-Test	10.46
†p<0.10 *p<0.05 **p<0.01 ***p<0.001				

Table 3.4 ROA predicted by *V-score* versus Hall *et al.* (2001)'s *originality* measure, 4-lag specification models

22. Discussion and conclusion

Our results showed that the distance-score methodology of the *V-score* provided a superior basis for interpreting the content patterns of antecedent patents. *V-Scores* seem better-suited to capture the potential convergence of emerging technologies because their weighting system reflects the evolving frequency of particular combinations of technological-class codes as technology is diffused. To the extent that patents synthesize exotic knowledge from pre-existing patents the first granted patent that shows unusual interaction patterns among diverse technologies may be classified as being a radical innovation (Ahuja & Lampert, 2001; Garcia & Calantone, 2002; Dahlin & Behrens, 2005) or boundary-spanning invention (Tushman & Scanlan, 1981; Banerjee & Cole, 2010; March, 1991; Rosenkopf & Nerkar, 2001) if its pattern of cited precedents were indeed unusual. The innovation is incremental if it contains the same pattern of codes as does the focal-patent's claims. Analysis of the full scope of a focal-patent's claims (its *core*) reflects a firm's ability to prosper from its inventiveness since firms must exploit potential applications for their inventions soon after they are granted. Very quickly after an unexpected antecedent has been identified, other inventors will seek ways to add that novel knowledge to their own inventions' claims if published insights from a patent's grant are efficacious. As was suggested by Fleming (2001), with time, the number of *non-core* technology-class codes in patent antecedents will become fewer in number as patents are granted for increasingly broad claims.

V-scores represent a new way to interpret patent's technological content. The measure proposed can be of help for both researchers and practitioners as it can be used as an effective proxy for the detection of breakthrough inventions, the identification of the firm's technological search strategies, the assessment of the firm's knowledge recombination capabilities, as well as the unveiling of the firm's exploitation/exploration dynamics.

Although more testing is warranted, it is plausible that results concerning patent *originality* would have reported different findings if the *V-score* had been used instead of a counting measure in extant studies such as those by Czarnitzki, Hussinger, and Schneider (2011), Lerner and Wulf (2007), or Valentini (2012). Conclusions regarding local search, organizational learning, and radical innovation may be better explained using *V-scores* to study them.

In summary, patent-content scores characterize the nearness of technological streams that focal patents built upon. *V-scores,* which are computed using a distance-measure methodology instead of a counting methodology, offer an effective way of representing a focal patent's claims vis-à-vis its antecedents—particularly if analysis of patenting activity using *V-scores* can better reflect a firm's inventive activities at a particular time in its organizational evolution. *V-scores* offer a method of representing the effects of firms' growth through internal inventions, alliances with outsiders, acquisitions for technology, or other longitudinal changes to the technological content of firms' corporate strategy because they capture the effects of external stimuli. *V-scores* may be more efficacious in forecasting the content of firms' organizational learning because of how they characterize the changes in firms' technology strategies.

Further analysis of the *V-score* is needed to understand the phenomena of how firms distribute their patenting efforts when commercializing their inventions. Large numbers of patents may indicate a protective posture where few novel inventions are commercialized (because firms may be risk-averse in protecting against imitation). Survivor firms often possess sufficient organizational slack to exploit their patented inventions selectively and many of them play it safe by investing in patent thickets and pursuing a fast-follower posture. Larger firms can learn from their mistakes with fewer adverse effects than smaller companies who must bet their existence on a single breakthrough invention (Cohen & Levinthal, 1990; Tellis & Goldner, 1996; Lewis, 1999; Catozzella & Vivarelli, 2014; Hussinger, 2012). Smaller firms who patent infrequently may have little choice but to commercialize their new inventions quickly even if they face greater risks of customer rejection. Thus *V-scores* can be used to test whether first-mover advantages (from early entry) are overrated when commercializing such inventions.

The size distribution of patent scores is also of potential interest. A fluctuating series of patent-content scores may indicate that acquisitions were made as an alternative to localized learning processes. If innovation-substitution occurs following acquisitions—a situation whereby the acquiring firm relies more heavily on the target's inventors instead of on in-house inventors, the pattern of patent-citation content scores will spike immediately after an acquisition and then decline sharply to reflect incremental innovations thereafter (Hitt, Hoskisson, & Ireland, 1990; Cassiman *et al*., 2005). As the acquiring firm assimilates its new sources of technological insights, temporary spikes in *V-scores* that reflect the appropriation process will be followed by lesser declines. But if the new knowledge has been assimilated successfully—from an acquisition, alliance, or non-localized search that reflects organizational learning—high average *V-scores* will converge more slowly thereafter and will feature more-complex focal-patent content patterns that will be reflected in the ΣW_i (*Core Score C*) portion of the *V-score*.

Patent-content measures, such as *V-scores*, which reflect the nature of firms' technological syntheses are useful because industries make progress when firms within them invent radically-new products―inventions that are often developed after exposure to knowledge outside of their local domains (Nelson & Winter, 1982). The patterns of firms' exploratory inventions can reflect patterns of exogenous technological confluence that will presage important industry changes (Schoenmakers & Duysters, 2010). Discontinuities in firms' *V-score* patterns can suggest important changes in industry context as well as help position competitors within an industry. Patent-citation content analysis continues to be an important analytical tool for understanding firms' inventive activity.

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