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Industry Relatedness in M&A

An empirical analysis on Acquisitions, Innovation, and Leveraged Buyouts

Doctoral Dissertation

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"Anyone who has never made a mistake,

has never tried anything new"

(A. Einstein)

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Contents

CHAPTER 1

Introduction

The chance of friendship or partnering between humans cannot be seen as a purely random phenomenon (e.g. Mcfarland, 1975; Boschma and Ellwanger, 2012). The same concept holds for the behaviour of companies when looking at target selection in mergers and acquisitions (M&A)[1].

This thesis addresses M&A from a dyadic perspective, that means by investigating the relation between the two particular companies that are actually involved in a deal. Specifically, it highlights the relevance of industry relatedness in acquisition strategy, defined as the degree to which the acquirer and the target are active in related markets. In fact, industry relatedness is shown to be a meaningful issue in target selection, as it is strictly linked with managerial decision and information asymmetries. Moreover, it refers to shared technological experiences, knowledge bases, and similar products and markets (Teece et al., 1994; Knoben and Oerlemans, 2006).

This topic has gained increasing interest within the investigation of firms' growth, concerning the direction of diversification into related or unrelated lines of business and the resulting corporate coherence (Teece, 1982; Teece et al., 1994; Piscitello, 2000; Neffke and Henning, 2008; Bryce and Winter, 2009). In this framework, the firm's choice to acquire and integrate another independent company into its organization is seen as an instrument of growth. According to the resource-based view of the firm (Penrose, 1995), companies possess asymmetrical abilities and an acquisition might be risen by both the purpose of product differentiation and synergy effects. M&A enable firms getting quick access to strategic assets, such as patents,

[1] For the purposes of this thesis, *M&A* and *acquisition* are used as interchangeable terms, due to the fact that most of the deals defined as mergers actually consists in acquisition. Anyhow, the sample has been carefully collected with real acquisitions as object, i.e. deals in which the acquirer, after the acquisition of the target, maintains its identity.

skilled labour, licences, brands, management capabilities, or valuable and new technology (Graebner, 2004) that the acquirer does not possess or can difficultly develop inside (see Cohen and Levinthal, 1990; Graebner, 2004). However, the decision of acquiring is not merely due to access to learning intents or to technological reasons (Hamel, 1991), but it can regard also the expansion of the market share or other market-structure related considerations, such as the market-entry by the desire to expand the firm's product range geographically (Cloodt et al., 2006). Again, whereas acquisitions occur in waves, they are sometimes simply driven by the general market conditions and opportunity (Matsushima, 2001; Huyghebaert and Luypaert, 2010).

In the light of this, the first step of the research carried out in this thesis contributes to the literature through the construction of a measure of industry relatedness for the acquisition market. In fact, M&A related literature used to concentrate mostly on the determinants of acquiring (e.g. Matsusaka, 1993; Seth et al., 2000; Huyghebaert and Luypaert, 2010) as well as the characteristics of acquirers and targets (e.g. Powell, 1997; Capron and Shen, 2007; Tsagkanos et al., 2008; Brar et al., 2009), or the situation after the deal completion (e.g. Lubatkin, 1983), neglecting the relation between the two firms involved.

Specifically, the methodology presented in *Chapter 2* relies on the endogenous notion of proximity introduced by Teece et al. (1994) in corporate coherence investigation. In detail, the perspective adopted in this analysis is the acquirer viewpoint, in order to create an asymmetric industry relatedness index able to measure the *distance* from the target industry within each pair of possible sectors (at 3-digit of the NACE industry classification), where low distance corresponds to high relatedness.

Furthermore, the analysis concerns the observation of a whole country (The Netherlands) domestic acquisition market in a quite large span of time (1980-2005), that allowed a sample of more than 36,000 deals among more than 200 different sectors. Such a depth of analysis enabled a reliable mapping and understanding of the general phenomenon.

In fact, by means of this measure, this study shows that industry relatedness is an important driver of Dutch acquisition partnering, finding strong evidence that the selection of a target by an acquiring firm does not occur randomly. Specifically, I found the evidence that Dutch acquirers tend to select targets that are industrially more related than the average target; in other words, companies that belong to the same macro-area or industrial technology class are more likely to engage in deal. In fact, if the acquirer and the target are related it is easier to integrate knowledge and combine operations, duplicative functions can be reduced and economies of scales can be realized (Capron, 1999; Ahuja and Katila, 2001; Nesta and Saviotti, 2005; Boschma and Ellwanger, 2012). Again, their managers are more likely to exchange information, which affects the identification phase (Chatterjee et al., 1992), and the value of the target is more easily to determine.

This result is in line with corporate coherence framework, in which Penrose (1959) and later on several scholars underscored the importance for firms to stay close to their existing capabilities when expanding into new product markets (Teece et al., 1994; Breschi et al., 2003; Nesta and Saviotti, 2005). This concept, discussed also by Teece et al. (1994) through the notion of path-dependencies in company diversification, is built on the absorptive capacity paradigm, which is the firms' capability to process and value external knowledge (Zahra and George, 2002).

Furthermore, the average degree of relatedness differs considering different macro-areas or particular subsets of the whole market. This finding has been shown through the application of the asymmetric association measure suggested by Goodman and Kruskal (1954), in order to overcome a limitations of Teece et al.'s (1994) measure. In fact, this latter does not admit the possibility of comparing the index between samples having different size, as happens when clustering the whole market by acquirer industry or by its technology class. In particular, even if the average degree of association is always quite high, some sectors appears to be more close, such as *non-market service*, *market service except financial intermediaries* and *low-tech manufacturing*, than others that show a more diverse acquisition strategy, as *high-tech manufacturing* and in particular *financial intermediaries*. This result is also robust to a check performed by means of an OLS regression, which allowed controlling for other effects, such as demographic characteristics of the firms involved.

In *Chapter 3* the developed relatedness measure is implemented to identify which level of relatedness best contribute to innovation, also considering linkages between this aspect and other firm characteristics, using demographic and Community Innovation Survey data on the whole Dutch acquisition market. M&A and innovation are two strongly connected instruments for growth and competitive advantage (Schulz, 2007; Cefis, 2010), as a critical component of innovative performance is the ability to exploit external knowledge (see Cohen and Levinthal, 1990). In fact, building a successful innovation-based strategy requires resources and capabilities that are often difficult to develop internally. However, the effects of M&A on innovation is still a controversial topic, as literature has not yet reached a unified and sound background its judge (Schulz, 2007; Cefis and Ghita, 2008; Cefis, 2010).

This section assesses the innovative performance issue considering the effects of *novelty* and *synergies* generated through the acquisition of a more or less related target. On one hand, according to the absorptive capacity paradigm (Zahra and George, 2002), the acquisition of related knowledge implies a high exploitation of the *synergies* favouring economies of scale and scope in R&D (Hagedoorn and Duysters, 2002; Capron and Mitchell, 2004). However, if the acquired knowledge is too similar to the already existing base it can be disadvantageous, due to overlapping or even duplication of assets and resources. On the other hand, differentiation in resources between the acquirer and the target will enrich the acquiring firm's knowledge base, creating opportunities for learning from the *novelty* as the seed for future technological developments (Laursen and Salter, 2006; Miller et al., 2007).

Therefore, due to the combined effect of *novelty*, increasing with distance, and of *synergies*, increasing with relatedness, this study shows a non linear (inverted U-shape) influence of the industry relatedness of acquired and acquiring knowledge bases on innovative output, following the idea that it is sufficient distance, not greatest or lowest distance, that matters (see, among others, Ahuja and Katila, 2001; Cloodt et al., 2006; Miller et al., 2007).

Moreover, the analysis is then deepened considering the influence of three moderators on the impact of the industry relatedness on innovation. Specifically, in-house R&D of the acquirer, acquirer previous experience in acquisition activity, and the target size has been addressed as expected to affect the post-acquisition integration of the resource bases and hence also the production of innovative products. Specifically, previous involvement of the acquiring firm in R&D has positive effect on the innovative performance, independently on the industry relatedness, while acquisition of larger target firms should have higher industry coherence to reach high levels of innovative output. Finally, the experience helps the post-acquisition integration and innovative exploitation of the targets, even if they are not related, while acquirers with low experience can reach high level of innovative result only when the industry relatedness is high.

In conclusion, the consideration of the innovative performance due to the products both new to the firm and new to the market opened the possibility of further findings and interesting comparisons. More in detail, looking at the more restrictive definition of innovation "products new to the market" it was possible to highlight the unpredictability and non persistency of radical innovation, as both the lagged value of innovative sales and the acquisition experience are insignificant in relation to the generation of novelty for the market.

Finally, the last section *(Chapter 4)* takes a step forward considering a specific kind of acquisition activity, in which the acquirer is a financial investor. Specifically, the focus is on Leveraged Buyouts (LBO), defined as operations in which a specialized investment firm, called Private Equity (PE) firm, acquires a target company using a relatively small portion of equity and a relatively large portion of outside debt financing. Here, the concept of industry relatedness is addressed concerning the level of industrial specialization of the investor in portfolio selection and with reference to the exit strategy adopted by the PE.

Exiting the investment is a central aspect of PE process because returns can be finally measured (Cumming and Macintosh, 2003a; Wright et al., 2007; Kaplan and Stromberg, 2009). Moreover, the exit is subject to a potential information asymmetry arising between the investor and the final buyers and the extent of the asymmetry depends on the type of exit vehicle adopted. In particular, according to Kaplan and Stromberg (2009), the available exit methods are classified as follows: acquisition, secondary sale, initial public offering, and write-off. This study addresses the concept of PE firm investment specialization as a strategy to mitigate information asymmetry issues at the time of exit, and the consequent likelihood in the choice of an exit vehicle over the others. Specifically, PE firms specialized in a specific industry or stage of investment own a deeper knowledge of the competitive environment of acquired companies, reducing uncertainty as the PE firm gains more in-depth knowledge of companies in that market or stage (Cressy et al., 2007).

Among the main results, PE firms with higher industry specialization has been find more likely to exit their investments through acquisition, as a deep knowledge of a specific market enables PE firms to mitigate information asymmetries with the buyer. By contrast, PE firms with higher portfolio diversification are more prone to exit through quotation. Finally, a higher buyout-stage specialization decreases PE firms probability of writing-off their investments. The impact of both specialization dimensions has been tested through a competing risk model, performed on a sample of 533 LBO randomly collected both in North America and Europe over the period 2000-2009.

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CHAPTER 2

The importance of Industry Relatedness

in M&A

An empirical analysis of the Dutch Acquisition Market

Abstract

This paper investigates the external growth of a firm by means of acquisition, showing that the selection of a target by an acquiring firm does not occur randomly. This work gives a reliable mapping of the phenomenon, through the observation of a whole country (The Netherlands) domestic acquisition market in a quite large span of time (1980-2005), that allowed a sample of more than 36,000 deals regarding more than 200 different sectors. The first step of the analysis is the construction of a measure of industry relatedness for the acquisition framework, through the application of the relatedness measures introduced by Teece et al. (1994). The perspective adopted in the analysis is the acquirer viewpoint, in order to create an asymmetric industry relatedness index able to highlight its strategy. In detail, the index measures the "distance" from the target industry within each pair of possible sectors (at 3-digit of the NACE industry classification), where low distance corresponds to high relatedness.
Furthermore, the degree of relatedness differs considering different macro-areas or particular subsets of the whole market. This finding has been shown through the application of the asymmetric association measure suggested by Goodman and Kruskal (1954) in order to overcome some limitations of Teece et al.'s (1994) measure.

Keywords: Industry relatedness; acquisition; The Netherlands.

2.1 Introduction

The theoretical and empirical literature has extensively investigated firms' growth, whereas a central issue is what determines the direction of firm diversification, and in particular whether they diversify into related or unrelated lines of business (Teece, 1982; Teece et al., 1994; Piscitello, 2000; Neffke and Henning, 2008; Bryce and Winter, 2009). Moreover, a firm can choose two complementary growth paths: internal and external expansion.

In this framework, the firm's choice to acquire and integrate another independent company into its organization is seen as an instrument of growth and it can be risen by both the purpose of product differentiation and synergy effects. Moreover, according to the resource-based view of the firm (Penrose, 1995), companies possess asymmetrical abilities and M&A are a means of gaining knowledge and resources that the acquirer does not possess or can difficultly develop inside (see Cohen and Levinthal, 1990). In fact, through the acquisition process, a firm brings into the organization capabilities and resources that resides in the target firm. For example, a successful innovation strategy is often based on acquisition, as it enable firms getting quick access to strategic assets, such as patents, skilled labour, licenses, brands or management skills, or valuable and new technology (Graebner, 2004). If the acquirer has the absorptive capacity to understand how to use and integrate the bought resources, combining the two baskets would be a value-creating process (Cohen and Levinthal, 1990; Zahra and George, 2002). The existence of this effect is based on traditional cost efficiency theory, which assumes that economies of scale exist.

However, the decision of acquiring is not merely due to learning intents or to technological reasons (Hamel, 1991). It allows also the expansion of the market share or other market-structure related considerations, such as the market-entry by the desire to expand the firm's product range geographically (Cloodt et al., 2006). Furthermore, M&A can take place just due to opportunity; Weitzel and McCarthy (2011) show that poorly performing firms are often victims of hostile acquisitions when the acquirer considering the management inefficient or not able to well utilize their firm's assets (Palepu, 1986; Matsusaka, 1993). Otherwise, whereas acquisitions occur in waves, they are sometimes simply the "thing to do" (Matsushima, 2001; Huyghebaert and Luypaert, 2010); again, many other factors may entice companies to acquire a certain business, such as the characteristics of bidder and target, valuation and price of the target, its business portfolio, possessed knowledge, etc.

2.1.1 Industry relatedness in acquisition framework

Once a firm has decided to grow by means of acquisition, industrial relatedness, as the degree to which two firms are active in related markets, seems to be a crucial factor (Ahuja and Katila, 2001; Boschma and Ellwanger, 2012). Industry relatedness in the selection of the target and the resulting level of corporate coherence are concepts associated with shared technological experiences, knowledge bases and with similar products and markets (Teece et al., 1994; Knoben and Oerlemans, 2006). M&A literature talks about horizontal mergers if the acquirer and the target are industrially related and about conglomerates if both companies are completely unrelated. In this context, a well-established proposition is that a fundamental part of any firm's corporate strategy is its choice of what portfolio of businesses to compete in (Barney, 1991; Piscitello, 2000). Even if the question of how to choose among viable target markets remains, generally a firm will expand into those areas in which its resources deliver the greatest advantage (Penrose, 1959; Bryce and Winter, 2009).

Industrial relatedness is the result of strategic decision and information advantages. Penrose (1959) and later on several scholars underscored the importance for firms to stay close to their existing capabilities when expanding into new product markets. Specifically, if both the firms are active within the same industry their managers are more likely to know each other and to exchange information, which affects the identification phase (Chatterjee et al., 1992). Sharing operations gives advantage also during the phase of due diligence, because the value of the target is more easily to determine. This concept is built on the absorptive capacity paradigm, which is the firms' capability to process and value external knowledge (Zahra and George, 2002). Absorptive capacity reveals its main relevance in the exploitation of operational and market synergies (Homberg et al., 2009). If the acquirer and the target are related, it is easier to integrate knowledge and combine operations, duplicative functions can be reduced (Capron and Insead, 1999; Ahuja and Katila, 2001; Nesta and Saviotti, 2005) and economies of scales can be realized. A high relatedness helps also the post-M&A integration, as the acquirer has already the skills to understand and absorb the acquired capabilities (Cohen and Levinthal, 1990; Mowery et al., 1996; Duysters and Hagedoorn, 2000). Conversely, in unrelated deals realizing synergies is more difficult and more integration efforts are required, leading to less benefits and higher costs. For the discussed reasons, investors and strategy researchers value related acquisitions more than unrelated ones (Lubatkin, 1983; Matsusaka, 1993; Fan and Lang, 2000). Hence, targets in the same product market seem to be more attractive targets (Capron and Shen, 2007) and able to increase firm value (Martin and Sayrak, 2003).

Furthermore, Teece et al. (1994) discussed the notion of path-dependencies, recognizing that 'history matters'. This is due to learning, considered as a process involving repetition and experimentation which enables tasks to be performed better and quicker, and new production opportunities to be identified. Since learning tends to be local, opportunities for successful new developments will be 'close in' to previous activities and will thus be transaction and product specific (Nelson and Winter, 1982; Teece et al., 1994). More specifically, firms seem to choose to enter industries that are close to their existing line of business (Piscitello, 2000). Since the enterprise's firm-specific resources drive its diversification strategy, firms do not diversify in a random way but tend to add activities that relate to some aspect of the existing business or assets (Teece, 1982; Winter, 1987; Teece et al., 1994; Breschi et al., 2003). This kind of behaviour results in the exhibition of corporate coherence; by contrast, a firm fails to exhibit a coherent pattern of diversification when its activities are randomly distributed across industrial fields (Teece et al., 1994; Breschi et al., 2003).

According to the above introduced background, this paper investigates the external growth of a firm by means of acquisition, expecting to find a considerable average level of relatedness in the process(Boschma and Ellwanger, 2012). In particular, the aim is to show that the selection of a target by an acquiring firm does not occur randomly, against the null hypothesis of random associations between activities. Furthermore, the analysis concerns the observation of a whole country (The Netherlands) domestic acquisition market in a quite large span of time (1980-2005), that allowed a sample of more than 36,000 deals among more than 200 different sectors.

Such a depth of analysis enabled a reliable mapping and understanding of the general phenomenon.

The first step of the analysis is the construction of a measure of industry relatedness for the acquisition framework. In detail, I applied the relatedness measures introduced by Teece et al.'s (1994), which relies on an endogenous notion of proximity. This methodology, based on the co-occurrence concept, is said to have marked an important step forward in the research of relatedness and, as suggested by Bryce and Winter (2010), it can be applied to a wide range of issues in strategic management, corporate finance and industrial economics. Therefore, the hereby proposed index is constructed in the spirit of this tradition, due also to its ability in capturing business aspects of the merge, like the sharing of managerial competences or financial advantages between different fields (Pehrsson, 2006), that are not limited exclusively to the existence and strength of technological spillovers.

In this study the acquisitions are seen as purely dyadic phenomena, as they usually occur between solely two companies. Even if a firm can acquire more than one company, only in very exceptional cases multiple acquisitions are realized in the same instant. Aware of that, I decided to focus the attention on the acquirer perspective, in order to create an asymmetric industry relatedness index able to highlight the acquirer strategy. In such a way, the *distance* between acquirer and target industries within each pair of possible sectors (at 3-digit of the NACE industry classification) has been measured, where low distance corresponds to high relatedness.

Furthermore, another expectation is that the degree of relatedness differs considering different macro-areas or particular subsets of the whole market. So, the analysis has been deepened observing particular clusters of the market and calculating for each of them a measure of asymmetric association, based on Goodman and Kruskal (1954) methodology. This second method has been necessary to face a limitation of the relatedness index; in fact, this latter does not admit the possibility of comparing the index between samples having different size, as happens when clustering the whole market by acquirer industry or by its technology class.

Finally, to test the robustness of the results found in this way, an OLS regression has been ran, allowing also controls for other effects, such as demographic characteristics of the firms involved.

The outline of this chapter is as follows. In the next section an overview of the literature is given, with regard at the main approaches in relatedness measurement. Then, section 2.3 discusses the data and the sample used and section 2.4 presents the methodology for the index construction. In section 2.5 Goodman and Kruskal (1954) methodology is performed to measure the asymmetric association. Section 2.6 provides a robustness analysis and, finally, section 2.7 concludes the study.

2.2 Measures of relatedness: previous approaches

Given the importance of industry relatedness, it has become crucial to reliably measure how strongly related industries are to one another. Measures of relatedness are designed to assess the degree of commonality (of some sort) within pairs of activities. In standard diversification measures, industry relatedness is typically based on the hierarchical structure of the standard industrial classification (SIC) system. According to this approach, developed by Caves (1981), the closer together industries are within this classification system, the more related they are thought to be. In particular, businesses in different 4-digit industries but the same 3-digit industry are 1 'unit' apart, whereas businesses whose closest connection is their 2-digit industry memberships are 2 'units' apart, and so forth (Teece et al., 1994).

However, actual relatedness cannot be directly inferred from the hierarchical structure of the SIC system, as it does not represent an underlying relatedness scale (e.g. Teece et al., 1994; Robins and Wiersema, 1995; Bryce and Winter, 2009). In fact, for historical reasons the SIC system usually reflects a broad logic of vertical structure and primary raw material[2]. Therefore, the number of digits two industries share supplies no clear message about the strategic significant relationships among activities, since the SIC hierarchy does not consistently reflect relationships among valuable resources in the ways that firms actually combine them to create value (Bryce and Winter, 2009).

As a response to the perceived shortcomings, a number of alternative approaches have been proposed. For instance, in the 1980s, Scherer (1982) constructed relatedness

[2] Thus, for example, functionally substitutable products made of steel, aluminium, and plastic appear in different two-digit industries because of the underlying difference in primary feed stock. This virtually guarantees that the knowledge about how to produce a functionally similar product lies scattered around the SIC system (Bryce and Winter, 2009).

matrices for almost 50 industries based on estimated technology flows, through very detailed empirical analyses. Later, Farjoun (1994) based relatedness on similarity in the mixes of occupations that have been employed by different industries, and also Robins and Wiersema (1995), in order to test propositions suggested by the resource-based view of the firm, proposed a non-SIC-hierarchy-based measure. Yet, another approach has been based on similarities in upward and downward linkages in input-output tables (Lemelin, 1982; Fan and Lang, 2000). Klavans' (1989) index of technology relatedness is also based on input patterns, using the amount of overlap in occupational categories as an index. Further methods are based on micro-level data, such as Engelsman and Van Raan (1991) that used the fact that some patents are filed in multiple technology classes as evidence for the technological relatedness between these classes. The use of patents as a source of information has the advantage that it stays very close to the notion of technological relatedness.

More recently, a number of scholars have turned to co-occurrence analysis to assess inter-industry relatedness (Teece et al., 1994; Piscitello, 2000; Breschi et al., 2003; Nesta and Saviotti, 2005; Neffke and Henning, 2008; Bryce and Winter, 2009). Co-occurrence analysis measures the relatedness between two industries by assessing whether two industries are often found together in the same economic entity. Firstly proposed by Teece et al. (1994), its peculiarity is the development of an index that, using SIC data, goes beyond input considerations. They suggested that the co-evolution of economic units and the selection process drive the market, leading to the survival of those units characterized by the more efficient mix of activities. In this framework, the survivor principle is based on the idea that economic competition leads to the disappearance of relatively inefficient organizational forms or combinations of businesses; as a result, activities that are more related tend to appear together, inside the same unit, with higher frequency. With other words, by moving away from pure SIC hierarchies they looked directly at the frequencies with which activities are combined in multiproduct firms, observing the diversification patterns of firms themselves. The number of firms simultaneously active in a pair of fields (co-occurrences) has been adopted to directly measure the relatedness of the two fields and the actual degree of relatedness is finally obtained by comparing the observed number of co-occurrences with what would have been obtained under the absence of any relatedness among the fields of activity[3].

As discussed in Bryce and Winter (2009), this endogenous notion of proximity can be applied to a wide range of issues in strategic management, corporate finance, and industrial economics and it possesses several advantages. Some authors extended Teece et al.'s (1994) considerations to technology relatedness, focusing their attention on patents technological classes, using patents frequency or citation. For instance, instead of implementing the measure to industry SIC codes, Nesta and Saviotti (2005) and Breschi et al. (2003) applied it to technologies. They assumed that the frequency with which two technology classes are jointly assigned to the same patent application is a proxy for the strength of their technological relationship, or relatedness. Again, Hidalgo et al. (2007) used the number of times two industries display revealed comparative advantage (the co-occurrence) in a single country, here considered as the entity. The general logic behind this method is that some co-occurrences are more likely than others, because one of the involved classes is larger than average, defining distance between product categories in terms of conditional probabilities. Moreover, Neffke and Henning (2008) developed a methodology to distil relatedness relations between industries from product portfolios, which basic idea is that if two products are produced in the same plant, this is an indication of relatedness between the industries the two products are a part of. Their index, called revealed relatedness, measures then the revealed existence of economies of scope between industries. Finally, Bottazzi and Pirino (2011) recently showed that using Monte Carlo p-scores as measure of relatedness provides cleaner and homogeneous estimates, overcoming some drawbacks concerning Teece et al.'s (1994) methodology.

2.3 The data and the sample

The data source of this study is the Business Register (BR), a micro-economic database collected in a systematic and continuous way by the Central Bureau of Statistics

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[3] The test of the random hypothesis is built on the properties of the hypergeometric distribution. According to this concept, it is straight forward to derive the expected number of links for each industry pair and then to compare these expected values to the actual number of co-occurrences. See section 2.4 for a more detailed explanation.

Netherlands (CBS). The BR provides firm specific demographic characteristics of the entire population of firms, including self-employment, that means firms with 0 employees, registered for fiscal purposes in the Netherlands since 1993. It contains demographic and domestic employment data, sector of activity, and dates of entry and exit of a firm in/from the BR. For a given year, the dataset includes all firms that had been active during that year, not necessarily for the full duration of that year, and those that entered and/or exited during the year. Its comprehensive nature and fiscal purpose mean that the dates of inclusion and exclusion in the register are very close approximations of actual dates of market entry and exit (Cefis and Marsili, 2006; 2012).

Moreover, the annual BR allows mode of entry-in/exit-from the market to be identified. In such a way, the firms that were acquired by other firms, where the latter maintain their identity, could have been distinguished among all the other possible categories of a firm status mutation (such as entry/exit by spin-off, decomposition or amalgamation of business units, radical restructuring, failure or administrative changes). Using the datasets yearly available since 1995 until 2005, which however include also data regarding the operations concluded in the past, it was possible to identify 36,375 effective acquisitions that took place in the Dutch market over the period 1980-2005. Then, again through the BR dataset, I matched the acquired to the correspondent acquiring firms of the sample of M&A, in order to collect the demographic data of both. I gathered the NACE[4] industry code at 3-digit level of both the two firms involved in each deal identified, as it is the basis for the construction of the relatedness index.

2.3.1 Description of deals, acquirers and targets

The sample includes 36,375 real deals concluded in the Netherlands in the years 1980 to 2005. Those deals were undertaken by 23,652 companies, of which some were multiple bidders: 18,802 acquirers selected only one target, 2,587 acquirers two, 932 acquirers three, 818 four or five, 368 acquirers six to ten, 81 acquirers eleven to fifteen, 48 sixteen to thirty, 10 acquirers thirty-one to fifty and 6 acquirers fifty-one or more (at most 245) targets.

Table 2.1 depicts the deals clustering both the acquirers and the targets in the main industrial macro-categories: manufacturing, that involves 3,809 acquirers and

[4] See *Appendix 2.1* for more details about the industrial and technology classifications.

3,418 targets; service, that involves 29,022 acquirers and 29,794 targets; and other. In both manufacturing and service sectors the classes are also classified regarding the technology level. For each sector of activity, the acquirers and the targets are almost equally distributed.

Table 2.1 Descriptives of the deals clustering both the acquirers and the targets in the main industrial macro-categories: manufacturing, that involves 3,809 acquirers and 3,418 targets; service, that involves 29,022 acquirers and 29,794 targets; and other. In both manufacturing and service sectors the classes are also classified regarding the technology level.

Main Section	Acquirers		Targets	
	Obs.	%	Obs.	%
High-tech Manufacturing	229	0.63%	225	0.62%
Medium-tech Manufacturing	2,549	7.01%	1,615	4.44%
Low-tech Manufacturing	1,031	2.83%	1,578	4.34%
Total manufacturing	3,809	10.47%	3,418	9.40%
Market Service ex Fin. intermediation	21,642	59.50%	22,585	62.09%
Financial Intermediation	2,856	7.85%	2,736	7.52%
Non-market Service	4,524	12.44%	4,473	12.30%
Total Service	29,022	79.79%	29,794	81.91%
Other	3,544	9.74%	3,163	8.70%
Total	36,375	100%	36,375	100%

Again, considering the univocal 23,652 acquiring companies, Table 2.2 shows how they are clustered into the above presented industrial macro-categories and it gives descriptive statistics of the acquisition activity. In detail, values are considered in natural logarithm and each couple of rows presents the mean and the standard deviation (in parenthesis) of a pair of sectors, while the last column contains the result of the mean difference test between them. The general average is quite low, with each bidder acquiring 1.5 targets; observing the two main macro-areas, the *service* sector is barely more active (mean: 1.53) than the *manufacturing* (mean: 1.45). More precisely, the most active sector is *non-market service*, where, on average, a bidder acquires 1.90 targets, followed by *financial intermediaries* (mean: 1.61), *market service except financial intermediaries* (1.48), *high-tech manufacturing* (1.44), and *low-tech manufacturing* (1.41).

Table 2.2 Descriptive statistics grouped by acquirer industry: Manufacturing (high-tech and low-tech manufacturing) and Service (market service except financial intermediaries, financial intermediaries, and non-market service). Considering the univocal 23,652 acquiring companies, Table 2.2 gives descriptive statistics of the acquisition activity. Values considered in natural logarithm. Mean value and standard deviation (in parenthesis) are reported.
T test performed as: mean (first column considered) - mean (second column considered), for each couple of sectors, respectively.
*, **, and ***: statistically significant at the 10% , 5%, and 1% level, respectively.

No of acquisitions	Acquirer's Industry: Main Sections							Mean difference test
	Manufacturing	*High-tech Manufacturing*	*Low-tech Manufacturing*	*Service*	*Market Service ex Fin. Int.*	*Non-Market Service*	*Financial Int.*	
Obs.	2,627	159	1,200	18,850	14,699	2,390	1,761	
Mean	1.45			1.53				1.42
Std. dev.	(1.16)			(3.11)				
Mean		1.44	1.41					-0.34
Std. dev.		(1.15)	(1.08)					
Mean					1.48	1.90		6.07***
Std. dev.					(3.24)	(1.97)		
Mean					1.47		1.61	-1.80*
Std. dev.					(2.56)		(6.58)	
Mean		1.44					1.61	-0.33
Std. dev.		(1.15)					(6.58)	
Mean					1.53		1.61	-1.12
Std. dev.					(2.49)		(6.58)	

Tables 2.3 and 2.4 aim to present a first sight on the acquisition market, observing the firms' attitude to acquire a company from the same or a similar industry. As discussed in the previous section, the main reason in favor to this behavior is the possibility to realize synergy effects, that arises from related resources, such as similar products, technologies, distribution channels, and routines (see, among others, Chatterjee, 1986; Sirower, 2000; Homberg et al., 2009), in order to benefit from economies of scope and scale.

Table 2.3 gives descriptives of the target sectors involved in the deals within each industrial class of the acquirer. The deals in which the acquirer belongs to the service sector, for each subclass of it, are quite exclusively done within the specific division, respectively (within *non-market service* about 81%, within *market service except financial intermediaries* 84%, and within *financial intermediaries* 46%). The subgroup of financial intermediaries spans its activity also in the remainder of the market service (about 44%), but only in merely part (about 3%) in the manufacturing. Anyhow, the activity of the service firms is quite completely concentrated within the service sectors (more than 93% of the deals). Regarding the manufacturing companies, their activity is more spanned: about 56% of the acquisitions are within the manufacturing macro-category, while in about 39% of the cases a service firm has been chosen as target. Finally, looking at the technology level of the acquirer, most of the acquisitions within the manufacturing macro-category involves target companies in the same technology class.

Table 2.3. Descriptive statistics of the sectors involved in the deals within each industrial class of acquirers.

Main Sections	Acquirer's Industry: *Manufacturing*		Acquirer's Industry: *High-tech Manufacturing*		Acquirer's Industry: *Medium-tech Manufacturing*		Acquirer's Industry: *Low-tech Manufacturing*	
Target's Industry:	Obs. 3,089		Obs. 229		Obs. 2,522		Obs. 1,031	
	Obs.	%	Obs.	%	Obs.	%	Obs.	%
High-tech Manufacturing	118	3.10%	93	40.61%	22	0.86%	3	0.29%
Medium-tech Manufacturing	1,049	27.54%	3	1.31%	1,027	40.29%	19	1.84%
Low-tech Manufacturing	990	25.99%	18	7.86%	418	16.40%	554	53.73%
Total manufacturing	2,157	56.63%	114	49.78%	1,467	57.55%	576	55.87%
Market Service ex Fin. intermediation	1,361	35.73%	99	43.23%	854	33.50%	408	39.57%
Financial Intermediation	91	2.39%	4	1.75%	65	2.55%	22	2.13%
Non-market Service	63	1.65%	7	3.06%	36	1.41%	20	1.94%
Total Service	1,515	39.77%	110	48.03%	955	37.47%	450	43.65%
Other	137	3.60%	5	2.18%	127	4.98%	5	0.48%
Total	3,809	100%	229	100%	2,549	100%	1,031	100%

Main Sections	Acquirer's Industry: *Service*		Acquirer's Industry: *Market Service ex Fin. intermediation*		Acquirer's Industry: *Non-Market Service*		Acquirer's Industry: *Financial Intermediation*	
Target's Industry:	Obs. 29,022		Obs. 21,642		Obs. 4,524		Obs. 2,856	
	Obs.	%	Obs.	%	Obs.	%	Obs.	%
High-tech Manufacturing	100	0.34%	86	0.40%	7	0.15%	7	0.25%
Medium-tech Manufacturing	457	1.57%	407	1.88%	10	0.22%	40	1.40%
Low-tech Manufacturing	546	1.88%	467	2.16%	37	0.82%	42	1.47%
Total manufacturing	1,103	3.80%	960	4.44%	54	1.19%	89	3.12%
Market Service ex Fin. intermediation	20,177	69.52%	18,334	84.71%	580	12.82%	1,263	44.22%
Financial Intermediation	2,520	8.68%	1,149	5.31%	57	1.26%	1,314	46.01%
Non-market Service	4,308	14.84%	561	2.59%	3670	81.12%	77	2.70%
Total Service	27,005	93.05%	20,044	92.62%	4,307	95.20%	2,654	92.93%
Other	914	3.15%	638	2.95%	163	3.60%	113	3.96%
Total	29,022	100%	21,642	100%	4,524	100%	2,856	100%

More in detail, Table 2.4 distinguishes between intra-sector and inter-sectors acquisitions, through the comparison of the NACE hierarchic codes at a 3-digit level of accuracy. Observing the whole sample, on average more than 51% of the acquirers targeted firms within their exact field of activity. This percentage is high also for the individual industrial subsamples of acquirers, in particular it is always higher than 42% except for the high-tech manufacturing (above 35%) and the financial intermediaries (above 26%). The reason of the latter two exceptions can be identified in the specific peculiarities of these two categories. On one hand, high-tech firms set their focal goal on knowledge, and then they need to search widely and deeply, with the aim of reaching more innovative result (Laursen and Salter, 2006), as the novelty increases with the industry distance from the target firm. On the other hand financial companies usually have financial gain as object, made on considerations and valuations that works often beyond the industry the target belongs to.

Table 2.4. Mapping of the market: number (second column) and related percentage on the total number (third column) of intra-sector acquisitions, defined as deals in which the acquirer and the target belong to the same industrial sector, at 3-digit of NACE industrial classification.

Acquirer's Industry:	Total number of M&A	Number of intra-sector M&A (at 3-digit detail)	Percentage of intra-sector M&A (at 3-digit detail)
High-tech Manufacturing	229	81	35.37%
Medium-tech Manufacturing	2,549	1,077	42.25%
Low-tech Manufacturing	1031	491	47.62%
Total manufacturing	3809	1,649	43.29%
Market Service ex Fin. intermediation	21,642	10,994	50.80%
Financial Intermediation	2,856	742	25.98%
Non-market Service	4,524	3,359	74.25%
Total Service	29,022	15,095	52.01%
Total	36,375	18,573	51.06%

2.4 A measure of industry relatedness in M&A

As introduced in the literature review, in this work I carry out in acquisition field the survivor measure of relatedness proposed by Teece et al. (1994), and later applied in several publications (among others, Piscitello, 2000; Breschi et al., 2003; Nesta and Saviotti, 2005; Bryce and Winter, 2009; Bottazzi and Pirino, 2011). To apply the spirit of this idea to the study of industrial relatedness, I assume that companies which are more related will be more frequently combined in a deal. Thus, if companies belonging to industry A very often acquire firm operating in sector B, it is possible to conclude that these industries are highly related. Conversely, sectors that are rarely or never combined are unrelated. If this is verified, it means that acquisition strategy can be hardly seen as a purely random phenomenon (random hypothesis).

By definition, this measure is built on an endogenous analysis of the acquisition market, observing the deals effectively and successfully realized in the country in a quite wide span of time (25 years). More precisely, both the acquirer and the target must be fiscally registered in The Netherlands, and cross-border deals are not considered in this work for two reasons. First, the empirical investigation requires a closed system because, as deepened later, the index is affected by the sample size: choosing a specific country and analysing its whole acquisition market imply the possibility of mapping such national market. Second, cross-border deals often follow a different logic and are based on other motives than domestic deals. In fact, cross-border M&A are often seen as the main form of foreign direct investment and as an instrument to get access to new markets; even political, legal or cultural factors might play a role in target selection.

2.4.1 The methodology

In order to operationalise the concept, I define K as the total number of deals in the dataset (36,375), and the two samples of firms involved: the acquirers (A) and the targets (T). Let $B_{ia} = 1$ if acquirer firm a is active in industry i, and 0 otherwise; as well, let $G_{jt} = 1$ if the target firm t is active in field j. Accordingly, the number of acquirers belonging to industry i and the number of acquired firms belonging to j are then $N_i = \sum B_{ia}$ and $M_j = \sum G_{jt}$, respectively. The basis of the industry classification used is the NACE hierarchy[5], made available by the BR database at 4-digit. To the extent of this study and to encompass the complexity of the calculations, the accuracy of the activity definition has been limited at 3-digit, identifying anyway more than 200 possible industries involved. As described above, the measure here built is endogenous and goes beyond the raw hierarchic definition of the NACE classification. This means that does

[5] Since our sample is obtained from the BR datasets in the span 1995-2005, we firstly controlled for the coherence in the industrial classification. In fact in this span the classification NACE Rev. 1 have been updated by NACE Rev. 1.1. See Appendix 2 for more details.

not matter how many digit of a classification two companies share if for some reason they never combine in a M&A. In fact, the belonging to the same section of the NACE code does not tell much about the economic advantage faced by the firms matching in a deal (Bottazzi and Pirino, 2011).

Using the introduced notation, it was then possible to indicate the number of deals that show the co-occurrence of industry *i* (as acquirer) and *j* (as target), i.e. a firm operating in industrial sector *i* that acquired a company active in *j*, as follows: $o_{ij} = \sum B_{ia}G_{jt}$. Moreover, examining the M&A behaviour, firms very often realize a deal within their own industry, due to expansion of the market share or other reasons. In this case, for example, if both the acquirer and the target belong to the same sector *i,* in the notation it is given as $o_{ii} = \sum \mathrm{B}_{ia}G_{it}$.

Consequently, by applying this count to all the possible pairs of industrial fields, I obtained 204*204 (the number of the acquirer's possible sectors multiplied by the number of the target's possible sectors) equal to 41,616 combinations of either different and identical activities. This latter involves the creation of an asymmetrical square matrix, called co-occurrences matrix Ω, whose generic cell is o_{ij}.

Acquisition partnering is the outcome of complex search and decision processes by both the potential acquirer and the potential target. For the aim of this work, the bidder perspective has been chosen. Hence, the direction acquirer-target of the relatedness index matters (that is, it is different to consider the relatedness between sectors *i-j* or *j-i*, when the first refers to the acquirer and the second to the target). Indeed, conversely with the previous applications of the index (see Teece et al., 1994; Breschi et al., 2003; Nesta and Saviotti, 2005; Bryce and Winter, 2009; Bottazzi and Pirino, 2011), the matrix cannot be symmetric.

However, the raw count of the number of observed co-occurrences cannot be directly taken as a measure of relatedness between two industrial sectors, because it is biased by the sample size and also by the number of firms belonging to each sector, since its spectrum [0, min (N_i, M_j)] is pair dependent. In fact, o_{ij} not only increases with the relatedness of *i* and *j*, but also with the size of N_i and/or M_j; on one hand, if N_i and/or M_j are large, one would expect the two industries to be linked by a fair number of deals, even if there is little relatedness between them. On the other hand, if N_i and/or M_j are small, one would not expect to see very many linkages even if there is substantial synergy.

Therefore, the information in o_{ij} must be adjusted for the value that would be expected under the hypothesis the acquisition strategy is random, that means performing a test of randomness through the comparison of the real number and the hypothetical value in absence of any acquisition strategy. If a particular relationship among industrial sectors exists, the observed value of the co-occurrences is expected to be non-random, i.e. some pairs of sectors appear more or less frequently combined in a deal than randomness would suggest.

To accomplish this adjustment, Teece et al. (1994) proposed to consider as random benchmark the hypergeometric probability distribution of co-occurrences X_{ij}, representing, in this study, the expected outcomes of a random matching of acquirers' and targets' sectors.

More precisely, the K (both acquiring A and acquired T) firms are randomly assigned to the 204 possible sectors, in such a way the number of firms (both A and T) belonging to a particular sector is fixed and equal to the actual number observed, $N_i = \sum B_{ia,}$ and $M_j = \sum G_{jt}$ respectively. I take the population size K to be a given number as well, and postulate the equal likelihood of all distinct company for the possible sectors.

Following Bryce and Winter (2009), the formulation of the expression of the hypergeometric distribution proposed by Teece et al. (1994) is here detailed, with the idea of explaining as better as possible the methodology. More in detail, some of the acquirers belonging to sector i acquired a firm operating in sector j to the extent x. This is equivalent to the number of ways of selecting x from a total of N_i firms, or $\binom{N_i}{x}$. With the target firms (T) involved in the deals specified, there are $(M_j - x)$ positions in the M_j subsample to be acquired by firms (among A) that are not also active in i. The number of ways of selecting these is the number of ways of selecting $(M_j - x)$ from a possible $(K - N_i)$ firms, or $\binom{K - N_i}{M_j - x}$.

Then the number of distinct ways of choosing a target belonging to industry j that is consistent with the specified deal is the product of the answer to the first question and the answer to the second, or $\binom{N_i}{x}\binom{K - N_i}{M_j - x}$. To turn this count into a probability for x, it was divided by the number of possible ways of specifying the membership of j in total; i.e., when the constraint of the acquisition is dropped, which is $\binom{K}{M_j}$.

Thus, the level of randomly occurring deals in which acquirers operating in sector i (of size N_i) buy a target belonging to sector j (of size M_i) is a is a hypergeometric random variable[6]:

$$(1) \qquad P\left[X_{ij} = x\right] = \frac{\binom{N_i}{x}\binom{K-N_i}{M_j-x}}{\binom{K}{M_j}}, \quad x \leq \max\left\{N_i,\ M_j\right\}$$

The mean μ_{ij} (2) and variance σ^2_{ij} (3) of X_{ij} are as below: (population K, number of acquirers belonging to sector i, N_i, and number of targets belonging to sector j, M_j).

$$(2) \qquad \mu_{ij} = E\left(X_{ij}\right) = \frac{N_i M_j}{K}$$

$$(3) \qquad \sigma_{ij}^2 = \mu_{ij}\left(\frac{K-N_i}{K}\right)\left(\frac{K-M_j}{K-1}\right)$$

Applying the test of randomness to acquisitions framework, when the actual number of joint occurrences o_{ij} observed between the activity field i of the acquirer and j of the target greatly exceeds the expected value μ_{ij} of the random co-occurrence X_{ij}, then the two industries are highly related. The existence of pairs that are represented more frequently than suggested by the random model necessarily implies a complementary set of relatively underrepresented pairs, that is when $o_{ij} < \mu_{ij}$, then activity classes i and j are poorly related. Underrepresentation does not imply some sort of negative relatedness, but only that the incentives to combine such pairs of industries in an acquisition is weak relative to the stronger forces affecting the over-represented pairs (Bryce and Winter, 2009). Thus the relatedness index ρ_{ij} is defined standardizing the observed value of the co-occurrences using the mean (2) and the standard deviation (3) of the hypergeometric distribution as:

[6] For further information on the hypergeometric distribution, see Feller (1957).

$$(4) \qquad \rho_{ij} = \frac{o_{ij} - \mu_{ij}}{\sigma_{ij}}$$

which measures how much standard deviations away the observed values are from their expected values under the null (random) hypothesis. Since large values of ρ are very unlikely under the null, their observation implies that some "deterministic" mechanisms are forcing the two fields to appear together so often, whence their large relatedness (Bottazzi and Pirino, 2011). Going back to the discussion of inter-sector deals, I would like to specify that the relatedness index ρ differs even between different inter-sector deals, such as ρ_{ii} and ρ_{jj}. This is due to the index construction terms, where both the number of co-occurrences and the parameters of the hypergeometric distribution (2) and (3) are affected by the size of the observations.

2.4.2 Testing the random hypothesis: results

As proposed by Breschi et al. (2003), a major advantage of the ρ_{ij} is the possibility of calculating the P-value for each element ρ_{ij} under the null hypothesis of independence between industries and therefore to evaluate the statistical significance of the relation among them. Moreover, following the empirics of Breschi et al. (2003), co-occurrences matrices like Ω have been calculated also clustering the whole population of acquirers by the number of acquisitions realized in the span of time considered, i.e. the subsamples of companies which acquired only one target, up to two targets, up to three targets and so on till up to 245 that coincides with the whole sample. Then, the ρ_{ij} index and the associated P-values have been calculated for all the combinations within the different subsets of acquirers. By means of this methodology, it was possible to observe the effect of different acquisition thresholds on the average degree of relatedness among sectors (Bottazzi and Pirino, 2011).

More in detail, table 2.5 reports the main statistics of the measure by showing minimum, maximum, mean, median and standard deviation for each category and also the absolute number and percentage of cases (i.e. pairs of acquirer's – target's sectors) with statistically significant P-value (10% level). For each acquisition thresholds the table reports also the total number of deals and the number of pairs actually observed among all the possible ones (see above, 204*204 sectors = 41,616 possible couples o_{ij}).

Table 2.5 Test of randomness and descriptive statistics of the relatedness index ρ_{ij} in acquisition field. Measure of relatedness performed on the whole sample of deals and considering the number of acquisitions realized by each acquirer as thresholds. For instance, allowing for the more comprehensive threshold, "up to 245" acquisitions, I created a co-occurrences matrix as 204*204 industries (the number of the acquirer's possible sectors multiplied by the number of the target's possible sectors) equal to 41,616 cells or possible dyads. Among these latter, only 4,543 dyads are actually observed on the market. The number of dyads with negative and positive value of the index, and then the number and the percentage of cases with significant P-values (at 10% level) are displayed in the table as well. The analysis is performed on the Dutch acquisition market in the span 1980-2005.

				Negative index			Positive index			Statistics				
# Acquisitions	# M&A	# Possible couples	# Observed couples	#	# Signif.	% Signif.	#	# Signif.	% Signif.	Min	Max	Mean	Median	S.d.
(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(l)					
Only 1	18,828	41,004	3,499	38,785	812	2.09%	2,219	1,253	56.47%	-7.38	137.21	0.13	-0.14	4.48
Up to 2	24,002	41,616	3,929	39,185	1,098	2.80%	2,431	1,394	57.34%	-7.55	154.92	0.15	-0.16	5.15
Up to 3	26,798	41,616	4,138	39,101	1,215	3.11%	2,515	1,432	56.94%	-8.28	163.69	0.16	-0.17	5.41
Up to 5	30,068	41,616	4,315	39,019	1,427	3.66%	2,597	1,477	56.87%	-9.32	173.40	0.17	-0.18	5.76
Up to 10	33,014	41,616	4,449	39,028	1,684	4.31%	2,588	1,493	57.69%	-10.08	181.70	0.16	-0.19	5.96
Up to 15	34,046	41,616	4,482	38,983	1,649	4.23%	2,633	1,538	58.41%	-9.92	184.51	0.18	-0.18	6.17
Up to 30	35,009	41,616	4,508	38,976	1,694	4.35%	2,640	1,533	58.07%	-9.88	187.11	0.19	-0.18	6.28
Up to 50	35,423	41,616	4,519	38,969	1,721	4.42%	2,647	1,540	58.18%	-10.02	188.21	0.19	0.18	6.33
Up to 245	36,375	41,616	4,543	38,971	1,782	4.57%	2,645	1,546	58.45%	-10.16	190.72	0.19	-0.18	6.42

Legend of the columns:

(a) Acquisition threshold: number of acquisitions in which each specific acquirer is involved.
(b) Number of deals for each threshold.
(c) Number of possible "acquirer's industry-target's industry" couples.
(d) Number of observed "acquirer's industry-target's industry" couples (id est cells of the co-occurrences matrix with not-zero value, that means combinations of industries really occurred in the sample).
(e) Number of cells with a negative index of relatedness.
(f) Number of cells with a negative and statistically significant index of relatedness.
(g) Percentage of cells with a negative and statistically significant index of relatedness among the negative cells (d)
(h), (i), and (l): definition as (e), (f), and (g) respectively, but for positive values of the index

Simply looking at the minimum, maximum, and mean values of the index, it is easy to understand that the distribution is strongly asymmetric. Most of the possible couples of industries almost never combines, i.e. the index has a negative value, while few couples show strong relatedness. Again, a small percentage of the couples with negative index are significant (about 4.5% if consider the whole sample is considered, that is including acquirers having realized up to 245 acquisitions), meaning that most of these couples basically never occurs. Conversely, more than 58% of the couples with positive index are significant (again, considering the whole sample). These evidences make us are able to reject the null (random) hypothesis: the observed acquisition market shows that some industries are more related (or less related) that it would happen under the random hypothesis. Furthermore, as in the research of Breschi et al. (2003), the percentage of cases with non-random (positive or negative) relationships among industrial sectors increases by including acquirers with higher acquisition experience, i.e. acquirers that in their story have acquired several firms. Indeed, I am able to reject the null hypothesis of randomness in acquisitions for all the clusters of acquirers, or rather for each row of table 2.5.

Furthermore, the computed measures and the study of randomness has been repeated for specific industrial subsets of the whole market. More precisely, I clustered by the acquirer's field of activity[7], as: *manufacturing* (then subdivided in high-tech and *low-tech manufacturing*) and *service* (then subdivided in non market service, *market service except financial intermediaries* and *financial intermediaries*). Again, the outputs allow the rejection of the random hypothesis in each case[8].

2.4.3 Discussion of the limitations of this measure

A limitation of this relatedness measure is that its magnitude is not limited to a certain range, but is affected by the size of the sample considered. This problem can be easily understood looking at the calculation procedure, as in equation (2), (3), and (4). Due to this matter, the choice to consider the acquisition market at a whole country

[7] To classify the activities in high or low technology we followed Eurostat definition applied on NACE classification. See *Appendix II* for more details.
[8] The output of the index measure clustering for the acquirer's sector and for the number of acquisitions threshold (min, max, mean, median and standard deviation of the index) as well as the P-values are reported in *Appendix I*, Table A-G.

level. However, this fact makes incorrect the comparison of index's minimum, maximum, mean or median values between different subsamples, such as when clustering the market by acquirer's industry or by the number of acquisitions performed. Indeed, this methodology is not able to permit us to make comparisons between the different tables (different industries) or between the rows within each table, increasing the number of deals included when allowing for multiple acquisitions. This problem will be overcome in the next section, through the construction of a specific measure, the Goodman Kruskal asymmetric index of association.

A second drawback comes from the discussion of the methodologies in measuring industry relatedness presented by Bottazzi and Pirino (2011). They highlighted some problems arising with the choice of the random association mechanism as done by Teece et al. (1994). With reference to the original formulation of the methodology adopted in corporate coherence, they argued on the correct number of constrains that should be taken into account in the formulation of the null hypothesis, as the benchmark against which the observed degree of coherence is measured. More in detail, they obtained that both the number of firms belonging to each industrial class and the number of fields in which each firm is active (the firm scope) should be preserved in the random assignment of the occupancies to sectors, when computing the probability that two sectors appear in the same firm. Conversely, Teece et al.'s procedure implies that only the number of firms active in each industrial sector is fixed, and equal to the value observed in the actual data, while no constraints are imposed on firms' scope. In principle, the mechanism allows any firms to be active in all sectors. As a direct consequence of this assignment process, the implied distribution of firm scope converges to a binomial. This contrasts with the Paretian shape of the scope distribution often observed in industrial data (Bottazzi and Pirino, 2011). In their paper, Bottazzi and Pirino (2011) suggested to overcome the problem using Monte Carlo p-scores as measure of relatedness provides cleaner and homogeneous estimates.

Even if the method of Teece et al. (1994) has been followed in the creation of the measure, I assume that this drawback is not very prominent in the present application. Bottazzi and Pirino (2011) showed how the null on which Teece et al. method is based implies that the distribution of sectors across the different firms (the scope) is almost uniform. In fact, in the construction, the so called "scope" in coherence study is always fixed and equal to two, i.e. the sectors of the acquirer and the target companies. Moreover, in the empirics, the industries of the firms involved in each deal are taken from two distinguished samples, the acquirers' and the targets' one. For these reasons, I assume that the here developed benchmark works as a good approximation of the actual data distribution, making this measure theoretically correct.

2.5 Mapping of the market: a measure of association

With the aim of overcoming the issue of comparability between the subsets of the industrial acquisition market, the use of an asymmetric association index has been proposed, more precisely the lambda (λ) developed by Goodman and Kruskal (1954). The fact that this measure is asymmetric is needful since, as previously discussed, the focus of the study is the acquirer strategy in target selection.

Goodman and Kruskal (1954) lambda is a measure of proportional reduction in error in cross tabulation analysis largely used in probability theory and statistics. For any sample with a nominal independent variable and dependent variable (or ones that can be treated nominally), it indicates the extent to which the modal categories and frequencies for each value of the independent variable differ from the overall modal category and frequency. In other words, λ coefficient assesses the predictability of the state of a characteristic on one item (presence or absence) given the state on the other item. Specifically, lambda measures the proportional reduction in error using one item to predict the other.

Empirically, the basis for the λ calculation is the co-occurrences matrix Ω, where also the choice of the position of the acquirer/target sectors on the rows/columns is meaningful. In fact the power of this association coefficient is its uni-directionality, then the independent variable X (acquirer sector) has to be set on the rows while the dependent one Y (target sector) lies on the columns.

λ can be calculated with the equation[9] below:

$$(5) \qquad \lambda(Y|X) = \frac{\varepsilon_1 - \varepsilon_2}{\varepsilon_1}$$

[9] See Goodman and Kruskal (1954) and their following works (Goodman and Kruskal, 1959; 1963; 1972) for a more detailed explanation of the argument.

where:

ε_1 is the overall non-modal frequency

ε_2 is the sum of the non-modal frequencies for each value of the independent variable

As a shorthand, the lengthy procedure to obtain the value of λ through equation (5) can be overcome as

(6) $$\lambda(Target\ sector|Acquirer\ sector) = \frac{\sum_i^R O_{r,c} - O_{.,c}}{O - O_{.,c}}$$

where:

r [1, R] and c [1, C] identify, respectively, the rows (acquirer sector *i*) and the columns (target sector *j*) of the co-occurrences matrix[10] Ω, which each cell is o_{ij}.

$O_{n,m}$ = max $(o_{n,1}, o_{n,2}, \ldots, o_{n,C})$, that is the maximum value of co-occurrences in each row, i.e. the maximum value of co-occurrences for each acquirer sector *i*;

$O_{.,m}$ = max $(o_{.,1}, o_{.,2}, \ldots, o_{.,C})$, that is the maximum of the total value of co-occurrences in each column, i.e. the maximum of the total value of co-occurrences for each target sector *j*.

O, the total number of co-occurrences (for example 36,375 when studying the whole sample).

A main reason to use this methodology is that Goodman and Kruskal's lambda (λ) is not affected by the size of the sample, and its values ranges from zero (no association between independent and dependent variables) to one (perfect association), that makes the measure comparable between different samples.

[10] See section 2.4.1 for more details about the construction of the co-occurrences matrix Ω.

Table 2.6. Goodman and Kruskal measure of association (lambda). Sample grouped by the acquirer industry: Manufacturing (high-tech and low-tech manufacturing) and Service (market service except financial intermediaries, financial intermediaries, and non-market service).

# Acquisitions	Acquirer's Industry: *Whole sample*		Acquirer's Industry: *Manufacturing*		Acquirer's Industry: *High-tech Manufacturing*		Acquirer's Industry: *Low-tech Manufacturing*	
	# M&A	λ	# M&A	λ	# M&A	λ	# M&A	λ
Only 1	18,828	0.43	2,038	0.40	127	0.33	594	0.41
Up to 2	24,002	0.45	2,726	0.41	161	0.34	814	0.41
Up to 3	26,798	0.45	3,083	0.42	188	0.32	898	0.40
Up to 5	30,068	0.46	3,478	0.42	206	0.31	995	0.40
Up to 10	33,014	0.47	3,735	0.43	229	0.33	1,058	0.41
Up to 15	34,046	0.47	3,809	0.43	/	/	/	/
Up to 30	35,009	0.48	/	/	/	/	/	/
Up to 50	35,423	0.48	/	/	/	/	/	/
Up to 245	36,375	0.48	/	/	/	/	/	/

# Acquisitions	Acquirer's Industry: *Service*		Acquirer's Industry: *Market Service ex fin. int.*		Acquirer's Industry: *Non-market Service*		Acquirer's Industry: *Financial Intermediation*	
	# M&A	λ	# M&A	λ	# M&A	λ	# M&A	λ
Only 1	15,141	0.41	12,141	0.39	1,465	0.55	1,571	0.10
Up to 2	19,080	0.44	14,933	0.40	2,435	0.60	1,747	0.11
Up to 3	21,241	0.45	16,433	0.40	2,978	0.62	1,864	0.12
Up to 5	23,765	0.46	18,106	0.41	3,686	0.63	1,999	0.12
Up to 10	26,076	0.47	19,653	0.42	4,287	0.63	2,136	0.12
Up to 15	26,840	0.48	20,182	0.42	4,387	0.63	2,271	0.13
Up to 30	27,657	0.48	20,791	0.43	4,476	0.64	2,390	0.16
Up to 50	28,071	0.48	21,111	0.43	4,524	0.64	2,435	0.15
Up to 245	29,022	0.48	21,642	0.43	/	/	2,856	0.19

Table 2.6 shows the values of the association index for the whole sample and also clustering by the number of acquisitions and by the acquirer market, coherently with the approach for the test of the random hypothesis discussed in the previous section. More precisely, the whole market has been clustered into: *manufacturing* (then subdivided in *high-tech* and *low-tech manufacturing*) and *service* (then subdivided in *non market service*, *market service except financial intermediaries* and *financial intermediaries*).

Concerning the whole sample, the output reports that the degree of association in acquisition strategy is quite high (0.41) and it even increases till 0.48 when allowing for multiple acquisitions. This means that the synergy concept becomes even more important in large corporations, following the notion of coherence and growth along a common path (Teece et al., 1994; Piscitello, 2000), for which firms over time add activities that relate to some aspect of existing activities. Firms build laterally on what they have got, bearing certain technological and market similarities with the old and in order to pursue capabilities common with existing products lines (Teece et al., 1994).

Furthermore, *low-tech manufacturing* and *market service except financial intermediaries* have values of the index about the general mean. Instead, a higher level of association is observed in *non-market* subset of the service group, as expected for particular sectors as education, health and social activities. Conversely, the value of the λ is lower when considering the *high-tech manufacturing*, coherently with the matter that this group includes the most innovative firms, which activity is mostly driven by knowledge and technological development. In fact, innovation search refers to the idea that the acquirer looks for new knowledge that resides in the target firm, and brings this knowledge into the organization through the acquisition process (Cefis and Ghita, 2008). Some degrees of differentiation in resources between the acquirer and the target will enrich the acquiring firm's knowledge base, creating opportunities for learning from the novelty as the seed for future technological developments (Laursen and Salter, 2006; Miller et al., 2007).

The level of association is even more when looking at the *financial intermediaries* sample. In fact, this latter has a wider strategy in the choose of the target, due to the specific economic role of this kind of activity, often more addressed to the financial gain in the medium-low period than the build of a corporate. Especially, when the acquirer is a pure financial actor the relation between its activity and the activity of the target is almost meaningless.

2.6 Robustness analysis

In order to support the findings of the Goodman and Kruskal (1954) analysis, I investigate through an OLS model whether the relatedness in the target selection is affected by the industry the acquirer belongs to. I expect to find different level of relatedness in acquisition strategy amongst the specific macro-areas of the market. Hence, the dependent variable $Relat_{ij}$ has been modelled as a function of the acquirer's industry dummies and some other firm-specific dimensions of the firms, such as size and age of both the acquirer and the target.

2.6.1 The variables

Table 2.7 contains a detailed presentation of the whole set of variables used and their construction.

Table 2.7. Definition of the variables.

	Definition of explanatory variables
Dependent variable	
Relat	Industry relatedness index between acquiring and acquired firms. Calculated as: ln [1 + min (index ρ_{ij} value)]
Independent variables	
Exper	Natural logarithm of the number of acquisition concluded by the acquirer at the moment of the deal in object
Acq_size	Ln of the number of acquirer's domestic employees, at the M&A
Acq_age	Ln of the age of the acquirer, at the M&A
Tar_size	Ln of the number of target's domestic employees, at the M&A
Tar_age	Ln of the age of the target, at the M&A
Industry dummies	Dummy variables for the acquiring firms. Precisely: *Htech_manuf*: high-tech manufacturing; Mtech_manuf: medium-tech manufacturing; *Ltech_manuf*: low-tech manufacturing; *NM_Service*: non market service; *M_service_Ex_Fin*: market service except financial intermediaries; *Fin_intermediaries*: financial intermediaries; *Other_ABC:* agriculture (A), fishing (B) and mining (C) sections of NACE classification; *Other_EF:* electricity (E) and construction (F) sections of NACE classification.
Year dummies	Dummy variables, *GDP_high* and *GDP_low*, corresponding respectively to the high (1997 and 1999) and low (2002 and 2003) peaks of the GDP in The Netherlands

Dependent variable

Industry relatedness index. With the aim of implementing the industry index developed in Section 2.4 in the regression model, it has been linearly transformed in a way that entails it to take only positive values, assuring hence the possibility to calculate the natural logarithm.

$Relat_{ij} = ln\ [1 + min\ (\rho_{ij})]$ where "ρ_{ij}" refers to the value of the index developed in the previous Section (2.4).

Independent variables

Acquisition experience. Consistent with Ingram and Baum (1997) and Haleblian and Finkelstein (1999), Organizations' acquisition experience (*Exper*) is measured by the number of acquisitions that the bidders made before the deal in object.

Firms' size and age. As a measure of *size,* I used the number of domestic employees, taken at the year of the M&A. In this respect, the BR has the advantage of reporting the firm size down to zero employees (or self-employment). Then, the *age* of the firms has been calculated from the foundation to the year of the M&A. The BR is records the year in which a firm is included in the database, and it is a the best proxy of its date of birth. Size and age has been collected for both the acquiring (*Acq_size, Acq_age*) and the target (*Tar_size, Tar_age*) firms. Values always expressed in logarithm terms.

Industry dummies. The sample includes two main divisions of the industrial sectors, based on NACE Rev. 1.1 classification: manufacturing and service; the other sectors operating in the market, such as agriculture and constructions, are included in the definition "other". I aggregated the sectors belonging to the manufacturing category into three groups (low, medium, and high technology) according to the technological intensity proposed by Eurostat and based on NACE classification at 3-digit level. Moreover, the service market has been divided between non-market and market services, and again among this latter the financial intermediaries have been distinguished. Among "other" sectors, the first group aggregates agriculture, fishing and mining; while the second group includes electricity and construction. See the definition of the variables (Table 2.7) and the NACE classification in appendix *II* for a more detailed explanation.

Year dummies. Year controls refer to two year dummy variables, *GDP_high* and *GDP_low*, corresponding respectively to the highest (1997 and 1999) and the lowest (2002 and 2003) peaks of the GDP in The Netherlands in the span considered.

The model specification

The model is estimated using an OLS estimator:

$$\begin{aligned}\underline{\text{(Relat}})_{ij,} = \; & \alpha + \beta_1 \text{Exper}_{i\,t} + \beta_2 \text{Acq\_age}_{i,t} + \beta_3 \text{Acq\_size}_{i,t} + \beta_4 \text{Tar\_age}_{j,t} + \\ & \beta_5 \text{Tar\_size}_{j,t} + \beta_6 \text{GDP\_high}_{t} + \beta_7 \text{GDP\_low}_{t} + \beta_8 \text{Htech\_manuf}_{i} + \\ & \beta_9 \text{Mtech\_manuf}_{i} + \beta_{10} \text{Ltech\_manuf}_{i} + \beta_{11} \text{NM\_Service}_{i} + \\ & \beta_{12} \text{M\_service\_Ex\_Fin}_{i} + \beta_{13} \text{Fin\_intermediaries}_{i} + \beta_{14} \text{Other\_ABC}_{i} + \\ & \beta_{15} \text{Other\_EF}_{i} + \varepsilon_i\end{aligned}$$

2.6.2 Descriptive statistics

The variables needed for this analysis, specifically age and size of the companies, were available only for a subsample of 27,754 pairs of acquirers and targets over the whole sample of 36,375 deals. However, even if the actual sample is reduced, its composition remains coherent with the complete sample; in particular intra-sector deals (14,977) are more common than inter-sectors deals (12,777), equal to 54% of the pairs observed, very close to the percentage observed over the complete sample (51%).

Tables 2.8-2.13 provide a general overview of the sample considered, categorising the deals with reference to the NACE industrial classification (at 3-digit level) the acquirer belongs to. In detail, in the tables discussed in the current section, the number of acquisitions is expressed by the its real number, the firms size by the number of employees, and the firms age by the number of years from the foundation. Univariate analysis and mean difference test are performed comparing, in each table, different pairs of acquirer’s industrial classes.

Specifically, table 2.8 compares the two main macro-areas of acquirers: *manufacturing* and *service* firms. *Service* group of acquirers shows a higher average level of relatedness (about 74 vs 57) and have a more intense acquisition activity. Moreover, *service* acquirers are larger but they target, on average, smaller companies compared to what *manufacturing* firms use to do. Looking at the age, manufacturing acquirers are older, as well as the targets that they select.

Table 2.8. Descriptive statistics grouped by the acquirer industry: Manufacturing and Service sectors. T test performed as: mean (service sector) - mean (manufacturing sector). The number of acquisitions is expressed in real number, the firms size by the number of employees, and the firms age in years from the foundation.
*, **, and ***: Statistically significant at the 10% , 5%, and 1% level, respectively.

	Manufacturing Obs. 3,002		Service Obs. 22,055		
Variable	Mean	Standard Deviation	Mean	Standard Deviation	Mean difference test
Relat	56.71	49.28	73.65	61.67	14.40***
No of acquisition	2.52	2.64	8.30	28.01	11.27***
No of employees of the acquirer	318.06	1,870.53	653.39	311.60	5.76***
No of employees of the target	103.89	1,150.14	85.55	1,015.93	-0.91
Age of the acquirer	9.71	12.64	5.65	9.90	-20.35***
Age of the target	12.57	12.69	10.70	11.33	-8.32***

Table 2.9 reports the same statistics as above, comparing this turn *high-tech* and *low-tech manufacturing* acquirers. Here, *high-tech* acquirers have a more diverse strategy (the mean relatedness is equal to 45, against about 67 for *low-tech* category). *High-tech* acquirers are larger and younger than *low-tech*, and their targets as well.

Table 2.10 compares *market* and *non-market service*. This latter shows a more related acquisition strategy; specifically, it shows the highest average level of relatedness (above 129) among all the clusters, coherently with what emerged in the Goodman and Kruskal association analysis. Moreover, *non-market service* acquirers are smaller but they target, on average, larger companies compared to what *market service* firms use to do. Regarding the age, *non-market service* acquirers are younger but their targets are, on average, older.

Table 2.9. Descriptive statistics grouped by the acquirer industry: High-tech and Low-tech Manufacturing. T test performed as: mean (low-tech manufacturing) - mean (high-tech manufacturing). The number of acquisitions is expressed in real number, the firms size by the number of employees, and the firms age in years from the foundation.
*, **, and ***: Statistically significant at the 10% , 5%, and 1% level, respectively.

Variable	High-tech Manufacturing Obs. 183 Mean	Standard Deviation	Low-tech Manufacturing Obs. 1,358 Mean	Standard Deviation	Mean difference test
Relat	45.26	41.67	67.35	52.67	5.44***
No of acquisition	2.54	2.25	2.37	2.19	-0.98
No of employees of the acquirer	1,684.98	7,134.92	283.10	631.30	-7.05***
No of employees of the target	412.41	3247.46	74.29	217.50	-3.78***
Age of the acquirer	7.27	10.45	9.91	12.82	2.67***
Age of the target	9.81	12.41	12.97	12.86	3.18***

Table 2.10. Descriptive statistics grouped by the acquirer industry: Market and Non-Market Service. T test performed as: mean (non-market service) - mean (market service). The number of acquisitions is expressed in real number, the firms size by the number of employees, and the firms age in years from the foundation.
*, **, and ***: Statistically significant at the 10% , 5%, and 1% level, respectively.

Variable	Market Service Obs. 15,940 Mean	Standard Deviation	Non-Market Service Obs. 3,933 Mean	Standard Deviation	Mean difference test
Relat	61.56	52.66	129.18	69.22	68.67***
No of acquisition	9.19	30.70	4.18	6.05	-10.19***
No of employees of the acquirer	694.02	3,411.85	466.20	784.25	-4.16***
No of employees of the target	78.68	1,113.90	117.21	263.65	2.15**
Age of the acquirer	6.01	10.17	3.98	8.37	-11.67***
Age of the target	9.79	11.02	14.91	11.78	26.04***

Again, Table 2.11 considers *financial intermediaries* and *market service except financial intermediaries*. *Financial intermediaries* show a more diverse acquisition strategy; specifically, they present the lowest average level of relatedness (about 35) among all the clusters, coherently with what emerged in the Goodman and Kruskal association analysis. Moreover, they have the most intense acquisition activity, measured in number of acquisition realised, coherently with the statistics of Table 2.2. Then, they are first category in terms of size (more than 3 thousands of employees) and they are quite young (less than 4 years).

Table 2.11. Descriptive statistics grouped by the acquirer industry: Financial Intermediaries and Market Service except Fin. Intermediaries. T test performed as: mean (market service except fin. intermediaries) - mean (fin. intermediaries). The number of acquisitions is expressed in real number, the firms size by the number of employees, and the firms age in years from the foundation.
*, **, and ***: Statistically significant at the 10% , 5%, and 1% level, respectively.

	Financial Intermediaries Obs. 2,182		Market Service ex Fin. Int. Obs. 15,940		
Variable	Mean	Standard Deviation	Mean	Standard Deviation	Mean difference test
Relat	34.80	34.95	65.22	53.61	25.76***
No of acquisition	31.21	70.49	6.18	17.78	-37.05***
No of employees of the acquirer	3,184.48	7,081.98	353.10	2,325.11	-37.75***
No of employees of the target	111.96	1,551.63	74.13	1,039.73	-1.48
Age of the acquirer	3.69	8.97	6.33	10.28	11.41***
Age of the target	10.72	10.87	9.67	11.03	-4.17***

Table 2.12. Descriptive statistics grouped by the acquirer industry: Financial Intermediaries and High-tech Manufacturing. T test performed as: mean (high-tech manufacturing) - mean (fin. intermediaries). The number of acquisitions is expressed in real number, the firms size by the number of employees, and the firms age in years from the foundation.
*, **, and ***: Statistically significant at the 10% , 5%, and 1% level, respectively.

	Financial Intermediaries Obs. 2,182		High-tech Manufacturing Obs. 183		
Variable	Mean	Standard Deviation	Mean	Standard Deviation	Mean difference test
Relat	34.80	34.95	45.26	41.67	3.82***
No of acquisition	31.21	70.49	2.54	2.25	-5.50***
No of employees of the acquirer	3,184.48	7,081.97	1,684.98	7,134.92	-2.74***
No of employees of the target	111.96	1,551.63	412.41	3,247.46	2.24**
Age of the acquirer	3.68	8.97	7.27	10.45	5.12***
Age of the target	10.72	10.87	9.81	10.41	-1.08

Table 2.13. Descriptive statistics grouped by the acquirer industry: Financial Intermediaries and Service ex Financial Intermediaries. T test performed as: mean (service ex financial intermediaries) - mean (fin. intermediaries). The number of acquisitions is expressed in real number, the firms size by the number of employees, and the firms age in years from the foundation.
*, **, and ***: Statistically significant at the 10% , 5%, and 1% level, respectively.

Variable	Financial Intermediaries Obs. 2,182 Mean	Standard Deviation	Service ex Fin. Int. Obs. 19,873 Mean	Standard Deviation	Mean difference test
Relat	34.80	34.95	77.88	62.47	31.67***
No of acquisition	31.21	70.49	5.78	16.17	-41.82***
No of employees of the acquirer	3,184.48	7,081.97	-375.48	2,111.85	-41.56***
No of employees of the target	111.96	1,551.63	82.65	938.68	-1.27
Age of the acquirer	3.68	8.97	5.87	9.98	9.76***
Age of the target	10.72	10.87	10.78	11.38	-0.05

Finally, Table 2.12 and 2.13 show that *financial intermediaries* prefer a wider acquisition strategy (both in terms of relatedness and number) also compared with *high-tech manufacturing* acquirers and the remainder part of the service sector, respectively.

2.6.3 Results

Before running the regression, a correlation analysis has been performed in order to detect if any problem of multicollinearity amongst the variables exists (see Table 2.14). High simple correlation is shown only between the experience and the size of the acquirer (equal to 0.65); however, both the variables are considered in the study as they impliy two different concepts. Moreover, the demographic characteristics of the firms are here introduced as control variables.

Table 2.14. Descriptive statistics and correlation matrix. Observations: 27,754.
* Statistically significant at the 10% level.

	Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Relat	3.76	1.14	1															
2	Exper	0.86	1.13	.10*	1														
3	Acq_size	3.63	2.39	.26*	.64*	1													
4	Tar_size	2.26	1.84	.30*	.05*	.34*	1												
5	Acq_age	1.05	1.33	-.04*	.08*	.23*	-.19*	1											
6	Tar_age	1.86	1.26	.22*	-.01*	.16*	.45*	-.16*	1										
7	GDP_high	0.18	0.38	-.13*	.22*	-.37*	-.16*	-.14*	-.11*	1									
8	GDP_low	0.30	0.46	.04*	.13*	.15*	.04*	.04*	.11	-.30*	1								
9	Htech_manuf	0.01	0.08	-.02*	-.01*	.01*	.01*	.01*	-.01	-.01	-.01	1							
10	Ltech_manuf	0.05	0.21	-.01*	-.15*	.03*	.04*	.06*	.02*	-.02*	.01	-.01*	1						
11	Mtech_manuf	0.07	0.29	-.06*	-.04*	.02*	.03*	.06*	.01*	-.02*	.01*	-.01*	-.05*	1					
12	NM_Service	0.65	0.48	.26*	.05*	.21*	.24*	-.10*	.15*	-.10*	.01	-.03*	-.09*	-.09*	1				
13	Fin_intermediaries	0.08	0.27	-.15*	.14*	.05*	-.10*	-.09*	.01*	.07*	.02*	-.02*	-.06*	-.06*	-.11*	1			
14	M_service_Ex_Fin	0.57	0.49	-.07*	-.07*	-.23*	-.15*	.02*	-.14*	.07*	-.04*	-.09*	-.26*	-.27*	-.47*	-.33*	1		
15	Other_ABC	0.02	0.12	-.01	-.04*	-.04*	-.03*	.01*	-.01*	.01	-.01	-.01*	-.02*	-.02*	-.05*	-.03*	-.14*	1	
16	Other_EF	0.07	0.26	.01	.03	.06*	-.01	.07*	.01	-.02*	.03*	-.02*	-.06*	-.06*	-.11*	-.08*	-.32*	-.03*	1

Table 2.15. This table reports the results of the OLS regression, using as dependent variable the linear transformation of the industry relatedness index ρij. The results support again the evidences emerged thought the application of the Goodman and Kruskal (1954) index. Standard error is given in parentheses.

*, **, and ***: Statistically significant at the 10% , 5%, and 1% level, respectively.
Note: standard error is given in parentheses.

Dep. Variable: Relat	coefficient (standard error)
Htech_manuf	-0.055*
	(0.080)
Ltech_manuf	0.278***
	(0.037)
NM_Service	0.808***
	(0.030)
Fin_intermediaries	-0.238***
	(0.034)
M_service_Ex_Fin	0.332***
	(0.026)
Other_ABC	0.453***
	(0.056)
Other_EF	0.317***
	(0.034)
Exper	0.014*
	(0.008)
Acq_size	0.083***
	(0.004)
Tar_size	0.093***
	(0.004)
Acq_age	-0.031***
	(0.005)
Tar_age	0.091***
	(0.005)
GDP_high	-0.029
	(0.018)
GDP_low	0.001
	(0.014)
Constant	2.774***
	(0.031)
N of observations	27,754
R-squared	0.183
Adj R-squared	0.183
F statistics	443.46***

The results of the OLS regression are reported in Table 2.15, supporting again the evidences emerged in the application of the Goodman and Kruskal (1954) index, as discussed in the previous section.

The main interest is again the acquisition strategy and how it is affected by the sector the acquirers belong to, enhanced by the high significance of the acquirers' industry dummies hereby showed. In detail, the acquirers belonging to the *high-tech manufacturing* expand more diverse (low relatedness), while the *low-tech* class is more likely to realize related deals, considering the *medium-tech manufacturing* companies as reference benchmark. Concerning then the *service* category, the firms belonging to its subsamples *market service except financial intermediaries* and, even more, *non-market service* are more likely to target related companies. Conversely, the *financial intermediaries* prefer to search widely on the market. Finally, both the *other* classes of acquirers, *Other_AB, i.e.* agriculture (A), fishing (B) and mining (C) sections of NACE classification; and *Other_EF, i.e.* electricity (E) and construction (F) sections of NACE classification, present a high related acquisition strategy.

To assure robustness to the empirics, controls for the demographic characteristics of both the firms involved in each specific deal have been added, finding high significance in the results. In particular, the experience in acquisition and the size of the acquirer impact positively on the relatedness, showing that the more firms grow, the more they tend to diversify in a coherent way. Considering the acquirer age, it has been found that younger firms, that by definition have to deal more with uncertainty, tend to grow in a more related way. Conversely, older firms are more likely to diversify and, over the years, to be more vertically integrated (Teece et al., 1994).

Relating to the characteristics of the target, both size and age positively affect the relatedness. In fact, the integration of the target is affected by its organization, which is greater and more complex (in terms of people, knowledge and routines) in older and larger firms. Moreover, according to the absorptive capacity argument (Cohen and Levinthal, 1990), the integration of an unrelated firm is more difficult. Consequently, the firms that acquire larger targets benefit more from a coherent strategy. Finally, the results are also robust to the year dummy controls.

2.7 Conclusions

This study shows that industry relatedness is an important driver of Dutch acquisition partnering. Taking the acquirer perspective, I found strong evidence that the selection of a target by an acquiring firm does not occur randomly. By means of the construction of an asymmetric measure of industry relatedness, based on the methodology introduced by Teece et al.'s (1994). In detail, the *distance* between acquirer and target industries has been measured within each pair of possible sectors (at 3-digit of the NACE industry classification), where low distance corresponds to high relatedness. Moreover, I found the evidence that Dutch acquirers tend to select targets that are industrially more related than the average target; in other words, companies that belong to the same macro-area or industrial technology class (such as *high/low-tech manufacturing*) are more likely to engage in deal. This result is in line with corporate coherence framework (Teece et al., 1994; Breschi et al., 2003; Nesta and Saviotti, 2005).

Furthermore, the average degree of relatedness differs considering different macro-areas or particular subsets of the whole market. This finding has been shown through the application of the asymmetric association measure suggested by Goodman and Kruskal (1954), in order to overcome a limitations of Teece et al.'s (1994) measure. In fact, this latter does not admit the possibility of comparing the index between samples having different size, as happens when clustering the whole market by acquirer industry or by its technology class. In particular, even if the average degree of association is always quite high, some sectors appears to be more close, such as *non-market service*, *market service except financial intermediaries* and *low-tech manufacturing*, than others that show a more diverse acquisition strategy, as *high-tech manufacturing* and in particular *financial intermediaries*. This result is also robust to a check performed by means of an OLS regression, which allowed also controls for the demographic characteristics of the firms involved.

In conclusion, this study opens up the possibility for several research challenges as the hereby developed measure constitutes a workable tool that helps the understanding of intrinsically intangible nature of competencies (Nesta and Saviotti, 2005). An ongoing research implies the effort in understanding and quantifying the effects of a more or less diversified acquisition strategy to the economic and innovative performances reached by the acquirers. In fact, next chapter aims to identify which level of relatedness best contribute to innovation, also considering linkages between this aspect and other firm characteristics.

Appendix *I*. Test of randomness on market clusters

I performed the measure of the relatedness index ρ_{ij} clustering for the main industrial subsets the acquiring firm belongs to. Again, as discussed in Section 4, I tested the random hypothesis in acquisition market through the analysis of the index itself and the related P-values. More precisely, I clustered by the industry of the acquirer, as: manufacturing (then further partitioned in high tech and low tech manufacturing) and service (then further partitioned in non market service, market service except financial intermediaries and financial intermediaries). Again, the outputs allow the rejection of the random hypothesis in each case.

Table A. Test of randomness and descriptive statistics of the relatedness index ρ_{ij} in acquisition field. In this table I consider only the deals in which the acquirer belongs to the industrial section: ***manufacturing***. The number of acquisitions realized by each acquirer is considered as thresholds. For instance, allowing for the more comprehensive threshold, "up to 15" acquisitions, I created a co-occurrences matrix as 97*180 industries (the number of the acquirer's possible sectors multiplied by the number of the target's possible sectors) equal to 17,458 cells or possible dyads. Among these latter, only 1,141 dyads are actually observed on the market. The number of dyads with negative and positive value of the index, and then the number and the percentage of cases with significant P-values (at 10% level) are displayed in the table as well. The analysis is performed on the Dutch acquisition market in the span 1980-2005. The legend for a detailed description of the columns is common for all the tables of this section of the Appendix and follows the last Table of this Appendix (G).

				Negative index			Positive index			Statistics				
# Acquisitions	# M&A	# Possible couples	# Observed couples	#	# Signif.	% Signif.	#	# Signif.	% Signif.	Min	Max	Mean	Median	s.d.
(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(l)					
Only 1	2,038	15,936	773	15,235	63	0.41%	701	470	67.05%	-3.25	45.13	0.05	-0.12	2.15
Up to 2	2,726	17,072	938	16,247	101	0.62%	825	543	65.82%	-3.63	52.20	0.06	-0.13	2.37
Up to 3	3,083	17,169	1023	16,291	112	0.69%	878	553	62.98%	-3.68	55.52	0.06	-0.14	2.45
Up to 5	3,478	17,363	1090	16,433	136	0.83%	930	575	61.83%	-3.82	58.97	0.06	-0.14	2.58
Up to 10	3,735	18,426	1135	17,460	148	0.85%	966	599	62.01%	-3.94	61.11	0.06	-0.15	2.64
Up to 15	3,809	17,458	1141	16,494	152	0.92%	964	598	62.03%	-3.91	61.72	0.07	-0.15	2.66

Table B. Test of randomness and descriptive statistics of the relatedness index ρ_{ij} in acquisition field. In this table I consider only the deals in which the acquirer belongs to the industrial section: ***high-technology manufacturing***, as a subset of the manufacturing section. The number of acquisitions realized by each acquirer is considered as thresholds. For instance, allowing for the more comprehensive threshold, "up to 8" acquisitions, I created a co-occurrences matrix as 11*53 industries (the number of the acquirer's possible sectors multiplied by the number of the target's possible sectors) equal to 583 cells or possible dyads. Among these latter, only 106 dyads are actually observed on the market. The number of dyads with negative and positive value of the index, and then the number and the percentage of cases with significant P-values (at 10% level) are displayed in the table as well. The analysis is performed on the Dutch acquisition market in the span 1980-2005. The legend for a detailed description of the columns is common for all the tables of this section of the Appendix and follows the last Table of this Appendix (G).

				Negative index			Positive index			Statistics				
# Acquisitions	# M&A	# Possible couples	# Observed couples	#	# Signif.	% Signif.	#	# Signif.	% Signif.	Min	Max	Mean	Median	s.d.
(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(l)					
Only 1	127	484	66	425	10	2.35%	59	35	59.32%	-3.43	11.23	-0.16	-0.33	1.21
Up to 2	161	495	82	420	7	1.67%	75	41	54.67%	-2.84	12.65	0.04	-0.28	1.49
Up to 3	188	517	90	436	8	1.83%	81	50	61.73%	-2.65	11.07	1.50	-4.18	1.50
Up to 5	206	550	99	461	7	1.52%	89	54	60.67%	-2.75	11.60	0.03	-0.30	1.49
Up to 10 (8)	229	583	106	488	9	1.84%	95	58	61.05%	-2.88	12.25	0.04	-0.31	1.54

Table C. Test of randomness and descriptive statistics of the relatedness index ρ_{ij} in acquisition field. In this table I consider only the deals in which the acquirer belongs to the industrial section: ***low-technology manufacturing,*** as a subset of the manufacturing section. The number of acquisitions realized by each acquirer is considered as thresholds. For instance, allowing for the more comprehensive threshold, "up to 10" acquisitions, I created a co-occurrences matrix as 11*53 industries (the number of the acquirer's possible sectors multiplied by the number of the target's possible sectors) equal to 3,955 cells or possible dyads. Among these latter, only 325 dyads are actually observed on the market. The number of dyads with negative and positive value of the index, and then the number and the percentage of cases with significant P-values (at 10% level) are displayed in the table as well. The analysis is performed on the Dutch acquisition market in the span 1980-2005. The legend for a detailed description of the columns is common for all the tables of this section of the Appendix and follows the last Table of this Appendix (G).

				Negative index			Positive index			Statistics				
# Acquisitions	# M&A	# Possible couples	# Observed couples	#	# Signif.	% Signif.	#	# Signif.	% Signif.	Min	Max	Mean	Median	s.d.
(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(l)					
Only 1	594	3,332	227	3,127	28	0.90%	205	152	74.15%	-4.36	19.87	0.05	-0.16	1.74
Up to 2	814	3,780	278	3,529	42	1.19%	251	187	74.50%	-4.69	22.06	0.05	-0.16	1.89
Up to 3	898	3,780	292	3,520	44	1.25%	260	192	73.85%	-5.00	23.17	0.06	-0.17	1.97
Up to 5	995	3,815	302	3,551	49	1.38%	264	195	73.86%	-5.03	24.40	0.06	-0.17	2.05
Up to 10	1,031	3,955	325	3,672	52	1.42%	283	202	71.38%	-4.93	25.16	0.06	-0.17	2.06

Table D. Test of randomness and descriptive statistics of the relatedness index ρ_{ij} in acquisition field. In this table I consider only the deals in which the acquirer belongs to the industrial section: ***service***. The number of acquisitions realized by each acquirer is considered as thresholds. For instance, allowing for the more comprehensive threshold, "up to 245" acquisitions, I created a co-occurrences matrix as 85*192 industries (the number of the acquirer's possible sectors multiplied by the number of the target's possible sectors) equal to 16,320 cells or possible dyads. Among these latter, only 2,946 dyads are actually observed on the market. The number of dyads with negative and positive value of the index, and then the number and the percentage of cases with significant P-values (at 10% level) are displayed in the table as well. The analysis is performed on the Dutch acquisition market in the span 1980-2005. The legend for a detailed description of the columns is common for all the tables of this section of the Appendix and follows the last Table of this Appendix (G).

				Negative index			Positive index			Statistics				
# Acquisitions	# M&A	# Possible couples	# Observed couples	#	# Signif.	% Signif.	#	# Signif.	% Signif.	Min	Max	Mean	Median	s.d.
(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(l)					
Only 1	15,141	16,065	2,414	14,662	691	4.71%	1,403	740	52.74%	-8.43	114.95	0.09	-0.21	4.56
Up to 2	19,080	16,150	2,630	14,656	864	5.90%	1,494	795	53.21%	-8.95	129.39	0.10	-2.23	5.23
Up to 3	21,241	16,235	2,728	14,712	983	6.68%	1,523	825	54.17%	-9.65	136.43	0.11	-2.24	5.56
Up to 5	23,765	16,235	2,816	14,698	1,115	7.59%	1,537	838	54.52%	-10.86	141.39	0.12	-0.25	5.96
Up to 10	26,076	16,235	2,889	14,691	1,237	8.42%	1,544	861	55.76%	-11.51	148.31	0.13	-0.25	6.31
Up to 15	26,840	16,320	2,908	14,784	1,274	8.62%	1,536	862	56.12%	-11.53	150.60	0.13	-0.26	6.41
Up to 30	27,657	16,320	2,929	14,767	1,335	9.04%	1,553	852	54.86%	-11.47	152.84	0.13	-0.26	6.56
Up to 50	28,071	16,320	2,940	14,774	1,372	9.29%	1,546	857	55.43%	-11.60	154.18	0.13	-0.26	6.64
Up to 245	29,022	16,320	2,964	14,763	1,423	9.64%	1,557	872	56.01%	-11.71	156.80	0.13	-0.26	6.76

Table E. Test of randomness and descriptive statistics of the relatedness index ρ_{ij} in acquisition field. In this table I consider only the deals in which the acquirer belongs to the industrial section: ***non-market service***, as a subset of the service section. The number of acquisitions realized by each acquirer is considered as thresholds. For instance, allowing for the more comprehensive threshold, "up to 50" acquisitions, I created a co-occurrences matrix as 19*102 industries (the number of the acquirer's possible sectors multiplied by the number of the target's possible sectors) equal to 1,938 cells or possible dyads. Among these latter, only 402 dyads are actually observed on the market. The number of dyads with negative and positive value of the index, and then the number and the percentage of cases with significant P-values (at 10% level) are displayed in the table as well. The analysis is performed on the Dutch acquisition market in the span 1980-2005. The legend for a detailed description of the columns is common for all the tables of this section of the Appendix and follows the last Table of this Appendix (G).

				Negative index			Positive index			Statistics				
# Acquisitions	# M&A	# Possible couples	# Observed couples	#	# Signif.	% Signif.	#	# Signif.	% Signif.	Min	Max	Mean	Median	s.d.
(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(l)					
Only 1	1,465	1,805	319	1,558	93	5.97%	247	159	64.37%	-6.44	35.81	0.09	-0.26	2.86
Up to 2	2,435	1,824	346	1,558	132	8.47%	266	172	64.66%	-10.47	45.94	0.18	-0.24	3.82
Up to 3	2,978	1,881	361	1,600	154	9.63%	281	194	69.04%	-14.91	56.43	0.24	-0.27	4.71
Up to 5	3,686	1,919	385	1,627	152	9.34%	292	194	66.44%	-17.09	55.41	0.25	-0.24	4.69
Up to 10	4,287	1,938	400	1,634	169	10.34%	304	201	66.12%	-20.26	59.76	0.28	-0.24	5.02
Up to 15	4,387	1,938	400	1,632	175	10.72%	306	209	68.30%	-20.69	60.45	0.28	-0.24	5.08
Up to 30	4,476	1,938	402	1,630	174	10.67%	308	202	65.58%	-20.49	61.06	0.28	-0.25	5.15
Up to 50	4,524	1,938	402	1,630	174	10.67%	308	204	66.23%	-20.83	61.39	0.29	-0.24	5.18

Table F. Test of randomness and descriptive statistics of the relatedness index ρ_{ij} in acquisition field. In this table I consider only the deals in which the acquirer belongs to the industrial section: ***market service except financial intermediaries***, as a subset of the service section. The number of acquisitions realized by each acquirer is considered as thresholds. For instance, allowing for the more comprehensive threshold, "up to 245" acquisitions, I created a co-occurrences matrix as 61*190 industries (the number of the acquirer's possible sectors multiplied by the number of the target's possible sectors) equal to 11,920 cells or possible dyads. Among these latter, only 2,280 dyads are actually observed on the market. The number of dyads with negative and positive value of the index, and then the number and the percentage of cases with significant P-values (at 10% level) are displayed in the table as well. The analysis is performed on the Dutch acquisition market in the span 1980-2005. The legend for a detailed description of the columns is common for all the tables of this section of the Appendix and follows the last Table of this Appendix (G).

				Negative index			Positive index			Statistics				
# *Acquisitions*	# M&A	# Possible couples	# Observed couples	#	# Signif.	% Signif.	#	# Signif.	% Signif.	Min	Max	Mean	Median	s.d.
(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(l)					
Up to 1	12,141	11,726	1,883	10,656	544	5.11%	1,070	589	55.05%	-9.09	102.60	0.08	-0.22	4.24
Up to 2	14,933	11,787	2,062	10,655	644	6.04%	1,132	634	56.01%	-10.14	113.56	0.09	-0.24	4.66
Up to 3	16,433	11,909	2,138	10,768	714	6.63%	1,141	651	57.06%	-10.13	118.47	0.09	-0.24	4.89
Up to 5	18,106	11,899	2,197	10,836	1000	9.23%	1,063	588	55.32%	-10.68	102.68	-0.04	-0.28	4.74
Up to 10	19,653	11,889	2,242	10,734	884	8.24%	1,155	668	57.84%	-10.48	123.42	0.10	-0.26	5.49
Up to 15	20,182	11,945	2,256	10,793	919	8.51%	1,152	667	57.90%	-10.68	122.62	0.10	-0.26	5.59
Up to 30	20,791	11,930	2,265	10,772	946	8.78%	1,158	665	57.43%	-10.55	127.80	0.10	-0.27	5.73
Up to 50	21,111	11,930	2,277	10,772	984	9.13%	1,158	673	58.12%	-10.43	128.81	0.10	-0.27	5.81
Up to 245	21,642	11,920	2,280	10,761	1,017	9.45%	1,159	670	57.81%	-10.52	134.27	0.11	-0.27	5.94

Table G. Test of randomness and descriptive statistics of the relatedness index ρ_{ij} in acquisition field. In this table I consider only the deals in which the acquirer belongs to the industrial section: ***financial intermediaries***, as a subset of the service section. The number of acquisitions realized by each acquirer is considered as thresholds. For instance, allowing for the more comprehensive threshold, "up to 245" acquisitions, I created a co-occurrences matrix as 5*124 industries (the number of the acquirer's possible sectors multiplied by the number of the target's possible sectors) equal to 620 cells or possible dyads. Among these latter, only 282 dyads are actually observed on the market. The number of dyads with negative and positive value of the index, and then the number and the percentage of cases with significant P-values (at 10% level) are displayed in the table as well. The analysis is performed on the Dutch acquisition market in the span 1980-2005. The legend for a detailed description of the columns is common for all the tables of this section of the Appendix and follows this last Table G.

				Negative index			Positive index			Statistics				
# *Acquisitions* *(a)*	# M&A (b)	# Possible couples (c)	# Observed couples (d)	# (e)	# Signif. (f)	% Signif. (g)	# (h)	# Signif. (i)	% Signif. (l)	Min	Max	Mean	Median	s.d.
Only 1	1,571	550	214	400	26	6.50%	150	48	32.00%	-15.04	22.36	-0.03	-0.26	2.09
Up to 2	1,747	555	223	405	29	7.16%	150	49	32.67%	-16.10	25.40	-0.03	-0.28	2.28
Up to 3	1,864	565	230	405	33	8.15%	160	51	31.88%	-16.50	26.08	-0.03	-0.29	2.33
Up to 5	1,999	575	234	416	38	9.13%	159	59	37.11%	-17.54	26.60	-0.03	-0.32	2.37
Up to 10	2,136	585	247	409	37	9.05%	176	62	35.23%	-17.49	27.79	-0.05	-0.37	2.39
Up to 15	2,271	595	252	421	39	9.26%	174	67	38.51%	-16.91	26.73	-0.06	-0.41	2.39
Up to 30	2,390	610	262	426	46	10.80%	184	70	38.04%	-17.14	28.58	-0.05	-0.43	2.46
Up to 50	2,435	610	261	425	43	10.12%	185	69	37.30%	-17.76	28.30	-0.05	-0.45	2.47
Up to 245	2,856	620	282	430	54	12.56%	190	85	44.74%	-16.03	29.42	-0.06	-0.51	2.64

Legend of the columns:

(a) Acquisition threshold: number of acquisitions in which each specific acquirer is involved.
(b) Number of deals for each threshold.
(c) Number of possible "acquirer's industry-target's industry" couples.
(d) Number of observed "acquirer's industry-target's industry" couples (id est cells of the co-occurrences matrix with not-zero value, that means combinations of industries really occurred in the sample).
(e) Number of cells with a negative index of relatedness.
(f) Number of cells with a negative and statistically significant index of relatedness.
(g) Percentage of cells with a negative and statistically significant index of relatedness among the negative cells (d)
(h), (i), and (l): definition as (e), (f), and (g) respectively, but for positive values of the index.

Appendix *II.* NACE industrial classification

NACE Rev. 1 is a 4-digit activity classification which was drawn up in 1990. It is a revision of the «General Industrial Classification of Economic Activities within the European Communities», known by the acronym NACE (**N**omenclature statistique des **a**ctivités économiques dans la **C**ommunauté **e**uropéenne) and originally published by Eurostat in 1970. NACE Rev. 1 in turn underwent a minor update in 2002 to establish NACE Rev. 1.1. Since the sample is obtained from the BR datasets in the span 1995-2005, I firstly controlled for the coherence in the classification. Eurostat uses an aggregation of the manufacturing industry according to technological intensity and based on NACE Rev. 1.1 at 3-digit level for compiling aggregates related to medium/high-technology and medium/low-technology. Following a similar approach as for manufacturing, Eurostat defines also the sector as knowledge intensive services (KIS) or as less knowledge-intensive services (LKIS).

Main Sections of NACE Classification.

Section	Code	Definition
MANUFACTURING: Section D		
High Technology		
Subsection DG	24.4	*Manufacture of pharmaceuticals, medicinal chemicals and botanicals products*
Subsection DL	30	*Manufacture of office machinery and computers*
Subsection DL	32	*Manufacture of radio, television and communication eq. and apparatus*
Subsection DL	33	*Manufacture of medical, precision and optical inst. watches and clocks*
Subsection DM	35.3	*Manufacture of aircrafts and spacecrafts*
Medium Technology		
Subsection DF	23	*Manufacture of coke, refined petroleum products and nuclear fuel*
Subsection DG	24	*Manufacture of chemicals and chemical products, excluding 24.4*
Subsection DH	25	*Manufacture of rubber and plastic products*
Subsection DI	26	*Manufacture of other non-metallic mineral products*
Subsection DJ	27-28	*Manufacture of basic metals and fabricated metal products*
Subsection DK	29	*Manufacture of machinery and equipment n.e.c.*
Subsection DL	31	*Manufacture of electrical machinery and apparatus n.e.c.*
Subsection DM	34-35	*Manufacture of transport equipment, excluding 35.3*

Table to be continued..

.. Table continued.

Section	Code	Definition
MANUFACTURING: Section D		
Low Technology		
Subsection DA	15-16	*Manufacture of food products, beverages and tobacco*
Subsection DB	17-18	*Manufacture of textiles and textile products*
Subsection DC	19	*Manufacture of leather and leather products*
Subsection DD	20	*Manufacture of wood and wood products*
Subsection DE	21-22	*Manufacture of pulp, paper and paper products; publishing and printing*
Subsection DN	36-37	*Manufacturing n.e.c.*
SERVICE		
Market Service	**50-74**	
Section G	50-52	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods
Section H	55	Hotels and restaurants
Section I	60-64	Transport, storage and communication
Section J	**65-67**	**Financial intermediation**
Section K	70-74	Real estate, renting and business activities
Section L	75	Public administration and defence; compulsory social security
Non Market Service	**80-93**	
Section M	80	Education
Section N	85	Health and social work
Section O	90-93	Other community, social and personal service activities
OTHER		
Section A	01-02	Agriculture, hunting and forestry
Section B	05	Fishing
Section C	10-14	Mining and quarrying
Section E	40-41	Electricity, gas and water supply
Section F	45	Construction
Section P	95	Private households with employed persons
Section Q	99	Extra-territorial organizations and bodies

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CHAPTER 3

The effect of Industry Relatedness on Post M&A Innovative Performance

Abstract

This paper investigates the effects of relatedness between mergers and acquisitions' (M&A) partners on the post-acquisition innovative performance, using demographic and Community Innovation Survey data on the whole Dutch acquisition market. The aim is to analyze the phenomenon from an industry point of view implementing the relatedness index developed, following Teece et al. (1994) endogenous methodology, in the previous Chapter.
Due to the combined effect of *novelty,* increasing with distance, and of *synergies*, increasing with relatedness, I found a nonlinear (inverted U-shape) impact of the relatedness of acquired and acquiring knowledge bases on innovative output. The focus of the research is related also to absorptive capacity concept, and the results show that some characteristics of both the acquirer and the target work as moderator effects on the integration of the resource bases. Specifically, previous involvement in in-house R&D of the acquirer has positive effect on the innovative performance, while acquisition of larger targets implies higher industry coherence to reach high levels of innovative performance. Finally, the experience in acquisition helps the post-deal integration and the innovative exploitation of the targets. The analysis of both "to the firm" and the more restrictive definition "to the market" innovative performance gives robustness to the results.

Keywords: Relatedness; Innovation; M&A; Heckman two-stage.

3.1 Introduction

M&A and innovation are two strongly connected instruments for growth and competitive advantage, and therefore they are fundamental to each firm's competitive advantage (Schulz, 2007). As a matter of fact, a critical component of innovative performance is the ability to exploit external knowledge (see Cohen and Levinthal, 1990), as building a successful innovation-based strategy requires resources and capabilities that are often difficult to develop internally. In this framework, innovation search refers to the idea that the acquirer looks for new knowledge that resides in the target firm, and brings this knowledge into the organization through the acquisition process.

However, the effects of M&A on innovation is still a controversial topic, as literature has not yet reached a unified and sound background its judge (Schulz, 2007); however there is a growing body of evidence (Hagedoorn and Cloodt, 2003; Cassiman et al., 2005; Cassiman and Veugelers, 2007) that if a deal is motivated by the goal of acquiring new technology and it is complemented by efficient management of the knowledge transfer, it can positively affect innovative performance (Cefis and Ghita, 2008). Moreover, an important determinant of the ability to successfully engage in an innovation project is the integration process. Similar to the concept of absorptive capacity (Zahra and George, 2002), it refers to the capability of the acquirer to assimilate the acquired firm's resources into the organization and it is strictly linked with the industry relatedness between the current technological frontier and the acquired knowledge base.

This study assesses the innovative performance issue considering the effects of *novelty* and *synergies* generated through the acquisition of a more or less related target. On one hand, according to the absorptive capacity paradigm, acquisition of related knowledge implies a high exploitation of the synergies and will have the most positive impact on a firm's post-M&A innovative performance (Hagedoorn and Duysters, 2002; Zahra and George, 2002; Capron and Mitchell, 2004). However, the acquisition of knowledge that is too similar to the already existing knowledge base is disadvantageous, as the acquiring firm will have to bear the costs of obtaining and transferring external knowledge without any relevant enrichments of its existing knowledge base (Cohen and Levinthal, 1989). On the other hand, differentiation in resources between the acquirer and the target will enrich the acquiring firm's knowledge base, creating opportunities for learning from the *novelty* as the seed for future technological developments (Laursen and Salter, 2006; Miller et al., 2007).

Therefore, due to the combined effect of *novelty*, increasing with distance, and of *synergies*, increasing with relatedness, this study shows a non linear (inverted U-shape) influence of the industry relatedness of acquired and acquiring knowledge bases on innovative output, following the idea that it is sufficient distance, not greatest or lowest distance, that matters (see, among others, Ahuja and Katila, 2001; Cloodt et al., 2006; Miller et al., 2007).

This study, coherently with existing research focused on the relationship between technology relatedness and innovation performance in the high-tech segment, aims to extend previous findings (Ahuja and Katila, 2001; Cloodt et al., 2006) to a complete multi-industries context. In fact, while previous works concentrated the analysis on the relatedness of technologies and measured both relatedness and innovative output exclusively through patents, the contribution is the introduction of the industry index developed in the previous chapter. This measure follows Teece et al. (1994) methodology and it is based on the whole Dutch acquisition market.

Moreover, after the acquisition, firms need primarily to focus on full integration of their resource bases in order to produce and sell innovative products (Cefis, 2010). I posit that some characteristics of both the acquiring and the target firms influence how easy it is to transfer knowledge from the target to the acquirer at different degrees of distance. Specifically, I test how the impact of the industry relatedness on innovation is moderated by three variables: the in-house R&D of the acquirer, the target size, and the previous experience in acquisition activity.

This study should be interpreted as a close complement to research on acquisitions as a means to facilitate knowledge transfer with the aim of generate innovative performance, as the relatedness of the acquired firm is an important factor in the choose of the target. The inclusion of various control variables and model specifications increased confidence in the analysis, as the study of both the innovative "to the firm" and "to the market" performances gives robustness to the results.

The empirical part of the analysis uses data for the Netherlands from the Community Innovation Surveys (seven CIS waves, from CIS2 to CIS5). These data were integrated with data from the Business Register (BR) database compiled by the Central Bureau of Statistics/Statistics Netherlands (CBS), providing a comprehensive data set on innovation and M&A. In particular, a post-acquisition integration period of two to four years after the deal, and also a pre-acquisition span of two to three years have been allowed to get appropriate information on the acquirer's attitude to innovation.

The chapter is organized as follows. Section 3.2 provides a brief review of the theoretical background to the research and presents the hypotheses. Sections 3.3 and 3.4, respectively, provide descriptions of the data sources and the sample, and introduce the methodology used for the research. Section 3.5 describes the dependent and independent variables. The results of the univariate and multivariate (Heckman 2-stage models) analyses are reported in Section 3.6, and Section 3.7 offers a summary discussion and some final remarks.

3.2 Literature background and Hypotheses

3.2.1 Direct effect of industry relatedness on innovation: novelty vs. synergies

The aim of this study is to investigate the effect of industry relatedness between M&A partners on the post-acquisition innovative performance of the acquiring firm. Industrial relatedness refers to the degree to which two firms are active in related markets. This is associated with shared technological experiences and knowledge bases (Knoben and Oerlemans, 2006) and with similar products and markets. Industrial high/low relatedness is mainly the result of strategic decision, although information advantages might play a little role, too. It is the firm's ability to acquire, transfer and integrate the acquired firm's knowledge base into the knowledge base of the acquiring firm that creates a sustainable competitive advantage (Barney, 1986). This notion is based on the concept of absorptive capacity, which is the firms' capability in processing and valuing external knowledge (Cohen and Levinthal, 1990; Zahra and George, 2002). The question remains, however, which degree of industrial relatedness is most beneficial for a post deal innovative output.

On one hand, acquisition can be seen as a way for the buyer to search for *novelty*, a strategic renewal both in the form of the products (ideas) and employees (skills) of the target firms. Scholars suggest that knowledge is one of the principal inputs into the innovation process, and a firm must continually acquire a diverse and novel body of knowledge that will serve as the seed for future technological developments (Nelson and Winter, 1982; Rosenkopf and Almeida, 2003; Miller et al., 2007). A firm should have the capability to identify and acquire externally generated knowledge that is critical to its operations (Zahra and George, 2002). Acquirers who have open search strategies – those who search widely and deeply – tend to be more innovative (Laursen and Salter, 2006), as the novelty increases with the industry distance from the target firm. A firm that diversifies its technology gains access to new knowledge and can also receive more spillovers from other fields (Garcia-Vega, 2006). Acquiring diversity may mitigate core rigidities and path dependencies (Nelson and Winter, 1982; Fleming, 2001; Quintana-García and Benavides-Velasco, 2008), and combinations of distant knowledge may produce novel solutions and develop new capabilities that accelerate the rate of invention (March, 1991; Gavetti and Levinthal, 2000; Quintana-García and Benavides-Velasco, 2008). Skills from one product market can be applied to other fields to generate more innovation. However, if the knowledge base of the acquirer is too far from the acquired knowledge, the absorption process becomes very difficult (Cohen and Levinthal, 1990; Duysters and Hagedoorn, 2000), and the novelty is relatively less useful. The acquirer risks to be not able to take advantage from the novelty. Greater distance leads to inventions of greater impact, but unrelated technologies often require a radical change in the way of organizing research (Kogut and Zander, 1992) which can easily be counterproductive (Dosi, 1988; Ahuja and Katila, 2001).

On the other hand, acquisitions are also performed to exploit *synergies* between each other assets. These synergies are possible when there is a degree of similarities among activities of the buyer and the target firms. Synergies facilitate knowledge integration and to combine operations, duplicative functions can be reduced (Capron and Insead, 1999). This is similar to the exploitation of economies of scale and scope in R&D, as with larger pool of assets and market power, a firm has more resources and incentives to innovate. Market concentration and size lead to a shorter innovation lead-time and the possibility to engage in larger combined projects (Gerpott, 1995; Hagedoorn and Duysters, 2002). In other words, from the synergies point of view specialization is an advantage. Indeed, the absorptive capacity argument suggests that a high relatedness should help the post-M&A integration, as the acquirer has already the skills to understand and absorb the acquired capabilities (Cohen and Levinthal, 1990; Mowery et al., 1996; Duysters and Hagedoorn, 2000). The ability of a company to increase its corporate coherence positively influences the innovative performance (Piscitello, 2005). Moreover, from an organizational learning perspective, this positive effect lies in the ability to better evaluate and utilize related than unrelated externally acquired knowledge (Cohen and Levinthal, 1990).

However, the greatest benefits from synergies are achieved when there is a certain degree of divergence between the buyer and the target, and they are not close to perfect overlapping or even duplication of assets and resources. Novelty and engineering capabilities that are too similar to the already existing knowledge of the acquiring company will contribute little to the post-M&A innovative performance. Some degree of differentiation in technological capabilities between the firms may enrich the acquiring firm's knowledge base and create opportunities for learning (Pakes and Griliches, 1984; Ghoshal, 1987; Cohen and Levinthal, 1989; Griliches, 1990; Hitt et al., 1996). Moreover, acquisitions realized in the acquirer's own market, or in a very close sector, are generally done with different reasons than innovation, such as expansion of the market share.

Due to the combined effect of *novelty*, increasing with distance, and of *synergies*, increasing with relatedness, a non linear influence of the industry relatedness is expected between M&A partners on the subsequent innovation performance of the acquiring firm. According with previous results (see, among others, Ahuja and Katila, 2001; Cloodt et al., 2006; Miller et al., 2007), it is sufficient distance, not greatest or lowest distance, that matters.

Beyond a certain threshold, additional search for novelty becomes unproductive, because the lack of the exploitation of synergies has more weight than the high level of novelty acquired by the firm. In fact, the positive impact of M&As on innovation depends basically on a firm's ability to integrate the novelty through synergies and to alter existing routines in the organization of its research (Capron and Mitchell, 2004).

Hence, I expect that the combination of the novelty and synergy effects gives a non-linear relationship inverted-U shaped (Ahuja and Katila, 2001; Cloodt et al., 2006; Keil et al., 2008). Even Miller et al. (2007), looking at the transferring of knowledge across divisions in a diversified firm, found that knowledge that is somewhat similar to researchers' current base, but is also somewhat different, is likely best. On the one hand, the acquired knowledge has to show enough overlap to facilitate the synergies in the post-integration process. On the other hand, the combination of knowledge bases requires enough novelty to make a substantial contribution to the post-M&A innovative performance.

Hypothesis 1: The industry relatedness of the acquired firm will be curvilinearly (inverted U shape) related to the post-M&A innovative performance of the acquiring firm.

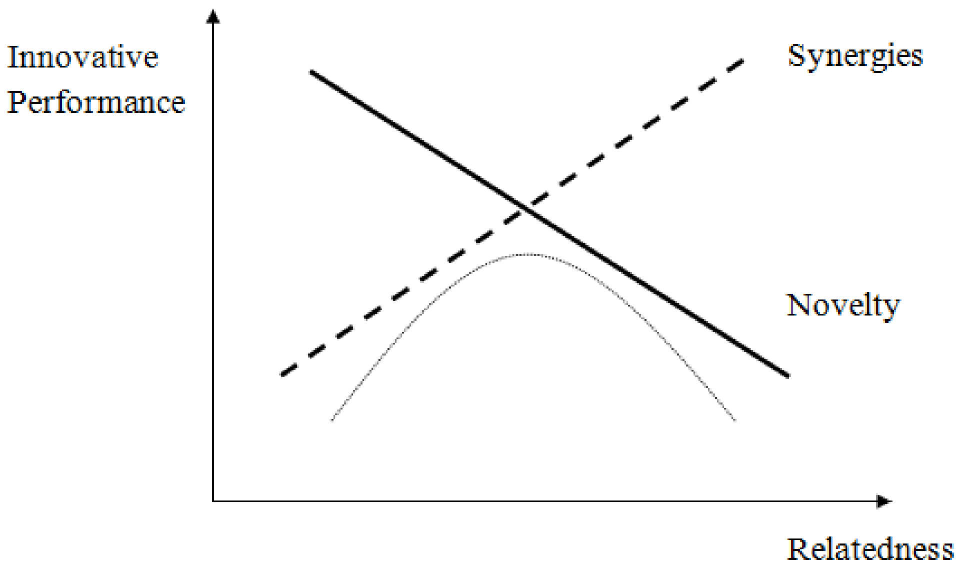

Figure 3.1 Novelty and synergies in the effect of industry relatedness on innovative performance.

3.2.2 Interactions or moderating effects

The challenge for companies is not just to acquire knowledge bases but also to integrate them in order to produce and sell innovative products (Haspeslagh and Jemison, 1991; Ahuja and Katila, 2001; Cefis, 2010). In fact, while acquisition and assimilation are dimensions of "potential" capacity, transformation and exploitation capabilities are dimensions of "realized" absorptive capacity (Zahra and George, 2002). The utilization of the acquired knowledge goes through the integration of a distinct organization, with its own practices and structure. When distance is low, knowledge transfer may simple consist in the almost replication of routines from the target firm to the acquirer. When distance is high the routines of the target need to be integrated with the routines of the buyer and the transfer of knowledge is not simply replication with some adaptation, but require deep understanding and assimilation.

The impact of the industry relatedness on innovation is supposed to vary with some characteristics of both the acquiring and the target firms, which are expected to affect the easiness of the knowledge transfer. Specifically, I test how the relation relatedness/innovation is moderated by three variables: the in-house R&D of the acquirer, the target size, and the previous experience in acquisition activity.

3.2.2.1 In-house R&D

Absorptive capacity and R&D activity are closely linked. This is consistent with Laursen and Salter (2006) and Cohen and Levintal (1990), who argue that R&D not only does generate genuinely new knowledge, but it also enhances the firms' ability to integrate and exploit existing knowledge from the external environment.

In the post-acquisition process, a dimension of the absorptive capacity is the assimilation (Zahra and George, 2002). It refers to the routines and processes that allow a firm to analyze, process, interpret, and understand the information obtained from external sources (Szulanski, 1996; Kim, 1997)**.** Indeed, companies need a strong in-house technological infrastructure to optimally learn new technological capabilities (Vanhaverbeke and Peeters, 2005) and, after the novelty has been assimilated, to harvest and incorporate knowledge into its operations (Tiemessen et al., 1997; Van Den Bosch et al., 1999). The exploitation phase requires retrieving knowledge that has already been created and internalized for use (Lyles and Schwenk, 1992). This means that external knowledge acquisition and internal R&D are complements, reinforcing each other's innovative productivity (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998; Duysters and Hagedoorn, 2000). Even when the distance is high, a strong and consolidate internal R&D increases the ability of the buyer to understand and adapt the knowledge of the target to its own domain.

Moreover, previous works (e.g. Cohen and Levinthal, 1990; Cefis, 2010) found that a firm's post-merger behaviour favours in-house R&D, in order to integrate the knowledge, competences and capabilities that have been acquired by merging with or by buying another firm. However, the integration does not regard only knowledge, but it requires many other efforts, such as the organization of operations and personnel, the reduction of overlapping functions and other costs that absorb energy and resources (De Man and Duysters, 2005; Cefis and Ghita, 2008), producing negative effects on R&D spending (Schenk, 2006).

Hence, I expect that acquirers that have already a consolidated experience in research activity are better able to exploit and integrate the acquired technology, leading to higher innovative performance.

Hypothesis 2a: For every level of industry relatedness, the higher the previous expense in R&D invested by the acquiring firm, the greater the innovative performance realized after the acquisition.

3.2.2.2 The size of the target

The size of targets has long been implied as important (Kitching, 1967; Haspeslagh and Jemison, 1991). Size has been frequently used as a control variable in transfer research (Finkelstein and Haleblian, 2002; Hayward, 2002; Zollo and Singh, 2004), because scholars seem to agree that it affects integration. In an organization knowledge is stored in people and in routines (Nelson and Winter, 1982) and the ability to integrate the target firm is influenced by the complexity of the target organization, which is greater in larger firms. In fact, larger acquired firms need more complex integration steps, which make the process more time consuming and full of risks (Haspeslagh and Jemison, 1991; Chakrabarti et al., 1994; Capron and Mitchell, 2004). Due to such problems, the integration of a large knowledge base requires additional effort, leaving fewer resources for the innovative endeavour (Ahuja and Katila, 2001). Pathways of communication, routing of work and authority, and formal and informal organizational structures all have to be adapted to incorporate the acquired unit's knowledge (Gerpott, 1995).

Hence, according again to the absorptive capacity argument (Cohen and Levinthal, 1990), the integration of an unrelated firm is more difficult and this issue can be even enhanced when the target is a large complex organization. Consequently, I posit that firms that acquire larger targets benefit more from coherence. In other words, when the market distance is high it is easier to integrate knowledge if the target is a small and flexible organization, which has not/less established strong routines.

Hypothesis 2b: The innovative performance after the acquisition of unrelated targets benefits from their small dimension. Large targets can be successfully integrated only if the relatedness is high.

3.2.2.3 The experience in acquisition

The third moderator considered is the acquisition experience of the acquirer. It is a mechanism by which firms attain target selection and integrate skills. Transfer theory focuses on a "transfer effect", which refers to the process by which a certain experience influences subsequent activities, but literature shows mixed evidence about whether such experience is sufficient to ensure superior acquisition performance (Cormier and Hagman, 1987; Hayward, 2002; Ellis et al., 2011). For example, when acquirers appropriately use routines developed through prior acquisitions in a focal acquisition, transfer effects from experience are positive; but when those routines do not fit the new context, transfer effects from experience may be negative (Finkelstein and Haleblian, 2002).

In this analysis I do not have information about the degree of relatedness of the previous deals, but it is well known that both related and distant acquisition gives some advantages in future practices integrations. On one hand, the experience in different acquisitions helps firms to evaluate whether and how implementation routines are suited to their acquisitions, and by virtue of this variety, firms become better equipped to identify and respond to growth opportunities (Weick, 1979). Moreover, distal market experience has a positive effect on a firm's efforts to leverage its technology experience into new products. (Mcevily et al., 2004). On the other hand, acquiring a series of highly similar businesses promotes specialized learning about that business (Hayward, 2002).

Firms may be able to exploit knowledge even serendipitously, without systematic routines, but the presence of such routines provides structural, systemic, and procedural mechanisms that allow firms to sustain the exploitation of knowledge over extended periods of time (Zahra and George, 2002). The outcome of systematic exploitation routines is the persistent creation of new goods, systems, processes, knowledge, or new organizational forms (Spender, 1996), and it can create a sustainable competitive advantage (Barney, 1986). If a firm has experience in carrying out M&A (she may have a formal department and management dedicated to mergers and acquisitions) it may have developed skills and practices that help the integration of future target firms. Even Haspeslagh and Jemison (1991) and Jansen (2002) stress the importance of a very well-planned post-merger integration period to allow an efficient transfer of strategic capabilities from the target to the acquiring firm. This is also confirmed by Cassiman and Colombo (2006) that found evidence that an efficient management of the post-M&A integration process can lead to improved innovative performance. In fact, when a firm acquires a knowledge base it obtains access not only to the acquired firm's internally created knowledge but also to a larger external domain of knowledge (Cohen and Levinthal, 1990) that is helpful in the following deals (Lubatkin, 1983).

The investigation concerns how the ability in integration and exploitation of external knowledge developed through previous deals interact with the industry relatedness of the focal one. I expect that acquirers with higher expertise are able to generate innovative performance for every level of relatedness, while a low experience permits essentially the successful integration of related targets.

Hypothesis 2c: The greater the experience in M&A of the acquiring firm, the greater the innovative performance realized for each level of relatedness. Acquirers with low experience can reach high level of innovative result only when the industry relatedness is high.

3.3 The data and the sample

An unique dataset have been constructed combining economic and firm-level data from two different data sources: the Dutch BR and the CIS, which provide respectively firm specific demographic characteristics and firm level information on innovation behaviour and technological change. Both data sources were made available by the Central Bureau of Statistics Netherlands (CBS).

The first database is the Business Register (BR), a comprehensive database of the entire population of firms registered for fiscal purposes in the Netherlands since 1993. It contains demographic and domestic employment data, sector of activity, and dates of entry and exit of a firm in/from the BR. For a given year, the dataset includes all firms that had been active during that year, not necessarily for the full duration of that year, and those that entered and/or exited during the year. Because of the comprehensive scope of the dataset, (actual) entry and (actual) exit defined with respect to the inclusion in or exclusion from the dataset, as reported in the BR, are close proxies for actual dates of entry and exit in/from the market (Cefis and Marsili, 2006).
In addition, the dataset specifies the reason for inclusion or exclusion of a firm, and a specific variable allows distinguishing the entries and exits of a firm due to M&As from all other types of operations (such as birth/death, takeover, spin-off, restructuring, decomposition of business unit or administrative changes). Using the datasets yearly available since 1995 until 2005, which however include also data regarding the operations concluded in the past, it was possible to identify 36,375 effective acquisitions that took place in the Dutch market over the period 1980-2005. Moreover, again through the BR dataset, the acquiring firms have been matched to the acquired (or target) firms in order to obtain the demographic data (as age, size, industry) for a sample of 27,754 deals[11].

The CIS database gathers information on the extent and characteristics of firms' innovation activity, technological performance and organisational change. In the Netherlands, the CIS is conducted on a two-yearly basis. Each wave covers the three year period prior to the survey. The CIS data allow a more accurate identification of patterns of innovation at firm level than other innovation indicators (see among others Cassiman and Veugelers, 2002; Kleinknecht et al., 2002; Mairesse and Mohnen, 2002; Cefis and Ghita, 2008). To date, firm level data from seven CIS waves are available at the CBS, covering the period 1994–2008.

In analysing the effects of M&A's characteristics on firms innovative performance, I allow for a post-acquisition integration period of two to four years

[11] Among the 36,375 deals registered in the span 1980-2005, the sample is reduced to 27,754 due to the availability of demographic data in the BR database.

following firms M&A involvement, and also a pre-acquisition span of two to three years to get appropriate information on the acquirer's attitude to innovation. More precisely, using the BR the date of the acquisition of each deal has been identified and the demographic characteristics, at that date, of both the acquirer and the target firms have been collected. Then, with reference at the acquisition date, I carefully completed the database attaching the previous and the following acquirer's CIS waves, following some tricks for the deals realized in even/odd years, to allow for the most appropriate pre/post acquisition period. For example:

Acquisition realized in an even year:

M&A date: 1996; CIS_PRE: 1994-1996; CIS_POST: 1998-2000

M&A date: 1998; CIS_PRE: 1996-1998; CIS_POST: 2000-2002

Acquisition realized in an odd year:

M&A date: 1997; CIS_PRE: 1994-1996; CIS_POST: 1998-2000

M&A date: 1999; CIS_PRE: 1996-1998; CIS_POST: 2000-2002

I would like also to specify that both the previous and post CIS waves considered refer only to the acquired firm, being that one the object of interest. Figure 3.2 schematizes how the data sources, as described above, have been combined.

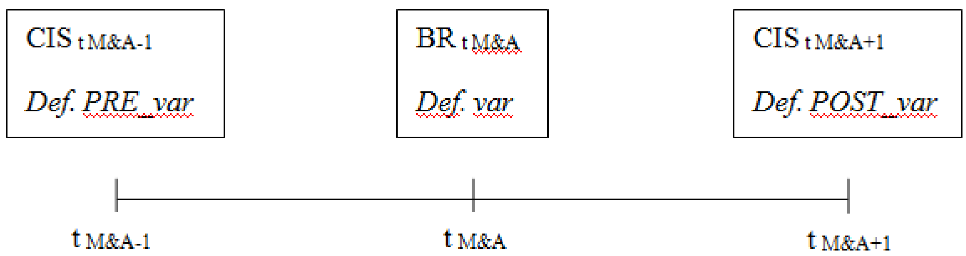

Figure 3.2 *Dataset structure.*

The availability of the CIS waves at the CBS, and the method of the dataset construction limited the time frame of the analysis to acquisitions realized between 1996 and 2005, from BR, and covering all the seven CIS waves: CIS 2 (1994-1996), CIS2.5 (1996-1998), CIS3 (1998-2000), CIS3.5 (2000-2002), CIS4 (2002-2004), CIS 4.5 (2004-2006), and CIS 5 (2006-2008).

Moreover, by definition, the firms included in the CIS surveys are extracted from those present year by year in the BR in order to create a stratified random sample, based on size class, region and industry sector. So, not all the firms involved in M&As are included the CIS surveys, and even the average response rate is lower than 70-60%. For these reasons, in detail, the integration of the databases led to a unique cross-sectional dataset of 1,736 observations (deals), with firms belonging to manufacturing, service and construction industries.

Finally, the sources and collection of BR and CIS datasets are completely independent. The first is a product of a national data tracking exercise for fiscal purposes, which is conducted in a systematic and continuous way by the CBS. The CIS is an European-level survey administered periodically (at regular intervals) by the CBS, which was designed by Eurostat. There is no interdependence in the design of the two databanks. The empirical analysis is based, therefore, on the combination of two different and independent sources of data, implying that there are no common method bias problems (Cefis and Marsili, 2012).

3.4 The methodology

A two-stage Heckman model have been implemented in order to take into account the selectivity issue arising from the decision about whether to invest money in development of innovative products, processes and technologies. The main issue of selectivity is that the income due to the sale of new or improved products is only available for those firms active in innovation.

This issue is analogous to the one that raises when estimating a labour supply function, where income data is only available for those active in the labour market (Love and Roper, 2002; Griffith et al., 2006). Also R&D expenditure and innovation costs can be observed only for those firms that spend more than a certain amount on these activities (Crepon et al., 1998; Benavente, 2006). Although a firm appears to be not involved in the development of new or improved products, this should be interpreted as its decision not to get involved in these activities, because they consider it too risky, or too difficult given their internal organisational structure and internal competences and capabilities at that moment, or because the funds at their disposal are insufficient for undertaking innovation activities.

Following Cefis (2010), that investigated the effects of M&As on corporate research and development strategies, with the aim of accounting for the selectivity issue a two-stage Heckman model has been estimated. The framework of a sample selection model allows for: (1) a Probit model for the firm's decision to invest or not in innovative activities, estimating the sample selection term[12] λ; and (2) a model to test the impact of the variables of interest on the innovative sales realized by the acquiring firm, corrected for selectivity bias.

The selection model can be written as follows:

$$z^*_i = W_i \alpha + e_i,$$
$$z_i = 0 \quad \text{if} \quad z^*_i \leq 0,$$
$$z_i = 1 \quad \text{if} \quad z^*_i > 0,$$

where z_i is the firm's choice to invest in innovation activities, and W_i the set of the variables that explain the firm's choice.

The second model is an OLS regression estimating the expected value of y conditional on $z = 1$ and other explanatory variables denoted by X . The specification of the OLS model is of the form:

$$y^*_i = X'_i \beta + u_i,$$
$$y_i = y^*_i \quad \text{if} \quad z_i = 1, \quad y_i \text{ not observed} \quad \text{if} \quad z_i = 0,$$

where y^*_i is the innovative turnover realized by the firm.

The Heckman 2-stage estimator requires 'exclusion restrictions' (Heckman, 1979): i.e. variables that are likely to affect the probability of investing in innovation, but are unrelated (orthogonally) to the turnover generated by the sale of innovative products.

The selection function, therefore, includes a set of explanatory variables W, which contains some X factors, but must also add other factors that do not appear in X . In the selection model, the dependent variable is a dummy, indicating whether a firm is or not an innovator. The independent variables are acquirer's size, age, technological class and

[12] λ expresses the effect of the unmeasured firms' characteristics on firms' innovation investment decision. In the Heckman 2-stage model, the value of this factor is added as an additional proxy in the second stage – the OLS regression.

a number of proxies that capture problems experienced by the firm, in the process of considering innovation activity, related to financial risk, lack of knowledge or market uncertainties that in any way impeded or affected the innovative process and their decision ultimately to invest/not invest in innovation (Cefis, 2010).

3.5 The variables

This study considers the impact of the industry relatedness index on the innovative performance of the acquirer after the deal. The Oslo Manual (Oecd, 1997), which provides guidelines for implementing the CIS, defines innovation as the introduction in the market of a new - or significantly improved - product (good or service) or the introduction in the firm of a significantly improved production process. In the analysis two definitions of innovative performance has been considered: (a) sales from "improved or new to the firm" products/services; and (b) a more restrictive definition of innovation: sales from "new to the market" products/services.

The variables used in the model, as defined in Section 3.3, belong to datasets referring to three different times: pre-acquisition ($t_{M\&A}$-1) variables, characterized by the prefix "*pre*" in the variable name; acquisition ($t_{M\&A}$) variables, defined without any prefix; and post-acquisition ($t_{M\&A}$+1) variables, characterized by the prefix "*post*" (see figure 3.2 presented in section 3.3).

Moreover, Table 3.1 contains a detailed presentation of the whole set of variables and their construction.

3.5.1 The selection model

The innovative performance can be observed only for firms that have decided to invest in innovative activities, which implies that the foreseeable payoffs from doing so are significant and the related risks are below a certain threshold. Given this, it is necessary to account for selectivity bias in the sample[13] (Cefis, 2010), by introducing a selection model to explain the firm's decision to undertake innovative activities.

[13] See Section 3.4 for a more detailed explanation of the two-stage Heckman model used to study the innovative performance realized by the acquirer firm.

Table 3.1. Definition of the variables.

	Definition of explanatory variables
Selection Model	
Post_innov	A dummy variable that takes the value of 1 if the firm developed or introduced any technologically changed or completely new to the firm product/service in the post-acquisition span
Post_innov_mkt	A dummy variable that takes the value of 1 if the firm developed or introduced any new to the market product/service in the post-acquisition span
Independent variables	
Pre_lack_fin	A dummy variable equal to 1 if the acquiring firm, before the M&A, do not start innovative project due to financial constraint
Pre_lack_know	A dummy variable equal to 1 if the acquiring firm, before the M&A, do not start innovative project due to lack of personnel/technological knowledge
Pre_lack_mkt	A dummy variable equal to 1 if the acquiring firm, before the M&A, do not start innovative project due to uncertainty or lack of sufficient information about the market
OLS Model	
Post_inn_sales	Turnover (in thousands of euro) of the acquiring firm due to improved or new to the firm products/services after the acquisition, in natural logarithm
Post_inn_sales_mkt	Turnover (in thousands of euro) of the acquiring firm due to new to the market products/services after the acquisition, in natural logarithm
Independent variables	
Relat	Industry relatedness index between acquiring and acquired firms. Calculated as: ln [1 + min (index value)]
Exper	Natural logarithm of the number of acquisition concluded by the acquirer at the moment of the deal in object
Pre_R&D	Ln of the acquirer's expenses (in thousands of euro) for in-house R&D, before the acquisition in object
Acq_size	Ln of the number of acquirer's domestic employees, at the M&A
Acq_age	Ln of the age of the acquirer, at the M&A
Tar_size	Ln of the number of target's domestic employees, at the M&A
Tar_age	Ln of the age of the target, at the M&A
Industry dummies	Dummy variables for both acquired and acquiring firms. Precisely: *MH_manuf*: medium/high-tech manufacturing; *ML_manuf*: medium/low-tech manufacturing; *KIS*: knowledge intensive service; *LKIS*: less knowledge intensive service; *constr*: construction
Year dummies	Dummy variables, *GDP_high* and *GDP_low*, corresponding respectively to the high (1997 and 1999) and low (2002 and 2003) peaks of the GDP in The Netherlands
Pre_inn_sales	Turnover (in thousands of euro) of the acquiring firm due to improved or new to the firm products/services before the acquisition, in natural logarithm
Pre_inn_sales_mkt	Turnover (in thousands of euro) of the acquiring firm due to new to the market products/services before the acquisition, in natural logarithm

3.5.1.1 Dependent variables

As dependent variable for the first step of the Heckman model, the Probit model, I used the binary proxy *Post_innov* for the innovative status of the acquirer after the acquisition. The variable acts as a differentiator for innovative versus non-innovative firms, and takes the value of 1 if the firm developed or introduced any technologically changed or completely new to the firm product/service during the three years to which the post-acquisition CIS wave refers.

There is a specific question in the CIS survey on which this dummy proxy is based: *"During the three years* (for example) *2002 to 2004, did your enterprise introduce new or significantly improved goods/services (exclude the simple resale of new goods purchased from other enterprises and changes of a solely aesthetic nature):*

a) *that were already available from your competitors in your market?" - Post_innov-*
b) *onto your market before your competitors in your market?" - Post_innov_mkt-*

3.5.1.2 Independent variables

Firm's decision to undertake innovative activities depends on firm-specific variables such as: financial, knowledge, and marketing constraints, perceived by companies as impeding their innovative activities. These are endogenous and exogenous factors to identify and capture the reasons affecting firms' engaging or not in innovative activities, and their innovative performance.

The first proxy – financial constraints – is a dummy variable measuring the lack of financial resources required for engagement in innovative activities that takes the value one if the company replies positively to the question: 'Has your company been faced with financial constraints due to which innovation projects have not started?' The remaining proxies have a similar structure (1/0 dummies). Knowledge constraints proxy captures whether firms have been reluctant to engage in innovative activities due to a lack of skills and knowledge embedded in the personnel or to a lack of managerial, organisational or technological capabilities in the firm.

The marketing constraints proxy tests whether the absence of innovative activities is due to uncertainty of outputs and future profits from innovation based on uncertain market

development of new products or lack of sufficient information about general market situation.
These three proxies of the possible obstacles for innovative activities (P*re_lack_fin, Pre_lack_know* and *Pre_lack_mkt*) come from the pre-acquisition CIS of the acquirer.

As explanatory variables for the probability of investing in innovation, I included acquirer firm's characteristics such as size, age and technological regime (NACE codes 3-digit classification)[14] calculated at the M&A moment, which have been proven to be relevant in shaping the innovative behaviour of firms (see among others Pavitt, 1984; Breschi et al., 2000; Marsili and Verspagen, 2002; Cefis and Ghita, 2008).

3.5.2 The innovative performance model

3.5.2.1 Dependent variables

Innovative performance. The interest relies on the effect of the industry relatedness index on the innovative performance of the acquirer after the deal. The challenge for acquiring companies is to integrate the knowledge bases, the competences and the capabilities acquired, with their own resources, in order to improve post-M&A innovative performance (Ahuja and Katila, 2001). The complexity of the post merger integration process demands a minimum time span of 2-3 years. In order to investigate post-acquisition innovative performance of Dutch firms, I considered the innovative sales registered in the CIS wave following the acquisition, which means allowing for a post-integration period of two to four years (Cefis and Ghita, 2008). Moreover, to be as clear as possible, even if a firm is a product innovator (both to the firm (a) and to the market (b) definitions), its value of innovative sales can be equal to zero if the novelty is still under development when the CIS survey is done.

Innovative sales:

a) *Post_inn_sales*, calculated as the turnover of the acquiring firm after the acquisition due to improved or new to the firm products/services, in natural logarithm of thousands of euro;

[14]All the firm's demographic variables (age, size and industry) are presented in a more detailed way in section 4.2.2

b) *Post_inn_sales_mkt*, calculated as the turnover of the acquiring firm after the acquisition due to new to the market products/services, in natural logarithm of thousands of euro.

3.5.2.2 Independent variables

Industry relatedness index. This variable refers to the measure of industry relatedness index that has been developed, following Teece et al.'s (1994) methodology, in the previous chapter. Again, as in the previous study, the index needs to be linearly transformed in such a way it can take only positive values, and then it is possible to calculate its natural logarithm.

Relat = ln [1 + min (index value)] where "index value" refers to the index ρ_{ij} developed in the previous Chapter.

The squared term of *Relat* is also included, as I expect a non-linear relationship Relat-Innovative performance. The interaction terms Relat-R&D expense, *Relat-Target size*, and *Relat-experience* have been also added into the model to test possible heterogeneity in the effect of Relat when the other parameters change.

3.5.3 Control variables

Acquisition experience. Consistent with Ingram and Baum (1997) and Haleblian and Finkelstein (1999), the acquisition experience (*Exper*) is measured by the number of acquisitions that the bidders in the sample made before the deal in object.
The squared term of *Exper* is also included, as I expected a non-linear relationship Exper-Innovative performance.

Expenses for in-house R&D. As proxy for internal innovation engagement I considered the expenses for the acquisition of hardware/software and new machinery; plus the costs of market research aimed directly at the market introduction of new products or services and R&D personnel training. This variable, labelled *Pre_R&D*, comes from the pre-acquisition CIS wave, and it contains the information about the specific skill and capability in research and development embedded in the acquiring firm, useful also in the post-acquisition integration of the acquired firm's know-how (Zahra and George, 2002). Only in-house R&D has been considered because, according to the literature (Cefis, 2010), it is more related to the post-acquisition integration process than other external innovation expenses, such as the purchase of patent rights, licences or other types of knowledge from third parties

Firms' size and age. As a measure of size, the number of domestic employees is considered, taken at the year of the M&A. In this respect, the BR has the advantage of reporting the firm size down to zero employees (or self-employment). Then, I measured the age of the firms, from their foundation, at the year of the M&A. In the BR is recorded the year in which a firm is added in the database, and it is a the best proxy of its date of birth. I collected both size and age of both the acquiring (*Acq_size, Acq_age*) and target (*Tar_size, Tar_age*) firms. Values always expressed in logarithm terms.

Industry dummies. The sample includes three main divisions of the industrial sectors, based on NACE Rev. 1.1 classification: manufacturing, service and construction. I decided to not consider other industries such as agriculture, fishing and mining due to the deep difference of these firms with the main object. Then, I followed the aggregation of manufacturing and service industries according to the technological intensity proposed by Eurostat and based on NACE classification at 3-digit level. Eurostat compiles aggregation related to medium-high and medium-low technology for manufacturing industry, and knowledge intensive (KIS) or less knowledge intensive (LKIS) services. See table 3.8 in appendix for a more detailed explanation.

Year dummies. I controlled for two year dummy variables, *GDP_high* and *GDP_low*, corresponding respectively to the highest (1997 and 1999) and the lowest (2002 and 2003) peaks of the GDP in The Netherlands in the span considered.
Finally, as control variable, I introduced the lagged value of the innovative performance as:

a) *Pre_inn_sales*, calculated as the turnover of the acquiring firm before the acquisition due to improved or new to the firm products/services, in natural logarithm of thousands of euro;

b) *Pre_inn_sales_mkt*, calculated as the turnover of the acquiring firm before the acquisition due to new to the market products/services, in natural logarithm of thousands of euro;

in relation to the first (a) or the more restrictive second (b) series of models.

The model specification

The selection model is estimated by

$$P(\text{Post\_innov})_{i,\,tM\&A+1} = \text{probit}\,(\beta_1\text{Pre\_lack\_fin}_{i,\,tM\&A-1} + \beta_2\text{Pre\_lack\_know}_{i,\,tM\&A-1} + \beta_3\text{Pre\_lack\_mkt}_{i,\,tM\&A-1} + \beta_4\text{Acq\_age}_{i,\,t} + \beta_5\text{Acq\_size}_{i,\,t} + \beta_6\text{Acq\_MHT\_man}_{i,\,t} + \beta_7\text{Acq\_MLT\_man}_{i,\,t} + \beta_8\text{Acq\_KIS}_{i,\,t} + \beta_9\text{Acq\_LKIS}_{i,\,t} + \beta_{10}\text{Acq\_constr}_{i,\,t} + v_i)$$

The second stage of the Heckman model, the OLS regression, captures the effects of industry relatedness on firms' innovative performance, controlling also for the firms' demographic and technological specificities, and any selection bias.

The following model is estimated using an OLS estimator:

$$(\underline{\text{P}}\text{ost\_inn\_sales})_{i,\,tM\&A+1} = \alpha + \beta_1\text{Pre\_inn\_sales}_{i,\,tM\&A-1} + \beta_2\text{Relat}_{i,\,t} + \beta_3\text{Exper}_{i,\,t} + \beta_4\text{Acq\_age}_{i,\,t} + \beta_5\text{Acq\_size}_{i,\,t} + \beta_6\text{Tar\_age}_{i,\,t} + \beta_7\text{Tar\_size}_{i,\,t} + \beta_8\text{pre\_R\&D}_{i,\,tM\&A-1} + \beta_9\text{GDP\_high}_{i,\,t} + \beta_{10}\text{GDP\_low}_{i,\,t} + \beta_{11}\text{Acq\_MHT\_man}_{i,\,t} + \beta_{12}\text{Acq\_MLT\_man}_{i,\,t} + \beta_{13}\text{Acq\_KIS}_{i,\,t} + \beta_{14}\text{Acq\_LKIS}_{i,\,t} + \beta_{15}\text{Acq\_constr}_{i,\,t} + \beta_{16}\text{Tar\_MHT\_man}_{i,\,t} + \beta_{17}\text{Tar\_MLT\_man}_{i,\,t} + \beta_{18}\text{Tar\_KIS}_{i,\,t} + \beta_{19}\text{Tar\_LKIS}_{i,\,t} + \beta_{20}\text{Tar\_constr}_{i,\,t} + \beta_{21}\lambda_i + \varepsilon_i$$

where λ is the Mills ratio capturing the sample selection bias estimated in the first stage using the Probit model.

In the estimation of the more restrictive models (b), I substitute *Post_innov* variable with *Post_innov_mkt* in the selection model, and *Post_inn_sales* and *Pre_inn_sales* with *Post_inn_sales_mkt* and *Pre_inn_sales_mkt* respectively in the OLS regression.

Finally, the model specification presented above is the base model. Since the interest is to test the U-shape with respect to industry relatedness and acquirer firm's experience, the squared term of the logarithm of the variables *Relat* and *Exper* are included into the models. Moreover, to test the set of hypotheses regarding the moderator effects, I successively added three interaction terms of *Relat* with respectively: *Pre_R&D*, *Tar_size,* and E*xper,* and also the squared values of these three interactions to test for their non linear effects.

3.6 Results

3.6.1 The univariate analysis

Table 3.2 focus on the mean differences between the two groups of firms: those involved in post-acquisition innovative activities and those not engaged in these kinds of activities, both for (a) to the firm and (b) to the market innovative status. The value of the relatedness index, the experience in acquisition of the acquirer (number of acquisition previously realized) and its previous involvement in R&D activity, as well as both the acquired and acquiring firms' size (number of employees) and age (in years) proxies are presented for both categories of deals, to reflect their potential importance in an investigation of post-acquisition innovative status. The mean values of relatedness and experience are clearly smaller for firms performing innovative activity, while the involvement in R&D is larger for this category of firms. The difference of the means of these three variable between the two groups is significant, both for (a) to the firm and (b) to the market innovative status. Moreover, the size of the acquirer is larger for both the kinds of innovators, but the difference is significant only in (a) "new to the firm" analysis.

Table 3.2 Univariate analysis: descriptive statistics grouped by innovator/non-innovator for (a) "improved or new to the firm" and (b) "new to the market" post-acquisition status. Real values reported, not in natural logarithm. Statistically significant at the 10% (*), 5% (**), and 1% level (***).

Variable	(a)					(b)				
	To the firm innovator obs: 512		To the firm non-innovator obs: 1224		obs: 1,736	To the market innovator obs: 362		To the market non-innovator obs: 1374		obs: 1,736
	Mean	S.d.	Mean	S.d.	Mean difference test	Mean	S.d.	Mean	S.d.	Mean difference test
Relat (value)	60.24	50.35	76.57	58.71	-5.49***	57.83	2.6	75.44	58.09	-5.28***
Exper (N acq.)	5.7	5.86	14.26	27.28	-7.02***	6.18	6.21	13.21	25.97	-5.10***
Pre_R&D (K euro)	2,724.72	18,773.57	359.51	1,986.01	4.35***	3,629	22,235.71	379.38	1,988.53	5.34***
Tar_age (years)	11.87	12.07	11.28	11.73	0.94	12.47	10.07	11.06	9.73	0.82
Tar_size (employees)	107.17	1,193.86	70.01	944.14	0.69	128.31	1,415.21	68.49	893.03	0.98
Acq_age (years)	16.37	13.43	16.81	13.71	-0.61	15.86	13.41	16.89	13.68	-1.27
Acq_size (employees)	984.25	4,311.56	657.71	1,287.08	2.41**	909.36	3,423.36	713.09	2,309.29	1.28
Pre_lack_fin	0.2	0.4	0.14	0.35	2.97***	0.2	0.41	0.14	0.35	2.54**
Pre_lack_know	0.44	0.49	0.23	0.42	9.17***	0.43	0.49	0.25	0.43	6.91***
Pre_lack_mkt	0.37	0.48	0.15	0.36	10.05***	0.38	0.48	0.17	0.38	8.90***

Table 3.3 describes the sample, grouping the observations by innovative status and acquirer firm's industry. It is evident that the fraction of innovator is larger for manufacturing than service and construction sectors. The lowest fraction of innovators is seen for less knowledge intensive service (LKIS).

Table 3.3. Descriptive statistics. Post-acquisition innovative status grouped by acquirer firm's industry.

Acquirer industry	Post-acquisition innovator	Post-acquisition non-innovator	% Innovator	Total
Medium/High tech manufacturing	50	42	0.54	92
Medium/Low tech manufacturing	129	108	0.54	237
Knowledge intensive service	168	280	0.38	448
Low knowledge intensive service	95	622	0.13	717
Construction	70	172	0.29	242
Total	512	1,224	0.29	1,736

3.6.2 The multivariate analysis

Table 3.4 and 3.5 provide descriptive statistics and correlation. The low correlation between independent and control variables and acceptable variance inflation factor (VIF) statistics suggest that multicollinearity of variables is not a problem in the analysis.

The effects of industry relatedness on innovative performance have been studied with reference to both (a) new to the firm and (b) new to the market products/services (Tables 3.6-3.7 a,b).

Table 3.4. Descriptive statistics of the variables used in the analysis.

Variable	Mean	s.d.	Median
Post_inn_sales	7.42	3.06	7.98
Post_inn_sales_mkt	7.68	2.65	8.05
Relat	3.74	1.17	4.37
Exper	1.55	1.23	1.38
Tar_age	1.94	1.18	1.94
Tar_size	2.35	1.82	2.56
Acq_age	2.31	1.28	2.7
Acq_size	5.77	1.16	5.58
Pre_R&D	1.68	2.87	0
Pre_lack_fin	0.16	0.36	0
Pre_lack_know	0.29	0.45	0
Pre_lack_mkt	0.22	0.41	0
Acq_MH_manuf	0.05	0.22	0
Acq_ML_manuf	0.13	0.34	0
Acq_KIS	0.25	0.43	0
Acq_LKIS	0.41	0.49	0
Acq_constr	0.13	0.34	0
Tar_MH_manuf	0.03	0.18	0
Tar_ML_manuf	0.08	0.27	0
Tar_KIS	0.42	0.49	0
Tar_LKIS	0.39	0.48	0
Tar_constr	0.07	0.25	0

Table 3.5. Correlation Matrix

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	*Post_inn_sales*	1																					
2	*Post_inn_sales_mkt*	.79*	1																				
3	*Relat*	-.09*	-.13*	1																			
4	*Exper*	.1	.04	.10*	1																		
5	*Tar_age*	.00	.07	.16*	-.1*	1																	
6	*Tar_size*	.09*	.13*	.24*	-.26*	.41*	1																
7	*Acq_age*	.07*	.03	-.09*	.01	-.05*	-.2*	1															
8	*Acq_size*	.28*	.29*	.04*	.49*	.00	.12*	.06*	1														
9	*Pre_R&D*	.26*	.27*	-.13*	-.5*	-.01	.05*	.05*	.19*	1													
10	*Pre_lack_fin*	.05	-.09*	.02	-.07*	-.06*	.04	-.08*	-.05*	.06*	1												
11	*Pre_lack_know*	-.02	.08	-.04*	-.02	.02	.05*	-.1*	.1*	.24*	.44*	1											
12	*Pre_lack_mkt*	-.05	.02	-.02	-.04*	.04	.02	-.05*	.03	.26*	.45*	.59*	1										
13	*Acq_MH_manuf*	.05	-.02	-.13*	-.16*	.03	.05	.04*	-.09*	.19*	.02	-.02	.00	1									
14	*Acq_ML_manuf*	.12*	.03	-.08*	-.23*	.01	.13*	.04*	.00	.18*	.09*	.09*	.09*	-.09*	1								
15	*Acq_KIS*	-.10*	-.11*	.02	-.02	-.16*	-.12*	-.1*	.00	.18*	.02	.01	-.02	-.14*	-.23*	1							
16	*Acq_LKIS*	.00	-.02	.16*	.15*	.12*	.05*	.00	.00	-.37*	-.08*	-.08*	-.14*	-.2*	-.33*	-.49*	1						
17	*Acq_constr*	-.07*	.16*	-.09*	.13*	.00	-.09*	.06*	.06*	-.01	-.02	.02	.13*	-.09*	-.16*	-.24*	-.34*	1					
18	*Tar_MH_manuf*	-.06	-.08	-.03	-.1*	.04*	.1*	.00	-.03	.15*	.03	.01	.04	.52*	-.01	-.11*	-.11*	-.03	1				
19	*Tar_ML_manuf*	.07	.05	.1*	-.19*	.06*	.17*	-.01	-.06*	.13*	.06*	.08*	.07*	-.02	.62*	-.17*	-.2*	-.09*	-.05*	1			
20	*Tar_KIS*	-.05	-.01	.34*	.05*	.26*	-.28*	.00	.04*	.12*	.02	.03	.00	-.1*	-.1*	.64*	-.48*	.04*	-.16*	-.25*	1		
21	*Tar_LKIS*	.04	-.03	.24*	.1*	.17*	.09*	.02	.00	-.24*	-.06*	-.08*	-.1*	-.06*	-.2*	-.44*	.75*	-.27*	-.15*	-.24*	-.69*	1	
22	*Tar_constr*	-.01	.10*	.11*	-.01	.08*	.11*	-.02	.00	-.01	.02	.01	.08*	-.02	-.08*	-.14*	-.21*	.56	-.05*	-.08*	-.23*	-.22*	1

Observations: 1,736.

* Statistically significant at the 10% level.

The results of the selection equation are presented in Table 3.6. As dependent variables are considered, respectively, the dummies (a) *Post_innov* and (b) *Post_innov_mkt* as proxies of the innovative status of the acquirer after the acquisition.

Table 3.6. The selection equation. The first stage of Heckman procedure (probit model) for: (a) sales from "improved or new to the firm" products/services and (b) sales from "new to the market" products/services. As dependent variables are considered, respectively, the dummies (a) *Post_innov* and (b) *Post_innov_mkt* as proxies of the innovative status of the acquirer after the acquisition.

	(a) new to the firm	(b) new to the market
Variable	coefficient (standard error)	coefficient (standard error)
Pre_lack_fin	-0.317***	-0.213*
	(0.104)	(0.107)
Pre_lack_know	0.377***	0.162*
	(0.092)	(0.098)
Pre_lack_mkt	0.541***	0.559***
	(0.101)	(0.105)
Acq_MH_manuf	1.278***	1.189***
	(0.148)	(0.151)
Acq_ML_manuf	1.164***	0.962***
	(0.103)	(0.108)
Acq_KIS	0.776***	0.660***
	(0.086)	(0.093)
Acq_constr	0.409***	0.339***
	(0.109)	(0.118)
Acq_age	-0.003	-0.044
	(0.027)	(0.028)
Acq_size	0.065**	0.105***
	(0.030)	(0.032)
Constant	-1.646***	-1.967***
	(0.190)	(0.205)
LR χ^2 (9)	306.33	211.03
Pseudo R^2	0.145	0.118
Log-likelihood	-899.734	-783.309
Number of observations	1,736	1,736

*, **, and *** Statistically significant at the 10%, 5%, and 1% level, respectively.
Note: Standard error is given in parentheses.

Financial constraints, as expected, are serious issues for the innovative activity, even after some years and the conclusion of an acquisition. Conversely, both the lack of knowledge and information about the market that hindered pre-acquisition innovative activity have positive impact on subsequent performance, when controlling for other factors. This means that the dearth of knowledge and market information works as a stimulus for the acquisition of external knowledge and to consequently overcome those lacks. The outcomes of the selection equation are equal concerning both concerning both (a) the firm and (b) the market innovative status.

Tables 3.7a and 3.7b present the results of the second stage of the Heckman model, that is the OLS regression, with, respectively (a) new to the firm and (b) new to the market innovative performance as dependent variable.

The first model (Model 1a and 1b) is the base model, without squared and interaction terms, while in Model 2 (2a and 2b) I insert the squared terms for relatedness and experience to test their non-linear impact on the innovative performance, controlling for all the other factors. The results confirm hypothesis 1, showing that the market relatedness between the companies involved in a deal has an inverted U-shaped effect on the turnover from innovation realized by the acquirer, observed in a 4-years span after the M&A. This finding means that, if the M&A is realized as a search strategy for external knowledge, an "optimal" market distance should exist between acquiring and acquired firm. This result is consistent both in (a) new to the firm and even more strongly in (b) new to the market series of models. In fact, the absolute size of the coefficients of relatedness and relatedness squared is always higher in (b) models than in (a) models.

Also the squared measure of experience has been added to control for its non linear impact on the innovative performance. I found that a U-shaped relation exists between prior acquisition experience and post-acquisition "new to the firm" (a) innovative performance, i.e. the initial benefits from experience quickly decrease and increase later as more experience is accumulated. This finding is consistent with the results obtained in researches focused on the relation between acquisition experience and firm acquisition performance (Ingram and Baum, 1997; Haleblian and Finkelstein, 1999).

Table 3.7a. The effect of industry relatedness on Post M&A Innovative Performance. Dependent variable: (a) sales from "improved or new to the firm" products/services**.** Standard error is given in parentheses.

Dependent variable	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)	(8a)	(9a)
	base		moderator: R&D		moderator: Tar size		moderator: Exper		All
Pre_inn_sales	0.081**	0.067**	0.066**	0.093***	0.075**	0.075**	0.057*	0.052	0.084***
	(0.034)	(0.034)	(0.334)	(0.034)	(0.033)	(0.033)	(0.034)	(0.033)	(0.032)
Relat	-0.269**	3.002**	3.090***	3.204***	2.666**	2.609**	3.229***	1.406	1.482
	(0.123)	(1.200)	(1.197)	(1.169)	(1.161)	(1.175)	(1.185)	(1.283)	(1.237)
(Relat)^2		-0.473***	-0.460***	-0.459***	-0.551***	-0.546***	-0.425**	-0.219	-0.297*
		(0.171)	(0.171)	(0.167)	(0.166)	(0.167)	(0.170)	(0.178)	(0.171)
Exper	-0.023	-0.891**	-0.868**	-0.622*	-1.046***	-1.056***	0.638**	-3.389***	-3.551***
	(0.159)	(0.398)	(0.397)	(0.389)	(0.385)	(0.386)	(0.565)	(1.284)	(1.230)
(Exper)^2		0.326**	0.325**	0.237*	0.386***	0.389***	0.324**	1.141***	1.060***
		(0.135	(0.135)	(0.133)	(0.131)	(0.131)	(0.134)	(0.269)	(0.257)
Tar_age	0.104	0.107	0.118	0.093	0.118	0.111	0.007	0.075	0.097
	(0.118)	(0.117)	(0.116)	(0.114)	(0.112)	(0.115)	(0.115)	(0.114)	(0.111)
Tar_size	-0.001	-0.012	-0.018	-0.057	-1.333***	-1.374***	0.000	-0.028	-0.968***
	(0.082)	(0.081)	(0.080)	(0.079)	(0.231)	(0.268)	(0.080)	(0.079)	(0.274)
Acq_age	-0.015	-0.025	-0.030	-0.028	-0.051	-0.058	-0.049	-0.058	-0.061
	(0.110)	(0.109)	(0.109)	(0.105)	(0.104)	(0.106)	(0.107)	(0.107)	(0.102)
Acq_size	0.934***	0.940***	0.975***	0.738***	0.853***	0.856***	0.954***	0.988***	0.731***
	(0.145)	(0.144)	(0.145)	(0.147)	(0.139)	(0.134)	(0.141)	(0.141)	(0.141)
Pre_R&D	0.153***	0.161***	0.358***	0.660***	0.166***	0.168***	0.181***	0.182***	0.665***
	(0.049)	(0.049)	(0.128)	(0.138)	(0.047)	(0.047)	(0.048)	(0.048)	(0.133)
*Relat*R&D*			-0.057*	-0.291***					0.759***
			(0.034)	(0.056)					(0.318)
*(Relat*R&D)* ^{2}				0.005***					-0.052***
				(0.001)					(0.015)
*Relat*tar_size*					0.361***	0.386***			-0.271**
					(0.066)	(0.101)			(0.055)
*(Relat*tar_size)* ^{2}						-0.007			0.004
						(0.002)			(0.000)
*Relat*exper*							-0.421***	0.673***	0.218**
							(0.111)	(0.332)	(0.103)
*(Relat*exper)* ^{2}								-0.055***	0.001***
								(0.016)	(0.002)

Table 3.7a to be continued…

..table 3.7a continued.

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	basis		moderator: R&D		moderator: Tar size		moderator: Exper		All
GDP_high	0.008	-0.037	0.116	-0.553	0.140	0.148	0.017	-0.025	-0.348
	(0.566)	(0.560)	(0.565)	(0.569)	(0.543)	(0.544)	(0.553)	(0.546)	(0.546)
GDP_low	-0.181	-0.164	-0.152	-0.006	-0.061	-0.052	-0.041	-0.073	0.037
	(0.287)	(0.285)	(0.284)	(0.278)	(0.276)	(0.277)	()0.283	(0.280)	(0.268)
Acq_MH_manuf	1.985**	1.827**	1.806**	1.450**	1.471*	1.445**	1.955**	2.180***	1.574*
	(0.833)	(0.831)	(0.832)	(0.802)	(0.798)	(0.801)	(0.817)	(0.815)	(0.777)
Acq_ML_manuf	1.352*	1.091	1.098	1.006	0.019	0.792	1.140	1.280*	1.087
	(0.710)	(0.714)	(0.715)	(0.687)	(0.685)	(0.690)	(0.702)	(0.699)	(0.666)
Acq_KIS	0.154	-0.211	-0.237	-0.271	-0.320	-0.341	-0.182	-0.118	-0.231
	(0.621)	(0.631)	(0.631)	(0.610)	(0.606)	(0.609)	(0.621)	(0.616)	(0.586)
Acq_constr	-1.188*	-1.451**	-1.566**	-1.359**	-1.918***	-1.929***	-1.647***	-1.797***	-1.993***
	(0.630)	(0.626)	(0.630)	(0.610)	(0.606)	(0.606)	(0.618)	(0.615)	(0.590)
Tar_MH_manuf	-1.287**	-1.528**	-1.322**	-1.350**	-1.290**	-1.281**	-1.730***	-1.661***	-1.231**
	(0.642)	(0.638)	(0.649)	(0.631)	(0.617)	(0.617)	(0.631)	(0.625)	(0.608)
Tar_ML_manuf	0.648	0.838*	0.998*	1.080**	0.791	0.795	0.576	0.056	0.846*
	(0.511)	(0.508)	(0.516)	(0.502)	(0.490)	(0.490)	(0.505)	(0.450)	(0.484)
Tar_KIS	0.348	0.490	0.572	0.625	0.521	0.523	0.417	0.465	0.645
	(0.432)	(0.430)	(0.431)	(0.420)	(0.415)	(0.415)	(0.424)	(0.419)	(0.402)
Tar_constr	0.897	1.121*	1.293**	1.361**	1.304**	1.328**	1.389**	1.640***	1.878***
	(0.651)	(0.646)	(0.651)	(0.637)	(0.625)	(0.630)	(0.641)	(0.637)	(0.617)
Constant	-1.007	-5.588**	-6.399***	-4.877**	-2.472	-2.328	-6.955***	-3.497	-0.741
	(1.512)	(2.317)	(2.362)	(2.308)	(2.287)	(2.332)	(2.313)	(2.497)	(2.547)
Mills (λ)	2.156***	2.131***	2.199***	1.842***	1.880***	1.851***	2.026***	2.116***	1.779***
	(0.608)	(0.602)	(0.605)	(0.583)	(0.576)	(0.583)	(0.592)	(0.591)	(0.567)
Rho	0.667	0.668	0.684	0.613	0.626	0.618	0.651	0.676	0.618
Wald X^2	128.38***	144.51***	147.13***	182.65***	193.48***	193.87***	163.47***	178.14***	249.50***
N of observations	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736

*, **, and *** Statistically significant at the 10%, 5%, and 1% level, respectively.
Note: Standard error is given in parentheses.

Table 3.7b. The effect of industry relatedness on Post M&A Innovative Performance. Dependent variable: (b) sales from "new to the market" products/services**.** Standard error is given in parentheses.

Dependent variable	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)	(7b)	(8b)	(9b)
	base		moderator: R&D		moderator: Tar size		moderator: Exper		All
Pre_inn_sales_mkt	-0.033	-0.034	-0.036	-0.023	-0.016	-0.017	-0.043	-0.045	-0.024
	(0.035)	(0.034)	(0.034)	(0.034)	(0.033)	(0.033)	(0.033)	(0.032)	(0.031)
Relat	-0.427***	5.634***	5.647***	5.534***	5.299***	5.258***	5.764***	3.653***	3.469***
	(0.130)	(1.161)	(1.158)	(1.133)	(1.124)	(1.142)	(1.119)	(1.246)	(1.201)
(Relat)^2		-0.873***	-0.856***	-0.824***	-0.932***	-0.928***	-0.786***	-0.535***	-0.537***
		(0.166)	(0.166)	(0.163)	(0.161)	(0.162)	(0.161)	(0.173)	(0.166)
Exper	-0.006	-0.267	-0.249	-0.109	-0.493	-0.501	1.782***	-2.280*	-2.538**
	(0.159)	(0.396)	(0.395)	(0.388)	(0.385)	(0.387)	(0.545)	(1.250)	(1.211)
(Exper)^2		0.080	0.078	0.035	0.160	0.163	0.044	0.853***	0.868***
		(0.132)	(0.131)	(0.129)	(0.129)	(0.129)	(0.127)	(0.257)	(0.247)
Tar_age	0.057	0.024	0.027	0.031	0.025	0.020	-0.026	-0.029	0.004
	(0.122)	(0.117)	(0.117)	(0.114)	(0.113)	(0.116)	(0.113)	(0.112)	(0.109)
Tar_size	0.153*	0.148*	0.140*	0.098	-0.951***	-0.978***	0.159**	0.114	-0.527**
	(0.082)	(0.079)	(0.079)	(0.078)	(0.229)	(0.267)	(0.076)	(0.076)	(0.263)
Acq_age	-0.106	-0.125	-0.129	-0.092	-0.161	-0.164	-0.157	-0.179*	-0.159
	(0.114)	(0.109)	(0.109)	(0.106)	(0.105)	(0.106)	(0.105)	(0.104)	(0.100)
Acq_size	0.716***	0.747***	0.767***	0.604***	0.658***	0.660***	0.736***	0.800***	0.619***
	(0.158)	(0.152)	(0.153)	(0.154)	(0.147)	(0.148)	(0.146)	(0.145)	(0.144)
Pre_R&D	0.162***	0.159***	0.293**	0.529***	0.166***	0.166***	0.185***	0.181***	0.596***
	(0.048)	(0.046)	(0.122)	(0.133)	(0.045)	(0.045)	(0.045)	(0.044)	(0.125)
*Relat*R&D*			-0.039	-0.217***					0.648**
			(0.033)	(0.054)					(0.314)
*(Relat*R&D)* ^{2}				0.004***					-0.057***
				(0.001)					(0.015)
*Relat*tar_size*					0.299***	0.315***			-0.221
					(0.059)	(0.101)			(0.050)
*(Relat*tar_size)* ^{2}						-0.001			0.003
						(0.002)			(0.001)
*Relat*exper*							-0.542***	0.567*	0.125
							(0.130)	(0.325)	(0.099)
*(Relat*exper)* ^{2}								-0.056***	0.001
								(0.016)	(0.002)

Table 3.7b to be continued..

...table 3.7b continued.

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	basis		moderator: R&D		moderator: Tar size		moderator: Exper		All
GDP_high	-3.206***	-3.261***	-3.133***	-3.652***	-3.107***	-3.104***	-3.190***	-3.421***	-3.629***
	(0.607)	(0.587)	(0.596)	(0.596)	(0.569)	(0.569)	(0.567)	(0.560)	(0.561)
GDP_low	0.194	0.283	0.285	0.279	0.319	0.323	0.433	0.415	0.402
	(0.261)	(0.273)	(0.272)	(0.266)	(0.264)	(0.264)	(0.264)	(0.260)	(0.248)
Acq_MH_manuf	0.930	0.386	0.354	0.122	-0.006	-0.021	0.513	0.911	0.454
	(0.807)	(0.788)	(0.788)	(0.768)	(0.761)	(0.765)	(0.757)	(0.757)	(0.731)
Acq_ML_manuf	-0.003	-0.658	-0.686	-0.610	-0.957	-0.973	-0.666	-0.440	-0.534
	(0.671)	(0.658)	(0.658)	(0.640)	(0.636)	(0.640)	(0.632)	(0.628)	(0.607)
Acq_KIS	-0.387	-1.146*	-1.218**	-1.275**	-1.347**	-1.358**	-1.073*	-0.953*	-1.203**
	(0.590)	(0.587)	(0.589)	(0.575)	(0.567)	(0.569)	(0.565)	(0.558)	(0.539)
Acq_constr	0.424	0.425	0.294	0.351	-0.203	-0.212	0.034	-0.130	-0.593
	(0.640)	(0.617)	(0.626)	(0.611)	(0.607)	(0.609)	(0.598)	(0.592)	(0.584)
Tar_MH_manuf	-1.385**	-1.810***	-1.651***	-1.613***	-1.484**	-1.477**	-1.924***	-1.883***	-1.417**
	(0.618)	(0.600)	(0.614)	(0.599)	(0.582)	(0.583)	(0.578)	(0.560)	(0.562)
Tar_ML_manuf	1.014**	1.380***	1.509***	1.540***	1.466***	1.468***	1.092**	1.044**	1.342***
	(0.510)	(0.496)	(0.507)	(0.496)	(0.480)	(0.480)	(0.481)	(0.473)	(0.463)
Tar_KIS	0.269	0.619	0.704*	0.739*	0.802*	0.802**	0.527	0.576	0.865**
	(0.424)	(0.413)	(0.419)	(0.409)	(0.401)	(0.401)	(0.399)	(0.392)	(0.382)
Tar_constr	0.389	0.422	0.592	0.543	0.958	0.976	1.080	1.435**	1.843***
	(0.726)	(0.702)	(0.716)	(0.700)	(0.687)	(0.693)	(0.689)	(0.683)	(0.672)
Constant	2.998**	-5.836**	-6.299***	-5.014**	-2.986	-2.882	-7.225***	-3.675	-1.583
	(1.680)	(2.344)	(2.373)	(2.335)	(2.237)	(2.386)	(2.271)	(2.446)	(2.504)
Mills (λ)	0.848	0.682	0.713	0.529	0.466	0.446	0.522	0.739	0.580
	(0.609)	(0.586)	(0.586)	(0.571)	(0.564)	(0.573)	(0.563)	(0.561)	(0.545)
Rho	0.356	0.302	0.315	0.243	0.217	0.208	0.243	0.341	0.285
Wald X^2	127.69***	166.27***	168.17***	193.55***	204.77***	204.90***	207.17***	226.52***	285.15***
N of observations	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736

*, **, and *** Statistically significant at the 10%, 5%, and 1% level, respectively.
Note: Standard error is given in parentheses.

Conversely, the experience has no impact on the development and sale of new to the market (b) products/services. A new to the market novelty represents a radical innovation, and this finding means that its development is independent from previous acquisition activity.

The lagged value of the innovative sales has been considered to control for the pre-acquisition innovative performance, as the persistence of innovation over time and M&A activity are strictly related (Cefis and Ghita, 2008). The results show a positive impact of the lagged term on the post-acquisition turnover generated by products/services new to the firm, while as well as the experience it is insignificant in relation to the novelty for the market, underling the unpredictability and non persistency of radical innovations.

Concerning the other control variables, I notice the positive impact of the size of both the target and the acquirer on the post-acquisition innovation, consistent with the idea that bigger knowledge base generates more innovation (Ahuja and Katila, 2001; Cloodt et al., 2006). Also the previous expense of the acquirer in internal R&D has a positive impact on the innovative sales, due to the benefits of research on the absorptive capacity, as discussed in the presentation of hypothesis 2c. Regarding the control variables discussed, except for the experience and the lagged innovative performance, both model (a) and (b) lead to the same results, and they will be still confirmed also in the following more complex equations (2a/b to 9a/b).

In Models 3-9 I consider the moderator effects: in-house R&D (models 3-4), target size (models 5-6), and the previous experience in acquisition activity (models 7-8) on the relation between industry relatedness and innovation.

Hypothesis 2: I test if the impact of the R&D moderator is linear (Model 3) or not linear (Model 4) and I find its inverted U-shaped relation with the innovative performance. To better understand this result figure 3.3a/b reports how the effect of industry relatedness change due to high/low level of R&D activity. Looking at the graph it is possible to see a positive impact of internal R&D expense realized by the acquirer prior the deal on the innovative turnover for each level of market relatedness, confirming hypothesis 2. Looking again at the figure, it is shown that the (a) new to the firm innovation benefits more the (b) new to the market one from the previous involvement in R&D.

Figures 3.3-3.5 Representation of the impact of three moderating effects: interaction of the relatedness index with, respectively, acquirer pre-deal R&D expense (3), target size (4), and acquirer experience in acquisitions (5).

Figure 3.3a and 3.3b: Moderating effect of R&D expense respectively on (a) new to the firm and (b) new to the market innovative performance.

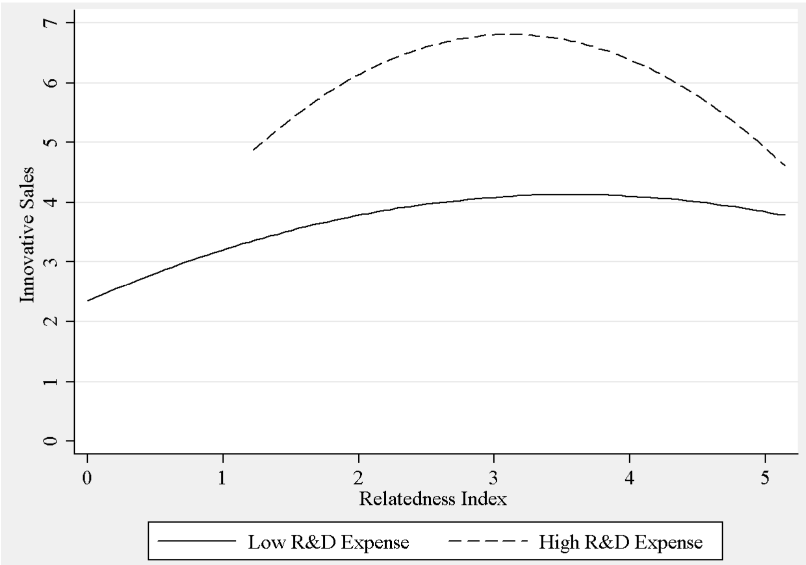

Figure 3.3a

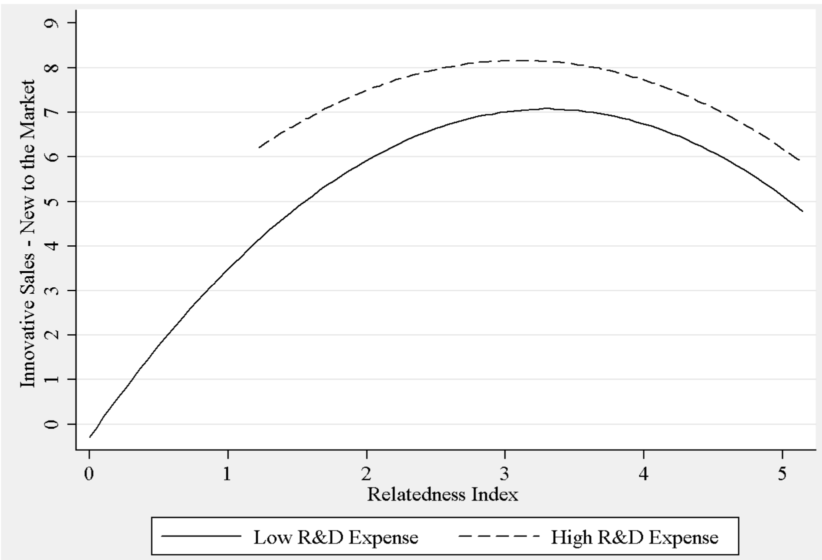

Figure 3.3b

In the same way Model 5 and 6 focus on the effect of the target size moderator, providing evidence of its linear impact on the innovative performance both for (a) and (b) equations.

Figure 3.4a/b depicts how firms that acquire larger targets benefit more from coherence in acquisition for the purpose of innovation. In fact, the maximum of the inverted U-shaped curve that expresses the impact of the market relatedness index on the innovation performance is obtained in correspondence of higher market relatedness in presence of larger targets than for smaller ones. This means, in other words, that if the acquired firm is relatively small it can be integrated to generate innovation independently on the industry relatedness. Conversely, a large target needs to be related to allow the exploitation of the knowledge embedded. Therefore, hypothesis 2b is demonstrated.

Figure 3.4a and 3.4b: Moderating effect of target size respectively on (a) new to the firm and (b) new to the market innovative performance.

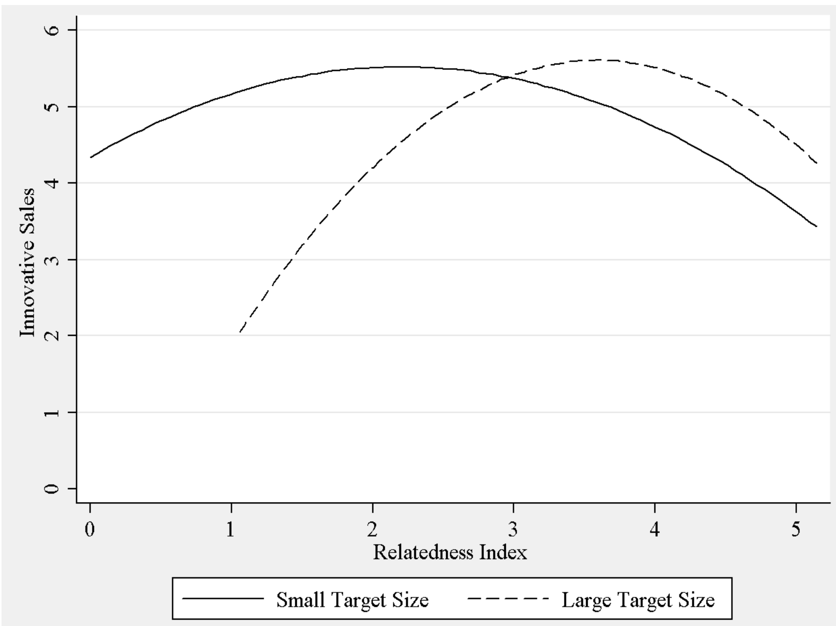

Figure 3.4a

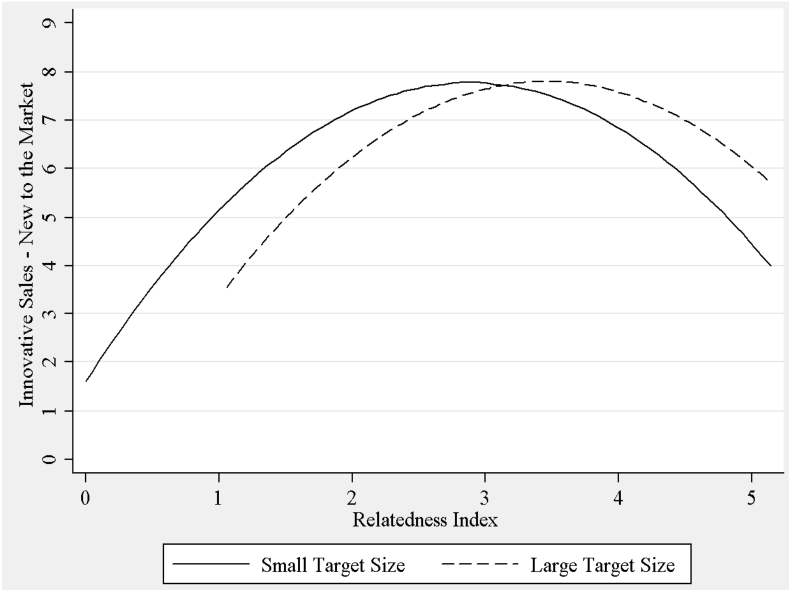

Figure 3.4b

Again, in Model 7 and 8 the last hypothesis 2c is verified. The interaction effect of experience and industry relatedness shows a non linear U-shaped relation with innovative performance. Representing the moderator effect in a plot (Figure 3.5a/b) it is shown that acquirers with higher expertise are able to generate innovative performance for every level of relatedness, while a low experience permit essentially the successful integration of related targets.

Finally, the variables analyzed in the previous steps are introduced all together in Model 9.

Figure 3.5a and 3.5b: Moderating effect of acquirer experience respectively on (a) new to the firm and (b) new to the market innovative performance.

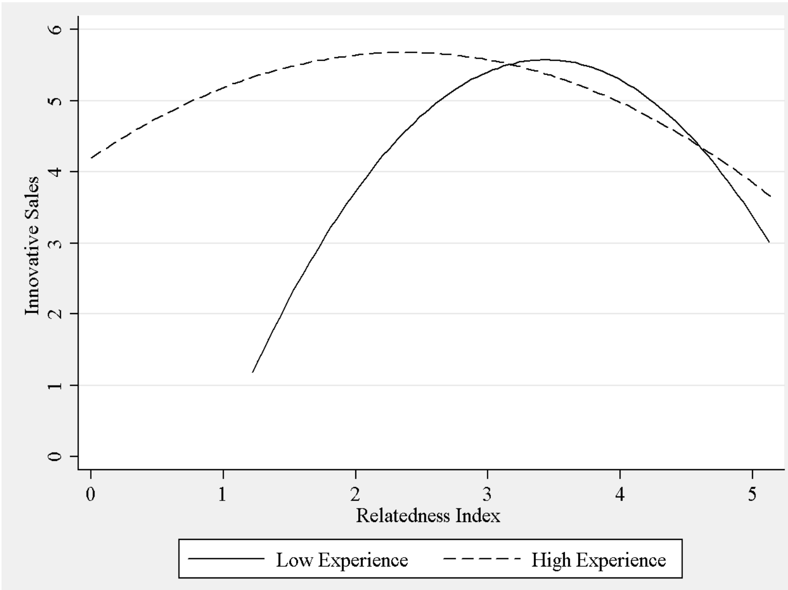

Figure 3.5a

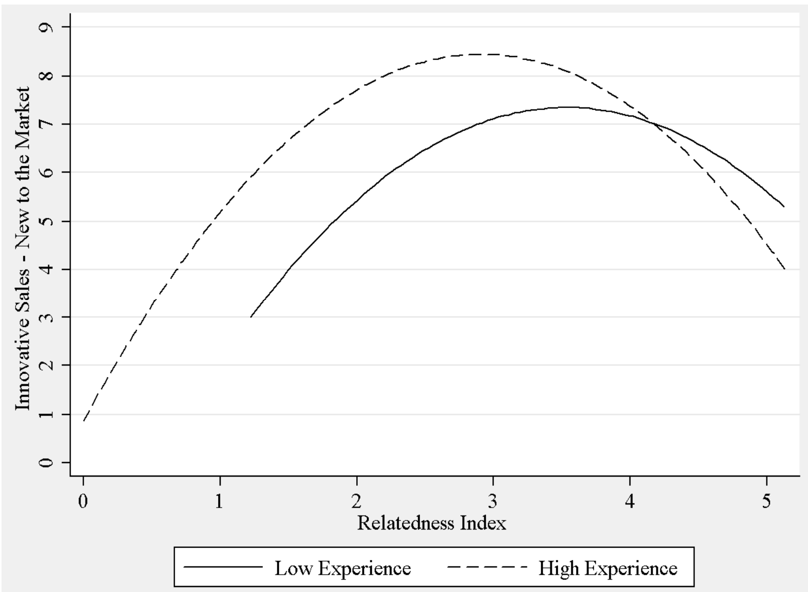

Figure 3.5b

3.7 Conclusions

This study should be interpreted as a close complement to research on acquisitions as a means to facilitate knowledge transfer with the aim of generate innovative performance. The relatedness of the acquired firm is an important factor in the choose of the target in the acquisition process. According to the absorptive capacity paradigm, acquisition of related knowledge implies a high exploitation of the synergies and will have the most positive impact on a firm's post-M&A innovative performance (Hagedoorn and Duysters, 2002; Zahra and George, 2002; Capron and Mitchell, 2004). However, the acquisition of knowledge that is too similar to the already existing knowledge base is disadvantageous, as the acquiring firm will have to bear the costs of obtaining and transferring external knowledge without any relevant enrichments of its existing knowledge base (Cohen and Levinthal, 1989). Some degrees of differentiation in resources between the acquiring and acquired firm will enrich the acquiring firm's knowledge base, creating opportunities for learning from novelty and improving innovative performance (Laursen and Salter, 2006; Miller et al., 2007).
The results of this study indicate support for the theoretical predictions, showing a nonlinear (inverted U-shape) impact of the relatedness of acquired and acquiring knowledge bases on innovative output. This suggests that to increase both "to the firm" and "to the market" innovative performance through M&As, companies have to target firms with moderately related knowledge bases, avoiding targets with knowledge bases that are either too unrelated or too closely related.

Observing a whole country market, the study extends previous findings to a complete multi-industries context, coherently with existing research focused on the relationship between technology relatedness and innovation performance in the high-tech segment, such as Cloodt et al. (2006) and Ahuja and Katila (2001). In fact, even if they concentrated the analysis on the relatedness of technologies and measured both relatedness and innovative output exclusively through patents, their results support the inverted U-shaped relation too.

Consequently, another contribution of this study is the measure of relatedness used, since the interested relies on a more general view than the transfer of technology and knowledge through patents. Indeed, I implemented in the models the industry index developed in the previous chapter following Teece et al. (1994) methodology, based on the study of the whole Dutch acquisition market.

Concerning the moderator effects, previous involvement of the acquiring firm in R&D has positive effect on the innovative performance, independently on the industry relatedness, while acquisition of larger target firms should have higher industry coherence to reach high levels of innovative output. Finally, the experience helps the post-acquisition integration and innovative exploitation of the targets, even if they are not related, while acquirers with low experience can reach high level of innovative result only when the industry relatedness is high.

The inclusion of various control variables and model specifications increased confidence in the results, as the analysis of both "to the firm" and "to the market" innovative performance gives robustness to the conclusions. More in detail, all the expectations are confirmed also looking at the more restrictive definition of innovation, but highlighting the unpredictability and non persistency of radical innovation, as both the lagged value of innovative sales and the acquisition experience are insignificant in relation to the generation of novelty for the market.

This paper has also several implications for managerial practice. Notably, it suggests that managers that intend to perform acquisition with the aim of acquire external knowledge and consequently generate innovation must take care of the industry relatedness degree. Moreover, they can predict or prevent some issues deeply valuing their internal capability such as experience and R&D ability. On this basis they can pursue a higher innovative result by choosing an appropriate target or improving their own routines to better integrate the new knowledge.

Appendix: NACE industrial classification

NACE Rev. 1 is a 4-digit activity classification which was drawn up in 1990. It is a revision of the «General Industrial Classification of Economic Activities within the European Communities», known by the acronym NACE and originally published by Eurostat in 1970. NACE Rev. 1 in turn underwent a minor update in 2002 to establish NACE Rev. 1.1. Since the present sample is obtained from the BR datasets in the span 1995-2005, I firstly controlled for the coherence in the classification. Eurostat uses an aggregation of the manufacturing industry according to technological intensity and based on NACE Rev. 1.1 at 3-digit level for compiling aggregates related to medium/high-technology and medium/low-technology. Following a similar approach as for manufacturing, Eurostat defines also the sector as knowledge intensive services (KIS) or as less knowledge-intensive services (LKIS).

Table: Main Sections of NACE Classification.

Section	Code	Definition
MANUFACTURING: Section D		
Medium/High Technology		
Subsection DG	24	Manufacture of chemicals and chemical products
Subsection DK	29	Manufacture of machinery and equipment n.e.c.
Subsection DL	30-33	Manufacture of electrical and optical equipment
Subsection DM	34	Manufacture of motor vehicles, trailers and semi-trailers
Subsection DM	35	Manufacture of transport equipment, excluding 35.1
Medium/Low Technology		
Subsection DA	15-16	Manufacture of food products, beverages and tobacco
Subsection DB	17-18	Manufacture of textiles and textile products
Subsection DC	19	Manufacture of leather and leather products
Subsection DD	20	Manufacture of wood and wood products
Subsection DE	21-22	Manufacture of pulp, paper and paper products; publishing and printing
Subsection DF	23	Manufacture of coke, refined petroleum products and nuclear fuel
Subsection DH	25	Manufacture of rubber and plastic products
Subsection DI	26	Manufacture of other non-metallic mineral products
Subsection DJ	27-28	Manufacture of basic metals and fabricated metal products
Subsection DM	35.1	Building and repairing of ships and boats
Subsection DN	36-37	Manufacturing n.e.c.

Table to be continued…

... Table continued.

Section	Code	Definition
SERVICE		
Knowledge Intensive Service (KIS)		
Section I	61	Water transport
Section I	62	Air transport
Section I	64	Post and telecommunications
Section J	65-67	Financial intermediation
Section K	70-74	Real estate, renting and business activities
Section M	80	Education
Section N	85	Health and social work
Section O	92	Recreational, cultural and sporting activities
Less knowledge Intensive Service (LKIS)		
Section G	50-52	Motor trade
Section H	55	Hotels and restaurants
Section I	60	Land transport; transport via pipelines
Section I	63	Supporting and auxiliary transport activities; activities of travel agencies
Section L	75	Public administration and defence; compulsory social security
Section O	90	Sewage and refuse disposal, sanitation and similar activities
Section O	91	Activities of membership organization n.e.c.
Section O	93	Other service activities
Section P	95-97	Activities of households
Section Q	99	Extra-territorial organizations and bodies
OTHER		
Section F	45	Construction

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CHAPTER 4

The Effect of Specialization on the Exit Strategy of Private Equity Firms

Abstract

This paper addresses the Private Equity (PE) exit strategies, focusing on two specificities of PE firm behaviour: specialization by industry and by stage. In order to test the impact of both specialization dimensions, a sample of 533 Leveraged Buyouts has been randomly picked in US and Europe over the period 2000-2009. Both the type (IPO, acquisition, SBO, and write-off) and the timing of exit decision has been considered by implementing competing-risks models. The main findings show that the PE firms with higher industry focus are more likely to exit their investments through acquisition, as a deep knowledge of a specific market enables PE firms to mitigate information asymmetries with the buyer. By contrast, PE firms with higher portfolio diversification are more prone to exit through an IPO. Moreover, a higher stage (buyout) specialization decreases PE firms probability of writing-off their investments.

Keywords: Leveraged Buyouts; Private Equity; Exit Strategies; Specialization; Competing-risks model; IPO; M&A, Secondary Buyouts

4.1 Introduction

Less than 20 years after the previous crash, the last decade (2000s) showed an important resurgence of leveraged buyouts (LBOs). United States and the rest of the world experienced a second LBO boom, both in terms of number and size of deals, driving the interest in both academic and practitioner literature (Cumming et al., 2007; Kaplan and Stromberg, 2009). In an LBO, a specialized investment firm, called Private Equity (PE henceforth) firm, acquires a target company using a relatively small portion of equity and a relatively large portion of outside debt financing. The typical PE firm is organized as a limited partnership and it raises capital through closed-end funds. Since most of these funds have a fixed contractual lifetime, usually ten years, exiting the investment is a central aspect of PE process. Moreover, most of PE returns arise in the form of capital gains and they can ultimately be measured only at the exit (Cumming and Macintosh, 2003a; Wright et al., 2007; Kaplan and Stromberg, 2009). Therefore, PE's investments usually depend on exit potential (Schwienbacher, 2005; Cumming et al., 2006) and the investigation of how PEs exit their investments is primary to the understanding of the LBO process. In fact, there is evidence that the prospective suitability of the various exit methods is considered by PEs to be an important factor in deciding whether to invest in a company (Black and Gilson, 1998; Cumming and Macintosh, 2003a).

According to Kaplan and Stromberg (2009), the available exit methods are classified as follows: acquisition exit (M&A), secondary sale (SBO), Initial Public Offering (IPO), and write-off. With the exception of the last mentioned, each represents a business opportunity that may not have presented itself without initial PE involvement. Moreover, this decision is strictly related to the characteristics of the two parties involved in the deal (the PE firm and the target) and also to the contextual conditions, such as capital market trends, fundraising or country features (e.g. Cumming et al., 2006; Cressy et al., 2007).

When the PE exits its investments, there is a potential information asymmetry arising between the investor and the buyers, and the extent of the asymmetry depends on the type of exit vehicle adopted. Different buyers are well positioned compared to others to resolve information asymmetries, and evidence (Cumming and Macintosh, 2003a) shows that the investor, as seller, will generally select that form of exit that results in a sale to the buyer(s) best able to resolve information asymmetry.

Earlier research (Norton and Tenenbaum, 1993; Bottazzi et al., 2004; Cressy et al., 2007; Gompers et al., 2008) introduces two strategic dimensions of PE firm behaviour: firm investment specialization by industry and by stage. I address the concept of PE firm investment focus as a strategy to mitigate information asymmetry issues at the time of exit, and the consequent likelihood in the choice of an exit vehicle over the others.

PE firms specialized in a specific industry or stage of investment own a deeper knowledge of the competitive environment of acquired companies, reducing uncertainty as the PE firm gains more in-depth knowledge of companies in that market or stage (Cressy et al., 2007). A key element in PE investment is the creation and development of a network of industry contacts that are suitable to identify good investment opportunities as well as the know-how to manage and add value to these investments.

In order to test the impact of both specialization dimensions, a sample of 533 LBOs has been randomly picked in North America and Europe over the period 2000-2009. In the framework of survival analysis (see Giot and Schwienbacher, 2007), I implemented a competing risk model which enabled us to perform a joint analysis of both the type and the timing of exit decision as well as their dynamic interplay. Moreover, the work takes into account all potential exit routes mentioned as well as the duration of the investment.

I argue that PE firms with higher industry focus are more likely to exit their investments through acquisition, as the PE firm plays as a role of channel between the target and the final strategic buyer, using its skills in mitigating information asymmetries.

In fact, in a sale of the entire firm to a third party, the buyer, usually a large company in the same or similar business as the purchased firm, will often be a strategic acquirer and will often integrate the company's technology with its own following the acquisition.

As expected, the findings show a positive link between industry specialization and acquisition exit; on the other hand, I found a negative likelihood of quotation for PE firm with specific sector orientation. This evidence is consistent with Cumming and

Macintosh (2003a), that suggest that one of the main advantages of a sale of the company in its entirety (as in an acquisition exit) over an IPO is that it is most likely to result in the realization of transaction synergies. Moreover, this result suggests the existence of two main PE firm strategies in exit decision: market specialist and IPO specialist. A market specialist PE firm uses industry specialization as the preferred strategy to solve informational asymmetries through knowledge of both the investee company and the market in which it works; the PE firm has indeed deep expertise to make the investee firm attractive for a strategic acquirer. By contrast, the results suggest diversification as an alternative strategy, whereas PE firm selects investee company with the aim of quotation, regardless of the industrial sector.

Secondly, I also predict that the stage specialization should be associated with higher success of the investment, supported by the idea that investors with more expertise in LBOs have less probability to fail. Indeed, the empirical model shows that specialization decreases the probability of writing-off, even if it does not show a significant impact on any of the successful exit channels (IPO, acquisition, SBO). The result is consistent with the work of Cressy et al. (2007), which shows a very little systematic effect of this characteristic of PE firms on profitability or growth.

Finally, controls for the main PE firm's and investee company's characteristics have been added in the analysis; in such a way, this paper provides the opportunity of testing on LBOs the subsistence of main results confirmed by Venture Capitalists (VC) exit literature, highlighting similarities and differences between the two markets. In fact, because of combined effect of limited publicly available information for private companies and the overlapping nature of the sponsors involved in PE activities, exit behaviour of PE firms remains almost an unexplored area, despite its importance for industry survival and economic growth (Espenlaub et al., 2010). VCs have traditionally been more frequently studied in academic work. However, empirical analysis usually did not distinguish between early and later stage investors (e.g. Schwienbacher, 2005), even if there are a lot of different aspects that distinguish between PE firms and VCs, such as the majority versus minority control, the PE firms' highly leveraged capital structures and the pursuit of financial, governance and operational engineering (Jensen, 1986; Kaplan and Stromberg, 2009).

Exploring the dynamics that influence PE exit strategies is a topic of central interest, because it can suggest a private investee company, given its characteristics, what it should expect from the buyout of a specialized vs. diversified PE, and it also helps target companies' managers in dealing with PE investors. In fact, in the process of locating a suitable investor, it is important to be able to categorize potential investors based on their investment preferences and understand the criteria that investors from various categories use to evaluate their prospective investments (Carter and Van Auken, 1994; Cressy et al., 2007).

The reminder of the paper is organized as follows. Section 4.2 provides a brief review of the literature and develops testable hypotheses about PE firm's specialization by industry and by stage. Section 4.3 describes the sample and the methodology applied in the study. In Section 4.4 the variables used in the analysis and the descriptive statistics are reported. Section 4.5 presents empirical results and findings. Sensitivity analysis is presented in Section 4.6. Finally, the conclusion is discussed in Section 4.7.

4.2 Theoretical framework and Hypotheses

Academic studies of LBO behavior have mirrored the growth in the private equity market. Jensen (1989), who wrote his seminal paper in the wake of the 1980's LBO boom, argued that the LBO organizational form, which combined high leverage levels, concentrated ownership, and high-powered incentives, was a superior way to deal with corporate governance problems in firms. This hypothesis was supported in the empirical work studying the 1980's buyouts, such as Kaplan (1989; 1991) and Smith, which documented significant gains in profitability, productivity, and financial performance for firms after being acquired in LBOs. As the private equity market continued to grow in the late 1990's and 2000's, subsequent work (such as Acharya et al., 2009; Lerner et al., forthcoming) large corroborated the positive view of the earlier studies, finding that LBOs have a positive effect on firm performance.

The exit process is of central interest because private equity investments typically don't pay dividends; rather returns are derived from capital gains upon exit and a private equity's decision to invest usually depends on exit potential (Schwienbacher, 2005; Cumming et al., 2006). As a consequence, private equity returns are directly linked to the exit from an investment.

There are four main exit methods in LBO field (Kaplan and Stromberg, 2009; Wright et al., 2009): (1) initial public offering (IPO) - the entrepreneurial firm is listed on a stock exchange for the first time; (2) acquisition or trade sale (M&A), where the company is purchased by a third party, in general by a strategic acquirer; (3) secondary sale (SBO) - the PE sells the company to another PE investor; and (4) write-off (or liquidation) as the investors walk away from the investment with little or no return. Kaplan and Stromberg (2009) analysed a large sample of more than 17,000 LBO transactions, collected from CapitalIQ database in 1970-2007 span, and among the empirical evidences they presented the worldwide distribution of exit manners over time. Looking at the whole period of analysis they obtained that, conditional on having exited, the most common route is the sale of the company to a strategic (nonfinancial) buyer, followed by secondary leveraged buyout and IPO, and finally write-off[15].

Because of combined effect of limited publicly available information for private companies and the overlapping nature of the sponsors involved in PE activities, VCs have traditionally been more frequently studied in academic work, otherwise empirical analysis usually did not distinguish between early and later stage investors (e.g. Schwienbacher, 2005). Moreover, while IPO exits by VC funds have been researched quite extensively[16] due to the greater amount of information available for IPO exits (the only public exit in that information must be disclosed in a prospectus), a stock market listing is however one out of several ways to exit private equity investments.

Since Venture Capitalists are, as the PE firms, Private Equity operators their investments have some analogies. However, there are a lot of different aspects that distinguish these two operators, first of all the well known point that, in a typical

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[15] The acquisition exit occurs in 38 percent of exits. The second most common exit is a secondary leveraged buyout (24 percent); this route has increased considerably over time. Initial public offerings, where the company is listed on a public stock exchange (and the private equity firm can subsequently sell its shares in the public market), account for 14 percent of exits; this route has decreased significantly in relative importance over time. Moreover, at least 6 percent of deals have ended in write-off or reorganization, given the high debt levels in these transactions, but not all cases of distress may be recorded in publicly available data sources and then some of these cases may be "hidden" in the relatively large fraction of "unknown" exits (11 percent), (see Kaplan and Stromberg, 2009).

[16] See, among others, Gompers (1995; 1996), Black and Gilson (1998), Cumming and Macintosh (2003a) Schwienbacher (2005).

leveraged buyout transaction, the private equity firm buys majority control of an existing or mature firm. This arrangement is distinct from venture capital firms that typically invest in young or emerging companies, and typically do not obtain majority control (Kaplan and Stromberg, 2009).

The behaviour of LBOs exits remains almost an unexplored area in the study of private equity firms, despite its importance for industry survival and economic growth (Espenlaub et al., 2010).

Some studies have analyzed LBOs in relation to increase in operating performance and profitability (Cressy et al., 2007) or to returns realized by the investor (see Nikoskelainen and Wright, 2007; Acharya et al., 2009), and in more recent years also concerning corporate governance (e.g. Cornelli and Karakas, 2010, study some PE characteristics, but only referred to their behaviour during the investment, such as governance improvement of target structure).

Referring however to VC literature, recent empirical research has considered the determinants of exit choice; main studies of exits report that exit choices are determined by information asymmetry between the seller and buyer of venture capital investments, a country's legal environment, market liquidity and the sector of a portfolio company (Cumming and Macintosh, 2003a; Cumming et al., 2006; Cressy et al., 2007; Giot and Schwienbacher, 2007). Cumming and Johan (2008) investigated the associations between pre-planned exits and the structure of venture capital contracts. Evaluating 223 entrepreneurial companies from 11 continental European countries, they found that VCs often pre-plan their exits, either through IPO or M&A. Furthermore, some studies in Europe showed that exits through M&A are more likely than IPO exits, while in the US exits through IPO are more likely than via M&A route (Behnke and Hültenschmidt, 2007; Giot and Schwienbacher, 2007; Isaksson, 2007).

4.2.1 The effect of specialization

Black and Gilson (1998), Cumming and Macintosh (2003a; 2003b), Cumming et al. (2006) and others rank order the exit vehicles by the quality of the entrepreneurial firm (from highest to lowest): IPOs, acquisitions, secondary sales, buybacks[17] and write-offs. One of the many driving principles underlying this ordering (among more than a dozen different factors that could affect the ordering) relates to information asymmetries. In order to maximize the capital gain upon exit, a private equity will choose the exit vehicle for which the new owners are best able to resolve information asymmetry. When informational asymmetries are lowest, the new owners are willing to pay more for the company. As it is typically most difficult for new owners in an IPO to mitigate informational problems (see Pagano et al., 1998), Cumming et al.(2006) stated that venture capitalists will only take public the best quality firms for which informational asymmetries are least pronounced.

Moreover the dramatic growth of the PE industry since the mid '90s and the ensuing competition created pressure on PE firms to redefine their investment strategies to gain competitive advantage over their peers (Harper and Schneider, 2004; Cressy et al., 2007). Recent industry reports show that many PE firms tend to circumscribe their activities by accurately choosing industries to include in their portfolios whilst others divide their organizational structure into separate units devoted to specific industries or stage of development, with the idea of accruing and exploiting industry expertise to competitive advantage (Bishop, 2004; Evca, 2005). Whilst little work has been done to test the effects of investment specialization, Gompers et al (2008) found that investments made by US VCs with a greater degree of industry specialization tended to be more successful, measured by a greater likelihood of profitable exit (i.e. IPO, acquisition, merger).

Cressy et al. (2007), analysing the main reasons that drive PE companies to specialisation, reported that the specialist has a potential competitive advantage over its peers arising from two main sources: (a) reduced information asymmetries as the firm learns more about e.g. the average company's ‘private’ probability of success in that industry or stage (Eisenhardt, 1989); (b) reduced uncertainty (via tighter posterior probabilities of success) as the firm gains more in-depth knowledge of companies in that area or stage. Set against this of course must be the ‘cost’ of reduced portfolio

[17] Following Kaplan and Stromberg (2009) definition of LBOs' “Manner and timing of exit”, buyback is not considered in our analysis (see also Cressy et al., 2007); this exit route is presented exclusively in VC framework. This should not exclude the possibility of Buyback in LBO, but it is not possible to distinguish this specific strategy using main datasets, and it may be hidden in the fraction of “unknown” second sale exit.

diversification, a well known means to control risk exposure by reducing unsystematic or specific risks. On the other hand, a high degree of specialization is useful for controlling risk as well as for gaining access to networks and information; Norton and Tenenbaum (1993) suggest that due to their information advantage in certain technologies or markets, and the high fixed costs of gaining expertise in other technical and products areas, it does not make economic sense for private equity investors to seek portfolio diversification. Investors seek to manage operating and technical risks by gaining access, by means of their reputation in their specialization, to information flows and deal flows in networks. Moreover, private equity firms use their industry and operating knowledge to identify attractive investments, to develop value creation plans for those investments, and to implement the value creation plans. A plan might include elements of cost-cutting opportunities and productivity improvements, strategic changes or repositioning, acquisition opportunities, as well as management changes and upgrades (Acharya et al., 2009).

In a sale of the entire firm to a third party, the buyer will often be a strategic acquirer. A strategic acquirer will usually be a large company in the same or similar business as the purchased firm, either as competitor, supplier, or customer, and will often integrate the company's technology with its own following the acquisition. That strategic acquirers are usually the same or a closely related business to the acquired firm is not merely accidental (Cumming and Macintosh, 2003a). Exit through trade sale, involve less informational asymmetries for the new owners than in the case of IPO strategy, and this is enhanced when the PE firm has a specific expertise in well definite industry.

This idea, (see Gompers et al., 2008) points to the importance of industry-specific human capital and suggests that a critical part of private equity investing is the network of industry contacts to identify good investment opportunities as well as the know-how to manage and add value to these investments. These contacts and know-how come only from long-standing experience doing deals in an industry.

In this study, industry specialization is defined as a driving principle in solving information asymmetries, enhancing this concept in the case of exit through acquisition. In M&A exit in fact the PE firm plays as a channel in between the target and the final strategic buyer; as more the PE firm has specific market expertise, the easier should be the conclusion of the transaction.

The second dimension of specialization refers to the focus of the PE firm's portfolio by stage of investment (buyout versus seed, early stage or expansion). Because the types, qualities, and quantities of information about a firm are likely to be function of stage, one would expect that investors might specialize in specific stages of development where expertise in evaluation may be more valuable (Carter and Van Auken, 1994). However Cressy et al.(2007) found that stage specialization in LBOs field has only little effect in relation to investee firm post-buyout performance, I argue that PE firms specialized in LBO are able to provide more effective monitoring and advice. Later stage of investments needs higher concerned investors in management and operational engineering than early stage, and more expert investor can face up better this situation.

In the case of syndicated deals, I refer specifically to the diversification strategy adopted by the lead investors, based on previous evidence showing that they tend to exert a primary role and influence in such cases (Wright and Lockett, 2003; Cressy et al., 2007)[18].

The following two hypotheses are thus advanced:

Hypothesis 1*: Private Equity firms with higher industry specialization will exit their investments by acquisition.*

Hypothesis 2*: Private Equity firms with higher stage specialization will have less probability of exit their investments by write-off.*

[18] Syndicates consist of consortia of PE firms co-investing in a company and sharing a joint pay-off. Each syndicate involves a numbers of firms. One of them will typically act as a leader, initiating the transaction and coordinating the consortium's activities, with other firms participating as 'followers'. Previous US research has shown that the lead investor holds on average larger equity stakes compared with non-lead investors and tends to adopt a more hands-on approach than his colleagues, being much more involved in the monitoring and managing of the investee company (Gorman and Sahlman, 1989; Barry, 1994; Das and Teng, 1998). A UK study by Wright and Lockett (2003) based on a sample of 58 VC firms also provides empirical support for the dominant influence of lead VC firms in syndicated deals. Lead-investors were found to be much more likely to take charge of coordination tasks in syndicate activities, adopting a hands-on approach to the investee company. Finally such lead-firms tended to select and structure the deal and hold residual control rights ensuring timely decision-making of the consortium.

Private equity firms differ also widely in terms of age, size of funds under management, managerial style, affiliation, previous experience, (Cumming and Macintosh, 2003a; Bottazzi et al., 2004; Gompers et al., 2008) and all of these variables need to be quantified and factored into the estimation, as well as main controls for the investee firm, such as size, age and industry, and transaction and market features. Control variables implemented in the model are discussed in section 4.

4.3 Methodology and Data

4.3.1 Method: competing-risks model

The aim is to investigate whether PE firms specialization by industry and by stage affect their decision to choose one particular exit strategy over another. Therefore, I applied a Competing-risks regression based on the method of Fine and Gray (1999), that provides a useful alternative to Cox regression (Cox, 1972) for survival data in the presence of competing risks. Fine and Gray (1999) developed the proportional subdistribution hazards model, centred on directly assessing covariate effects on a Cumulative Incidence Function (CIF) for particular use in competing risks analysis.

The estimation with this method produces estimates of the exponentiated coefficients known as subhazard ratios. A positive (negative) coefficient means that the effect of increasing that covariate is to increase (decrease) the subhazard (that is to increase (decrease) the CIF across the board), and thus reduce (enlarge) the survivor time. While censoring merely obstructs from observing the event of interest, a competing event prevents the event of interest from occurring altogether. Moreover, when the competing risks (CR) are ignored and the CR observations are censored the analysis reduces to a ‘‘usual’’ time-to-event scenario; every time the CR observations are censored the estimation of the probability of event is incorrect and the interpretation of the effect of covariates is not clear due to the lack of knowledge of the independence between the event of interest and CR event. Instead, when the analysis is performed accounting for CR (and coded distinctly from the event of interest or the censoring) then the probability is correctly estimated and the modelling has a straightforward interpretation. The coefficient of a covariate thus estimated represents the effect of that covariate on the observed probabilities.

4.3.2 Sample and data source

The sample used in this study consists of 533 leveraged buyouts that took place in North America and Europe over the period 2000-2009. The decision to consider this time-window is relevant because it regards the second wave[19] of LBO industry, which occurs not only in the U.S. but also internationally. Hence the results of the study will not be biased by the presence of deals belonging to different environmental, industrial or specific contexts, as it was in the 1980s.

All the possible exit modes have been considered (see Section 4.2): IPO, M&A, SBO, Write-Off and Not-exited at 31/12/2009, (for the latter, PE investor should not have acquired the target company later than 2007). Data and information have been collecteusing the main deal databases, such as Thomson OneBanker[20] and Zephyr (Cressy et al., 2007), and also checking the official webpage of the PE observed. The sample has been randomly picked among all the deals realized in the span of time considered and controlling for the continuous presence of the PE in the target capital for the entire investment period and under the condition of availability of data. Concerning the data availability issue, it is necessary to highlight the well known challenge in the collection of PE-backed firms specific information, due to the limited publicly available information for private companies and the overlapping nature of the sponsors involved in PE activities (Levis, 2011).

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[19] Concerning to LBOs diffusion, Kaplan and Stromberg (2009) documented that leveraged buyouts first emerged as an important phenomenon in the 1980s, primarily in U.S., Canada, and to some extent U.K., where this first wave was dominated by relatively large transactions in mature industries (such as manufacturing and retail). Following the fall of the junk bond market in the late 1980s, public-to-private activity declined significantly, and was relatively scarce during the 1990s and early 2000s. In the mid-2000s, fewer than 20 years after the previous crash, LBOs transactions reappeared growing rapidly in numbers and size, when the United States (and the rest of the world) experienced a second leveraged buyout boom. LBO activity spread to new industries such as information technology/media/telecommunications, financial services, and health care while manufacturing and retail firms became less dominant as buyout targets. Buyouts also spread rapidly to Europe. From 2000–2004, the Western European private equity market (including the United Kingdom) had 48.9 percent of worldwide leveraged buyout transaction value, compared with 43.7 percent in the United States. Moreover, the pattern of private equity commitments and transactions over recent decades, subject to boom and bust cycles, suggests that credit market conditions may affect this activity and, furthermore, that private equity investors take advantage of systematic mispricings in the debt and equity markets.

[20] Venture Economics classifies all venture capital and private equity deals in 6 categories, according to the stage of development of the investee company: seed, early-stage, expansion, later-stage, buyout/acquisition, and other. We are interested “Buyout/Acquisition” deals.

For each deal, I checked for syndication, identifying the lead PE firm. Again, I collected the characteristics of this latter and I constructed for it measures of the degree of specialization, experience and size, as proposed by Cressy et al. (2007).
Regarding the targets, I looked for market and industrial data at the PE entry, and the market condition concerning each single deal. Moreover, the competing risks methodology used in the empirics also required the collection of the duration of each investment. In detail, I collected the exact duration, in months or fraction of month, for the exited investment, while I calculated the span between the entry of the PE until 31\12\2009 for the not-exited ones. Finally, testing the hypotheses on a sample spread on North America and Europe permits the understanding of a general result (Kaplan and Stromberg, 2009), while most of the previous studies have been concern US markets only, while European countries have received little academic attention. However, the model includes country and industry controls.

Table 4.1 provides the frequency of exit routes, calculated for the whole sample and considering geographical breakdown. Among the 533 investment in the dataset, 28 companies (10% of concluded deals) were exited by means of IPO, 179 exited by a private sale, precisely 107 acquisition (38%) and 72 secondary sales (25.5%) and 74 ended up as write-offs (26.5%); the remainder 252 companies in the data have not been exited yet. The data are similar in size and scope to other hand-collected datasets in academic venture capital research (see, Lerner and Schoar, 2005 , for a sample of 210 private equity transactions in developing countries, and the work of Nikoskelainen and Wright, 2007, made on 321exited UK LBOs) and moreover the fractions of exit methods are coherent with the worldwide analysis performed by Kaplan and Stromberg (2009) in Leveraged Buyouts field. Finally, the sample spans to U.S. (263 observations) and Europe, this latter distinguished between United Kingdom (177 deals) and the rest of Europe, with 93 observations. A breakdown of exit route by PE firm country is presented in Table 4.1 as well. It shows that acquisition exit is the most common strategy within all three groups and, as expected, IPO exit is more popular in U.S. (11% of the deals), due to the presence of more active market, than in Europe (8.8%).

Table 4.1 Sample breakdown by exit strategy and country. The table presents the distribution of the sample by exit strategy and by country. The sample consists of 533 LBOs that took place in North America and Europe over the period 2000-2009. I considered all the possible exit modes (see Section 4.2): IPO, M&A, SBO, Write-Off and Not-exited at 31/12/2009, (for the latter, PE investor should not have acquired the target company later than 2007).

Country	*IPO Observations*	*Acquisition Observations*	*SBO Observations*	*Write-off Observations*	*Not-exited Observations*	*Total Observations*
North America	16	53	30	45	119	263
UK	7	35	25	23	87	177
EU ex UK	5	19	17	6	46	93
Total	28	107	72	74	252	533

4.3.3 Investment duration

A factor that should be taken into account in PE exit analysis regards the duration of the investment. Kaplan and Stromberg (2009) found that the median holding period for individual leveraged buyout transactions in their sample is roughly six years, but this has varied over time; also Wright et al. (2007) reviewing evidence on the development and effects of private equity and management buyouts in OECD countries, found that exit tends to take place 3-5 years after the buyout.

Recently, together with the increasing in SBOs numbers, private equity funds have been accused of becoming more short-term oriented, preferring to “flip” their investments rather than to maintain their ownership of companies for a sustained time. Again, because of the high fraction of secondary buyouts in recent years, the individual holding periods understate the total time in which leveraged buyout firms are held by private equity funds. Furthermore, results in VC framework showed how different exit strategies have different duration distribution, even if the literature offers empirical results which seems to be each other incompatible (e.g. Cumming and Johan (2008) found that investments in target companies that have concluded with an IPO have a shorter duration than the other routes, as opposed to Félix et al. (2008) that showed how exits by acquisition are faster than IPO ones).

Coherently with Cumming and Johan (2008), Table 4.2 shows that investments concluded by means of IPO have a shorter duration than the other routes. However, this evidence is confirmed in U.S. and UK, but not in the rest of Europe, probably due to the lower liquidity of the stock market.

Furthermore, the longer the private equity firm's investment duration is, the more likely the following exit vehicles will be used (in decreasing order of likelihood): IPOs, acquisitions, secondary buyouts and write-offs. This evidence is almost coherent with Cumming and Macintosh (2003a) research in venture capital field, where the unic difference in likelihood is that they found shorter duration for secondary sales than acquisition. Finally, the duration of the investment is higher for investee firms that eventually were liquidated, always greater than 40 months with respect to each geographical location.

Table 4.2 Sample duration breakdown by exit strategy and country.

Country	*IPO*		*Acquisition*		*SBO*		*Write-off*		*Not-exited*	
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
North America	31.72	14.98	37.31	20.44	38.64	15.23	40.42	27.09	46.94	19.16
UK	26.91	9.52	38.65	18.42	41.15	18.53	43.94	24.54	54.14	22.30
EU ex UK	39.21	23.34	37.21	17.82	35.59	21.34	41.59	31.42	60.52	23.96

4.4 Variables and summary statistics

4.4.1 Empirical variables

A listing of the variables used in the empirical analysis along with their definitions is provided in *Table 3*. Some explanation for the choice of these variables now follows.

Industry specialization is defined by the *Industry Focus* variable, which permits to distinguish between industry specialist versus generalist strategies. Industry specialization proxy is calculated as the percentage of PE portfolio investment realized in its primary industry prior to the time of the investment in question, multiplied by a dummy taking value of 1 when the target sector belongs to PE primary industry, 0 otherwise. So this variable takes percentage values when the target company belongs to PE primary industry, 0 otherwise[21]. *BO Stage Focus*, created as the number of buyout dedicated funds divided by the total number of funds managed by the PE firm at time of the investment, is a dimension of specialization that refers to the focus of PE firm's portfolio by stage of investment (buyout versus seed, early stage or expansion), as proposed by Cressy et al. (2007).

[21] In the definition of our original measure or Industry specialization we referred to, among others, to Cumming et al. (2006), Gompers et al.(2008), and Cressy et al. (2007).

Table 4.3 Definition of the variables used in the empirical analysis.

	Definition of explanatory variables
Theoretical independent variables	
Industry Focus	The percentage of PE portfolio investment realized in its primary industry multiplied by a dummy taking value of 1 when the target sector belongs to PE primary industry, 0 otherwise, at buyout instant[22].
BO Stage Focus	The number of Buyout specific funds divided by the total number of funds managed by the PE firm at buyout.
PE Control variables	
PE Age	Age of the PE firm at entry moment (log of years).
PE Funds	The number of funds managed by the PE firm at time of entry (log of number).
PE Efficiency	The number of firms in the portfolio divided by the number of funds managers.
Captive PE	A dummy variable equal to 1 if the investor is bank, insurance or government affiliated.
Syndication	Syndication size (log of number).
Co-investment	Dummy variable equal to 1 if there was more than 1 PE fund within the same PE organization that financed the target firm.
PE country dummy variables	Country dummy variables (specifically: North America, UK and Europe except UK).
Duration of investment	The number of months from the date of first PE investment to the date of exit (or to December 2009 if unexited).
TG Control variables	
TG Age	Age of the target at buyout (log of years).
TG employees	Number of target employees (log of number).
TG High-tech	A dummy variable equal to 1 if the target belongs to a high-tech industry (defined at 4-digit SIC code).
Further controls	
Window of opportunity	A dummy variable equal to 1 for main fundraising years (2006-2007-2008).
MSCI	The MSCI index is the country-specific Morgan Stanley Index for Market Capitalization; the value of the index 1-year prior the exit is implemented, on a 100-base with 100 representing the index value in the year 2000 (log of MSCI).

It is further important to control for the PE firm's and the investee company's characteristics, as suggested, among others, by Cumming et al. (2006) and Cressy et al. (2007) for a comprehensive analysis of the exit strategies.

Private Equity firm variables used as proxy of age and size, insert as control variables, are respectively the numbers of years of experience (*PE Age*) and the number

[22] For more detail on the construction of this variable see Section 4.2 in the text.

of funds managed (*PE Funds*) at the moment of the investment. I define investor efficiency (*PE Efficiency*) as the ability of its managers to run different investments, and consequently efficient LBO firm should employ more skilled managers. A proxy for this characteristic, implemented as the number of firms in the portfolio at entry moment divided by the number of funds' managers, was firstly suggested by Cumming et al. (2006) in the study of venture capital exit related to legality, where they used it as a more correct dimension of experience rather than using the simple number of portfolio companies. The *PE Captive* dummy is a variable equal to 1 if the investor is bank, insurance or government affiliated, 0 otherwise in case of independent PE firms.

Syndicated investments imply investment partners to the Lead PE who may contribute to the selection and will contribute to the financing of candidate companies (Wright and Lockett, 2003; Cressy et al., 2007; Nikoskelainen and Wright, 2007). Following Wright et al. (1995) and Nikoskelainen and Wright (Nikoskelainen and Wright, 2007), the size of the equity syndicate (*Syndication*) is measured by the number of participating institutions. The data identifies the lead PE firm for each syndicated buyout, but do not include the ownership (investment) distribution of the participating institutions and therefore a more accurate measure of each participant's influence cannot be constructed (Nikoskelainen and Wright, 2007). The number of institutions does however serve as a proxy for the size of the investment.

A deeper control in syndication dimension is *Co-investment* dummy variable, which takes value equal to 1 if there was more than 1 PE fund within the same PE organization that financed the target firm.

Coherently with main works, I also control for investor's country, because although there are numerous similarities between the US and Europe (e.g., some aspects of monitoring intensity), there are also important differences, in particular with respect to the duration of exit stage, the use of convertible securities, the replacement of former management and deal syndication. In addition, I distinguish UK from the rest of Europe: the UK venture capital industry is the second largest in the world, next to the US in terms of Private Equity investments and accounts for 57 percent of total European Private Equity investments (BVCA 2006 and Espenlaub et al., 2010).

In the empirical tests I also consider a number of investee company's characteristics, such as size (number of employees used as proxy, *TG Employees*) and age in years (*TG Age*), both calculated at the buyout; and high-technology sector dummy (*TG_hightech*).

I expect that investment dimension is positively related to IPO exit and a short holding period, coherently with previous findings in VC operations as Wright et al. (1995) and Nikoskelainen and Wright (2007), that also proved how the size of the buyout is influential in determining returns. Moreover, smaller companies may be more difficult to exit due to the lack of interest from large industrial buyers and because they do not meet the scale required for a public listing (Nikoskelainen and Wright, 2007). Furthermore I control for investee company age, given the evidence that, even if target companies involved in buyouts are usually in the mature phase of their cycle, younger company are usually riskier investments, and so have more probability of fail.

High-technology investee firms are characterized by intangible assets, and indeed information asymmetries are likely to be more pronounced (see Behnke and Hültenschmidt (2007), that find that start-up biotech companies were increasingly choosing M&A exits over IPO exits). I identified high-tech sectors at 4-digit SIC code level using Tech-America SIC definition and the definition of British Columbia high technology sector performed by Miller and Adams (2001).

With the expression *window of opportunity* I identify a dummy for a particular moment in which the whole world experienced an extremely high fundraising level for investing in buyouts, that happened in years 2006-2007-2008, with the main pick in 2007 after which started a decline[23] (evidence from Kaplan and Stromberg (2009) and Thomson OneBanker).

Finally, as proxy for market condition we use MSCI, the standard equity price index from Morgan Stanley, to control for the state of the stock markets at the time of the exit, as Cressy et al, (2007) and Armour and Cumming (2006)

[23] By the end of 2006, private equity sponsors were engaging in transactions totaling more than $800 billion per year, and raised funding amounting to $227 billion in 2006, $312 billion in 2007 and $290 billion in 2008, after that quickly declined to 67 billion in 2009. Moreover before 2006 the fund raising never overcome the value of 169 billion (source: Venture Expert Statistics).

4.4.2 Descriptive statistics

In this section, I provide a descriptive analysis of the dataset. Estimation results for the competing risks model are given in the next section.

The main summary statistics for the dataset are presented in Table 4.4, which contains mean, standard deviation and minimum and maximum values of the variable implemented in the analysis, for the whole sample. Table 4.5 and Table 4.6 provide a breakdown of the variables by exit strategy and country.

Table 4.4 Descriptive statistics for the whole sample. Table 4.4 presents the main summary statistics for the whole sample, which contains mean, standard deviation and minimum and maximum values of the variable implemented in the analysis. The sample size is 533 observation, except for Morgan Stanley Capital Index, MSCI, not collected for not-exited investments (sample size equal: 281).

Variables	***All Sample***				
	Observations	***Mean***	***Std. Dev.***	***Min***	***Max***
Specialization variables					
Industry Focus	533	0.31	0.19	0	1
BO Stage Focus	533	0.58	0.33	0	1
PE variables					
PE Age	533	22.68	17.50	0	93
PE Funds	533	18.24	20.17	0	79
PE Efficiency	533	0.69	0.58	0	3.77
Captive PE	533	0.20	0.40	0	2
Syndication	533	0.83	1.45	0	9
Co-investment	533	0.11	0.31	0	1
TG variables					
TG Employees	533	2,675.79	8,051.96	3	115,500
TG Age	533	29.32	33.48	1	271
TG High-tech	533	0.37	0.48	0	1
Window of opportunity	533	0.26	0.44	0	1
MSCI	281	105.15	28.93	50.83	327.17

Observing Table 4.5 and 4.6 it is possible to see that the PE firms involved in IPO exit are younger (mean value about 17 years); this is even enhanced when looking at the U.S. market. This is coherent with venture capital grandstanding theory, first proposed by Gompers (1996). Gompers, using a sample of 433 IPOs explained that younger venture capital firms take companies pubic earlier than the older ones, in order to establish a reputation and successfully raise capital for new funds.

Table 4.5 Descriptive statistics by exit route. Table 5 provides a breakdown of the variables by exit strategy, IPO, acquisition, SBO, write-off and not exited investments, showing mean and standard deviation. Variables are defined in Table 4.3.

	IPO		***Acquisition***		***SBO***		***Write-off***		***Not-exited***	
	Mean	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***
Specialization variables										
Industry Focus	0.25	0.18	0.34	0.19	0.32	0.18	0.34	0.18	0.29	0.19
BO Stage Focus	0.62	0.38	0.59	0.34	0.66	0.33	0.38	0.38	0.58	0.31
PE variables										
PE Age	17.04	11.18	19.57	19.16	18.24	16.49	23.03	15.79	25.80	17.54
PE Funds	14.96	17.55	9.53	9.68	10.54	12.65	19.45	18.91	24.14	23.54
PE Efficiency	0.75	0.79	0.55	0.54	0.61	0.56	0.88	0.85	0.71	0.44
Captive PE	0.21	0.42	0.23	0.43	0.29	0.46	0.19	0.39	0.15	0.37
Syndication	1.04	1.90	0.52	1.09	0.40	0.78	2.16	2.10	0.68	1.20
Co-investment	0.25	0.44	0.06	0.23	0.70	0.26	0.24	0.43	0.08	0.27
TG variables										
TG Employees	7,276.71	10,936.19	1,731.22	2,723.07	2,926.08	5,753.95	1,730.37	4,827.19	2,771.75	10,111.65
TG Age	41.07	48.10	33.58	43.28	32.94	27.43	13.15	21.96	29.92	29.63
TG High-tech	0.29	0.46	0.36	0.48	0.32	0.47	0.54	0.50	0.35	0.48
Window of opportunity	0.46	0.51	0.61	0.49	0.58	0.50	0.22	0.41	0.01	0.09
MSCI	102.14	19.41	112.52	32.63	111.76	29.40	89.21	17.29	-	-

Table 4.6 Descriptive statistics by exit route and by country. It provides a breakdown of the variables by exit strategy, IPO, acquisition, SBO, write-off and not exited investments, and by country, North America, United Kingdom and Europe except UK, showing mean and standard deviation.

Variables		***IPO***		***Acquisition***		***SBO***		***Write-off***		***Not-exited***	
	Country	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***
Specialization variables											
	North America	0.23	0.18	0.38	0.22	0.29	0.16	0.35	0.19	0.31	0.19
Industry Focus	UK	0.30	0.17	0.30	0.18	0.29	0.22	0.33	0.19	0.30	0.19
	EU-UK	0.22	0.21	0.31	0.16	0.41	0.17	0.24	0.21	0.26	0.21
	North America	0.56	0.39	0.49	0.33	0.53	0.37	0.47	0.39	0.48	0.31
BO Stage Focus	UK	0.77	0.36	0.74	0.29	0.74	0.27	0.41	0.33	0.64	0.29
	EU-UK	0.67	0.39	0.60	0.40	0.76	0.26	0.82	0.21	0.70	0.27
PE variables											
	North America	15.13	11.58	16.81	18.41	20.30	17.42	17.27	10.53	21.87	13.22
PE Age	UK	20.71	6.45	26.40	18.91	21.04	13.92	37.26	16.58	35.17	19.15
	EU-UK	18.00	15.46	14.68	19.24	10.47	16.79	11.67	8.21	18.24	16.95
	North America	18.13	19.28	9.89	10.11	11.33	12.82	14.60	16.18	30.64	27.66
PE Funds	UK	13.71	18.43	12.20	10.01	13.56	15.29	32.61	19.30	23.43	18.80
	EU-UK	6.60	6.77	3.63	4.06	4.71	3.22	5.33	5.39	8.70	7.29
	North America	0.90	1.00	0.50	0.61	0.72	0.75	1.00	1.03	0.75	0.53
PE Efficiency	UK	0.49	0.28	0.56	0.37	0.68	0.37	0.66	0.19	0.69	0.29
	EU-UK	0.62	0.37	0.66	0.59	0.33	0.22	0.81	0.81	0.65	0.45
	North America	0.13	0.34	0.23	0.42	0.37	0.49	0.27	0.45	0.13	0.34
Captive PE	UK	0.14	0.38	0.17	0.38	0.32	0.48	0.00	0.00	0.17	0.41
	EU-UK	0.60	0.55	0.37	0.50	0.12	0.33	0.33	0.52	0.17	0.38
	North America	1.63	2.31	0.57	1.15	0.30	0.53	2.07	2.03	0.62	1.15
Syndication	UK	0.14	0.38	0.43	0.74	0.48	1.00	2.13	2.14	0.76	1.44
	EU-UK	0.40	0.89	0.58	1.46	0.47	0.80	3.00	2.68	0.67	0.79

..to be continued

…Table 4.6 continued

Variables	Country	IPO		Acquisition		SBO		Write-off		Not-exited	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Co-investment	North America	0.31	0.48	0.04	0.19	0.03	0.18	0.17	0.39	0.02	0.16
	UK	0.14	0.38	0.05	0.28	0.16	0.37	0.39	0.50	0.17	0.38
	EU-UK	0.20	0.45	0.05	0.23	0.00	0.00	0.17	0.41	0.04	0.21
TG variables											
TG Employees	North America	7838.94	13433.02	1760.28	2498.62	2582.27	3371.91	1847.78	5014.13	4259.51	14283.31
	UK	9183.43	7596.14	1580.14	3184.35	1735.08	2290.24	1913.74	5126.99	1092.44	1821.37
	EU-UK	2808.20	3389.86	1928.47	2527.76	5284.29	10492.57	146.83	119.29	2099.09	4150.63
TG Age	North America	22.81	19.37	29.13	41.01	35.73	33.39	16.02	25.98	30.09	30.19
	UK	90.71	70.45	40.00	50.40	35.08	26.02	10.09	13.93	25.48	24.41
	EU-UK	30.00	31.09	34.16	35.15	24.88	14.59	3.33	3.67	37.89	35.58
High-tech target	North America	0.31	0.48	0.32	0.47	0.40	0.50	0.49	0.51	0.29	0.46
	UK	0.14	0.38	0.46	0.51	0.20	0.41	0.70	0.47	0.48	0.50
	EU-UK	0.40	0.55	0.26	0.45	0.35	0.49	0.33	0.52	0.22	0.42
Window of opportunity	North America	0.50	0.52	0.72	0.45	0.53	0.51	0.20	0.40	0.01	0.09
	UK	0.29	0.49	0.43	0.50	0.60	0.50	0.22	0.42	0.01	0.11
	EU-UK	0.60	0.55	0.63	0.50	0.65	0.49	0.33	0.52	0.00	0.00
MSCI	North America	105.03	20.59	111.08	36.18	103.61	25.44	87.83	15.27	-	-
	UK	91.02	10.79	105.58	22.64	115.07	29.38	91.49	21.14	-	-
	EU-UK	108.46	21.90	129.34	33.49	121.26	33.62	90.81	17.47	-	-

In fact, due to the listing, younger VC are able to send a signal of ability to the market, reaching an exit channel which is usually reserved for investment of major success (Gompers, 1996; Cochrane, 2005; Bienz and Leite, 2008).

IPO exits show also the lowest PE industrial focus orientation, with average equal to 25%, against about 34% of other exit routes, and a mean level of syndication dimension of 2 PE firms, higher than acquisition and SBOs strategies. The largest syndicate is exhibited in write-off exit, meaning that this dimension is not a related to successful exit. Regarding the pattern of co-investment for the different exit routes, secondary exit presents the largest mean value (70%), followed by write-off and SBOs (around 24% and then acquisition (6%). Moreover, investee firms with larger size are more linked to quotation, while smaller ones are exited more through acquisition or liquidation. Looking at high-tech industries, the smallest fraction of investee companies operating in these sectors is showed to be exited by IPO; in contrast, more than 50% of liquidated firms are high-tech.

4.5 Empirical results

As indicated in Section 4.3, competing risks models based on the method of Fine and Gray (1999) have been performed. The correlation matrix is presented in Table 4.7, while the empirical results are presented in Table 4.8.

IPO exit

Regarding the IPO exit strategy, results reported in Table 4.8 show that industry focus decreases the propensity of choosing this exit strategy. This means that PE firms don’t develop a specific industrial expertise with the exit scope of quotation. This finding suggests the diversification as an alternative strategy, as the PE firm selects the investee company with the aim of quotation, regardless to industrial sector.

Syndication seems not have impact on this strategy, while his specific dimension of co-investment has a significant positive effect.

Moreover, investment dimension is positively related to IPO exit and a short holding period, coherently with previous findings in VC operations as Wright et al. (1995) and

Table 4.7 Correlation matrix. This table presents the correlation coefficients across selected variables, as defined in table 4.3. Correlation are provided for the whole sample of 533 observation, except for Morgan Stanley Capital Index, MSCI, not presented for not-exited investments (sample size equal: 281).

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	PE Age (1+log)	1															
2	PE Funds (log)	0.42	1														
3	BO Stage Focus	-0.03	-0.31	1													
4	PE Efficiency	0.18	0.14	-0.29	1												
5	PE Captive	-0.03	-0.20	-0.06	0.27	1											
6	Industry Focus	-0.01	-0.02	-0.07	-0.01	-0.09	1										
7	PE_USA	-0.07	0.01	-0.24	0.11	0.05	0.07	1									
8	PE_Eu_ex_Uk	-0.28	-0.32	0.14	-0.08	0.07	0.00	-0.46	1								
9	PE_UK	0.30	0.25	0.14	-0.06	-0.11	-0.07	-0.70	-0.31	1							
10	Syndication (log)	0.15	0.17	-0.09	0.16	-0.05	-0.05	0.08	-0.05	-0.04	1						
11	Co-investment	0.11	0.17	-0.03	0.10	-0.09	-0.05	-0.05	-0.09	0.12	0.52	1					
12	TG Employees (log)	-0.15	-0.11	0.15	-0.17	0.05	-0.07	0.08	0.04	-0.11	-0.19	-0.09	1				
13	TG Age (log)	-0.02	-0.12	0.31	-0.18	-0.02	0.05	-0.10	0.01	0.10	-0.24	-0.15	0.37	1			
14	MSCI (log)	-0.15	-0.09	-0.09	-0.08	-0.03	-0.06	-0.12	0.21	-0.03	-0.14	-0.09	0.10	0.09	1		
15	TG_hightech	-0.08	-0.13	-0.08	0.00	0.08	-0.02	0.02	0.10	-0.10	-0.17	-0.12	0.12	0.07	0.62	1	
16	Window of opportunity	0.09	0.13	-0.06	0.14	-0.10	-0.10	0.00	-0.06	0.05	0.16	0.11	-0.18	-0.18	-0.02	0.00	1

Nikoskelainen and Wright (2007), that also proved how the size of the buyout is influential in determining returns.

Table 4.8 Competing risks model, performed with the method of Fine and Gray (1999). All the possible exit strategies (IPO, acquisition, SBO and write-off) have been considered in the analysis. Non-exited firms are taken into account as right-censored (at the date of the analysis) observations.
Estimated coefficient are presented, while the robust standard errors of White (1980) are given in parentheses.
A ***, ** and * indicates that the coefficient is significant at the 1%, 5% and 10% respectively.

	(1) IPO	(2) M&A	(3) SBO	(4) Write-off
Industry Focus	-1.959*	1.121**	0.237	0.319
	(1.041)	(0.519)	(0.692)	(0.696)
BO Specific Funds	0.553	-0.217	0.623	-0.749*
	(0.725)	(0.296)	(0.433)	(0.449)
PE Age (1+log)	-0.0507	-0.105	-0.181	0.0344
	(0.207)	(0.127)	(0.153)	(0.143)
PE Funds (log)	-0.104	-0.432***	-0.0156	-0.135
	(0.265)	(0.114)	(0.171)	(0.149)
PE Efficiency	0.504	-0.395	0.0424	0.0344
	(0.348)	(0.245)	(0.217)	(0.189)
PE Captive	0.156	0.0430	0.375	0.0381
	(0.471)	(0.240)	(0.285)	(0.332)
PE_USA	0.281	0.409	-0.201	0.857*
	(0.558)	(0.291)	(0.337)	(0.444)
PE_UK	-0.336	0.561*	0.0885	0.365
	(0.737)	(0.309)	(0.336)	(0.478)
Syndication (log)	-0.716	-0.465**	-0.633**	0.627***
	(0.563)	(0.222)	(0.300)	(0.180)
Co-investment	1.714**	-0.322	0.184	0.288
	(0.765)	(0.479)	(0.514)	(0.322)
TG Employees (log)	0.558***	0.0122	0.0540	-0.218**
	(0.123)	(0.0563)	(0.0856)	(0.0964)
TG Age (log)	0.130	-0.00478	0.174*	-0.582***
	(0.211)	(0.0912)	(0.103)	(0.146)
Window of opportunity			1.121***	-0.590*
			(0.249)	(0.306)
TG_hightech		0.178		0.0513
		(0.210)		(0.273)
Observations	533	533	533	533
Wald test (chi-square)	68.35***	45.60***	32.14***	150.59***
Log pseudolikelihood	-150.94	-604.45	-409.26	-366.87

Acquisition exit

As hypothesized (Hp. 1) the results show a positive impact of the industry specialization for the exit through acquisition. As presented in Section 4.2, this idea (see Gompers et al., 2008) refers to the importance of industry-specific human capital and suggests that a critical part of private equity investing is the network of industry contacts to identify good investment opportunities as well as the know-how to manage and add value to these investments. These abilities take to a deep knowledge of a specific market, and hence a more propensity to sell the investment to strategic acquirers.

In relation to syndication effect on exit there is an evidence of a negative impact of this determinant on acquisition exit, by contrast with most of VC investigation that links syndication with positive and successful outcome, considering it as a signal of profitable investment and referring to the benefits of skills and expertise collaboration. Concerning then the control variables presented in the model, PE size affects negatively M&A exit, that means that smaller LBO firms have more propensity to realize M&A, and have a shorter presence in the target as well (exit earlier). This evidence can be interpreted coherently as an extension to M&A of venture capital grandstanding theory, first proposed by Gompers (1996). Gompers explained how, in order to establish a reputation and successfully raise capital for new funds, young venture capital firms take companies pubic earlier than older venture capital firms, using a sample of 433 IPOs. Thanks to the listing, younger VC are able to send a signal of ability to the market, reaching an exit channel which is usually reserved for investment of major success (Gompers, 1996; Cochrane, 2005; Bienz and Leite, 2008).

Moreover, there is no evidence on the impact of buyout specialized and captive investors, and of PE firm efficiency. In relation to country dummy variables, results show a positive impact of United Kingdom on acquisition, coherently with Schwienbacher (2005) that found that European venture firms prefer to exit via the M&A route. The significance of UK dummy variable compared to the reference case, Europe except UK, permits also to confirm the UK higher developed market in LBO field, second only after United States.

A further control for high-tech investee company is added, but without showing significant impact.

SBO exit

Regarding secondary sales, as well as for M&A, syndication negatively affects the probability of this exit route. Other PE firm characteristics seem to not impact on SBOs. On the other hand, referring to target features, older investee companies have more propensity to be sold to another private equity; older firms are more problematic and difficult to be restructured, and hence they can need more LBO investment rounds to reach a more successful exit as IPO or acquisition.

Finally, further control for window of opportunity is added, showing as expected a strong impact. Higher funding disposability incentives PE firms to undertake also less profitable or more risky investments, acquiring, among others, company already involved in leveraged buyouts Hotchkiss et al. (2011).

Write-off exit

Buyout specialization has little effect on exit strategy, decreasing the probability of write-off, confirming the second hypothesis. This result is quite intuitive, supported by the idea that investors with more expertise in LBO has less probability to fail. Stage specialization, however, does not show particular impact on a positive exit channel (IPO, acquisition, SBO) more than one other; it is also coherent with the work of Cressy et al. (2007), which showed a very little systematic effect of this PE firm characteristic on profitability or growth.

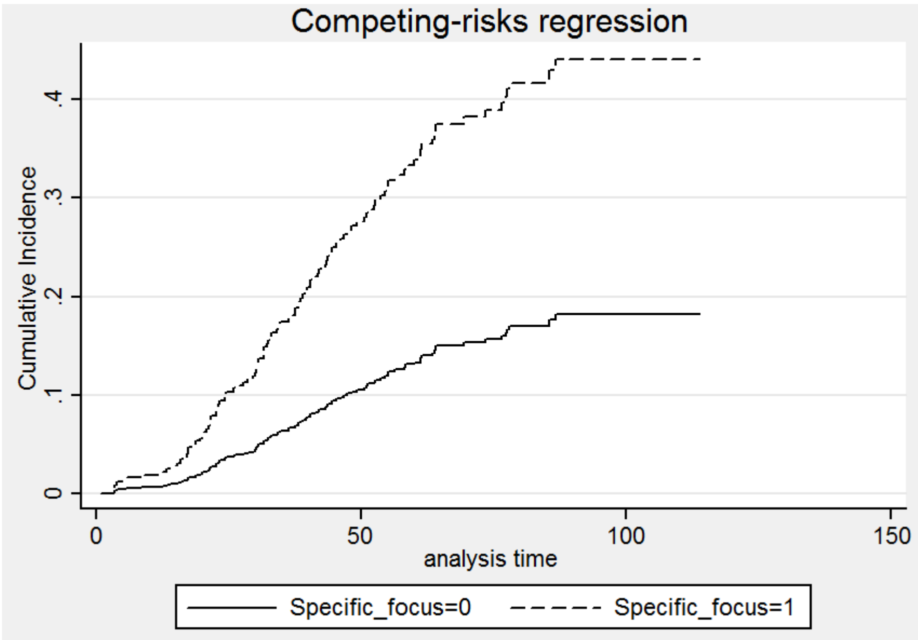
Moreover, syndication affects positively the probability of this exit route, showing a negative effect of big syndicate on successful conclusion of investments. Industry and stage focus, and other PE characteristics do not have effect on write-off, while North American PE firms show more propensity to realise fail. As discussed above, US LBO market is more developed, and among a higher number of buyouts also the possibility of liquidation will increase.

Relating to target firms characteristics, younger and smaller companies suffer more write-off risk, due to the lower amount of the investment involved. Moreover, Hotchkiss et Al. (2011) analysing PE industry in relation to financial distress, reported that unprofitable operations are more likely to be liquidated when they are PE-backed.

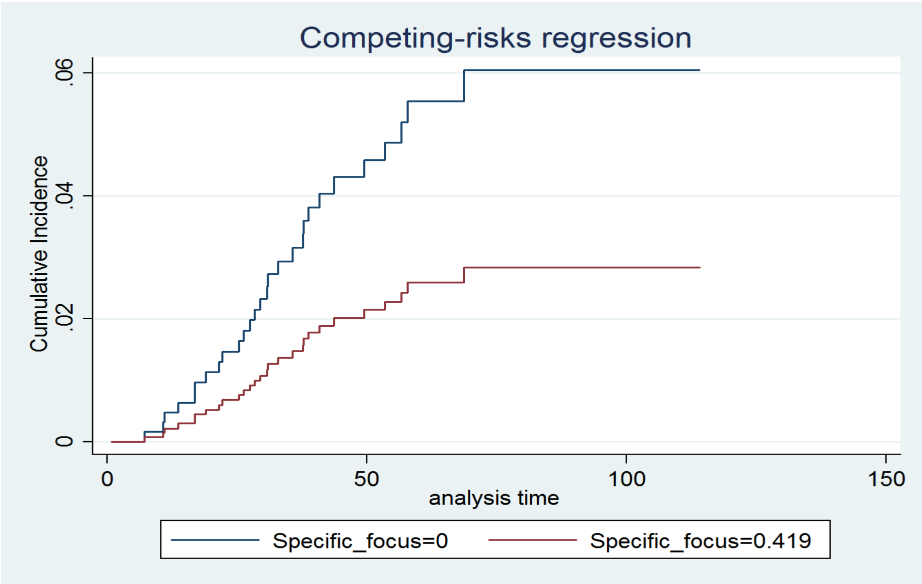
Fine and Gray (1999) imposed a proportional hazards assumption on the subdistribution hazards and gave estimators and large sample properties. This method takes into account other events and does not make any assumptions about their independence between the event time and censoring distribution, i.e., the censoring mechanism is independent of disease progression.

Hence, the proportionality assumption behind competing-risks regressions has been tested modelling time-varying coefficient: confirming that a coefficient is time invariant is one way of testing the proportional-subhazards assumption. Proportional subhazards implies that the relative subhazard is fixed over time, and this assumption would be violated if a time interaction proved significant; no indication that this assumption has been violated has been found (tests not reported for brevity).

Figure 4.1. CIF functions for IPO, Acquisition, Secondary Buyout and write-off exit; duration considered in months. Cumulative Incidence Function for IPO and acquisition exits as a function of PE firm Industry focus. All duration start at the entry of the PE firm in the investment. The x-axis denotes the number of months elapsed, while the y-axis gives the cumulative incidence probability via the specific route.



4.1a CIF: IPO exit: impact of Industry focus



4.1b CIF: M&A exit: impact of Industry focus

Figure 4.1 reports the plot of the Cumulative Incidence Function for IPO and M&A exit strategies, with the scope of representing the impact of extreme values of industry specialization variable on quotation and acquisition exit probability. The value of the other variables is set to the average. Specifically, Figure 1.1 shows how, for high level of sector focalization the probability of exit through IPO within 70 months (6 years) is roughly 2%, and near 6% when the investment strategy is diversified. On the other hand, Figure 1.2 shows how, for low level of sector focalization the probability of exit through M&A within 70 months (6 years) is roughly 15%, and near 45% when the investment strategy is more concentrated.

4.5.1 Sensitivity Analysis

Several robustness checks have been taken into account. Specifically, in Table 4.9 controls for market condition are reported. There is evidence that IPO pricing is subject to psychological factors, and not merely investment fundamentals and the operation of these psychological factors may result in periodic overvaluations of IPO firms. Indeed, IPOs will be particularly attractive means of exit during these periods of overvaluation. There is also evidence that venture capitalists can time market cycles and take their EFs public at just the right time to capture peaks in the market. Furthermore, the central conjecture in Black and Gilson (1998) is that active stock markets facilitate IPO exits and therefore active venture capital markets.

Table 4.9 Competing risks model, performed with the method of Fine and Gray (1999), adding the control for Market Capitalization with regard to IPO and write-off exits. All the possible exit strategies (IPO, acquisition, SBO and write-off) have been considered, while the not-exited deals are hereby excluded from the analysis, due to the impossibility of measure the MSCI of the year of exit. The sample size is then reduced to 281 observations. Estimated coefficient are presented, while the robust standard errors of White (1980) are given in parentheses.
A ***, ** and * indicates that the coefficient is significant at the 1%, 5% and 10% respectively.

	(1) IPO	(2) MeA	(3) SBO	(4) Write-off
Industry Focus	-2.260*	1.121**	0.237	0.196
	(1.184)	(0.519)	(0.692)	(0.678)
BO Specific Funds	0.513	-0.217	0.623	-0.895*
	(0.776)	(0.296)	(0.433)	(0.523)
PE Age (1+log)	0.0785	-0.105	-0.181	0.102
	(0.212)	(0.127)	(0.153)	(0.149)
PE Funds (log)	0.190	-0.432***	-0.0156	0.142
	(0.278)	(0.114)	(0.171)	(0.152)
PE Efficiency	0.490	-0.395	0.0424	-0.0344
	(0.315)	(0.245)	(0.217)	(0.206)
PE Captive	-0.161	0.0430	0.375	-0.174
	(0.508)	(0.240)	(0.285)	(0.394)
PE_USA	-0.138	0.409	-0.201	0.121
	(0.555)	(0.291)	(0.337)	(0.457)
PE_UK	-0.810	0.561*	0.0885	-0.0753
	(0.630)	(0.309)	(0.336)	(0.513)
Syndication (log)	-0.794	-0.465**	-0.633**	0.662***
	(0.637)	(0.222)	(0.300)	(0.171)
Co-investment	1.510	-0.322	0.184	-0.0287
	(0.967)	(0.479)	(0.514)	(0.295)
TG Employees (log)	0.497***	0.0122	0.0540	-0.221**
	(0.125)	(0.0563)	(0.0856)	(0.0989)
TG Age (log)	0.250	-0.00478	0.174*	-0.442***
	(0.209)	(0.0912)	(0.103)	(0.161)
Window of opportunity			1.121***	-0.944**
			(0.249)	(0.379)
TG_hightech		0.178		0.276
		(0.210)		(0.248)
MSCI (log)	-0.500			-1.741***
	(0.696)			(0.620)
Observations	281	533	533	281
Wald test (chi-square)	47.65***	46.92***	55.91***	205.38***
Log pseudolikelihood	-138.35	-604.06	-398.92	-335.41

However, in Cumming et Al. (2006) work, the first in providing a direct test of the expected impact, there is no evidence of increase in the probability of IPO that is directly associated with the size of a country market capitalization, against the conventional wisdom. As proxy for market condition I used MSCI, the standard equity price index from Morgan Stanley measured one year before the exit, to control for the state of the stock markets at the time of the exit, see Cressy et al, (2007) and Armour and Cumming (2006). The main results were not materially different from what obtained in Table 4.8, and both the hypotheses are confirmed as well. Moreover, consistently with Cumming et al. (2006), stock market capitalization is statistically unrelated to the probability of a PE-backed company achieving an IPO in the sample, even if the results show that MSCI indicator decreases the probability of ending a buyout via write-off.

Moreover, I also estimated the competing-risks models clustering for PE firms, and no significant changes in the results have been found. Syndication impact was tested also substituting the syndication dimension with a simple syndication dummy (such as Cressy et al., 2007), supporting again the findings.

Finally, a Multinomial logit estimation has been run (Table 4.10) concerning the probability of IPO, acquisition, SBO, write-off, and not-exited outcomes, performed with the same variables used in the Competing Risk. The regression is performed on a 5-years span, that means that the investments have to be exited within at most 5 years to be considered exited; there were 137 not-exited observations skipped from the full sample of 533, due to the lack of possibility of tracking them for at least 5 years. Regression table reports only the marginal effects, not the multinomial logit coefficients, in order to explicitly indicate the economic significance of the results (standard logit coefficients are available upon request).

A Multinomial logit model does not take into account the impact of time duration of the investment in the analysis, as survival methods can do, and in so doing it is less performing than the more complex Competing risks model. However, I ran a Multinomial logit in addition to the main competing risks model as a robustness test to assess the direct impact of the determinants on exit decision, showing the likelihood of each exit strategy versus the others, as a corroboration of the results.

Table 4.10 Multinomial logit regression analysis of exit outcomes. This table presents multinomial logit estimation of the probability of IPO, acquisition, SBO, write-off, and not-exited outcomes as a function of PE industry and stage specialization, PE firm characteristics and investee company characteristic. The numbers presented are the marginal effects, not the multinomial logit coefficients, in order to explicitly indicate the economic significance of the results. The regression is performed on a 5-years span, that means that the investments have to be exited within at most 5 years to be considered exited; there were 137 not-exited observations skipped from the full sample of 533, due to the lack of possibility of tracking them for at least 5 years. The robust standard errors of White (1980) are used. ***, **, * significant at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	IPO	MeA	SBO	Write-off	Not-Exited
Industry Focus	-0.152**	0.202**	0.037	0.153	-0.239**
	(0.067)	(0.110)	(0.096)	(0.097)	(0.121)
BO Stage Focus	0.026	-0.061	0.102	-0.016*	-0.052
	(0.043)	(0.062)	(0.065)	(0.053)	(0.079)
PE Age (1+log)	-0.007	-0.015	-0.028	0.037	0.013
	(0.012)	(0.026)	(0.023)	(0.019)	(0.031)
PE Funds (log)	0.005	-0.053	0.031	0.003	0.015
	(0.014)	(0.027)	(0.025)	(0.016)	(0.029)
PE Efficiency	0.023	-0.047	-0.002	0.012	0.015
	(0.017)	(0.038)	(0.031)	(0.023)	(0.038)
PE Captive	-0.001	-0.015	0.061	0.036	-0.082
	(0.031)	(0.051)	(0.045)	(0.039)	(0.064)
PE_USA	0.034	0.058	-0.024	0.046	-0.114*
	(0.036)	(0.056)	(0.049)	(0.046)	(0.063)
PE_UK	0.012	0.086	-0.011	-0.018	-0.069
	(0.045)	(0.063)	(0.050)	(0.050)	(0.071)
Syndication (log)	0.012	-0.066	-0.095**	0.096***	0.053
	(0.023)	(0.042)	(0.040)	(0.023)	(0.042)
Co-investment	0.106**	-0.112	-0.017	0.036	-0.013
	(0.510)	(0.096)	(0.093)	(0.042)	(0.097)
TG Employees (log)	0.035***	-0.003	-0.003	-0.017*	-0.012
	(0.009)	(0.011)	(0.012)	(0.011)	(0.014)
TG Age (log)	-0.005	-0.006	0.029**	-0.051***	0.031*
	(0.011)	(0.015)	(0.014)	(0.012)	(0.020)
TG_hightech		0.016		0.008	0.021
		(0.044)		(0.032)	(0.050)
Window of opportunity			0.116***	-0.112**	-0.199***
			(0.033)	(0.037)	(0.048)
Observations	396				
Wald test (chi-square)	177.44***				
Log pseudolikelihood	-470.29				
Pseudo R2	0.19				

As presented in table 4.10, this model confirmed both the hypothesis evidencing also a negative impact of industry specialization on write-off. This latter evidence supports the idea that PE firms that developed higher skills in specific markets have less probability of failure. Also stage specialization maintains a negative impact on write-off.

4.6 Conclusion

This paper provides new stylized facts on the competing exit possibilities for PE firms involved into leveraged buyouts. PE firm's investment usually depends on exit potential; therefore, exiting the investment is a central aspect of PE process.

I address PE exit strategies, focusing on two specificities of PE firm behaviour: specialization by industry and by stage. The concept of PE firm investment focus is here analysed as a strategy to mitigate information asymmetry issues at the time of exit, and the consequent likelihood in the choice of an exit vehicle over the others. With a sample of randomly picked 533 Leveraged Buyouts in US and Europe over the period 2000-2009, I consider both the type (IPO, acquisition, SBO, and write-off) and the timing of exit decision by implementing competing-risks models. This methodology allows the computation of the probability (sub-hazard rate) of the different exit routes, conditional on competing events, on the time already elapsed and on covariates included in the model (Cressy et al., 2007; Giot and Schwienbacher, 2007).

The findings show that PE firms with higher industry focus are more likely to exit their investments through acquisition, as the PE firm plays as a role of channel between the target and the final strategic buyer, using its skills in mitigating information asymmetries. In fact, in a sale of the entire firm to a third party, the buyer, usually a large company in the same or similar business as the purchased firm, will often be a strategic acquirer and will often integrate the company's technology with its own following the acquisition.

On the other hand, I found a negative likelihood of quotation for PE firm with specific sector orientation. This evidence is consistent with Cumming and Macintosh (2003a), that suggest that one of the main advantages of a sale of the company in its entirety (as in an acquisition exit) over an IPO is that it is most likely to result in the realization of transaction synergies.

This result suggests the existence of two main PE firm strategies in exit decision: market specialist and IPO specialist. A market specialist PE firm uses industry specialization as the preferred strategy to solve informational asymmetries through knowledge of both the investee company and the market in which it works; the PE firm has indeed deep expertise to make the investee firm attractive for a strategic acquirer. By contrast, the results suggest diversification as an alternative strategy, whereas PE firm selects investee company with the aim of quotation, regardless of the industrial sector.

Regarding to the second hypothesis, the empirical model shows that specialization decreases the probability of writing-off, even if it does not show a significant impact on any of the successful exit channels (IPO, acquisition, SBO). The result is consistent with the work of Cressy et al. (2007), which shows a very little systematic effect of this characteristic of PE firms on profitability or growth.

Exploring the dynamics that influence PE exit strategies is a topic of central interest, because it can suggest a private investee company, given its characteristics, what it should expect from the buyout of a specialized vs. diversified PE, and it also helps target companies' managers in dealing with PE investors. In fact, in the process of locating a suitable investor, it is important to be able to categorize potential investors based on their investment preferences and understand the criteria that investors from various categories use to evaluate their prospective investments (Carter and Van Auken, 1994; Cressy et al., 2007).

Moreover I analyse the hazard of different exit route in relation to the duration of the investment, finding different mean duration for the exit strategies studied, the shortest in case of IPO and the longest for liquidation, consistently with Cumming and Johan, 2008, and Cumming and Macintosh 2003a. I checked also PE firms characteristics at country level, and found that UK investors are more likely to exit via acquisition while US ones face the highest risk of write-off.

The findings in Europe and North America LBOs transaction show that syndication enhanced the failure probability, and it has a negative impact both on acquisition and SBO exits, by contrast with most of VC investigation that links syndication with positive and successful outcome, considering it as a signal of profitable investment and referring to the benefits of skills and expertise collaboration. Only few researchers stressed the risk-sharing motivation behind the decision to syndicate, or agency costs and coordination problems. Syndication is less frequent in LBOs than in early stage investments, but for a well understanding of this result I have also to stress the difference between the two kinds of deals: first of all the nature of the investment, which implies majority control of mature firms in case of LBOs, with significant use of leverage and the applying of deep financial, governance, and operational engineering. These arrangements, united with a strong influence in the investee board, make PE deal management really different from typical VC strategies. Among other elements I controlled in the model, I confirm the positive impact of target size on IPO exit, as largely discussed in quotation research, and that stock market capitalization is statistically unrelated with the probability of a PE-backed company achieving an IPO, coherently with Cumming et al. (2006) that provided a first direct test on stock and PE markets relation. Moreover, the model shows that older investee companies have more probability to be sold to another private equity. Exit through SBO has more likelihood during the years defined as 'window of opportunity', when the high funds disposability incentives PE firms to undertake also less profitable or more risky investments. In relation to write-off exit, younger and smaller investee companies suffer more bankruptcy risk.

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