



Paper to be presented at the

DRUID Society Conference 2014, CBS, Copenhagen, June 16-18

## **OPTIMAL ABSORPTIVE CAPACITY IN TECHNOLOGY-BASED FIRM ACQUISITIONS: IMPACT OF RELATEDNESS AND STRUCTURE**

**Senem Aydin**

Bocconi University

Department of Management and Technology

senem.aydin@phd.unibocconi.it

### **Abstract**

This study examines the determinants of efficiency in absorbing external knowledge, i.e. efficiency factor, in technology-based firm acquisitions and how it relates to the merged entity's innovative performance. Drivers of efficiency factor are identified as knowledge structure, i.e. technological complexity of target firm's knowledge stock, and knowledge relatedness, i.e. technological distance between acquirer and target firms' knowledge stocks. Testing a sample of between- and within-industry acquisitions undertaken during 2000-2008, for target firms in six U.S. manufacturing industries, it is found that technological distance between the acquirer and target firms' knowledge stocks has a negative impact on efficiency factor; while, technological complexity positively affects efficiency factor. Moreover, efficiency factor has an inverted U-shaped relationship with the merged entity's innovative performance, suggesting that there is an optimum level of absorption in exploiting external knowledge.

## **INTRODUCTION**

In the recent decades, firms began to rely more heavily on external knowledge and technologies to achieve rapid innovation, maintain their technologies at the frontier and get ahead of the product market competition (Arora and Gambardella, 2010; Leone and Reichstein, 2012). Acquisition of external technology is also seen as a means for firms to broaden their knowledge stock (Cohen and Levinthal, 1989; Huber, 1991) and improve their combinative capabilities through the synthesis of existing and acquired technological knowledge (Kogut and Zander, 1992). Among the possible sources of external technology transfer, acquisition of technology-based firms is considered as one of the prominent firm strategies (Leonard-Barton, 1995; Bresman, et.al, 1999; Ahuja and Katila, 2001; McEvily, et.al, 2004; Kale and Puranam, 2004; Graebner, et.al., 2010). However, in order to innovate, firms need not only to acquire external technological knowledge, but also to leverage it by exploiting and recombining with the existing technological competencies (McEvily, et.al., 2004). This is one of the main challenges of acquiring firms which desire to enhance their innovativeness.

In order to improve their innovativeness, firms need to recognize the value of external knowledge, assimilate it, and apply to commercial ends. This ability is defined as absorptive capacity (AC) by Cohen and Levinthal (1990), it is positioned as a key concept in firms' innovative processes (Cohen and Levinthal, 1989) and drew considerable scholarly interest in the subsequent 25 years. Extending this concept and reconceptualizing AC as a dynamic capability, Zahra and George (2002) distinguish among four dimensions of AC, i.e. acquisition, assimilation, transformation and exploitation. They argue that AC is composed of two subsets, potential and realized AC which have complementary roles in extracting value

from external knowledge. In particular, potential AC (PAC) is associated with firms' receptiveness to acquisition and assimilation of external knowledge; whereas, realized AC (RAC) reflects the firms' capacity to transform and exploit the assimilated knowledge. They argue that firms focusing on PAC are able to continuously renew their knowledge stock, but they may suffer from the costs of acquisition without gaining the benefits of exploitation (Zahra and George, 2002). Conversely, firms focusing on RAC may attain short-term benefits through exploitation but fall into a competence trap. Therefore, they propose the term '*efficiency factor*' ( $\eta$ ) which denotes the ratio of RAC to PAC. The efficiency factor indicates that, due to variations in their capabilities to exploit knowledge, firms differ in value generation from external knowledge acquisition. Since value generation is mainly through RAC (Grant, 1996), they assert that firms which achieve high efficiency factor increase their innovative performance. Adding to this line of literature, in their critical review of Zahra and George's (2002) reconceptualization of AC, Todorova and Durisin (2007) affirm the importance of efficiency in absorbing external knowledge for firm innovativeness and the need for an empirically meaningful definition. They suggest that 'the ratio of the knowledge embodied in successful new processes or products to the knowledge that enters the boundaries of the organization' can be analyzed as an efficiency factor for external knowledge absorption. Moreover, in their comprehensive review of AC, Volberda, et.al. (2010) argue that due to the lack of cost consideration in developing AC in the literature, the issue of whether there is an optimum level of AC does not appear to be raised. They claim that prior literature on AC implicitly assumed that maximum AC is highly desirable, although in the presence of organizational costs of developing and maintaining AC, optimum AC may not be equal to maximum AC. Thus, they call for future research to identify optimum AC and its determinants. In sum, the prior literature on AC highlights the importance of efficiency in absorbing external knowledge and the optimum level of AC on firm's innovative

performance. Interestingly, despite more than two decades of presence of the AC concept and a growing body of theoretical advancements in the construct (e.g. Zahra and George, 2002; Todorova and Durisin, 2007; Volberda, et.al., 2010), empirical research on AC largely focused on R&D rates in various industries, managerial antecedents and interorganizational antecedents of AC<sup>1</sup>, and overlooked the efficiency factor, its antecedents and how it affects the firm's innovative performance.

Building on Zahra and George's (2002) conceptualization and following Todorova and Durisin's (2007) redefinition, this study focuses on the efficiency factor which is defined here as 'the ratio of the external knowledge embodied in innovative output to the external knowledge that enters the boundaries of the firm', and empirically explores its antecedents and its impact on innovative performance. Efficiency factor presents how much of the external knowledge acquired by the firm is actually exploited to create innovative output. In their seminal piece, Cohen and Levinthal (1990) claim that external knowledge characteristics, such as complexity of the external knowledge and relatedness between the prior knowledge and external knowledge have important implications for the development of AC and, in turn, innovative performance. In line with their specification, antecedents of efficiency factor are identified here as knowledge structure of the target firm; i.e. technological complexity, which refers to the density of linkages among the target firm's pre-deal technological assets, and knowledge relatedness; i.e. technological distance between the acquirer and target firms' pre-deal knowledge stocks. In addition, this research investigates

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<sup>1</sup>For a bibliometric analysis of AC, see Volberda, et.al. (2010) study which presents the analyses performed by the Centre for Science and Technology Studies, Leyden University, for the period 1992-2005.

<sup>2</sup> Acquirer firms are not constrained by industry affiliation to allow for the analysis of both between- and within industry acquisitions.

<sup>3</sup>Similar specifications are widely used in technology acquisition literature (e.g. Granstrand and Sjolander, 1990;

the impact of efficiency factor on firm's innovative performance and explores the optimal level of AC.

This paper aims to make three main contributions to the AC literature. First, this study advances the research on AC by extending the theoretical definition of efficiency factor. Following Todorova and Durisin's (2007) redefinition of the concept developed by Zahra and George (2002), a reconceptualization of efficiency factor is provided. Second, this research theorizes on and presents the first empirical assessment of the antecedents of efficiency factor. Prior empirical research on AC is rather focusing on the organizational antecedents of PAC and RAC (e.g. Jansen, et.al, 2005), and antecedents of PAC (e.g. Fosfuri and Tribo, 2008). Third, this study presents how efficiency factor is related to the innovative performance of the firm. Prior literature on AC concentrates on PAC's impact on innovative performance (Fosfuri and Tribo, 2008), how PAC and RAC affect market performance and financial performance (Brettel, et.al., 2011) and the efficiency factor's impact on financial performance (Therin, 2007). To date, empirical research on efficiency factor's impact on innovative performance and the optimum level of AC is still lacking and Volberda, et.al. (2010) call for future research on evaluation of optimal AC. This study addresses this gap in the literature by empirically testing the optimal AC for firm innovativeness.

## **THEORY AND HYPOTHESES**

Technology-based firm acquisition is the rising trend among established firms in high-tech industries (Agarwal and Helfat, 2009). Acquirers pursue technology-based firm acquisitions to tap the innovative potential of target firms through attaining their strategically valuable technological knowledge (Graebner, et.al., 2010). The ability of the firm to exploit external

knowledge is an essential component of innovative capabilities (Chesbrough, 2003; Laursen and Salter, 2006). Firms endowing higher levels of AC can generate greater value from external knowledge acquisition and increase their innovative performance (Tsai, 2001). Zahra and George (2002) argue that AC is a multidimensional construct. They identify four distinct but complementary processes that compose a firm's AC: acquisition, assimilation, transformation and exploitation of external knowledge. Acquisition refers to the firm's ability to identify and acquire externally generated knowledge; yet, assimilation refers to the firm's routines and processes that allow it to analyze, process, interpret, and understand external knowledge (Zahra and George, 2002). In their view, these two components of AC constitute PAC, which helps firms to process and internalize external knowledge and reconfigure the knowledge stock. PAC influences innovative performance through the flexibility of resources and capabilities. The other two components of AC are transformation and exploitation of external knowledge; where the former refers to the ability of the firm to combine existing knowledge stock with the newly assimilated knowledge, while the latter refers to the firm's ability to incorporate acquired and transformed knowledge into its innovative operations. Consisting of these two components, RAC helps the firm to leverage on the absorbed external knowledge. They argue that RAC influences innovative performance through creation of new knowledge and development of new products. Without the effective functioning of RAC, PAC cannot improve firm's innovative performance. Therefore, they identify the ratio of RAC to PAC as the efficiency factor and assert that the firm which achieves or maintains high efficiency factor can increase its innovative performance. This dichotomous view of AC is criticized by Todorova and Durisin (2007), who put forward that assimilation component of PAC and transformation component of RAC are not sequential but rather alternative processes of developing cognitive structures which help the firm to combine external knowledge with the existing knowledge stock. Therefore, identification of assimilation and

transformation as parallel processes of combining external and existing knowledge renders it impossible to disentangle AC into two distinct subsets. Hence, Todorova and Durisin (2007) assert that the problems with the clear differentiation of the two subsets of AC, cast doubts on their appropriateness in measuring their distinct effects in empirical studies of value creation. Moreover, they claim that ‘the term potential refers to the new knowledge that enters the organization and is not yet assimilated or transformed, rather than to the capacity to absorb new knowledge, which is an organizational process’ (Todorova and Durisin, 2007). Nevertheless, they affirm that the efficiency in absorption of external knowledge remains as an essential concept in extracting value from external knowledge acquisition. They reconceptualize this construct as the ratio of the external knowledge embodied in successful new processes and products to the knowledge that enters the firm boundaries. With this broader conceptualization, efficiency factor accounts for the ability of the firm to create value from the acquired external knowledge.

In the theoretical model proposed by Zahra and George (2002), efficiency factor is proposed to be influenced by social integration mechanisms. In order to increase mutual understanding and comprehension of the external knowledge (Garvin, 1993), it needs to be shared among the members of the firm (Spender, 1996). Social integration mechanisms have the role to facilitate the sharing and exploitation of the knowledge. Thus, it is proposed that use of social integration mechanisms reduces the gap between RAC and PAC, thereby increasing the efficiency factor (Zahra and George, 2002). However, in this theorizing, it is not clear whether the social integration mechanisms only increase transformation and exploitation of the assimilated knowledge which increases RAC for a given level of PAC, or they also influence knowledge assimilation through increasing ‘mutual understanding and comprehension of the external knowledge’ (Garvin, 1993). In the latter case, PAC is expected

to increase as well; thus, the resultant effect of social integration mechanisms on efficiency factor, when it is specified as the ratio of RAC to PAC remains ambiguous. Moreover, the focus on organizational mechanisms overlooks the role of the nature of external knowledge and relatedness of the prior knowledge stock with external knowledge as the key determinants of AC in Cohen and Levinthal's (1990) theoretical model. This study reintroduces the structure of the external knowledge and relatedness of the prior knowledge stock with the external knowledge as important factors which not only determine the level of AC but also the efficiency factor in extracting value from external knowledge. Prior literature on AC focuses on the effect of knowledge structure (e.g. Kogut and Zander, 1992; Szulanski, 1996; Simonin, 1999) and knowledge relatedness (e.g. Ahuja and Katila, 2001; Puranam and Srikanth, 2007; Makri, et.al., 2010; Sears and Hoetker, 2014) on assimilation of the external knowledge. Following this line of research, here it is argued that knowledge structure and knowledge relatedness also have an impact on the ability of the firm to exploit acquired external knowledge; thereby influence the efficiency in absorption of external knowledge. The proposed model is depicted in Figure-1.

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Figure-1 about here

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The first antecedent of efficiency factor is knowledge structure; in particular, complexity of the acquired external knowledge. In their review of AC literature, Lane, et.al. (2006) claim that the focus of earlier research is on two aspects of Cohen and Levinthal's definition; i.e. how the nature of knowledge influences firm's ability to recognize valuable external knowledge and the firm's ability to assimilate that knowledge. They emphasize that in addition to the lack of empirical evidence, the influence of the knowledge structure on firm's

ability to exploit has received relatively little attention, reflecting the underlying assumption that mere acquisition enhances firm's innovative performance. Challenging this assumption, the new model proposes that efficiency in extracting value from acquired external knowledge is influenced by the knowledge structure. Prior literature on AC identifies knowledge characteristics such as complexity, ambiguity (Simonin, 1999) and tacitness (Kogut and Zander, 1992; Inkpen and Dinur, 1998; Ranft and Lord, 1998; Simonin, 1999) as barriers to knowledge transfer and absorption. Cohen and Levinthal (1990) claim that complexity of the external knowledge determines the ease of learning which, in turn, affects the firm's incentives to learn and invest in AC. Knowledge complexity refers to the complementarity of technological assets (e.g. patents) linked to a particular technological knowledge (von Graevenitz, et.al., 2013). In other words, a technology becomes more complex as the density of interdependence among the technological assets increases. In an attempt to better understand the link between knowledge structure and invention, Fleming and Sorenson (2001) develop a theory which regards invention process as a recombinant search over technology landscapes. They suggest that inventors might face a 'complexity catastrophe' when they attempt to combine highly interdependent technologies. Complexity arises not only because of the recombination problem of the knowledge elements but also due to the potential number of combinations that can be realized (Fleming and Sorenson, 2001). Empirical research on knowledge complexity indicates that it has a negative impact on the firm's innovativeness (Simonin, 1999). Cohen and Levinthal (1989) explain this effect as follows: an increase in the knowledge complexity requires higher internal R&D for its absorption; thus, the cost of absorption increases. This means that, for a given level of R&D expenditure, knowledge absorption decreases with knowledge complexity, which in turn decreases innovative performance. However, concerning the efficiency in absorbing acquired external knowledge a reverse effect is expected. Earlier work point out that AC of the firm is

enhanced by the development of routines that pursue resource recombination and knowledge complexity (Galunic and Rodan, 1998; Van den Bosch, et.al., 1999), which in turn, enables the firm to recognize and assimilate more complex external knowledge. Likewise, as the knowledge becomes more complex, the firm needs to absorb more areas of knowledge content, as well as understand the interlinkages between the different content areas (Garud and Nayyar, 1994). For instance, especially in technology fields where technological knowledge is developing cumulatively, later inventions are embracing a higher rate of prior art. Due to this characteristic, as firms continue to innovate, the interdependencies among technological assets increase and render the technology highly complex. Exploitation of this type of technological knowledge requires combination and recombination of a higher rate of prior technological assets. In sum, in technology-based acquisitions, innovations of the newly merged entity are expected to leverage on a larger portion of target firm's knowledge stock as the complexity of that knowledge increases. Thus, the efficiency in absorbing external knowledge, namely efficiency factor, is positively associated with the complexity of the acquired external knowledge.

Hypothesis 1 (H1): *Complexity of target firm's knowledge stock is positively related to the merged entity's efficiency in absorbing external knowledge.*

The second antecedent of efficiency factor is knowledge relatedness. Eisenhardt and Santos (2002) identify knowledge relatedness as one of the main factors influencing the external knowledge transfer. Relatedness of unifying knowledge stocks of the acquirer and target firms is seen as one of the prominent determinants of firm innovativeness (Lubatkin, 1983; Singh and Montgomery, 1987; Seth, 1990; Lane and Lubatkin, 1998; Ahuja and Katila, 2001;

Puranam and Srikanth, 2007). Relatedness refers to the content of the technological knowledge of the firms (Ahuja and Katila, 2001) and it is expected to have an impact on the ability of the acquirer to exploit the acquired technology depending on its level of AC (Cohen and Levinthal, 1990). The theory on AC asserts that firm's ability to use external technological knowledge is greater if the relatedness is high between external and prior knowledge stocks. In situations where the acquirer and target firms have distant knowledge stocks, integration of the knowledge stocks is likely to be resource consuming or counter to the routines of the acquirer (Haspeslagh and Jemison, 1991; Singh and Zollo, 1997) which hamper the exploitation of the external knowledge. Thus, knowledge utilization is expected to be low in technologically distant firm acquisitions. On the contrary, AC theory argues that in very similar acquisitions little can be added to the innovative performance due to duplicates and redundancies in knowledge (Cohen and Levinthal, 1990, Ahuja and Katila, 2001). Combining very similar technological stocks may produce less novel innovative output (Makri, et.al., 2010). This view is mostly supported by empirical research. For instance, Ahuja and Katila (2001) found an inverted-U shaped relationship between knowledge relatedness and post-acquisition innovative output. Similarly, Cloudt, et.al (2006) found that relatedness between the acquired and acquiring firms' knowledge stocks has an inverted-U shaped relationship with the acquiring firm's innovative performance. However, Makri, et.al, (2010) found no relationship between knowledge relatedness, i.e. technological similarity, and innovative quantity.

Concerning the efficiency in absorbing acquired external knowledge, i.e. efficiency factor, relatedness of the external knowledge is expected to increase its exploitation in subsequent innovations. Acquirers leverage on external knowledge by combining and recombining acquired knowledge with the prior knowledge stock (Kogut and Zander, 1992). Combining

and recombining external and prior knowledge requires alignment of two knowledge stocks (Dinur, et.al., 1998). If the acquired external knowledge has a significantly different content than the prior knowledge stock, this may delay its comprehension and absorption by the acquirer (Leonard-Barton, 1995). Conversely, very similar knowledge stocks may have little to add to the knowledge exploitation of the merged entity (Cohen and Levinthal, 1990, Ahuja and Katila, 2001, Makri, et.al., 2010). If the target firm's knowledge stock is very similar to the acquirer's, the acquirer might not leverage on that knowledge due to duplications and redundancies. When two knowledge stocks are very similar, it is expected that no acquisition will take place. Therefore, it is assumed that the acquirer will undertake acquisition of a target firm only when the target firm's knowledge stock is somewhat different than the acquirer's prior knowledge stock. In this case, the hampering effect of very similar knowledge stocks may not be observed while the negative impact of very distant acquisitions may still be notable. These arguments suggest that in technology-based acquisitions knowledge exploitation is enhanced when acquirer and target firms endow similar technological knowledge stocks and hampered as the technological distance between the acquirer and target firms widens. Therefore, it is expected that technological distance between the acquirer and target firms' knowledge stocks is negatively associated with the efficiency in absorbing external knowledge.

Hypothesis 2 (H2): Technological distance between the acquirer and target firms' *knowledge* stocks is negatively related to *the merged entity's efficiency in absorbing* external knowledge.

In their seminal paper, Cohen and Levinthal (1990) argue that 'because AC is intangible and its benefits are indirect, one can have little confidence that the appropriate level, to say

nothing of the optimal level, of investment in AC is reached'. Although it is hard to determine the optimum level of AC a priori and invest accordingly, theoretical developments in the AC literature highlighted the importance of efficiency in absorbing external knowledge and its impact on firm innovativeness (Zahra and George, 2002; Todorova and Durisin, 2007). In their reconceptualization of AC, Zahra and George (2002) claim that a high efficiency factor, i.e. a high ratio of RAC to PAC, is positively associated with future innovative performance. They argue that externally acquired knowledge undergoes multiple processes before the acquirer firm can successfully exploit it and to enhance acquirer's innovativeness, RAC would approach PAC. This view is questioned by other researchers, arguing that firms may not always be better off by fully realizing their PAC in dynamic environments (Volberda, et.al, 2010). Although RAC promotes innovation, the resultant products and services may rapidly converge to industry standards and become obsolete relative to current environmental demands (Sorensen and Stuart, 2000). The latter view also found some empirical support, Jansen, et.al. (2005), in line with their findings, expect that organizational units with baseline levels of RAC and high levels of PAC will obtain above-normal performance in dynamic markets.

In their review of AC literature, Volberda, et.al. (2010) claim that there is little consideration of the cost of developing AC, changing it, or in some way taking advantage of a firm's AC. However, developing AC is costly and it is overlooked in the prior research. For this reason, the issue of whether there is an optimum level of AC is not questioned in the literature. Maximum AC is implicitly assumed to be desirable, although in the presence of organizational costs of building and maintaining AC, optimum AC may not be equal to maximum AC (Volberda, et.al., 2010). Regarding the efficiency in absorbing external knowledge, optimum AC can be less than maximum AC due to two reasons depending on the

relevance of the acquired external knowledge for the subsequent innovative activities of the firm. First, although the acquired knowledge can be totally useful for the acquirer firm's innovative activities, the cost of assimilation and exploitation of all the acquired knowledge stock may exceed the benefits of the innovative activities; i.e. the revenue to be generated by product innovations and/or the cost reduction to be achieved by process innovations. In this case, the acquirer may prefer to exploit a portion of the acquired knowledge stock which results in an optimum AC which less than the maximum level. Second, not all of the acquired knowledge may be useful for the acquirer's innovative activities. Due to information asymmetries and the uncertainty regarding the usefulness of the acquired knowledge, the acquirer may only ascertain the true value of the knowledge ex post and realize that only some portion of the acquired knowledge is useful for its subsequent innovative activities. Again, in this case, the acquirer may prefer to exploit less than total of the acquired knowledge which induces the optimum AC less than the maximum level. Consistent with these explanations, it is hypothesized that the optimum AC which facilitates innovative performance is less than maximum AC. Therefore, an inverted U-shaped relationship between efficiency factor and innovative performance is expected.

Hypothesis 3 (H3): The *merged entity's efficiency in absorbing external knowledge* has an inverted U-shaped relationship with innovative performance.

## **METHODS**

### **Data and Sample**

In order to test the hypotheses of this study, a sample of technology-based firm acquisitions executed for target firms in six U.S. manufacturing industries during the period of 2000-2008 is used. A major strength of using technology-based firm acquisitions is that, with this specification, it is easy to determine the timing and amount of external technological knowledge that enters the firm boundaries and the level of its exploitation in the subsequent innovative activities. The selection of the industries follows the rationale of having a pool of target firms which provide enough variance in IP intensity, as it is announced by a recent report of USPTO (USPTO IP-Report, 2012), to capture the variance in knowledge exploitation in different industries. For this purpose, three industries with the highest IP-intensity; i.e. computer and peripheral equipment (NAICS 3341), communications equipment (NAICS 3342), semiconductor and other electronic components (NAICS 3344); and three less IP-intensive industries; i.e. plastics and rubber products (NAICS 326), motor vehicles, trailers and parts (NAICS 3361-63), nonmetallic mineral products (NAICS 327), are selected where the latter group is characterized by having below-average IP-intensity but still endowing high enough technological knowledge which can be redeployed by the acquirer. The initial sample of acquisitions is obtained from Bureau van Dijk's ZEPHYR database and included all between- and within-industry acquisitions for the period 2000-2012 in the specified IP-intensive and less IP-intensive industries. This resulted in 3,666 acquisition-deals for target firms affiliated primarily to the selected industries<sup>2</sup>. From this population, acquisitions less than 100% equity stake and acquisitions of the remaining stakes are eliminated. To determine the technology-based firm acquisitions, deals with target firms which have at least 5 technological assets (e.g. patents) before the acquisition are identified<sup>3</sup>.

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<sup>2</sup> Acquirer firms are not constrained by industry affiliation to allow for the analysis of both between- and within industry acquisitions.

<sup>3</sup> Similar specifications are widely used in technology acquisition literature (e.g. Granstrand and Sjolander, 1990; Ernst and Vitt, 2000; Ahuja and Katila, 2001; Puranam and Srikanth, 2007). For instance Ahuja and Katila (2001) identified technology acquisitions as deals with target firms which have at least one technological input.

This filtering ended up with 520 technology-based firm acquisitions. Data is further constrained to measure the efficiency factor within four years following the acquisition; therefore, sampling is ended by year 2008. After implementing these filters and constraints, and the deductions due to missing values, the final sample consisted of 356 acquisition-deals.

## **Measures**

### **Dependent Variable**

**Innovative Performance:** This construct is measured by the number of granted patent for which the application is made by either acquirer or target firm within 4 years following the acquisition deal. This specification follows the rationale of accounting for the overall innovativeness of the merged entity and taking into account the possibility that the merged entity may keep applying patenting under the name of target firm when it is not fully integrated. Data for the number of patent applications are gathered from USPTO database.

### **Independent Variables**

**Efficiency Factor:** This construct is measured by the share of pre-deal target patents exploited by either acquirer or target firm within 4 years following the acquisition deal. A patent is considered to be exploited if it received a forward citation from acquirer or target firm patents within the specified time period after the deal. In order to account for the overall knowledge exploitation of the merged entity, i.e. not just to account unidirectional knowledge transfer from target firm to the acquirer, both acquirer and target forward citations to the pre-deal target patents are examined. Data for patents and forward citations are gathered from

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Similarly, Ceccagnoli and Hicks (2012) determine high-tech target firms with endowment of at least 15 technological inputs.

USPTO database. Traditionally, patent forward citations are used as a measure of invention quality (e.g. Trajtenberg, 1990; Valentini, 2012) because they are considered to be a reflection of ‘the ability of a set of patents to support future inventions by creating a “ripple effect” to stimulate subsequent patents’ (Makri, et.al., 2010). However, there is another body of research which considers citations as an evidence of inter- or intra-firm knowledge transfer (Almeida et al., 2002; Rosenkopf and Almeida, 2003; Song, et.al, 2003). Citations are assumed to be an indicator of successful transfer of knowledge with its tacit and codified components (Almeida and Kogut, 1999; Almeida et al., 2002; Jaffe and Trajtenberg, 1996; Jaffe, Trajtenberg, and Fogarty, 2002; Jaffe et al., 1993; Song et al., 2003). Puranam and Srikanth (2007) use post-acquisition forward citations from acquirer patents’ to pre-deal target firm patents as a measure of the leverage of target firm technological knowledge codified in patents and residing in employees. In this study, this measure is advanced by adding target firm’s self-citations to the pre-deal patents from post-deal ones to have a more comprehensive account of the innovative activity produced by the merged entity. Forward citations received by target firm patents from acquirer’s or target’s subsequent patents in the post-acquisition period indicate that these patents are exploited by the merged entity and a new body of technological knowledge is created by combining and advancing the acquired knowledge.

A major concern about the use of patent citations as an indicator of spillovers and knowledge transfer is that citations are argued to be a noisy indicator which can be interpreted in several different ways than actual knowledge flow (Jaffe et al., 1998). In particular, it is asserted that ‘where citations are added by the patent examiner, we cannot judge whether or not the applicants were aware of the cited patent’ (Criscuolo and Verspagen, 2008). In this study, the post-deal forward citations measured are either target firm’s self-citations or acquirer’s

citations, which in total can be considered as post-deal self-citations of the merged entity. Thus, the applicant is supposedly aware of the cited patent and these citations are proper indicators of knowledge exploitation.

Technological Distance: Following Jaffe's (1986) measure of technological proximity, this construct, is measured by examining the extent to which pre-deal acquirer and target firm have patents in the same patent classes. This measure is aiming at capturing the position of one firm relative to the other in the technology space (Sampson, 2007). The technological distance between two firms is calculated by creating a vector for each firm to measure the distribution of its patents across patent classes, denoted as  $F_i=(F_1...F_n)$ ,  $n=1,...,473$  (473 is the total number of patent classes in USPTO database) and by calculating the formula below:

$$\text{TECHDIST} = 1 - \frac{F_i F_j'}{\sqrt{(F_i F_i')(F_j F_j')}}$$

where  $i \neq j$ . This measure is ranging between 0 and 1, higher values are indicating greater technological distance between the acquirer and target firms. For patent classes, the emphasis is given on the primary patent class assigned to the patent by checking the 3-digit patent class code and not digging into sub-classes which is the common method used in studies that apply Jaffe's formula (e.g. Sampson, 2007; Makri, et.al., 2010). In cases where acquirer firm has no patents to calculate the technological distance, depending on the type of acquisition (i.e. between- or within-industry), the average technological distance of that type of acquisitions is used and to account for any systematic error created in the variable, a control variable (TDDUMMY) is added, which takes value of 1 when the average is inserted and 0 otherwise.

Technological Complexity: Complexity of a technology is assumed to be increasing as the density of interdependence among the technological assets, i.e. patents, increases. Interdependence of the patents is assessed by the citation network among the patents. Clarkson (2005) proposes a density measure of the backward citations among a pool of patents taking into account the fact that younger patents can make more backward citations than the older ones. For the purposes of this study, technological complexity construct is measured by the weighted average citation network density among target firm's patents before acquisition (Clarkson, 2005). Density is measured as such:

$$\Delta_p = \frac{\sum_{n=1}^g \sum_{j=1}^g X_{nj}}{g(g-1)/2}$$

where  $\Delta_p$  is the density of citation network,  $n$  is the focal patent,  $g$  is the total number of patents of the target firm before acquisition,  $j$  is the citations to and from patent  $n$ . This is a measure between 0 and 1. As the density increases, the complexity of the technology increases as well.

### **Control Variables**

Several control variables are included in the analyses. First, to account for the impact of knowledge stock of the acquirer in exploiting acquired knowledge (Cohen and Levinthal, 1990), Acquirer's Knowledge Stock is controlled and measured by the number of pre-deal acquirer firm's patents. Second, the data is further controlled for the Target Firm's Knowledge Stock which is measured by the number of pre-deal target firm's patents. Third, empirical studies on patenting quality generally determine the level quality by the number of forward citations received by these patents (e.g. Valentini, 2012); therefore a measure of the

Number of Target Patents Cited Before Acquisition is included in the analyses. Fourth, to account for the acknowledgement of target firm's pre-deal knowledge stock by the acquirer, Number of Target Patents Cited by Acquirer Before Acquisition is contained in the analyses. Fifth, to control the effect of Prior Acquisition Experience of Acquirer Firm, a measure is included for the number of acquisitions undertaken by the acquirer within five years before the focal acquisition. The data for this variable is gathered from ZEPHYR database. Sixth, to control for the external knowledge inflows to the acquirer firm other than the focal acquisition, a measure for Prior Technology Licensing Experience of Acquirer Firm is contained in the analyses and it is measured by the number of technology licensing agreements made by the acquirer within five years before the focal acquisition. The data for this variable is gathered from FACTIVA database by searching 'company name' and 'licensing agreement' in press releases for the specified time period. Seventh, to control for the industry-level factors that may affect the knowledge exploitation and innovative performance, such as Industry Concentration, Herfindahl-Hirschman Index (HRFNDHL) is included, it is calculated by squaring the market share of each firm in the industry, and then summing the resultant numbers. Lastly, a number of dummy variables are created to specify acquisition characteristics, i.e. within- vs. between-industry, measured by Within-Industry Acquisitions (WITHINA), which takes the value of 1 when it is a within-industry acquisition and 0 if it is a between-industry acquisition; likewise, IP-intensive and less IP-intensive industries are differentiated by a dummy measure: IP-intensive Industries (IPINT) which takes the value of 1 when the target firm is operating in an IP-intensive industry and 0 otherwise, and Year dummies.

## **Model**

Due to the mediation effect theorized in the model, a hierarchical regression is chosen to test the hypotheses. The model consists of two discrete steps where the first step tests the impact of technological complexity and technological distance on the efficiency factor, including the controls, and the second step regression tests the effect of efficiency factor on innovative performance, including technological complexity, technological distance and controls in the regression.

The dependent variable of the first stage regression is the fraction of pre-deal target firm patents exploited after the acquisition and thus, bound between 0 and 1. A quasi-likelihood method is proposed by Papke and Wooldridge (1996) for the estimation of regression models with a fractional dependent variable based on the logistic distribution. The advantages of this regression model is that it can estimate the possible nonlinear relationships better than a linear model with conditional mean or log-odds transformed variables (Conti, 2013). This method is used in many similar studies which estimate fractional dependent variables (e.g. Adegbesan and Higgins, 2010; Conti, 2013; York and Lenox, 2013; Kleinbaum and Stuart, 2014). It is implemented using generalized linear model (GLM) in STATA with a Binomial variance function and a Logit link with robust standard errors (McDowell and Cox, 2004). Using this model, the first two assertions of the study are tested on efficiency factor.

The dependent variable of the second step regression, i.e. innovative performance, is a count variable, the number of granted patents to the merged entity; which is zero inflated; therefore, Negative Binomial model is chosen to account for overdispersion in the count data (Ver Hoef and Boveng, 2007).

To account for possible correlations among the error terms in the hierarchical regression model, a robustness check is provided with path analysis, which is a type of structural equation modeling (SEM) where each variable has only one indicator. Using a maximum likelihood estimator (MLE), this model simultaneously estimates the path coefficients and errors (Fosfuri and Tribo, 2008).

## **RESULTS**

### **Descriptive Statistics**

The descriptive statistics of the data are depicted in Table 1. According to the sampled data, the innovative performance of the merged entities ranges between 0 and 8380 patent applications within four years after the focal acquisition with the average of 232 patent applications. Furthermore, on average 13.2% of the target firm technological knowledge stock is exploited after the acquisition. Technology leverage goes up to 14.55% for IP-intensive industries; whereas, it drops to 8.76% in less IP-intensive industries. There is substantial variance in the independent variables, i.e. technological distance and technological complexity, and also in control variables such as industry concentration (HRFNDHL), acquirers' prior acquisition experience, size of acquirer's and target's existing technological knowledge stocks, number of target patents cited before acquisition and share of target firm patents cited by the acquirer before acquisition.

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Table 1 about here  
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Table 2 displays the correlations between variables. The independent variables technological distance and technological complexity are not highly correlated and also there are no high correlations between the independent variables and efficiency factor or innovative performance. Two controls are highly correlated with the innovative performance: acquirer's knowledge stock (0.590) and acquirer's licensing experience (0.578). Size of acquirer's knowledge stock is also highly correlated with acquirer's licensing experience (0.852). And lastly, the number of target patents cited before acquisition is highly correlated with the size of target's knowledge stock (0.998).

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Table 2 about here  
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### **Regression Results**

Table 3 presents the regression results for the first stage GLM estimations using Binomial family and Logit link (Papke and Wooldridge, 1996), reported with robust errors, on the total sample. Model 1 depicts the basic model with all controls. The independent variables are added to the basic model one by one. In the basic model (Model 1), the control variables show that the size of the target's knowledge stock has a significant positive effect on the efficiency factor ( $p < 0.05$ ), while the number of target firm patents cited before acquisition has a significant negative effect on efficiency factor ( $p < 0.05$ ). However, the number of target firm patents that are cited by the acquirer before the focal acquisition significantly increases efficiency factor ( $p < 0.1$ ). In order to test Hypothesis 1, knowledge complexity is added to the basic model. As it can be seen in Model 2, knowledge complexity has direct positive effect ( $p < 0.01$ ) on efficiency factor. This is the first evidence of the positive relationship between technological complexity and efficiency factor. In Model 3, to test Hypothesis 2,

technological distance is added to the regression, and the results indicate that it has a negative and significant effect on efficiency factor ( $p < 0.01$ ). Finally, Model 4 depicts the full model with all independent variables. Here, the results show that technological complexity has a positive and significant effect on efficiency factor ( $p < 0.01$ ), which confirms H1; whereas, technological distance has a negative and significant impact ( $p < 0.01$ ), supporting H2. These results indicate that all proposed direct effects on efficiency factor are confirmed.

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Table 3 about here  
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In the second stage analysis, the effect of efficiency factor on the merged entity's innovative performance is tested. Table-4 depicts the regression results for Negative Binomial estimations. In Model 1, the control variables are inserted in the regression. This analysis indicates that industry concentration, measured by Herfindahl Index, has a significant negative impact on the innovative performance ( $p < 0.05$ ); whereas, the size of acquirer's knowledge stock and the number of target firm patents cited by the acquirer have a positive and significant effect on innovative performance ( $p < 0.05$  and  $p < 0.1$  respectively). Moreover, acquirer's acquisition experience significantly increases innovative performance ( $p < 0.01$ ). Model 2 tests the effect of technological complexity and technological distance on innovative performance. This model shows that the impact of technological complexity on innovative performance is insignificant and technological distance has a negative impact on innovative performance ( $p < 0.1$ ). Model 3 tests H3, the curvilinear effect of efficiency factor on innovative performance. The results show that efficiency factor has a positive and significant

impact ( $p < 0.01$ ) on innovative performance and the squared term is also a negative and significant ( $p < 0.01$ ), which indicate that efficiency factor has an inverted U-shaped relationship with innovative performance, confirming H3. The inflection point is provided in Figure 2. The figure shows that innovative performance is maximized when 55.15% of external knowledge is exploited by the firm. Moreover, the results indicate that the effect of technological distance on innovative performance is fully mediated by efficiency factor; whereas the effect of technological complexity is partially mediated by efficiency factor. Technological complexity has a direct negative impact on innovative performance ( $p < 0.05$ ). This outcome is interpreted in detail in the discussion section.

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Table 4 about here  
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Figure 2 about here  
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### **Robustness Check**

As a robustness check, path analysis technique is used to estimate the theoretical model. A MLE model is implemented on STATA with pathreg command. The model is composed of two paths: one from technological complexity and technological distance to efficiency factor, including controls, and the other one from efficiency factor to innovative performance, including technological complexity, technological distance and controls. These two paths are

simultaneously estimated. The results are similar to the earlier hierarchical regression results (Table 5). The aforementioned antecedents of efficiency factor; i.e. technological complexity and technological distance, are both significant at 0.01 level. Efficiency factor has a significant inverted U-shaped relationship with innovative performance. Marginal effects of all variables are contained in the analyses.

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Table 5 about here  
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### **Sensitivity Analyses**

In order to make a finer grain analysis of the data and have a better understanding of the factors influencing efficiency factor and innovative performance in firm acquisitions, the data is reexamined through various subsamples. First, to better identify the objective of the acquisitions, in addition to the techniques applied in sampling steps, a subsample of ‘technology acquisitions’ is determined through the motives of acquisitions stated at the time of the acquisition in press releases. For this purpose, final sample of 356 acquisition-deals are further searched for their motives in press releases, through Factiva database with ‘company name’ and ‘target name’ around the deal date. Those announcements which refer to the use of target firm’s ‘technology’, ‘patent portfolio’ or ‘technological/innovative capabilities’ are labeled as technology acquisitions. As a result of this search, 223 of the 356 firm acquisitions came out to be technology acquisitions. This specification is considered to bring more precision about the motives of acquisitions. The results of the analyses are

provided in Table 6. The results are qualitatively similar to the total sample with the exception that the effect of technological distance on efficiency factor loses its significance.

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Table 6 about here  
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An additional test is conducted to examine the factors effective on different types of acquisitions, i.e. between- vs. within-industry. By splitting the total sample into two for between- and within-industry acquisitions, 183 between-industry and 173 within-industry acquisitions are identified. Results for these analyses are given in Table 7. The analyses of within-industry acquisitions show that the results are qualitatively the same with the total sample. The results for between-industry acquisitions are also quite similar to the total sample with the exception that the impact of technological distance on efficiency factor loses its significance.

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Table 7 about here  
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A final set of analyses are conducted to account for the differences arising from the characteristics of the target firms' industries. Depending on the characteristics of the industry, total sample is splitted into two for IP-intensive and less IP-intensive industries. This resulted in 271 IP-intensive industry and 85 less IP-intensive industry acquisitions. The results are provided in Table 8. It is shown that in IP-intensive industry acquisitions the results are

qualitatively similar to the total sample. In less IP-intensive industry acquisitions the results are slightly different than the total sample. While technological complexity significantly increases efficiency factor, the effect of technological distance is negative and insignificant. Conversely, it appears to have a positive and significant impact on innovative performance. Analyses also confirm the inverted U-shaped relationship between efficiency factor and innovative performance.

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Table 8 about here  
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## **DISCUSSION AND CONCLUSION**

This study examines the efficiency factor, its antecedents and how it affects innovative performance in technology-based firm acquisitions. Two main factors are identified to be influential in efficiency factor: technological complexity, which refers to the density of linkages among the target firm's pre-deal technological assets, and knowledge relatedness; i.e. technological distance between the acquirer and target firms' pre-deal knowledge stocks. In addition, this research investigates the impact of efficiency factor on the merged firm's innovative performance and explores the optimal level of AC. The results suggest that technological distance between the acquirer and target firm knowledge stocks negatively impacts efficiency factor; whereas, technological complexity has a positive effect on efficiency factor. Furthermore, efficiency factor has an inverted U-shaped relationship with innovative performance. These results are interpreted as follows. As Cohen and Levinthal (1990) proposed in their seminal paper, knowledge complexity determines the ease of learning which, in turn, affects the innovative performance of the firm. The results of this

study indicate that knowledge complexity has a positive impact on the efficiency factor as it is hypothesized; confirming the need to embrace a greater portion of the acquired knowledge to innovate when the knowledge structure is composed of highly interlinked technological assets. In addition, knowledge complexity is found to have a direct negative impact on firm's innovativeness which supports the earlier research on knowledge complexity and innovative performance relationship (Simonin, 1999). In the light of these results, it can be said that complexity of the acquired knowledge decreases firm innovativeness by reducing the number of patents produced by the firm; however, it increases the efficiency factor, meaning that, the patents produced by the merged entity includes a higher percentage of acquired knowledge when the technology has a complex structure.

Concerning the relatedness of the prior knowledge stock of the acquirer and the acquired knowledge, it is found that technological distance between the two knowledge stocks is decreasing the efficiency factor; in other words, a lower percentage of the acquired knowledge that is actually exploited by the merged entity when the acquired knowledge is distant from the prior knowledge stock of the acquirer. However, it has no direct impact on the innovative performance. There are two implications that come out of these results. Earlier research on technological distance's impact on innovative performance has found an inverted U-shaped relationship (Ahuja and Katila, 2001; Cloudt, et.al., 2006). Here it is found that this relationship is instead mediated by the efficiency factor. Prior literature on AC overlooked the mediation effect of efficiency factor on the relationship between technological distance and innovative performance. The second implication is that acquirers are undertaking technology-based firm acquisitions only when the target firm's knowledge stock is distant enough from its prior knowledge stock. Acquirers are well aware of the fact that acquisition of target firms which endow very similar knowledge stocks to its prior knowledge has little to

add to the innovative performance. Therefore, in technology-based firm acquisitions technological distance is found to have a negative impact on efficiency factor.

The relationship between efficiency factor and innovative performance is found to be curvilinear, indicating that efficiency factor enhances innovative performance up to a certain threshold, at which, the cost of developing AC exceeds the benefits of innovative value creation. This result is in line with the previous literature which theorizes that optimum AC can be less than the maximum level, when it comes to maximizing innovative performance (e.g. Volberda, et.al, 2010). Innovative performance is found to be maximized when the efficiency factor is 55%, in other words, when 55% of the acquired technological knowledge is exploited by the firm. This result, though it bases on US patenting data, is similar to the average use of patents (50.5%) by European inventors through internal exploitation for commercial or industrial purposes (Giuri, et.al., 2007). Although it is difficult to disentangle the underlying mechanisms in this empirical setting, two possible explanations are provided. First, the cost of exploiting the acquired knowledge may exceed the benefits of the innovative activities, which leads the acquirer to leverage on some portion of the acquired knowledge although it is fully useful for the acquirer's innovative activities. Else, not all of the acquired knowledge stock might be useful for the innovative purposes of the acquirer, which results in less than total utilization of acquired external knowledge. Data specification of this study does not allow determining which possible explanation is the main driver of the results. Thus, testing of these mechanisms is left for future research.

Sensitivity analyses on various subsamples provide a better understanding of the factors effective in the innovative performance. Considering technological complexity it can be said

that, it improves efficiency factor in all subsamples, and it is highly influential on both between- and within-industry acquisitions and also in IP-intensive and less IP-intensive industries. Moreover, it has a direct negative influence on the innovative performance in all subsamples with the exception of less IP-intensive industries where its effect is negative but insignificant. Instead, technological distance is significantly hampering efficiency factor and this effect is mostly observed in within-industry acquisitions and IP-intensive industries. The inverted U-shaped relationship between efficiency factor and innovative performance holds in all subsamples. Differences in the impact of factors on efficiency factor and innovative performance with regard to acquisition types and industries are venues for future research.

This study also has some limitations. First of all, determining the motives of acquisitions is problematic in technology-based firm acquisitions. In this study, to determine the technology-based firm acquisitions, it is assumed that deals with target firms which have at least 5 technological assets before the acquisition are acquired for their technology. Similar specifications are used in other studies on technology acquisitions (e.g. Granstrand and Sjolander, 1990; Ernst and Vitt, 2000; Ahuja and Katila, 2001; Puranam and Srikanth, 2007; Ceccagnoli and Hicks, 2012). However, this specification does not guarantee that these acquisitions are undertaken for their technologies. Therefore, additional search is executed on acquisition announcements in press releases to understand the intention of the acquirers. Even in this case, it is not certain whether acquirers hesitate to announce that they intent to use target's knowledge stock or they declare the use of target's technology although they do not intent to exploit. Additional research is needed to better specify the motives of acquisitions. Second, this study focuses on six industries, three IP-intensive and three less IP-intensive industries. The proposed model is tested on a specific IP regime, i.e. U.S. context, and the results may differ depending on the strength of the IP regime. Third, level of integration is

argued to be an important driver of the knowledge leverage in technology-based firm acquisitions (Birkinshaw, 1999; Ranft and Lord, 2002; Puranam, et.al., 2006; Puranam and Srikanth; 2007); and it is a factor not controlled in this research. Future research can advance this study by adding post-merger integration as another determinant of efficiency factor and innovative performance in technology-based firm acquisitions.

This research also provides implications for managers. Regarding innovative performance in technology-based firm acquisitions which aim at acquisition, assimilation and exploitation of external technology, managers are advised to appreciate factors affective at different levels, assess their external technology access along these factors and make their acquisition decision accordingly. To enhance the innovative value creation through M&As, managers are advised to target those firms which endow technologically similar, but not very similar, knowledge stocks. The impact of technological complexity is rather ambiguous. It is noted here that, complexity of the external knowledge has two contrasting effects; first, it enhances the exploitation of acquired external knowledge which, in turn, increases innovative performance; second, it decreases the innovative performance by reducing the number of innovative output produced. Therefore, it is not certain which effect will dominate in technology-based firm acquisitions. However, acquisition of target firms endowing technologically complex knowledge stocks is envisioned to be beneficial in the long-run for the acquirer by enhancing its capacity to learn more complex knowledge.

In conclusion, this study shows that structure and the relatedness of the external knowledge have an influence on innovative performance of the firm which is mediated through efficiency factor in technology-based firm acquisitions. It also shows that there is an

optimum level of AC which maximizes innovative performance. This paper advances our knowledge on how acquirer's create innovative value through M&As. Future research can expose how the effects of these factors vary depending on the post-merger integration decision. It is hoped that this research paves the way to refine future theorizing on this line of research.

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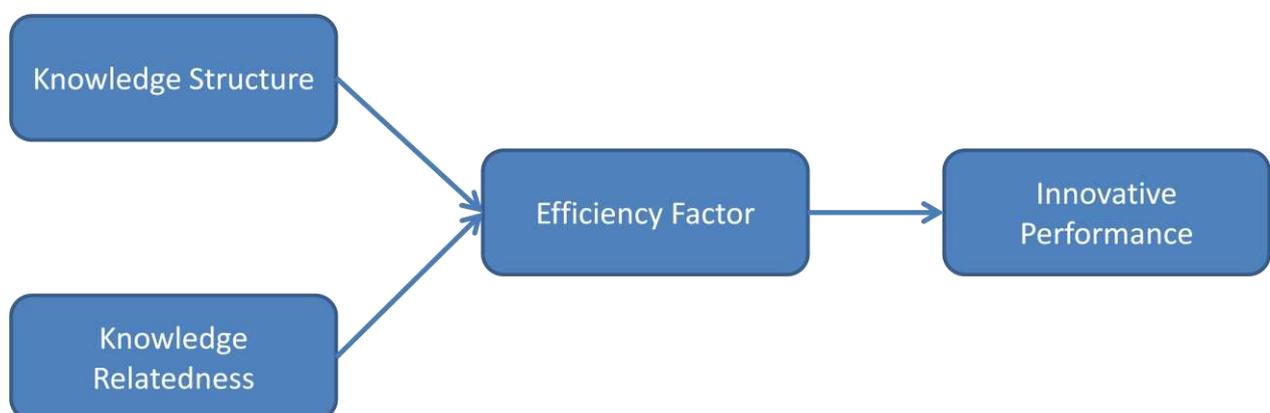
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## APPENDIX

**Figure-1 Theoretical Model**



**Table-1 Descriptive Statistics**

<b>Variable</b>	<b>Obs</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>
<b>Innovative Performance</b>	356	232.306	784.795	0	8380
<b>Efficiency Factor</b>	356	.132	.227	0	1
<b>Technological Distance</b>	356	.694	.272	0	1
<b>Technological Complexity</b>	356	.059	.087	0	.5368
<b>Herfindahl Index</b>	356	.146	.098	.050	.674
<b>Acquirer's Licensing Experience</b>	356	2.247	7.497	0	55
<b>Target's Knowledge Stock</b>	356	51.051	232.713	5	3591
<b>Acquirer's Knowledge Stock</b>	356	1001.747	3333.827	0	20210
<b>Number of Target Patents Cited</b>	356	42.610	203.744	0	3135
<b>Number of Target Patents Cited by Acquirer</b>	356	.069	.149	0	.875
<b>Acquirer's Acquisition Experience</b>	356	5.230	9.888	0	77
<b>Within-Industry Acquisitions</b>	356	.486	.501	0	1
<b>IP-Intensive Industry</b>	356	.761	.427	0	1

**Table-2 Correlations Matrix**

	1	2	3	4	5	6	7	8	9	10	11	12	13
1 <b>Innovative Performance</b>	1.000												
2 <b>Efficiency Factor</b>	0.141*	1.000											
3 <b>Technological Distance</b>	-0.025	-0.126*	1.000										
4 <b>Technological Complexity</b>	-0.069	0.304*	0.061	1.000									
5 <b>Herfindahl Index</b>	-0.031	-0.074	0.026	0.011	1.000								
6 <b>Acquirer's Licensing Experience</b>	0.578*	-0.019	-0.041	-0.030	-0.005	1.000							
7 <b>Target's Knowledge Stock</b>	0.289*	-0.002	-0.007	-0.100*	0.076	0.166*	1.000						
8 <b>Acquirer's Knowledge Stock</b>	0.590*	-0.019	-0.005	-0.044	0.029	0.852*	0.196*	1.000					
9 <b>Number of Target Patents Cited</b>	0.302*	-0.003	-0.012	-0.097*	0.076	0.168*	0.998*	0.191*	1.000				
10 <b>Number of Target Patents Cited by Acquirer</b>	0.310*	0.410*	-0.229*	0.181*	-0.102*	0.134*	0.017	0.145*	0.024	1.000			
11 <b>Acquirer's Acquisition Experience</b>	0.212*	-0.052	0.047	-0.056	0.064	0.341*	0.095*	0.404*	0.088*	0.049	1.000		
12 <b>Within-Industry Acquisitions</b>	0.105*	-0.015	-0.260*	-0.112*	-0.145*	0.076	-0.015	0.057	-0.012	0.043	0.058	1.000	
13 <b>IP-Intensive Industry</b>	0.135*	0.110*	-0.154*	0.000	-0.428*	0.147*	-0.061	0.126*	-0.060	0.138*	0.071	0.149*	1.000

**Table-3 Regression Results for the First Stage GLM Estimations**

VARIABLES	(1) Efficiency Factor	(2) Efficiency Factor	(3) Efficiency Factor	(4) Efficiency Factor
Technological Distance			-0.918*** (0.346)	-1.117*** (0.353)
Technological Complexity		6.015*** (1.145)		6.340*** (1.186)
HRFNDHL	-0.144 (1.368)	-0.068 (1.293)	-0.459 (1.468)	-0.440 (1.420)
Acquirer's Licensing Exp	-0.014 (0.025)	-0.017 (0.025)	-0.017 (0.025)	-0.018 (0.025)
Target's Knowledge Stock	0.015** (0.007)	0.017*** (0.006)	0.016** (0.007)	0.018*** (0.005)
Acquirer's Knowledge Stock	-2.12e-05 (5.56e-05)	-1.39e-05 (5.70e-05)	-1.65e-05 (5.42e-05)	-1.00e-05 (5.46e-05)
Num of Target Patent's Cited	-0.020** (0.010)	-0.022*** (0.008)	-0.021** (0.010)	-0.022*** (0.007)
Num of Target Patent's Cited by Acquirer	0.016* (0.008)	0.013** (0.006)	0.015* (0.008)	0.013** (0.005)
Acquirer's Acq. Experience	-0.011 (0.013)	-0.010 (0.012)	-0.007 (0.012)	-0.004 (0.011)
Within Industry Acquisition	-0.274 (0.244)	-0.035 (0.240)	-0.410* (0.245)	-0.202 (0.241)
IP-Intensive Industry	0.450 (0.287)	0.329 (0.270)	0.310 (0.289)	0.169 (0.261)
TDDUMMY	-1.304*** (0.476)	-1.520*** (0.414)	-1.287*** (0.484)	-1.510*** (0.421)
Constant	-2.261*** (0.534)	-2.984*** (0.502)	-1.530*** (0.585)	-2.137*** (0.565)
Observations	356	356	356	356

Robust standard errors in parentheses

Year Dummies are inserted

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Table-4 Regression Results for the Second Stage Negative Binomial Estimations**

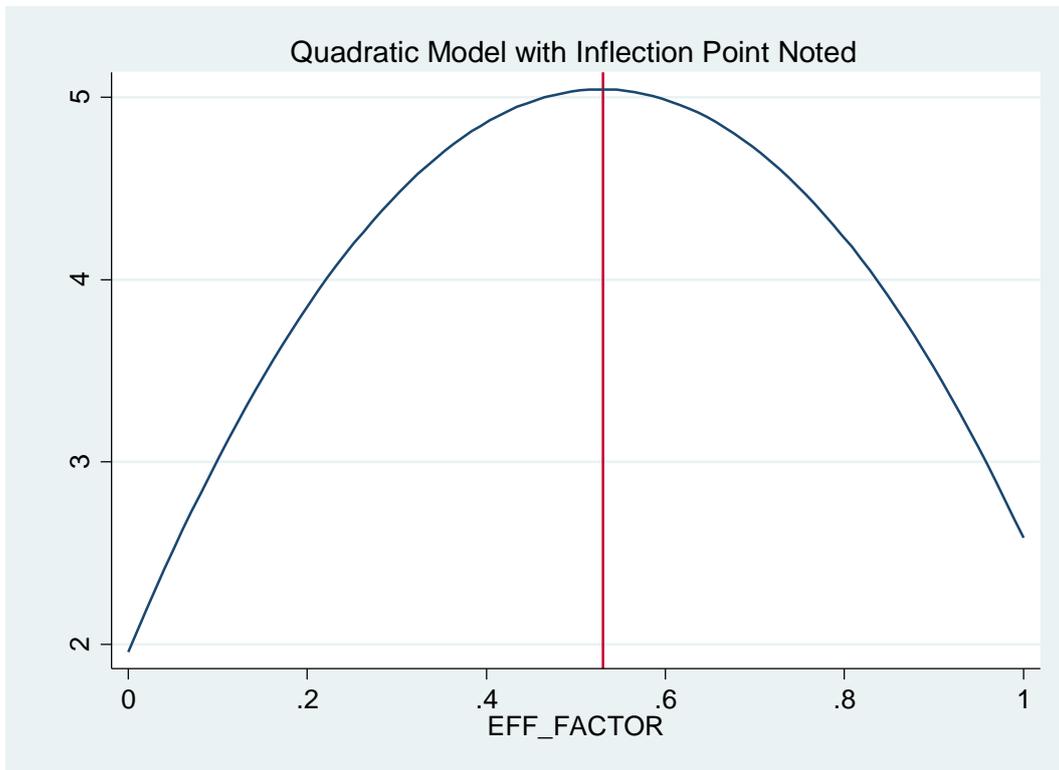
VARIABLES	(1) INNOVATIVE PERFORMANCE	(2) INNOVATIVE PERFORMANCE	(3) INNOVATIVE PERFORMANCE
Eff.Factor^2			-2.828*** (0.557)
Eff. Factor			3.188*** (0.414)
Technological Complexity		-0.158 (0.530)	-1.238** (0.501)
Technological Distance		-0.255* (0.138)	-0.058 (0.114)
HRFNDHL	-1.244** (0.622)	-1.348** (0.638)	-1.186** (0.583)
Acquirer's Licensing Exp	0.003 (0.007)	0.003 (0.007)	0.006 (0.006)
Target's Knowledge Stock	0.006 (0.004)	0.006 (0.004)	-0.001 (0.003)
Acquirer's Knowledge Stock	4.03e-05** (1.78e-05)	4.08e-05** (1.80e-05)	4.71e-05*** (1.41e-05)
Num of Target Patent's Cited	-0.006 (0.004)	-0.006 (0.004)	0.001 (0.003)
Num of Target Patent's Cited by Acquirer	0.002* (0.001)	0.002* (0.001)	-0.001 (0.001)
Acquirer's Acq. Experience	0.012*** (0.004)	0.012*** (0.005)	0.011*** (0.004)
Within Industry Acquisition	0.047 (0.078)	0.011 (0.080)	0.020 (0.072)
IP-Intensive Industry	0.155 (0.114)	0.115 (0.118)	0.116 (0.105)
TDDUMMY	-1.548*** (0.210)	-1.548*** (0.210)	-1.330*** (0.200)
Constant	0.728*** (0.207)	0.957*** (0.243)	0.735*** (0.221)
Inalpha	-2.151*** (0.401)	-2.184*** (0.409)	-7.158 (50.83)
Observations	356	356	356

Robust standard errors in parentheses

Year Dummies are inserted

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Figure-2 Quadratic Model with Inflection Point Noted**



**Table-5 Regression Results for the Path Analysis**

Path Analysis				
VARIABLES	(1)		(2)	
	Efficiency Factor	Beta	Innovative Performance	Beta
Eff. Factor <sup>2</sup>			-8.871*** (1.340)	-.664
Eff. Factor			9.894*** (1.088)	.933
Technological Distance	-.136*** (.044)	-.163	-.126 (.335)	-.014
Technological Complexity	.846*** (.131)	.325	-2.921*** (1.049)	-.106
HRFNDHL	-.050 (.130)	-.021	-1.704* (.990)	-.069
Acquirer's Licensing Exp	-.001 (.003)	-.043	.035 (.023)	.108
Target's Knowledge Stock	.002** (.001)	1.96	.007 (.007)	.714
Acquirer's Knowledge Stock	-2.68e-06 (6.81e-06)	-.039	.000*** (.000)	.297
Num of Target Patent's Cited	-.002** (.001)	-2.064	-.008 (.008)	-.650
Num of Target Patent's Cited by Acquirer	.001*** (.001)	.216	.001 (.004)	.016
Acquirer's Acq. Experience	-.000 (.001)	-.022	.034*** (.010)	.140
Within-Industry Acquisition	-.032 (.024)	-.070	.080 (.181)	.017
IP-Intensive Industry	.019 (.030)	.037	.375 (.229)	.067
TDDUMMY	-.116*** (.030)	-.205	-1.374*** (.234)	-.229
Constant	.141** (.061)		1.668*** (.469)	
Number of Observations	356		356	
R <sup>2</sup>	0.2049		0.5974	
sqrt(1-R <sup>2</sup> )	0.8917		0.6345	

Robust standard errors in parentheses

Year Dummies inserted

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Table-6 Regression Results for the Subset of Technology Acquisitions**

<b>Subset-1 Technology Acquisitions</b>			
VARIABLES	(1) Eff. Factor	(2) Innovative Performance	(3) Innovative Performance
Eff.Factor^2			-3.437*** (1.255)
Eff. Factor		2.891*** (0.588)	5.588*** (1.171)
Technological Distance	-0.525 (0.437)	0.590 (0.467)	0.501 (0.494)
Technological Complexity	5.386*** (1.459)	-5.105*** (1.183)	-4.878*** (1.211)
HRFNDHL	0.382 (1.487)	-2.191* (1.243)	-1.971 (1.288)
Acquirer's Licensing Experience	-0.011 (0.030)	0.035 (0.039)	0.039 (0.039)
Target's Knowledge Stock	0.015** (0.007)	0.020 (0.0243)	0.016 (0.024)
Acquirer's Knowledge Stock	-1.64e-05 (6.41e-05)	0.000** (8.74e-05)	0.000** (9.29e-05)
Num of Target Patent's Cited	-0.024** (0.009)	-0.027 (0.027)	-0.022 (0.027)
Num of Target Patent's Cited by Acquirer	0.098*** (0.031)	0.079*** (0.025)	0.067*** (0.025)
Acquirer's Acq. Experience	-0.011 (0.015)	0.060* (0.035)	0.062* (0.036)
Within Industry Acquisition	-0.124 (0.317)	-0.055 (0.245)	-0.140 (0.258)
IP-Intensive Industry	0.084 (0.340)	0.244 (0.362)	0.203 (0.374)
TDDUMMY	-1.407** (0.604)	-3.063*** (0.395)	-3.008*** (0.379)
Constant	-2.244*** (0.699)	2.868*** (0.885)	2.781*** (0.910)
lnalpha		0.771*** (0.087)	0.748*** (0.085)
Observations	223	223	223

Robust standard errors in parentheses

Year Dummies are inserted

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table-7 Regression Results for Within- and Between-Industry Acquisitions**

VARIABLES	Within-Industry Acquisitions		Between-Industry Acquisitions	
	(1) Eff. Factor	(2) Innovative Performance	(3) Eff. Factor	(4) Innovative Performance
Eff.Factor^2		-7.975*** (2.981)		-5.624*** (1.996)
Eff. Factor		8.139*** (1.722)		7.550*** (1.948)
Technological Distance	-1.376*** (0.477)	0.413 (0.519)	-0.552 (0.616)	-0.493 (0.658)
Technological Complexity	6.080*** (2.135)	-4.564** (2.298)	5.579*** (1.296)	-5.923*** (1.529)
HRFNDHL	0.422 (1.953)	0.422 (1.736)	-0.881 (1.933)	-1.208 (2.091)
Acquirer's Licensing Exp.	-0.005 (0.031)	-0.053 (0.067)	-0.025 (0.042)	0.040 (0.053)
Target's Knowledge Stock	0.040** (0.017)	0.024*** (0.009)	0.011*** (0.004)	0.009 (0.025)
Acquirer's Knowledge Stock	-3.29e-05 (6.87e-05)	0.000* (0.000)	2.13e-05 (0.000)	0.000 (0.000)
Num of Target Patent's Cited	-0.049** (0.020)	-0.027** (0.011)	-0.019*** (0.006)	-0.017 (0.027)
Num of Target Patent's Cited by Acquirer	0.022*** (0.007)	0.004 (0.008)	0.092** (0.038)	0.117*** (0.043)
Acquirer's Acq. Experience	-0.003 (0.012)	0.035 (0.042)	-0.018 (0.022)	0.091*** (0.031)
IP-Intensive Industry	0.338 (0.406)	1.635*** (0.464)	0.008 (0.377)	0.058 (0.372)
TDDUMMY	-0.600 (0.466)	-1.983*** (0.506)	-2.201*** (0.700)	-2.687*** (0.421)
Constant	-3.149*** (0.854)	1.406** (0.622)	-1.887** (0.737)	2.697** (1.177)
Inalpha		0.813*** (0.099)		0.937*** (0.088)
Observations	173	173	183	183

Robust standard errors in parentheses

Year Dummies inserted

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table-8 Regression Results for IP-Intensive and less IP-Intensive Industry Acquisitions**

VARIABLES	IP-Intensive Industry		Less IP-Intensive Industry	
	(1) Eff. Factor	(2) Innovative Performance	(3) Eff. Factor	(4) Innovative Performance
Eff.Factor^2		-4.968*** (1.237)		-9.919** (4.337)
Eff. Factor		7.664*** (1.106)		8.434*** (2.826)
Technological Distance	-1.199*** (0.407)	0.455 (0.458)	-0.108 (0.807)	1.684** (0.830)
Tech. Complexity	6.222*** (1.427)	-6.839*** (1.273)	7.298*** (2.811)	-2.329 (2.395)
HRFNDHL	-1.608 (2.087)	-2.267 (1.681)	-1.458 (1.424)	-3.785*** (1.138)
Acquirer's Licensing Exp	-0.015 (0.025)	0.043** (0.021)	0.234 (0.341)	0.168 (0.149)
Target's Knowledge Stock	0.027** (0.011)	0.026** (0.013)	0.013** (0.006)	0.025* (0.014)
Acquirer's Knowledge Stock	-8.75e-06 (5.41e-05)	0.000** (6.21e-05)	-0.000 (0.000)	0.001*** (0.000)
Num of Target Patent's Cited	-0.035** (0.014)	-0.031** (0.014)	-0.028*** (0.011)	-0.049** (0.020)
Num of Target Patent's Cited by Acquirer	0.022*** (0.008)	0.012** (0.005)	0.202** (0.084)	0.341*** (0.095)
Acquirer's Acq. Experience	0.002 (0.012)	0.072** (0.030)	-0.073 (0.045)	0.055*** (0.012)
Within-Industry Acquisition	-0.291 (0.295)	0.224 (0.217)	-0.054 (0.519)	-0.096 (0.346)
TDDUMMY	-1.449*** (0.538)	-3.366*** (0.337)	-1.243** (0.590)	-1.155*** (0.373)
Constant	-1.633*** (0.597)	3.120*** (0.552)	-4.417*** (1.132)	-0.342 (0.968)
Inalpha		0.913*** (0.076)		0.190 (0.191)
Observations	271	271	85	85

Robust standard errors in parentheses

Year Dummies inserted

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1