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Innovative performance of technological M&As:

The moderating role of M&A experience on knowledge overlap and non-overlap between target and acquiring firms in the bio-pharmaceutical industry

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Abstract

Technological mergers and acquisitions (M&As), in which the underlying goal of acquiring firms is to acquire knowledge and information, have become increasingly prevalent in the bio-pharmaceutical industry. I analyse the effects of the overlapping and non-overlapping knowledge base between target and acquiring firms. More specifically, I consider the quality, as well as quantity, of the overlapping and non-overlapping knowledge, and investigate their effect on post-deal innovative performance of the acquiring firm. Further, I investigate the role of prior M&A experience as the moderative capacity of the acquiring firm and investigate its moderating effect on this relationship. The analyses use a data set of 122 technological M&As from 80 different acquiring firms in the bio-pharmaceutical industry. No statistically significant relationship between either the quantity or quality of (non-) overlapping knowledge and innovative performance was found, nor a significant direct or moderating effect of M&A experience. A discussion of the signs of the coefficients, regardless of a lack of significance, provide potential insights into the effects of the nature of knowledge between the acquiring and target firm.

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1. Introduction

Within a constantly evolving environment, firms in high-tech industries are required to consistently update their technological knowledge base as to remain competitive (D'aveni, 1994). Amongst other things, internal research and development (R&D) efforts have been found to positively impact and advance the knowledge base of a firm (Hall & Bagchi-Sen, 2002). However, acquiring knowledge externally remains a crucial strategy as to maximise innovative performance (Kang, Jo & Jo, 2015). External sources of technological knowledge include licensing, alliances, joint ventures, and mergers and acquisitions (M&As) (Lee, 2010). M&As as a form of acquiring knowledge and technology, commonly referred to as technological M&As, have increased in popularity since the early 2000s. This phenomenon is especially prevalent in the bio-pharmaceutical industry, where R&D intensities are some of the highest in the world (DiMasi, Hansen & Grabowski, 2003). M&As often include significant risk and uncertainty for the acquiring firm, and thus identifying factors which influence the extent to which they are successful is imperative.

"Success" of a merger or acquisition can be measured by studying changes on the firm level, such as creating shareholder value or improving a firm's economic performance. While there is merit to these methods, studying the change of innovative performance is especially relevant in the bio-pharmaceutical industry, as firm knowledge is a key characteristic which gives firms competitive advantage over others. Analysing not only an output measure of knowledge following a M&A, but also comparing the nature of the knowledge, as well as overlapping and non-overlapping knowledge between the acquiring and target firm, is hence a topic of interest. A previous acquisition which exemplifies this is Gilead Sciences' acquisition of Triangle Pharmaceuticals in the first half of 2003. Both companies possessed high quality knowledge, with overlapping strengths in fighting infectious diseases. After Gilead Sciences acquired Triangle Pharmaceuticals, with the aim of acquiring the HIV treatment Emtriva, Gilead Sciences subsequently recombined the acquired treatment with its own HIV treatment, Viread, and developed Truveda, which became the standard drug in the HIV market (Han, Jo & Kang, 2016).

This example invites the question of the influence of the relative knowledge between the target and acquiring firm. Knowledge, however, can largely be considered an abstract term, and thus the question "How can we measure knowledge?" both from a quantitative, as well as from a qualitative aspect, must be addressed. This alone poses significant challenges, and yet is crucial for managers of acquiring firms seeking to valuate a potential target as accurately and holistically as possible. Even if we can quantify and qualify knowledge, analysing the nature of how the relative knowledge between the target and acquiring firms affects the acquirers' innovative performance can yield important findings for managers. This paper addresses these issues. Further, I consider the effect of prior M&A experience of acquiring firms, and whether experience strengthens or weakens the effect the relative knowledge bases of target and acquiring firms have on post-deal innovative performance.

The study of innovative performance of firms following this recent trend of mergers is important not only for managers of the respective acquiring firms, but also for policymakers and antitrust authorities. With the recent trends of "megamergers", where giants acquire other giants (such as Bayer's $18.4 billion acquisition of Schering in 2006), concerns over the competitive marketplace being harmed or innovation pipelines being disrupted are warranted.

Some fear that a more concentrated upstream market would reduce competition and experimentation for new discoveries and innovation, while also potentially increasing prices (Young, 2016). However, others argue that mergers could result in economies of scale and development which encourage more development and innovation. Also, with an increased concentration in the market place, doors may open for new, innovative entrants. (Richman et. al, 2016)

Previous literature on the economic performance of acquiring firms is rich. Besides analysing the effect on short term, economic outcomes, researchers have also considered how M&As impact the technological or innovative performance of the acquiring firm. Several studies have applied the resource-based view of the firm when considering the effect of M&A activity on innovative performance (Ahuja & Katila, 2001; Hagedoorn & Duysters, 2002; Desyllas & Hughes, 2010). The technological performance of a firm following a deal reflects the long-term effects of M&As, where possible synergistic effects of M&As can impact technological performance through developing new process or product related technologies from the combined companies. (Hagedoorn & Duysters, 2002). Technological M&As refer to deals where the acquiring firms' objective includes absorbing the knowledge of the target firm as to stimulate innovation or obtaining sustainable competitive advantages (Hamel 2000; Cloodt et al 2006). Previous literature in the field of technological M&As have considered the following factors impacting the subsequent innovation performance: whether the M&A is technological (Wagner, 2011; Valentini, 2012), characteristics of the acquiring firm (Desyllas and Hughes, 2010) and characteristics of the acquired firm (Cloodt et al. 2006).

In this study, I utilise a framework proposed by Han, Jo & Kang (2016) and adopt a two-dimensional approach to considering the nature of knowledge of both the acquiring and acquired firm. However, instead of conducting a multi-industry analysis of the high-tech sector, I focus on the bio-pharmaceutical sector. My analyses also go beyond the effect of knowledge (non-)overlaps between the two firms, and considers the role M&A experience plays in moderating the effect between knowledge (non-) overlap between the firms and innovative performance. After distinguishing between overlapping and non-overlapping knowledge between the target and acquiring firms, I analyse how both the quantity and quality of this knowledge overlap impact post-acquisition innovative performance.

After careful consideration and formulation of variables, no significant results were found from the observations used in my sample regarding knowledge or M&A experience. I suspect this to be attributable to several factors. First, the dataset used was taken from PATSTAT and USPTO database, while M&A deals were taken globally. It is possible that smaller companies would not file patents in the US system, and hence the dependent variable being slightly skewed. Also, with a lack of observations, standard errors of coefficients could be too great as to obtain a significant coefficient at a 10% level ($p<0.1$). Also, reliability regarding the patent dataset, and whether each acquiring company is accurately represented, is questionable. While more detail regarding the use of data and their limitations are discussed throughout the paper, the signs of the coefficients obtained in the results are interpreted, as to see whether they are in line with expectations. The effects of the characteristics of knowledge are mostly as expected, with overlapping and non-overlapping knowledge quality having a positive and negative effect respectively. However, the direct effect of M&A experience on post-deal innovative performance was found to be negative, which was surprising.

The paper is organised as follows. Section 2 describes technological M&As and formulates my hypotheses, with links to previous research. Section 3 presents the details of the data and method used in the research model. Section 4 depicts the results of the empirical analysis as well as the discussion, with section 5 providing limitations of the research, suggestions for related further research, and concluding remarks.

2. Theoretical background and hypotheses

2. 1 Technological M&As

Conventional theory suggests that M&As are undertaken for purposes such as increasing market share, achieving economies of scale and scope, diversification, and exposure or access to new markets (Berkovitch and Narayanan 1993; Hagedoorn and Sadowski, 1999). In contrary to these growth focused M&As, technological M&As are primarily undertaken as to a way to intensify the research and development activities and capabilities through the absorption of knowledge of acquired, target firms. Through the combination of the newly acquired knowledge with existing knowledge, new inventions and innovations are developed, which would not have otherwise been achievable under the acquiring firms' original knowledge base (Ahuja and Katila 2001). A literature review of M&As by Rossi, Tarba, and Raviv (2013) found that high-tech industry companies, including biotechnological and ICT companies, engaged in M&A activity with the primary motive to acquire the targets' firm knowledge. Previous research into sector specific technological M&A activity also arrived at the conclusion that firms aimed to achieve increased control over rival companies in highly volatile, R&D intensive industries (Hagedoorn & Duysters, 2002).

Analysing the factors which influence the post-deal innovative performance has received attention in prior papers. Hagedoorn & Duysters (2002) consider the strategic fit of the target and acquiring companies, while also considering the technological relatedness. Ahuja and Katila (2001) consider the relative and absolute size of the knowledge bases of the two respective firms, while Kang, Jo & Kang (2015) look at the technological digestibility between the firms. In this paper, I adopt a similar approach to Han, Jo & Kang (2016), which consider the nature of both the quantity and quality of overlapping, as well as non-overlapping knowledge of the target and acquirer.

2.2 Knowledge quality and innovation performance

Knowledge quality

The quality of knowledge can be viewed in terms of its specificity, complexity, and to the extent to which it is tacit (Kogut & Zander, 1992). Argote & Ingram (2000) argued that higher quality knowledge is more embedded in the people, tools, and networks of a firm. The ambiguity of the tacit nature of high quality knowledge hence could hinder the transfer of knowledge, especially when there is a lack of shared routines, or absorptive capacity (Uygur, 2013). The ambiguity caused by the tacitness, as well as the embeddedness of the knowledge in the target firms' organisation, would thus prevent perfect learning or absorption of high quality knowledge through conventional methods (Song, Almeida & Wu, 2003; Oguz & Sengun, 2011). However, I argue that whether these characteristics of higher knowledge quality are beneficial or detrimental to firms depends on whether the target firms' knowledge overlaps or not with that of the acquirer. The following section discusses these two scenarios in turn.

Overlapping knowledge quality

Overlapping knowledge can help to facilitate the transfer of high-quality knowledge from the target to acquiring firm following a M&A as an overlap in knowledge could indicate common processes and routines (Lane & Lubatkin ,1998) of both firms, as well as shared technology, cognitive bases, and technological know-how. This potentially improves the capability of the acquiring firm to absorb and assimilate the new knowledge, improving the knowledge transfer process (Phene, Tallman, & Almeida, 2012). Successful accumulation and assimilation of high quality knowledge, which could complement and improve existing knowledge bases of acquiring firms, is essential in further developing existing knowledge, as well as having a potentially large impact on originality and impact of innovation output (Trajtenberg 1990). It is normally comprised of more efficient routines and processes than relatively lower quality knowledge (Cho & Pucik, 2005), such that overlapping high-quality knowledge would allow firms to develop routines, processes, and usage of existing knowledge (Han, Jo & Kang, 2016). Hence, I formulate the first hypothesis.

H1: In technological M&As, the quality of knowledge base overlap between the acquiring and target firm will be positively related to the innovation performance of the acquiring firm

Non-overlapping knowledge quality

In the case of non-overlapping high-quality knowledge, the specific characteristics as mentioned before, such as high complexity, specificity, and tacit nature, make the knowledge transfer more difficult (Spender, 1989; Cloodt and Hagedoorn, 2006). This subsequently results in increasingly higher inefficiencies and integration-costs. These inefficiencies and integration costs result in a waste of firm resources, such as time and R&D resources, which have an associated opportunity cost, and could have otherwise been used to improve the core competencies of the acquiring firm. This would subsequently negatively impacting innovation performance (Jiang, Tan, & Thursby, 2011), as less resources would be devoted to the creation or assimilation of new knowledge based on the newly acquired knowledge. Han, Jo & Kang (2016) argue that while high-quality non-overlapping knowledge does possess significant combinative potential, the high integration costs and issues related to limited resource allocation would outweigh these potential benefits. In their analysis, which considers the high-tech industry, they find a negative relationship between high-quality knowledge overlap and innovative performance of acquiring firms. In summary, based on the argument that firm's acquiring non-overlapping high knowledge overlaps may lack absorptive capacity after acquiring this knowledge, as well as the negative effects outweighing the positive effects, I form the following hypothesis

H2: In technological M&As, the quality of knowledge base non-overlap between the acquiring and target firm will be negatively related to the innovation performance of the acquiring firm.

2.3 Knowledge quantity and innovative performance

Knowledge quantity

The quantity of knowledge of the target firm which either overlaps or doesn't with that of the acquiring firm influences the potential number of novel innovations as a result of recombination of knowledge. Previous research by Han et al. and Han, Jo & Kang (2016) argue that while knowledge quantity is an important aspect in subsequent innovation, the relationship was not necessarily a linear. The different implications for both overlapping and non-overlapping knowledge quantity are outlined below.

Overlapping knowledge quantity

Research has found that the extent to which the knowledge bases of the target and acquiring firm overlap significantly impacts the ability of acquirers to generate novel recombination's, which reflects the innovative performance of the acquiring firm (Sears & Hoetker, 2014). Two firms with a similar technological knowledge base would imply that the firms share a similar knowledge and recognition structure (Han, Jo & Kang, 2016), which would thus arguably allow a smoother transfer of both explicit and tacit knowledge (Cohen and Levinthal 1989). This similarity in knowledge helps the acquiring firm to absorb the new knowledge following the acquisition. Also, a similar knowledge base would, according to Kogut and Zander (1992) and Grant (1996), support the integration of knowledge for the acquiring firm, resulting in cohesive assimilation. A better similarity hence allows the acquiring firm to maximise the benefits of its absorptive capacity, and hence create subsequent knowledge (Lane and Lubatkin, 1998). When the quantity of knowledge overlap increases, there is a greater amount of recombination of knowledge possible, which, if in line with the core competencies of the firm, can further increase the combinative potential (Nonaka & Takeuchi, 1996).

However, if there is a large amount of overlapping knowledge, it is possible that a significant amount of knowledge which the firm acquires would be redundant, reducing future learning potential, and hence dampening new knowledge creation. In addition, this redundancy caused by the merging of similar knowledge resources could cause organisational disruption due to potential conflict between human resources within the firm (Sears and Hoetker, 2014). Large knowledge overlaps are thus also possibly detrimental to future innovation.

In summary, a low level of target overlap may provide ample opportunities for novel recombination's of knowledge, although the acquiring firm may not be able to recognise and successfully exploit this potential due to a low level of absorptive capacity, resulting in a waste of technological resources. However, a high level of overlap suggests the acquirer has the necessary absorptive capacity, but redundancy in knowledge due to a high level of similarity in knowledge and resources could stem future innovations and knowledge recombination's. Recognising that the relationship between knowledge quantity overlap and innovative performance is dependent on the relative magnitude of value creation and absorptive capacity, (Sears and Hoetker, 2014), I hypothesise that a moderate level of knowledge similarity would result in the best post-deal patenting output.

H3: In technological M&As, the quantity of knowledge base overlap between the acquiring and target firm will be curvilinearly (inverted U shape) related to the innovative performance of the acquiring firm.

Non-overlapping knowledge quantity

When the knowledge of two firms does not overlap, more time and effort is required to integrate and absorb the knowledge due to a lack of absorptive capacity of the acquiring firm (Lane & Lubatkin, 1998). When an excessive amount of non-overlapping knowledge is acquired, the overload of information could hinder the learning process and assimilation of new information through a delay in the transfer of the knowledge process (Hagedoorn & Duysters, 2002; Han, Jo & Kang, 2016). Hence, there could be high integration costs, and an inefficient transfer of knowledge following the technological M&As (Sears & Hoetker, 2014;

Ahuja & Katila, 2001). This disrupted process of knowledge creation and knowledge transfer would ultimately negatively influence innovation performance of the acquiring firm.

However, non-overlapping knowledge increases could, to a certain extent, positively impact innovative performance in the case that the absorption of non-overlapping knowledge could result in recombination's allowing the firm to diversify into different fields (Karim & Mitchel, 2000). The non-overlapping knowledge could then present opportunities for the acquiring firm to explore new fields, including routines and processes the acquiring firm didn't previously have (Ahuja & Lampert, 2001). Hence, non-overlapping knowledge presents opportunities for novel and recombination's of knowledge, which could contribute to a firms' explorative innovation. However, this positive contribution would only be liable until a certain quantity of knowledge, after which the acquiring firm would suffer from inefficiencies and higher integration costs due to a possible lack of absorptive capacity to successfully absorb excessive amounts of knowledge.

Further, a basic level of knowledge overlap could suggest a basic understanding of the problems and knowledge faced by the two respective firms (Lane and Lubatkin, 1998). Those which have a higher common knowledge will be able to relate to each other better, and be able to understand the routines' and knowledge, which could increase learning and mutual understanding. Hence, they can understand the tacit knowledge which would be exploited for commercial applications, as well as transforming the knowledge into new products, innovations, or inventions. (Rindfleisch and Moormon, 2001; Lane and Lubatkin, 1998)

H4: In technological M&As, the quantity of knowledge base non-overlap between the acquiring and target firm will be curvilinearly (inverted U shape) related to the innovative performance of the acquiring firm.

2.4 M&A experience

<u>Direct effect of M&A experience</u>

Hagedoorn & Duysters (2002) recognise that one of the main issues of M&As is that the acquiring firms may lack information of the target company, where target firms could potentially "window-shop" their research, technological capabilities, or knowledge. The lack of credible information before a deal is made could thus potentially lead to an inaccurate assessment being made of the target firm, resulting in the acquisition of a different knowledge base than anticipated. Hence, unexpected issues or dissimilarities arising from this misinformation could reduce the absorptive capacity of the acquiring firms when there is a non-overlap of knowledge.

An increase in M&A experience potentially suggests that acquiring firms have established a refined routine or valuation method which could potentially increase their absorptive capacity of knowledge. Makadok (2001) notes how experience in scanning the corporate market, as well as selecting the suitable targets with reference to the acquiring firms' strategy, could potentially improve post-deal performance of the acquiring firm. Firms with well established "resource picking" procedures could better anticipate the nature of acquired knowledge in advanced. Hence, not only could previous M&A experience improve the acquiring firms' capability to integrate, but also its ability in selecting appropriate targets. Following this, experienced M&A firms have an improved capability to deploy, transform, and exploit the acquired resources.

H5: An increase in M&A experience will increase the subsequent innovative performance of the acquiring firms

Moderating effect of M&A experience

Not only could M&A experience directly impact subsequent innovation of the acquiring firm, but it could strengthen the relationship between the knowledge characteristics and innovation performance. Previous work has studied the role of absorptive capacity of a firm as a moderator (Han, Jo & Kang, 2016; Fernald et al., 2017). Besides the direct effect which previous experience with M&As has on innovative performance, it can also moderate the relationship between our knowledge-based factors and innovative performance. Hayward (2002) notes that M&A experience is a factor which relates to the extent of which acquiring firms can facilitate knowledge absorption, and hence reduces conflicts between acquiring firms and their targets (Han, Jo & Kang (2016)). Hence, experience can improve the firms' capability to successfully integrate.

Prior experience in M&As in a similar industry and setting, and acquisition-specific capabilities which are gained through this experience could thus intensify the relationship by facilitating the transfer of knowledge from the target to acquiring firm (Kang, Jo & Kang, 2015). Experience in M&As can be seen as a catalyst as a transfer of knowledge through both helping to reduce the conflicts which could arise in M&As, as well as aiding firms integrate and cooperate. The flow of knowledge between the target and acquired firm is thus arguably strengthened by prior M&A experience.

As previously mentioned, increasing the M&A experience could see firms choosing better M&A deals and being able to absorb knowledge more efficiently. Hence, regarding the quality of the knowledge and the nature of the overlap, I expect that M&A experience would strengthen the relationship between the quality of the knowledge base overlap and innovative firm performance. The expected positive relationship between the quality of the knowledge overlap and innovative firm performance will be strengthened, as the benefits of high quality knowledge, such as novel recombination potential, will be more effectively realised. On the other hand, the negative effects of high quality knowledge non-overlap will be mitigated slightly with additional M&A experience. Besides the positive moderating effect of M&A experience on knowledge quality, similar reasoning can be applied to the moderating effect on the quantity of overlapping and non-overlapping knowledge. Firms which have experience in previously acquiring firms will be better able to absorb and integrate knowledge with low overlaps, as well as avoiding potential redundancies of high knowledge overlaps.

Based on above, I formulate the following sub hypotheses.

H5a: M&A experience has a positive moderating effect between the quality of the knowledge base overlap and innovative performance of the acquiring firm.

H5b: M&A experience has a positive moderating effect between the quality of the knowledge base non-overlap and innovative performance of the acquiring firm.

H5c: M&A experience has a positive moderating effect between the quantity of the knowledge base overlap and innovative performance of the acquiring firm.

H5d: M&A experience has a positive moderating effect between the quantity of the knowledge base non-overlap and innovative performance of the acquiring firm.

3. Data and Methodology

3.1 Data

M&A deal data from the bio-pharmaceutical industry was collected from Thomson One's SDC Platinum between 2000 and 2008. Technological M&As, or those where the primary aim of the acquiring firm is to absorb knowledge to create and sustain a technological advantage (Hamel 2000; Cloodt et. al,2006), were chosen where the target firm had been granted at least one patent in the five years prior to the deal. 122 deals from 80 different acquiring companies were collected. Over half of the companies in my sample were based in the United States, with 44 acquiring firms having their headquarters there. Besides these, 25 acquiring firms were based in Europe. Of these, 9 firms were from the U.K., 4 from Germany, 3 from Denmark, 2 from Switzerland and Ireland, and 1 from Sweden, The Netherlands, Iceland, Finland, and Belgium respectively. Six of the remaining firms were headquartered in Japan, three from Canada, and one from Israel and India. The sample includes deals from all the Big Pharma companies, excluding Pfizer and Sanofi, for which appropriate data was not available.

As to obtain an accurate sample of firms within the bio-pharmaceutical industry, only deals regarding firms related to General Pharmaceutical, Research and Development firms, and other biotechnological firms were collected from SDC Platinum. Following that, deals were further filtered and chosen exclusively from the following sub-industries: Medicinal and Botanical Manufacturing, Pharmaceutical Preparation Manufacturing. Medical Laboratories, Research and Development in Biotechnology and Testing Laboratories. Deals in which either the acquiring or target firm were not part of this industry (as classified by SIC code) were thus dropped.

Deals where acquiring firms purchased remaining assets were excluded, as well as deals where the target firm only sold a small part of their business, such as a specific product line. Patent data arguably reflects the technological ability of the firm as a whole, and it would not be reliable to analyse deals where only part of the firm was sold, as I could not accurately match certain patents to product lines. Lastly, deals with a value of less than US$1million were excluded, as well as those where less than 90% of the company was acquired. A lower value of US$1 million was chosen as to still include relatively small firms who had successfully been granted a patent in the study. Sears & Hoetker (2014) note a recent trend of new firms, or start-ups, being strong innovators, with a shift away from large incumbent firms. The lower value of US$ 1 million was used as to include these younger innovative firms.

Technological M&As have seen a rise in popularity since the start of the 2000s (Sleuwagen & Valenntini, 2006), and as to study this phenomenon, I take the lower bound of my sample starting from the year 2000. Fully detailed company patent data was only available up to 2013, and thus I took 2008 as my upper bound as to be able to observe patenting activity of the acquiring firms following the deal for the following 1-5 years. Further information regarding firm data was obtained from DataStream and Orbis. Information regarding patents was collected from the United States Patent and Trademark Office (USPTO) database, as well as utilising the PATSTAT database.

I focused on the bio-pharmaceutical industry for several reasons. Firstly, as a high-tech sector, the industry exhibits high technological and economic development uncertainty. Secondly, companies within the bio-pharmaceutical industry rely on technologically unrelated sources of innovation as to tackle issues of stagnant product pipelines, making technological M&As a topical area in this industry. (Fernald et al., 2017). Also, technological learning can be considered a key determinant in a knowledge-driven industry for firms to establish a competitive advantage (Bierly and Chakrabarti, 1996). The bio-pharmaceutical industry also encourages patenting, which allows for a more accurate measure, as many firms would be inclined to protect their valuable intellectual property (Jo, Park & Kang, 2016) The pharmaceutical industry has played a prominent role in the witnesses M&A waves over the last 20 years, with some of the largest deals witnessed. It is also the industry with the highest R&D intensity, with innovation being the most important dimension of competition between rival companies (Omaghi, 2009). Park & Kang (2016) note

"After the year 2000, the average R&D expenditure in the bio-pharmaceutical industry increased by 14%, but the success rate of clinical demonstrations decreased from 20% to 8%. This indicates that a paradigm shift in the industry took place around the year 2000, as productivity of R&D in the bio-pharmaceutical industry rapidly decreased."

This fall in productivity of internal R&D within companies thus arguably strengthens the motivations of bio-pharmaceutical companies to seek out technological acquisitions, another reason for making this industry one of particular interest.

3.2 Use of patent data

The use of patent data as a proxy for measuring innovation and technological change has been adopted by researchers for over 50 years (Trajtenberg, 1990). Patent data is not only well compiled and accessible, but it also is rich with information, including country of origin, forward citations, and patent classifications. (Archibugi, 1992) All of these make it an attractive proxy for researchers to use. Indeed, previous authors have utilised patent data when considering the effect of technological M&As (Hagedoorn & Duysters, 2002; Ahuja & Katila, 2001). However, scrutiny has also been cast on patents for their several limitations. First, not all new inventions or innovations are patented, or indeed patentable. Hence, total patents granted to a firm may not accurately represent its innovative performance (Kleinknecht, Van Montford & Brouwer, 2002). However, this study focuses on the bio-pharmaceutical industry, which is characterised by a high appropriability regime, which results in strong incentives for companies to patent new innovations or inventions (Hang, Jo & Kang 2016). This characteristic of the pharmaceutical industry hence reduces the likelihood of patents not accurately reflecting innovative performance.

3.3 Variables

<u>Dependent variable</u>

*Innovation performance***:** In this study, an output measure of innovative performance is chosen in favour of an input measure. I use a count value of the total number of patents which were granted to the acquiring firm following the M&A deal. Innovation output has previously been found to be directly related to the number of patents generated by the acquiring firm (Ahuja, 2000; Owen-Smith and Power, 2004). The innovative performance of the firm was measured as the number of patents granted to the acquiring firm between 1 and 5 years following the date that the deal went into effect. This lag of one year is to account for the time it takes for the firm to absorb and utilise the newly acquired knowledge (Makri, Hitt & Lane, 2010). The knowledge acquired from a patent arguably dissipates quite rapidly in a high technology industry such as the bio-pharmaceutical industry, with the patent potentially losing most of its value within 5 years (Van der Vrande, Vanhaverbeke, and Duysters, 2009).The patent count is not only a widely used method for innovation measures in previous research measuring innovation performance (Henderson and Cockburn, 1994; Rothaermal and Hess, 2007) but also highly correlated with other indicators of firms innovative performances, such as the number of new product introductions (Hagedoorn and Cloodt, 2006), making it a suitable proxy for my study.

<u>Independent variables</u>

Overlapping knowledge quality and non-overlapping knowledge quality

I employ a similar technique as to measure overlapping and non-overlapping knowledge quality as Han, Jo & Kang (2016). This requires two steps. The first is to classify the knowledge base as being overlapping or non-overlapping, while the second is to measure the qualitative aspect of the corresponding (non-) overlaps for each M&A deal. As to determine whether there is overlapping knowledge, I consider the three digit SIC class of the patents of the target and acquiring firm. Patents held by the target firm which share the same class as one or more patents held by the acquiring firm will be classified as a knowledge overlap, and those which did not are knowledge non-overlaps.

Second, to see the quality of the overlapping and non-overlapping knowledge components, I consider the impact of each patent, reflected by the number of forward citations (Trajtenberg, 1990) the patent received in the following 5 years of it being issued. Jaffe, Trajtenberg and Henderson (1993) found that the number of citations a patent received fell significantly after seven years of its application. Using the readily available five-year citation data of after the patent was granted thus adheres to their finding. The overlapping *knowledge quality* and *non-overlapping knowledge quality* are calculated as the average five-year citations of all the targets' firm's patents in the overlapping and non-overlapping patent classes. Patent citations in the following five years depict knowledge quality since it reflects the ability of the knowledge, or patents, held by the target firm to support future inventions. Firms with a high number of citations per patent hence create a "ripple effect".

Overlapping knowledge quantity and non-overlapping knowledge quantity

Following a similar approach as above to determine an overlap or non-overlap in knowledge between the two firms, *overlapping knowledge quantity* and *non-overlapping knowledge quantity* are thus the total number of patents in the overlapping and non-overlapping parts of the target firm's knowledge base before the effective deal date.

M&A experience

M&A experience was measured as the total number of acquisitions the acquiring firm had undertaken 10 years prior to the M&A deal taken in the sample. Deals which were undisclosed or incomplete were excluded. Both the direct effect of M&A experience was included, as was the interaction effect with the variables relating to knowledge (non-)overlap quantity and quality. When considering the effect of M&A experience a moderator between the independent variables and subsequent innovation of the acquiring firm, I consider the interaction effect between the two by generating a variable with *M&A experience * independent variable*.

<u>Control variables</u>

I control for a potential additional effects on the post-M&A innovative performance of the acquiring firm using certain variables which could also have an impact on the innovative performance of the firm.

R&D intensity[1]: Absorptive capacity can be intensified by accumulated knowledge and investment in technological capability (Cohen and Levinthal, 1989). A higher R&D intensity indicates a higher level of effort to innovate, which affects post-innovation performance. Further, Pakes and Griliches (1984) both found a statistical relationship between R&D and the number of patents, while Cloodt & Hagedoorn (2006) found that the marginal effect of R&D on patents does fall as R&D spending increases. The logged form is taken because it was previously found by Stock et al(2001) that there was indeed an inverse U shape relationship between R&D intensity and product performance, since if a firm focuses solely on increasing R&D intensity, then it may lead to attention being diverted somewhere else. In addition, other critical activities could be neglected (Han, Jo & Kang, 2016). Hence, due to this non-linear relationship of R&D intensity with innovative performance, I take the natural logarithm of R&D intensity.

Size of acquiring firm: To control for the effects of firm size, I took the natural logarithm of the total number of employees of the firm in the year the deal was effective.

*Knowledge base***:** To control for the knowledge base of the acquiring firm before the M&A deal took place, I control for the number of patents granted to the acquiring firm before the effective deal date. A large knowledge base, indicated by many patents previously held by the firm, could suggest a greater number of possibilities of novel recombination's of knowledge (Ahuja & Katila, 2001), which could impact the subsequent innovation following the M&A deal. Since a unique patent is, by definition, a unique and novel element of knowledge, the combined set of these represents a strong element of the knowledge base (Jaffe, Tajtenberg,

[1] Calculated as (R&D expenditure/ Total Revenue) * 100

and Henderson 1993). The natural log of this value is used in the model as to account for outliers which could skew the data.

Year dummy: In addition, year dummy variables are also included as to control for time-specific effects. However, most of these are insignificant.

3.4 Model

With the dependent variable being a non-negative count variable in terms of the number of patents granted to the acquiring firm, normally a Poisson model is used. However, the Poisson model is only suitable when the mean of the variable is equal to the variance. As seen in the following section, this is not the case, and due to this problem of over dispersion I utilise a negative binomial model for this analysis.

4. Results

4.1 Correlation matrix and descriptive statistics

Table 1: Correlation matrix

Variables	1	2	3	4	5	6	7	8	9
Innovative performance	1								
Overlapping knowledge quality	0.2791	1							
Non-Overlapping knowledge quality	-0.1138	0.2069	1						
Overlapping knowledge quantity	0.4537	0.3068	-0.0481	1					
Non-overlapping knowledge quantity	-0.3087	-0.1268	0.2166	0.0672	1				
M&A experience	0.5318	0.1524	0.0178	0.3063	-0.1165	1			
Acquirer size	0.5951	0.2116	0.0222	0.2743	-0.1123	0.6778	1		
Acquirer R&D intensity	-0.2216	-0.0869	-0.0502	-0.1283	-0.0296	-0.2841	-0.2239	1	
Acquirer knowledge base	0.8519	0.1924	-0.132	0.4298	-0.3106	0.6285	0.6434	-0.2043	1

Table 1 shows the correlation between each variable used in the analysis. There is a notably strong positively correlation between acquirer knowledge base and innovative performance. Somewhat surprisingly, there is also a negative correlation between innovative performance and acquirer R&D intensity. Both the quality and quantity of overlapping knowledge is positively correlated to innovative performance, while non-overlapping knowledge shows a negative correlation. Both M&A experience and acquirer size are positively related. With respect to the explanatory variables, there are no strong correlations reported in the table. Hence, the results from the correlation matrix do not raise any significant concerns for multicollinearity, which would lead to bias within the regression results reported later in Table 3.

Table 2: Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Innovative performance	122	106.0738	154.3373	0	505
Overlapping knowledge quality	122	1.562468	3.02805	0	19
Non-Overlapping knowledge quality	122	2.427186	5.510418	0	48
Overlapping knowledge quantity	122	1.113317	1.560446	0	7.146772
Non-overlapping knowledge quantity	122	1.010191	1.463075	0	6.811244
M&A experience	122	6.098361	6.605044	0	32
Acquirer size	122	7.931923	2.474403	1.609438	11.68435
Acquirer R&D intensity	122	3.373459	1.368433	0.641854	7.306558
Acquirer knowledge base	122	3.312717	2.343539	0	7.247081

Table 2 shows the descriptive statistics. Innovative performance of acquiring firms in my sample differs substantially. As expected, large, multinational pharmaceuticals dominate the upper values of innovative performance, with Roche Holding being granted the maximum 505 patents in from one to five years following its deal. The ten next best performing firms are also dominated by the Big Pharma's, under which Bristol-Myers, Astrazeneca, Genentech, and Abbott. 17 firms had zero patents granted, almost all of which were relatively small firms, with less than 1000 employees. The maximum overlapping quality of 19 should be interpreted with caution, as there was only one overlapping patent which had 19 forward citations.

The mean of *overlapping knowledge quality*, 1.56, compared to the 2.427 of *non-overlapping knowledge quality* as reported in table 1 suggests that firms acquire higher non-overlapping knowledge than overlapping knowledge. This suggests that, if done consciously with perfect information, acquiring firms in my sample tend to target firms with a higher quality of unknown, non-overlapping knowledge than common knowledge. However, when considering the natural logarithm values of overlapping and non-overlapping quantity, the mean of overlapping quantity is higher than that of non-overlapping quantity. This suggests that while the quality of non-overlapping is higher in general, the quantity of knowledge acquired is higher, on average, when overlapping. Bristol-Myers had the largest knowledge-overlap, followed by numerous other Big Pharma's. This makes intuitive sense, as large pharmaceutical companies also have the largest and widest knowledge bases, measured by the number of patents previously held. However, the Big Pharma firms also appear in observations where non-overlapping quantity is high, which suggests that they also target companies which do not share a lot of knowledge.

M&A experience ranges from 0 to 32, with the larger firm observations undertaking more acquisitions in the past than the smaller ones. This can be expected, since we have seen in theory and past trends that larger firms tend to acquire smaller ones a mean of replenishing product pipelines. Almost half the observations in my sample (49.18%) have a zero overlapping quality value, while exactly half have a zero non-overlapping value. 40.17% of firms have no overlapping knowledge quantity, and 44.26% have no non-overlapping quantity.

4.2 Regression results

Table 3: Negative binomial results

Dependent variable: Post-acquisition innovative performance	Model 1 *(SE)*	Model 2 *(SE)*	Model 3 *(SE)*	Model 4 *(SE)*	Model 5 *(SE)*	Model 6 *(SE)*
Control variables						
Acquirer size	0.173***	.2100***	0.2153***	0.2185***	0.2184***	0.2307***
	(-0.0671)	*(.0728)*	*(-0.0736)*	*(-0.0727)*	*(-0.0733)*	*(-0.072)*
Acquirer R&D intensity	0.123	0.121	0.1321	0.1115	0.1139	0.107
	(-0.0828)	*(-0.0823)*	*(-0.085)*	*(-0.0858)*	*(-0.087)*	*(-0.0866)*
Acquirer knowledge base	0.666***	0.682***	0.6713***	0.6703***	0.6619***	0.6020***
	(-0.0547)	*(-0.0561)*	*(-0.0597)*	*(-0.0589)*	*(-0.061)*	*(-0.0657)*
Independent variables						
M&A experience		-0.0233	-0.0223	-0.0245	-0.0252	-0.025
		(-0.0175)	*(-0.0177)*	*(-0.0175)*	*(-0.018)*	*(0.0174)*
Overlapping knowledge quality			0.0151	0.0155	0.0116	0.0031
			(-0.0300)	*(-0.02912)*	*(-0.0301)*	*(-0.0298)*
Non-overlapping knowledge quality				-0.0184	-0.0174	-0.0096
				(-0.0126)	*(-0.0128)*	*(-0.014)*
Overlapping knowledge quantity					0.0469	0.1506
					(-0.1602)	*(-0.1681)*
Overlapping knowledge quantity squared					-0.0033	-0.014
					(-0.0333)	*(-0.0341)*
Non-overlapping knowledge quantity						-0.1888
						(-0.176)
Non-overlapping knowledge quantity squared						0.0068
						(-0.0374)
/lnalpha	-0.441	-0.461	-0.464	-0.479	-0.483	-0.514
	(0.1654)	*(0.1664)*	*(0.1667)*	*(0.1666)*	*(0.1669)*	*(0.1660)*
Alpha	0.6434	0.6309	0.6290	0.6192	0.6169	0.598
	(0.1064)	*(0.1050)*	*(0.1048)*	*(0.1032)*	*(0.1030)*	*(0.0993)*
N	122	122	122	122	122	122
Year control variables	YES	YES	YES	YES	YES	YES
Log likelihood	-526.084	-525.234	-525.104	-524.166	-524.012	-521.587
Pseudo R2	0.1532	0.1546	0.1548	0.1463	0.1566	0.1605
Likelihood Ratio (LR)	190.39	192.09	192.35	194.23	194.53	199.38
Regression p-value		0	0	0	0	0

** p < .10; ** p<.05; *** p .01*

Table 3 shows the results of the first part of the analysis, which considers the direct effects of each independent variable without the interaction term. Model 1 includes only the control variables, where only acquirer size and the acquirer knowledge base are positive and significant, while acquirer R&D is positive but not significant. (*p value > 0.1).* Model 2 introduces M&A experience into the model, which was found to be negative yet insignificant. Model's 3 and 4 include the quality component of the knowledge. Overlapping knowledge quality was positively related to subsequent innovation performance, while non-overlapping knowledge quality was negatively related, yet both were statistically insignificant. Model 5 considers the quantity of overlapping knowledge, found to be positively related, as well as the squared term of overlapping knowledge. The negative sign suggests a non-linear relationship between overlapping knowledge quantity and subsequent innovation performance. Both these were, however, statistically insignificant. Model 6 includes all control and independent variables. While acquirer size and their knowledge base, which were consistently positive and strongly significant throughout each aforementioned model, remain positive and significant, they are the only variables which are significant. Non-overlapping knowledge is negative, and its squared term positive, again suggesting, as with overlapping knowledge quantity, a non-linear relationship with subsequent innovation performance. However, this is once again insignificant. Considering the results from Table 3, while signs of the independent variable coefficients are, for the most part, as expected, no significant support is evident for hypotheses 1 to 4.

Table 4: Negative binomial results with M&A experience interaction terms

Dependent variable: post-acquisition innovative performance	**Model 7** ***(SE)***	**Model 8** ***(SE)***	**Model 9** ***(SE)***	**Model 10** ***(SE)***
Control variables				
Acquirer size	.2307***	0.232***	0.233***	.236***
	(.0721)	*(0.0722)*	*(0.0723)*	*.0732*
Acquirer R&D intensity	.1073	0.107	0.105	.1113
	(.0874)	*(0.0866)*	*(0.0866)*	*(.0870)*
Acquirer knowledge base	.6017***	0.607***	0.606***	.6003***
	(.0665)	*(0.0663)*	*(0.0668)*	*(.0656)*
Independent variables				
M&A experience	-.0246	-0.0313	-0.0325	-.0290
	(0.0245)	*(0.0211)*	*(0.0274)*	*(.0195)*
Overlapping knowledge quality	.0041	0.00160	0.00355	.0038
	(0.0500)	*(0.0300)*	*(0.0298)*	*(.0298)*
Overlapping knowledge quality * M&A	-0.0002			
	(0.0076)			
Non-overlapping knowledge quality	-.0096	-0.0136	-0.00986	-.0106
	(.0140)	*(0.0157)*	*(0.0140)*	*(.0141)*
Non-overlapping knowledge quality * M&A		0.00135		
		(0.00261)		
Overlapping knowledge quantity	0.1509	0.161	0.133	.1600
	(0.1684)	*(0.168)*	*(0.175)*	*(.1681)*
Overlapping knowledge quantity * MA			0.00301	
			(0.00851)	
Overlapping knowledge quantity squared	-0.0137	-0.0163	-0.0149	-.0164
	(0.0341)	*(0.0341)*	*(0.0339)*	*(.0341)*
Non-overlapping knowledge quantity	-0.1890	-0.206	-0.185	-.2009
	(0.1758)	*(0.179)*	*(0.176)*	*(.1775)*
Non-overlapping knowledge quantity * MA				.0040
				(.0094)
Non-overlapping knowledge quantity squared	.0068	0.00872	0.00645	.0045
	(0.0374)	*(0.0376)*	*(0.0374)*	*(.0376)*
/ln alpha	-0.5138	-0.5154	-0.5151	-0.5162
	(0.1660)	*(0.1660)*	*(0.1660)*	*(0.1661)*
Alpha	0.5982	0.5973	0.5975	0.5968
	(0.0993)	*(0.0991*	*(0.0992)*	*(0.0991)*
N	122	122	122	122
Year control variables	YES	YES	YES	YES
Log likelihood	-521.586	-521.451	-521.524	-521.492
Pseudo R2	0.1605	0.1607	0.1606	0.1606
Likelihood Ratio (LR)	199.38	199.66	199.51	199.57
Regression *p*-value	0.000	0.000	0.000	0.000

** p < .10; ** p<.05 ; ***p<.1*

Table 4 includes the results with the interaction effects between the main independent variables and M&A experience. As with the previous models reported in table 3, acquirer size and acquirer knowledge base are significantly positively related to post-acquisition performance. Model 7 shows that the interaction effect between overlapping knowledge quality and M&A experience negative and insignificant. Model 8 includes the non-overlapping knowledge quality's knowledge and M&A experience. The interaction effect is positive, lending support to hypothesis 5b. However, the effect is insignificant at a 10% level. Model 9 shows a positive interaction effect between overlapping knowledge quantity and M&A experience, suggesting that there is a positive moderating effect of M&A experience. However, it is not significant. Lastly, model 10 considers shows a positive interaction effect between M&A experience and non-overlapping quantity, yet also not significant. As with the results in the first part of this paper in Table 2, besides size and acquirer knowledge base, no statistical significance supports hypotheses 5a, 5b, 5c, or 5d.

4.3 Discussion & Analysis

While the insignificance of all the independent variables in question lends no statistical support for my formulated hypotheses, 1-5, I will proceed to discuss the economic and managerial implications of the coefficients from both tables 3 and 4.

This analysis considers the two sided aspect of knowledge – both the quantitative and qualitative sides, as well as overlapping or non-overlapping knowledge. When considering the model with all independent variables included, the positive relationship between over-lapping knowledge quality between the target and acquiring firms is in contrast to the negative effect of high quality non-overlapping knowledge. This suggests the nature of knowledge should be a significant factor to consider for managers or companies seeking a technological acquisition. From a knowledge-based view, previous literature suggests that competitive advantages arise from the acquisition of highly asset-specific knowledge (Grant, 1996), as well as firms transferring and creating knowledge (Kogut 2001). In relation to this research, the knowledge-based view on the firm hence arguably encourages the acquisition of high quality knowledge. The drawback of the tacit nature of this high quality knowledge, which makes the transfer costly and inefficient (Han, Jo & Kang, 2016), and where potential routines or complexity embedded in the knowledge is novel to the acquiring firm, is shown by the negative coefficient of *non-overlapping knowledge quality*. Hence, managers should be careful while considering technological acquisitions not to get blind-sided by the prospect of acquiring high quality knowledge, without considering the similarity or overlapping nature of the knowledge. The results in this analysis hence suggest the importance for acquiring firms to distinguish beneficial, high quality overlapping knowledge, from potentially detrimental high quality non-overlapping knowledge.

The case of Gilead Sciences and Triangle Pharmaceuticals, as mentioned at the start of this paper, shows that, along with high quality knowledge overlap, the high knowledge base of the acquiring firm also positively influences the subsequent innovation. This result, shown as a control variable in the analysis, is supported in the results. Acquiring firms should focus on developing a broad scope of their knowledge base, as a larger and broader knowledge base increases the chances to have overlapping knowledge of the target firm, which could facilitate the transfer of knowledge and subsequently generate innovation. Firms should thus focus on not only broadening their knowledge base but also diversifying, if they aim to create successful innovation through technological M&As in the future, where deep internal knowledge provides firms with a greater ability to generate innovations from external, technological acquisitions.

A similar argument can be made when relating my findings to strategic literature. Research on technological M&As in the past has suggested that overlapping knowledge between the target and acquiring firm has a negative effect on subsequent innovative performance (Colombo & Rabbiosi, 2014; Sears & Hoetker, 2014), which suggests technological acquisitions should focus on targets with no overlap. However, by including the qualitative aspect of this overlapping knowledge, the positive coefficient of *overlapping knowledge quality* suggests the potential importance of considering this qualitative aspect. Further, previous research has also focused on knowledge quality as an output variable, post-M&A (Yang, Wei, & Chiang, 2014) or how to measure the quality of the target firms' knowledge (Valentini, 2012). By considering knowledge quality's effect on innovative performance, this analysis contributes towards the lacking literature in this aspect.

The non-linear relationship between knowledge overlapping quantity and innovative performance does indeed suggest that a greater knowledge overlap may not necessarily improve innovative performance in a linear manner. The maximum turning point for the overlapping quantity squared is larger than any maximum value of the dataset. Hence, while insignificant, including the squared term does not confirm that there is indeed an inverse U relationship between quantity overlap and innovative performance. The negative coefficient of non-overlapping knowledge quantity, with the positive squared term, once again shows a non-linear relationship between non-overlapping knowledge quantity and innovative performance. Hence, a moderate amount of non-overlapping knowledge could be best. This result is important for managers who want to diversify their knowledge base into different knowledge areas through technological M&As.

The M&A variable shows how M&A affects the innovation of both firms directly and indirectly. The negative coefficient could possibly suggest that firms which undertake a lot of M&As become too defocused on their core competencies and shift away from innovation and the invention of new products. Alternatively, as the dimensions of the M&A were not taken into account, potential motives of previous M&As could have led firms to diversifying into different areas, or also non-technological. Hence, M&A deals could have taken place without the benefits of those above being realised (acquisition-specific knowledge, experience), and which could lead to a negative effect if it distracts the firm from focusing on its R&D competencies. This was what happened to Abbott in the late 1990s, which focused primarily on numerous acquisitions, as well as attempting to acquire Alza in 1999 for $7.3 billion. The subsequent time spent on due diligence, integration, and breakup could have led to the slowed clinical activity and trials. However, Richman et. al (2017) argue that while this M&A activity could disrupt innovative output in the short run, it arguably laid down the groundwork for Abbott's acquisition of BASF/Knoll in 2000. Through the absorption of BASF/Knoll's technology, Abbott trialled and won approval of Humira, which became the world's top selling drug in the 2000s to treat arthritis and other autoimmune diseases.

M&A experience could thus only see a lagged beneficial effect, albeit disrupting innovative performance in the short term. However, our analysis also focuses on a rapidly developing technology market, such that M&A experience could in fact depreciate in value quite quickly if the valuation of knowledge changes quickly. In this case, the increased experience of M&A activity could wear off after a relatively low threshold, which counteracts the previous reasoning with Abbott as an example.

The positive moderating effect of M&A experience suggests that firms which have acquired specific capabilities do indeed show how resource picking could be beneficial. As mentioned earlier, the implications of our results require managers to successfully valuate and choose target firms, while being able to recognise and distinguish both the type of knowledge, as well as its quality. This result does make sense, as experience could increase the ability of firms to synergise the knowledge gained which is unrelated, or non-overlapping. In addition, acquiring firms which have increased acquisition-specific capabilities through previous recent acquisition experience, arguably increases their ability to successfully integrate and absorb this tacit knowledge, such that the inefficiencies are decreased.

While implications for management of acquiring firms are substantial, policymakers concerned about the fall in innovative outputs, or new medicines, can potentially also take lessons from the findings. First, the positive impact of overlapping knowledge quality, and negative finding of non-overlapping knowledge quality, suggests that policy makers should encourage deals in which the target possesses high quality knowledge. The previous knowledge base of firms is found to be positively significant. Hence, government and firm policies which encourage science and technology development would hence improves benefits of technologically driven M&As, aiding in their success. The negative effect of M&A experience, albeit insignificant, does support the views that an excess of M&A activity in the bio-pharmaceutical market could be detrimental for innovative activity. From this point, policy makers should implement stricter policies on the number of M&A deals large pharmaceuticals could undertake.

4.4 Robustness check

As a first robustness check, I use citation data of 3 years of the patents, rather than 5 years. Secondly, I use a dummy variable as an indicator of whether a company has undertaken a M&A in the last 10 years or not. (=1 if yes, =0 if no) Tables A1, A2, and A3, show the descriptive statistics and correlations using these different variables.

The results of these robustness tests as shown in table B1 show similar results and signs of coefficients as in my main analysis. However, of note is that when using the binary M&A variable, the coefficient of M&A becomes positive, rather than negative. However, it is insignificant.

Table's B2 and B3 show the interaction effects with the differently defined variables. The second part of the analysis shows no significance for any variables, other than the two control variables, size and knowledge base, which maintain the same positive sign. However, the interaction effect between non-overlapping knowledge quantity and M&A experience in the second test is negative, suggesting a strengthened negative relationship if the acquiring firm had undertaken an M&A in the last ten years.

As there are only 17 observations where the acquiring firm was granted zero patents following the deal, there is no rationale for using the zero-inflated negative binomial model. However, as seen in the descriptive statistics, the maximum value of *innovative performance* is quite high. As a third robustness check, I estimate the same equation, but using a Tobit model, which assumes a continuous dependent variable, but the count element being less relevant. The results of the Tobit model find a positive, significant effect of the size and knowledge stock of the acquiring firm, supporting my initial findings. While M&A experience is positive, it is also not statistically significant. The squared term of overlapping quantity is positive and significant, which does indeed suggest a non-linear relationship between overlapping quantity and innovative performance. Table B2, which shows the use of a Tobit model for the interaction terms, shows a significant positive coefficient of M&A experience in Model 7. This contrasts with what was found in my main analysis. Also, overlapping knowledge quantity was found to be significant and negative in model 7, 8 and 9, with the squared term positive and significant. This suggests a nonlinear, negative relationship, providing support to the idea previously put forward that an increase in acquired overlapping knowledge could potentially hinder innovative performance.

5 Limitations, further research, and conclusion

5.1 Limitations & Further research

The analysis undertaken suffers from several limitations. Firstly, and possibly most prevalent, is the short-coming in the data used. Synthesized patent data was only available up to and including 2013. M&A deals could thus only be taken up to 2008, as a five year gap was necessary as to observe the post-deal patenting activity of the acquiring firm. With this study focusing on post-2000 M&A deals specifically in the bio-pharmaceutical industry, and adhering to other previously outlined criteria, the final dataset only comprised of 122 observations. This arguably low number of observations could contribute to the lack of statistical significance of the coefficients of the independent variables, with the low observations resulting in higher standard errors. With several independent variables of interest, unobservable effects could only be controlled for using a few variables. However, technological performance of merged companies could be impacted by other unobservable effects, such as pipeline quality or the impact of cross-border activity (Onarghi, 2009).

Second, while there is merit in using patent class data to specify overlapping knowledge of companies, the USPC only categorizes the field of the invention, and not the nature of the invention (Han, Jo & Kang 2016). Potential issues due to the disparities in the nature of the inventions which are in the same class could be accounted for using qualitative data statistics on new product developments within the pharmaceutical industry. Besides data on patents being limited to class specification, the dataset used lacked *originality* and *generability* data on a majority of the patents. This prevented a further test of robustness being used with a different proxy for patent quality.

Third, the moderating effect of previous M&A activity was measured using a simple count measure of previous M&A deals ten years prior to the deal the acquirer made in the sample. However, the dimensions of these deals could vary in several different dimensions. These include factors such as deal size, technological and economic motivations, or cross-border deals. Also, whether the acquiring firm has previous collaboration experience with the target firm (i.e. licensing, alliance, joint ventures) could be substantially strengthen the moderating effect of this variable. Further research which develops and utilizes a scheme for accounting to this multi-dimensional approach to account for M&A experience could provide further insight and rationale for using M&A experience as a measure of absorptive capacity.

Further, while an evaluation of using patents as a proxy of innovative output detailed earlier argued they were reasonably good indicators, they can at best be “regarded as intermediate outcomes between acquisitions and value creation” (Ahuja & Katila, 2001). A further study could consider the effect of knowledge quality and quantity on different firm innovative performance measures. This could follow Fernald et al. (2017) method of considering new product introductions, or process enhancements within the bio-bharmaceutical industry. While knowledge may primarily influence inventions and innovations, the relationship between different dimensions of knowledge, and the economic performance of acquiring firms could be investigated. The effects of the quantity and quality of overlapping and non-overlapping knowledge could be further studied under a different scope. While this study focused on the bio-pharmaceutical industry due to the increase in activity of technological M&As, as well as knowledge being an important characteristic of the industry, comparing the suggested results found in two industries could be interesting to consider. However, studies using a multi-industry analyses (Cloodt & Hagendoorn, 2006; Han 2016) potentially fail to reliably account for unobservable industry specific effects.

An alternative method to count for the number of patents looks at the number which were applied for and subsequently granted in the similar 1-5 year period, rather than those which were granted. Hall et al (2001) argue that the actual time of the invention is closer to the application date than the grant date, as the grant date is dependent on the bureaucratic process which must happen in the USPTO, and thus subject to significant delays. However, it could be argued that delay between the initial application date and grant date is rather due to the review and amendments to the initial patent application, rather than bureaucratic issues. Further research could utilise this measure. In addition, the innovative output could consider not only the number of patents granted, but also combine it with the quality, using patent citation data or, if available, originality and generality, as used by Valentini (2012).

5.2 Conclusion

The study of external technological knowledge acquisitions attempts to guide firms faced with the strategic predicament of which route to take to increase innovation: concentrating on building internal knowledge or buying it through acquisitions. While the importance of a firms’ knowledge base, which had a significantly positive effect on post-deal acquisition, was controlled for, this study’s focal point concentrates on the relative characteristics of knowledge between the acquiring and target firm.

Without significant results to support my set of hypotheses, only the signs of the coefficient could be discussed. The results suggest that firms should consider a two-way approach when valuating target firms for technological acquisitions. First is identifying what knowledge from the target firm overlaps with the acquiring firms’ knowledge, and which does not, while subsequently evaluating the qualitative side of the overlapping and non-overlapping knowledge. Based on my findings, firms would benefit from acquiring overlapping knowledge of higher quality. However, high quality non-overlapping knowledge could be detrimental to innovative performance. Hence, it is important for firms to consider the overlap between the target and acquiring firms’ knowledge base as utilise the high-quality knowledge of the target firm as best as possible. Additionally, the potential non-linear relationship between knowledge quantity and innovative performance needs to be taken into consideration. Acquiring firms should thus carefully assess the quantity of knowledge they wish to acquire in acquisitions such that it does not overload and distract internal operations, potentially diverting firms away from their core competencies. A careful balance between too little knowledge overlap and non-overlap should be found, as to avoid potential information redundancies or absorption capabilities, which would negatively affect future innovative performance. Further, M&A experience could also play a role as an indicator of absorptive capacity, which moderates the relationship between knowledge and post-acquisition performance. The discussion and analysis regarding M&A experience provides insights for both policymakers, as well as M&A strategies for large, bio-pharmaceutical firms.

In conclusion, the overlap between the acquirer and target firms should be systematically exploited in technological M&As. Firms are more likely to benefit from overlapping knowledge quality than non-overlapping knowledge quality. Target firms with high quality overlapping knowledge should thus be favoured. However, as to pursue innovation in areas unfamiliar to the acquiring firm, it is arguably important that a moderate quantity of non-overlapping knowledge is acquired, as to ensure positive innovative outcomes from M&As in the bio-pharmaceutical industry. However, no strong conclusions can be made regarding the non-linear relationship between knowledge quantity and innovative performance. I suspect that technological acquisitions as means of external knowledge sources will continue to be prevalent in high-tech industries, specifically the bio-pharmaceutical industry, and believe careful evaluation of the knowledge of the target firm is essential as to maximise the potential for future innovation.

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APPENDIX A: CORRELATION & DESCRIPTIVE STATISTICS ROBUSTNESS CHECKS

Table A1: Correlation matrix using 3-year citations

Variables	1	2	3	4	5	6	7	8	9
Innovative performance	1								
Overlapping knowledge quality (3yr)	0.3216	1							
Non-Overlapping knowledge quality (3yr)	-0.1149	0.1582	1						
Overlapping knowledge quantity	0.287	0.0346	-0.0364	1					
Non-overlapping knowledge quantity	-0.1175	-0.0578	0.0093	-0.0101	1				
M&A experience (binary)	0.5318	0.2983	-0.021	0.0409	-0.0049	1			
Acquirer size	0.5951	0.3727	-0.025	0.0955	-0.0231	0.6778	1		
Acquirer R&D intensity	-0.2216	-0.1044	-0.0553	-0.0542	-0.0487	-0.2841	-0.2239	1	
Acquirer knowledge base	0.8519	0.2824	-0.104	0.3524	-0.1059	0.6285	0.6434	-0.2043	1

Table A2: Correlation matrix using binary M&A variable

Variables	1	2	3	4	5	6	7	8	9
Innovative performance	1								
Overlapping knowledge quality	0.2791	1							
Non-Overlapping knowledge quality	-0.1138	0.2069	1						
Overlapping knowledge quantity	0.287	0.0976	-0.0341	1					
Non-overlapping knowledge quantity	-0.1175	-0.0707	0.0397	-0.0101	1				
M&A experience(binary)	0.3166	0.1413	0.0761	0.057	0.0124	1			
Acquirer size	0.5951	0.2116	0.0222	0.0955	-0.0231	0.2276	1		
Acquirer R&D intensity	-0.2216	-0.0869	-0.0502	-0.0542	-0.0487	-0.3046	-0.2239	1	
Acquirer knowledge base	0.8519	0.1924	-0.132	0.3524	-0.1059	0.2799	0.6434	-0.2043	1

Table A3: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Innovative performance	122	106.0738	154.3373	0	505
Overlapping knowledge quality (3yr)	122	1.796828	3.437072	0	28
Non-Overlapping knowledge quality(3yr)	122	1.789089	4.307989	0	31
Overlapping knowledge quantity	122	1.113317	1.560446	0	7.146772
Non-overlapping knowledge quantity	122	1.010191	1.463075	0	6.811244
M&A experience	122	0.803279	0.399159	0	1
Acquirer size	122	7.931923	2.474403	1.609438	11.68435
Acquirer R&D intensity	122	3.373459	1.368433	0.641854	7.306558
Acquirer knowledge base	122	3.312717	2.343539	0	7.247081

APPENDIX B: Regression outputs robustness checks

Table B1: Robustness checks regression results without interaction terms

Dependent variable: post-acquisition innovative performance	**3 year citations (SE)**	**Tobit model (SE)**	**Binary M&A (SE)**
Control variables			
Acquirer size	0.227***	14.81***	0.195***
	(0.0717)	*(5.582)*	*(0.0679)*
Acquirer R&D intensity	0.0962	11.05	0.116
	(0.0843)	*(7.386)*	*(0.0911)*
Acquirer knowledge base	0.609***	37.49***	0.581***
	(0.0651)	*(5.574)*	*(0.0650)*
Independent variables			
M&A experience	-0.0263	1.699	0.0202
	(0.0171)	*(1.569)*	*(0.275)*
Overlapping knowledge quality	0.000636	3.442	0.00975
	(0.0242)	*(2.691)*	*(0.0292)*
Non-overlapping knowledge quality	-0.0258	-1.914	-0.00828
	(0.0196)	*(1.451)*	*(0.0138)*
Overlapping knowledge quantity	0.146	-21.61	0.122
	(0.161)	*(13.96)*	*(0.167)*
Overlapping knowledge quantity squared	-0.0128	7.027**	-0.00804
	(*0.0335)*	*(2.801)*	*(0.0341)*
Non-overlapping knowledge quantity	-0.169	-10.52	-0.189
	(0.171)	*(14.77)*	*(0.176)*
Non-overlapping knowledge quantity squared	0.00288	2.331	0.00674
	(0.0370)	*(2.960)*	*(0.0374)*
/ln alpha	-0.5217		-0.4957
	(0.1658)		*(0.1657)*
Alpha	0.5935		0.6091
	(0.0984)		*(0.1009)*
N	122	122	122
Year control variables	YES	YES	YES
Log likelihood	-521.001	-701.99	-522.581
Pseudo R2	0.1614	0.1084	0.1589
Likelihood Ratio (LR)	200.54	170.78	197.40
Regression *p*-value	0.000		0.000

** p < .10; ** p<.05 ; ***p<.1*

Table B2: Negative Binomial results with interaction effects: 3-year patent citations

Dependent variable: post-acquisition innovative performance	**Model 6**	**Model 7**	**Model 8**	**Model 9**
Control variables				
Acquirer size	0.226***	0.228***	0.229***	0.232***
	(0.0714)	*(0.0721)*	*(0.0720)*	*(0.0727)*
Acquirer R&D intensity	0.0883	0.0967	0.0939	0.101
	(0.0849)	*(0.0843)*	*(0.0844)*	*(0.0849)*
Acquirer knowledge base	0.616***	0.611***	0.613***	0.607***
	(0.0658)	*(0.0661)*	*(0.0662)*	*(0.0652)*
Independent variables				
M&A experience	-0.0382	-0.0289	-0.0341	-0.0300
	(0.0241)	*(0.0217)*	*(0.0272)*	*(0.0191)*
Overlapping knowledge quality	-0.0269	0.000423	0.00129	0.00123
	(0.0456)	*(0.0243)*	*(0.0242)*	*(0.0241)*
Overlapping knowledge quality * M&A	0.00343			
	(0.00493)			
Non-overlapping knowledge quality	-0.0237	-0.0280	-0.0262	-0.0266
	(0.0200)	*(0.0223)*	*(0.0197)*	*(0.0197)*
Non-overlapping knowledge quality * M&A		0.000830		
		(0.00411)		
Overlapping knowledge quantity	0.161	0.147	0.128	0.158
	(0.161)	*(0.160)*	*(0.167)*	*(0.161)*
Overlapping knowledge quantity * MA			0.00311	
			(0.00850)	
Overlapping knowledge quantity squared	-0.0160	-0.0133	-0.0142	-0.0158
	(0.0334)	*(0.0335)*	*(0.0333)*	*(0.0337)*
Non-overlapping knowledge quantity	-0.166	-0.172	-0.166	-0.184
	(0.171)	*(0.172)*	*(0.171)*	*(0.174)*
Non-overlapping knowledge quantity * MA				0.00392
				(0.00928)
Non-overlapping knowledge quantity squared	0.00266	0.00320	0.00261	0.00116
	(0.0369)	*(0.0370)*	*(0.0370)*	*(0.0371)*
/ln alpha	-0.5269	-0.5217	-0.5229	-0.5237
	(0.1660)	*(0.1658)*	*(0.1658)*	*(0.1659)*
Alpha	0.5904	0.5935	0.5928	0.5923
	(0.0980)	*(0.0984)*	*(0.0983)*	*(0.0983)*
N	122	122	122	122
Year control variables	YES	YES	YES	YES
Log likelihood	-520.668	-520.986	-520.940	-520.916
Pseudo R2	0.1618	0.1614	0.1615	0.1615
Likelihood Ratio (LR)	201.04	200.58	200.68	200.73
Regression *p*-value	0.000	0.000	0.000	0.000

** p < .10; ** p<.05 ; ***p<.1*

Table B3: Negative Binomial results with interaction effects: M&A dummy

Dependent variable: post-acquisition innovative performance	**Model 6**	**Model 7**	**Model 8**	**Model 9**
Control variables				
Acquirer size	0.192***	0.194***	0.192***	0.206***
	(0.0678)	*(0.0681)*	*(0.0689)*	*(0.0662)*
Acquirer R&D intensity	0.109	0.113	0.111	0.144
	(0.0918)	*(0.0929)*	*(0.0930)*	*(0.0912)*
Acquirer knowledge base	0.577***	0.582***	0.583***	0.560***
	(0.0651)	*(0.0653)*	*(0.0652)*	*(0.0641)*
Independent variables				
M&A experience	-0.0459	-0.0177	-0.0133	0.396
	(0.298)	*(0.345)*	*(0.305)*	*(0.332)*
Overlapping knowledge quality	-0.105	0.00969	0.00926	0.0101
	(0.195)	*(0.0293)*	*(0.0293)*	*(0.0289)*
Overlapping knowledge quality * M&A	0.117			
	(0.197)			
Non-overlapping knowledge quality	-0.00781	-0.0314	-0.00820	-0.00662
	(0.0138)	*(0.128)*	*(0.0138)*	*(0.0137)*
Non-overlapping knowledge quality * M&A		0.0233		
		(0.128)		
Overlapping knowledge quantity	0.124	0.124	0.0805	0.116
	(0.167)	*(0.168)*	*(0.232)*	*(0.167)*
Overlapping knowledge quantity * MA			0.0490	
			(0.191)	
Overlapping knowledge quantity squared	-0.00727	-0.00825	-0.00883	-0.00571
	(0.0343)	*(0.0341)*	*(0.0342)*	*(0.0344)*
Non-overlapping knowledge quantity	-0.203	-0.186	-0.193	-0.00913
	(0.177)	*(0.177)*	*(0.176)*	*(0.200)*
Non-overlapping knowledge quantity * MA				-0.266*
				(0.142)
Non-overlapping knowledge quantity squared	0.00987	0.00713	0.00872	0.00740
	(0.0377)	*(0.0375)*	*(0.0382)*	*(0.0379)*
/ln alpha	-0.5081	-0.4956	-0.4977	-0.5233
	(0.1681)	*(0.1656)*	*(0.1660)*	*(0.1654)*
Alpha	0.6016	0.6091	0.6080	0.5925
	(0.1012)	*(0.1008)*	*(0.1009)*	*(0.0980)*
N	122	122	122	122
Year control variables	YES	YES	YES	YES
Log likelihood	-522.411	-522.561	-522.548	-520.818
Pseudo R2	0.1591	0.1589	0.1589	0.1617
Likelihood Ratio (LR)	197.74	197.43	197.46	200.92
Regression *p*-value	0.000	0.000	0.000	0.000

* *p < .10; ** p<.05 ; ***p<.1*

Table B4: Tobit results with interaction effects

Dependent variable: post-acquisition innovative performance	**Model 6**	**Model 7**	**Model 8**	**Model 9**
Control variables				
Acquirer size	14.79***	15.02***	15.16***	13.89**
	(5.587)	*(5.522)*	*(5.563)*	*(5.606)*
Acquirer R&D intensity	10.97	11.53	9.938	10.22
	(7.467)	*(7.311)*	*(7.418)*	*(7.380)*
Acquirer knowledge base	37.51***	36.20***	38.17***	37.65***
	(5.582)	*(5.568)*	*(5.581)*	*(5.545)*
Independent variables				
M&A experience	1.592	3.250*	-0.232	2.582
	(2.142)	*(1.815)*	*(2.342)*	*(1.733)*
Overlapping knowledge quality	3.216	3.559	3.508	3.279
	(4.101)	*(2.663)*	*(2.679)*	*(2.680)*
Overlapping knowledge quality * M&A	0.0476			
	(0.652)			
Non-overlapping knowledge quality	-1.902	-0.486	-1.971	-1.683
	(1.461)	*(1.677)*	*(1.445)*	*(1.457)*
Non-overlapping knowledge quality * M&A		-0.405		
		(0.246)		
Overlapping knowledge quantity	-21.70	-23.68*	-26.28*	-23.58*
	(14.00)	*(13.86)*	*(14.51)*	*(13.98)*
Overlapping knowledge quantity * MA			0.842	
			(0.762)	
Overlapping knowledge quantity squared	7.037**	7.655***	6.731**	7.580***
	(2.804)	*(2.796)*	*(2.800)*	*(2.825)*
Non-overlapping knowledge quantity	-10.54	-7.170	-10.76	-8.042
	(14.78)	*(14.75)*	*(14.70)*	*(14.84)*
Non-overlapping knowledge quantity * MA				-0.997
				(0.852)
Non-overlapping knowledge quantity squared	2.337	1.878	2.417	2.932
	(2.961)	*(2.940)*	*(2.946)*	*(2.988)*
N	122	122	122	122
Year control variables	YES	YES	YES	YES
Log likelihood	-701.989	-700.651	-701.383	-701.312
Pseudo R2	0.1085	0.1102	0.1092	0.1093
Likelihood Ratio (LR)	170.79	173.46	172.00	172.14

** p < .10; ** p<.05; ***p<.1*