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Innovation Performance in Healthcare M&A: An Empirical Analysis

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Abstract

The relationship between mergers and acquisitions (M&A) and innovation in the healthcare sector (pharmaceuticals, biotechnology, medical devices, and life sciences) is investigated using a new self-generated dataset of 41 firms. Patents are used as proxy for innovation performance of acquiring firms. This work can also be seen as an extended replication study of Ahuja and Katila (2001) and Cloodt, Hagedoorn, and Van Kranenburg (2006). The extension comprises of newly added variables relatedness of acquirer knowledge and acquisition experience. The findings are consistent with previous research. Non-technological M&A appear to have a negative impact on the acquiring firm's innovation performance. The absolute size of acquired knowledge has a small positive effect. The relative size of acquired knowledge has a negative effect on the acquiring firm's innovation performance. The relatedness of the target knowledge base has a curvilinear impact on innovative performance. The relatedness of acquirer knowledge has a negative effect on innovation performance. Finally, the effect of previous acquisition experience is ambiguous. The findings of this study indicate that the firms' innovation performance can benefit from M&A by carefully selecting targets that provide the appropriate amount of "innovative" input.

Keywords: Mergers & Acquisitions; Innovation; Innovation Performance; Patents; Knowledge based view.

1. Introduction

1.1. M&A and Innovation

Mergers and Acquisitions (M&A) continue to be an important part of the business world in both developed and emerging economies. Worldwide M&A transaction volume has peaked in 2015 and has remained high ever since, with a value of completed deals over 3T$ and over 40,000 deals in 2019 before the COVID-19 outbreak (Thomson Reuters Eikon, 2021).

This indicates that M&A is a very popular instrument in corporate strategy. However, M&A and especially the success of M&A as a strategy is a mystery for both researchers and managers: contrary to expectations, a considerable number of deals has lead to negative cumulative abnormal returns or no value creation for shareholders of the acquiring company (Agrawal, Jaffe, & Mandelker, 1992; Datta, Pinches, & Narayanan, 1992; Jarrell & Poulsen, 1989; King, Dalton, Daily, & Covin, 2004). Even managers in charge consider plenty of deals as failed. In one study, about 50% of executive managers evaluated their deals as failed (Cartwright & Schoenberg, 2006). There are multiple explanations for why executives choose to conduct M&A and why M&A is still a very common growth strategy. One reason for M&A are personal motives of executives. Acquisitions might help them to achieve their growth goals and in turn increase their compensation. Besides managerial hubris, other common motives are: acquiring new business units for new markets, acquiring technology, improving performance by using synergies, and acquiring a foreign firm to enter a domestic market or diversifying a firm. M&A can also be a response to exogenous shocks such as crises, changes in regulation or technology breakthroughs of competitors (Chen, Hsu, Officer, & Wang, 2020; Pidun, 2019). Given the occurrence of M&A and that many deals fail from a financial standpoint, other research metrics could provide interesting insights on M&A and why firms still choose to conduct M&A (Haleblian, Devers, McNamara, Carpenter, & Davison, 2009). Such metrics could include the innovation performance, accounting measurements or the long term financial performance. Most empirical studies on M&A stem from financial management research with a focus on shareholder value creation (King et al., 2004; Zollo & Meier, 2008). Only a fraction of M&A research has been devoted to the link of M&A and innovation, mainly in the area of strategic management (Cassiman, Colombo, Garrone, & Veugelers, 2005).

During the last 30 years, the speed of innovation has increased rapidly (Makri, Hitt, & Lane, 2010) and innovation has become an important way to achieve and maintain

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a competitive advantage (Hitt, Hoskisson, Johnson, & Moesel, 1996). Technological innovation and product innovation have become an important part and motive in the M&A landscape (Chen et al., 2020). M&A can be a valuable strategy to enhance the innovation performance: e.g., to reduce the time to market, to expand a product portfolio, to develop technological capabilities, or to gain access to intellectual property or technology (Cassiman et al., 2005; Goedhart, Koller, & Wessels, 2017; Schweizer, 2005b). This led many larger established corporations to rely on small innovative firms as a source of innovation. This strategy avoids uncertain and resource- and time-consuming processes of internal innovation sourcing (Granstrand & Sjölander, 1990; Puranam, Singh, & Zollo, 2006). The importance of innovation and the unilateral research focus on financial performance calls for more research in the area of M&A.

This thesis aims at providing insights on M&A innovation performance by analyzing a sample of 41 firms active in the healthcare industry. Competition in this industry is particularly driven by innovation and technology (Danzon, Nicholson, & Pereira, 2005; Schweizer, 2005b; Simoens, 2008). The motivation behind this thesis is two-fold: First, this thesis tries to replicate the findings of Ahuja and Katila (2001) - "*Technological Acquisitions and the Innovation Performance of Acquiring Firms: a Longitudinal Study*". A first replication study by Cloodt et al. (2006) has already confirmed selected findings. This study analyzes the post-M&A patenting output of M&A in the healthcare industry as a proxy for innovation performance. The healthcare sector is known for a high-patent intensity and technology and innovation play an important role in competition. It is therefore very suitable for a replication study (Cockburn & Long, 2015). Furthermore, as the previous studies were conducted more than 15 years ago, applying the model to current data could provide additional information. Second, this thesis extends Ahuja and Katila (2001) by differentiating between acquirer and target knowledge relatedness, inspired by Sears and Hoetker (2014). This additional variable allows for a deeper analysis of the interaction of the target and acquirer knowledge and the resulting combination of knowledge. Likewise, a variable for acquisition experience will be introduced to the model.

The research question is therefore:
How does M&A activity affect the innovation output (measured by the number of patents granted) in the healthcare industry?

This thesis is organized as follows: First, the characteristics of the healthcare industry are described. Second, the theoretical foundation and important theories are explained. A short section presents previous studies on M&A and innovation performance of firms. Then, the hypotheses for the empirical analysis are developed out of the conceptual framework. Third, the empirical analysis follows, using a modification of the model of Ahuja and Katila (2001), with additional variables focusing on knowledge overlap of the involved firms. Lastly, the author shows the limits of the research, discusses the findings and outlines recommendations for future research.

1.2. M&A in the Healthcare Industry

The healthcare industry was selected as a research setting for this thesis for multiple reasons. First, the healthcare industry, especially the pharmaceutical industry, has played a major role in some of the largest international M&A deals, such as the acquisition of Wyeth by Pfizer for 68B$ and of Shire Pharmaceuticals by Takeda for 62B$ (Chee, 2018; J. Hall & Krauskopf, 2009). Second, the healthcare industry relies heavily on intellectual property protection by patents. As the European Patent Office (EPO) recently stated: "innovation in healthcare drove patenting activity in 2020: Medical technology was the leading field for inventions in terms of volume, while pharmaceuticals and biotechnology were the fastest-growing areas" (European Patent Office, 2021, para.1). Patents grant a temporary monopoly to commercialize an invention and are therefore very valuable in this industry (Arrow, 1962). On the other hand, patent expirations constantly force these firms to stay innovative and introduce new technologies and products. Third, competition in this industry is mainly driven by innovation in technology, research and development (R&D) productivity and R&D outputs (Ornaghi, 2009). Technological learning and the introduction of new products are expected to be a key for achieving a competitive advantage (Cloodt et al., 2006). M&A are therefore a popular strategy to get access to new technologies, products, distribution channels and market positions, since "the pace and magnitude of technological change may not allow firms to internally develop all technologies and capabilities they need to remain competitive" (Schweizer, 2005b, p. 1052).

According to the Global Industry Classification Standard (GICS), the healthcare industry can be classified into different sub-industries: healthcare equipment providers, healthcare services and providers, biotechnology, pharmaceuticals, and life sciences tools and equipment. Each of these sub-industries has its own characteristics, considering industry dynamics, consolidation, regulation, industry structure, and market size (MCSI Inc., 2021). These industries are all technology and R&D intensive, except for the sub-industry healthcare services and providers, which mainly includes healthcare insurance and hospital chains. Before evaluating this work's contribution to current literature, the main sub-industries are further investigated regarding their specific structure and the subsequent impact on this analysis.

Biotechnology & Pharmaceuticals. The pharmaceutical industry has seen a considerable amount of consolidation (Pidun, 2019). Many of these large-scale mergers in the pharmaceutical industry were motivated by increased economies of scale in R&D or production (Ascher, Bansal, Dhankhar, & Kim, 2020; Graves & Langowitz, 1993; The Economist, 2008). The volume of pharmaceutical M&A deals has been on the rise in the last years and the industry has encountered some large deals. In recent years some of the largest firms in the pharmaceutical area merged (Chee, 2018; J. Hall & Krauskopf,

2009). The number and volume of deals has peaked in 2019 before the COVID-19 crisis, with a total deal value of 414B$ (Ascher et al., 2020).

The biotechnology and pharmaceutical industry is characterized by substantial R&D investments, which are a risky undertaking as many developed drugs do not prove to be effective (enough) and fail to get approval for sale by regulatory authorities. The average capitalized cost of a new product in the bio-pharmaceutical market was estimated to be about 1.2B$ in 2003 (DiMasi, Hansen, & Grabowski, 2003). On average, firms spend about 18% of their revenue on R&D (Danzon, Epstein, & Nicholson, 2007). Furthermore, the industry is shaped by rapid innovation, technological complexity and highly specialized skills (Schweizer, 2005b). M&A is often used by larger pharmaceutical firms to gain access to small biotechnology or pharmaceutical firms, providing them with cash and support for clinical trials as well as marketing and sales activities or production capabilities (Ascher et al., 2020; Powell, Koput, & Smith-Doerr, 1996; Schweizer & zu Knyphausen-Aufseß, 2008).

Pharmaceutical firms depend heavily on innovation and the introduction of new drugs: about 75% of revenue of a drug is made within five years after approval (Higgins & Rodriguez, 2006). A study by Danzon et al. (2007) found that pharmaceutical firms tend to acquire firms when patents tend to expire or they expect gaps in their product pipeline.

There is considerable evidence that larger pharmaceutical firms are less innovative than smaller biotechnology firms (Graves & Langowitz, 1993; Ornaghi, 2009). With an active M&A strategy, larger firms are not only able to acquire innovation, but also to avoid the risk of developing drugs in-house. For each new approved drug on the market, about five went into clinical trials. Therefore, buying promising smaller firms (often with drugs in advanced clinical trials) can be cheaper than in-house development (Danzon et al., 2007, 2005).

Furthermore, CEOs of large pharmaceutical firms have obligations to shareholders, which expect value creation and increased profitability. This might lead them to focus on certain capabilities that improve the firm performance and maximize the shareholder wealth, such as commercialization and production. To avoid risk and enhance firm performance, managers might lean towards M&A as a substitute for internal R&D (Higgins & Rodriguez, 2006). Additionally, portfolios are often reorganized and improved, therefore firms often choose to divest or invest in adjacent fields (Ascher et al., 2020; Schweizer, 2005b).

Healthcare & Life Science equipment. The healthcare equipment industry is facing fierce international competition in both their product markets and their level of technology (Lin & Jang, 2010). As the rest of the healthcare industry, healthcare equipment and healthcare technology firms are highly R&D and technology intensive and invested on average 11.4% of revenues in R&D in 2002 in the US (Panescu, 2006). The complexity of products is continuously increasing, as products incorporate new features in microtechnology and often use cutting-edge materials (Panescu, 2006). The healthcare equipment sector is characterized by short product life cycles and constant introduction of new products. It has been estimated that up to 80% of profits originate from new products, introduced in the last five years (Simoens, 2008).

Global markets for medical devices tend to be fragmented and sometimes suffer from a lack of transparency. Device prices are often determined by regulation. In some countries, healthcare investments are often part of public spending, therefore firms might be dependent on state budgets (Simoens, 2008). Products depend heavily on regulation and approval by government authorities and need to undergo a separate approval process in several different countries (Lin & Jang, 2010).

The life science sector tools & services sector mainly includes companies that manufacture equipment for drug discovery, development and production (MCSI Inc., 2021).

2. Theoretical Background

This thesis aims to replicate and expand previous research by Ahuja and Katila (2001), by analyzing the effects of M&A on innovation performance in the healthcare industry. In this chapter, a theoretical framework is developed out of the knowledge-based view (KBV), the combinative capability, the absorptive capacity, as well as M&A performance. Additionally, this chapter includes a review of existing empirical studies. Finally, this chapter states the main empirical hypotheses which are derived out of the theoretical considerations and which will be tested in the empirical part of this thesis.

2.1. M&A Performance, Innovation Performance and Value Creation

Previous research has used different metrics to analyze M&A performance, depending on the area of research. While research in corporate finance has mainly relied upon financial metrics such as shareholder value or accounting measures, strategic management research has often relied upon shareholder value or more subjective variables derived from questionnaires (e.g., synergy realization) (Zollo & Meier, 2008).

Typically, the M&A performance is considered positive when either the accounting or the financial performance of the combined firms is larger than the performance of the separate entities (Barney, 1988; King et al., 2004; Zollo & Meier, 2008). Many studies use different time horizons, ranging from a couple of days to multiple years (Zollo & Meier, 2008). In contrast to financial metrics, the innovation performance of an acquirer can already be evaluated as positive when the post-acquisition innovation performance of the acquiring firm has improved. M&A can affect both: innovation input and innovation output (Ahuja & Katila, 2001; Cassiman et al., 2005). Evaluating the post-acquisition innovation output provides evidence on the efficiency of the resource transfer and combination process (Ahuja & Katila, 2001). Metrics for the innovation output can be patents (Ahuja & Katila, 2001)

or the rate of new product introduction (Capron & Pistre, 2002). An increased innovation performance should lead to an increased economic rent in the future.

In the context of innovation input, improving performance could lie for example in R&D synergies. R&D synergies can be created in various ways. An example is a merger of two firms doing research in similar biotechnology fields. A combined R&D program can lead to a significant breakthrough and therefore to a competitive advantage in one market (Henderson & Cockburn, 1996). Additional input resources, such as the knowledge and capabilities of one R&D team, enable the firm to enhance its innovation performance. Even non-technological resources might enhance the innovation performance, as a target can bring better commercialization capabilities (Kaul, 2012). Admittedly, in most cases, the target will take over most routines and processes of the acquirer (Reus, 2012).

Post-acquisition integration affects the performance as well, as different degrees of post-acquisition integration lead to different outcomes. There are four different ways to integrate target firms: absorption, preservation, holding and symbiosis (Haspeslagh & Jemison, 1991; Pidun, 2019). Firms that remain independent might stay innovative, but the acquirer might not be able to fully benefit from it (Datta & Grant, 1990). "Acquisitions can increase innovation adoption by altering the subsidiary's leadership structure and removing obstacles to change" (Barden, 2012, p. 1269).

However, if the firm is deeply integrated into the acquirer, it might lose its ability to innovate. In an acquisition, the productivity of R&D employees usually falls sharply and the retention of key R&D personnel is often difficult when R&D departments experience a loss of autonomy (Paruchuri & Eisenman, 2012).

Innovation inputs can be affected in a negative way, e.g., when the funding of R&D operations is reduced (Hitt et al., 1996).

Multiple factors affect value creation in M&A. The M&A process involves multiple steps with various pitfalls, from target selection to post-acquisition integration (Pidun, 2019). According to the KBV key challenges lay in identifying, valuing and incorporating resources or knowledge of the target firm (Reus, 2012).

2.2. Knowledge-Based View

2.2.1. Key Concepts

The resource-based view (RBV) sees the source of economic rents and competitive advantage in the resources and capabilities of a firm (Barney, 1991). The level of analysis is "on the distinctive resource profiles of individual firms and the processes, both at the firm and industry level, that lead to specific new resource combinations and induce or reinforce heterogeneity among firms" (Rugman & Verbeke, 2002, p. 770). Firms can only gain a competitive advantage if they implement a value generating strategy by using their resources and capabilities in a way that other firms cannot copy (Barney, 1991; Pidun, 2019). The knowledge-based view (KBV) can be considered a variant of the RBV, viewing the firm as a bundle of knowledge instead of resources and capabilities. This knowledge is not rooted in individuals, but rather in the firm's specific mechanisms of exploring and exploiting knowledge. Knowledge is the primary source of competitive advantage and value creation (Grant, 1996; March, 1991; Reus, 2012). Thus, knowledge is considered the most strategically significant resource of a firm. To gain future rents, firms should invest in assets "that correspond to a combination of current capabilities and expectations regarding future opportunities" (Kogut & Zander, 1992, p. 385). Innovations are the result of the firms' ability to reconfigure knowledge or combine existing and new knowledge within an organizational context (Grant, 1996; Henderson & Cockburn, 1996; Kogut & Zander, 1992). In general, the development of knowledge in a firm is idiosyncratic, reflecting the firm's particular history and experience (Cohen & Levinthal, 1989). Industry competition is driven on the basis of the firms' ability to generate and utilize knowledge efficiently and effectively for innovation (Nonaka, 1994). This idea follows Schumpeter's theory of economic development and innovation. Innovation is the main driver of progress and economic development, as well as competition among firms (Schumpeter, 1981). Firms combine knowledge to create innovation and therefore economic development:

"To produce other things, or the same things by a different method, means to combine these materials and forces differently ... Development in our sense is then defined by the carrying out of new combinations" (Schumpeter, 1981, pp. 65-66).

According to Kogut and Zander (1993), firms are superior in comparison to markets in organizing and transferring knowledge. While firms specialize in generating and transferring knowledge, the mechanism of M&A enables them to transfer knowledge across entities (Kogut & Zander, 1993).

Knowledge has certain properties that make it a strategically relevant resource and allow it to be a foundation for a competitive advantage. An important characteristic is tacitness (Kogut & Zander, 1992). Tacitness depends on the degree of codifiability of knowledge. Tacitness is based on the idea that human knowledge is beyond explicit understanding (so called Polyani's puzzle). This form of knowledge is especially relevant for a competitive advantage, as this kind of knowledge is hard to imitate or replicate by others. In an organizational context, this often comprises of know-why, know-how, and certain skills (Grant, 1996). Furthermore, knowledge is socially embedded into the networks of interpersonal relations among employees and other agents.

M&A can enable the firm access to new knowledge. However, acquiring knowledge, technology or capabilities is not enough. Firms need to be able to explore and exploit new knowledge to develop products or to innovate. This requires two forms of organizational capabilities: the combinative capability of a firm and the absorptive capacity of a firm (Reus, 2012).

2.2.2. Combinative Capability

Kogut and Zander (1992) introduce the concept of combinative capability. This concept refers to the firm's capability to exploit existing knowledge and the unexplored potential of technology, which is dependent on organizing and recombining knowledge. The combinative capability is the essential capability to innovate.

An important presumption is that the knowledge of a firm is socially constructed, resting in the organization of human resources (Kogut & Zander, 1992).

Therefore, the combinative capability is especially crucial in M&A, in order to learn from the acquired knowledge. "The knowledge of the firm has an economic value over market transactions when firm identity leads to social knowledge that supports coordination and communication" (Kogut & Zander, 1996, p. 502). Thus, the combinative capability depends on the firms' social community and its ability to organize, share and distribute knowledge. Firms that have a beneficial culture for knowledge sharing might be able to better exploit their knowledge (Bresman, Birkinshaw, & Nobel, 1999; Haspeslagh & Jemison, 1991).

Knowledge is of little value if it does not result in products. "The ability to indulge in a forward-looking development of knowledge is strongly contingent on the selection environment. Long-term survival involves a complex tradeoff between current profitability and investing in future capability. Future capabilities are of little value if the firm does not survive" (Kogut & Zander, 1992, p. 393). Apart from the combinative capability, the absorptive capacity of an organization determines the ability to generate value from knowledge.

2.2.3. Absorptive Capacity

Cohen and Levinthal (1990) define the absorptive capacity of a firm as the "ability to recognize the value of new information, assimilate it, and apply it to commercial ends" (Cohen & Levinthal, 1990, p. 128). Thus, the absorptive capacity of an organization depends on the ability to transfer knowledge between and within units and to exploit knowledge. Knowledge needs to be passed to the right location within the firm to be exploited. Cohen and Levinthal (1990) and Cohen and Levinthal (1989) see the absorptive capacity as a byproduct of R&D activities. Absorptive capacity is thus a function of prior knowledge. As learning is cumulative, the learning performance is highest when learning items are related to prior knowledge. In consequence, diversity of knowledge is very important, in order to relate new knowledge to what is already known (Cohen & Levinthal, 1990).

Correspondingly, the absorptive capacity is a dynamic capability, which develops and changes over time with the firm operating in different environments and markets (Zahra & George, 2002). Consequently, the absorptive capacity of a firm is (1) depending on the absorptive capacity of the individual members within the organization, (2) developing over time cumulatively and path-dependent and (3) depending on the ability to identify the correct points of contact for external and internal knowledge within the organization (Cohen & Levinthal, 1989, 1990; Reus, 2012).

The concept of absorptive capacity has been extended into potential and realized absorptive capacity. Potential absorptive capacity covers knowledge acquisition and assimilation capabilities, while realized capacity describes the ability of knowledge transformation and exploitation (Zahra & George, 2002).

In empirical research, the absorptive capacity has been operationalized in mainly two ways: R&D intensity and patents (Lane, Koka, & Pathak, 2006).

The absorptive capacity is a rather complex, multilayered concept, involving different factors, such as individual capabilities, firm capabilities and external factors (Lane et al., 2006).

There is a difference between the absorptive capacity and the combinative capability. The absorptive capacity describes how firms can explore their knowledge and absorb new knowledge, while combinative capability describes how firms can exploit their knowledge. Both capabilities are essential for a firm's ability to build knowledge-based resources.

2.2.4. Knowledge-Based View and M&A Innovation Performance

M&A marks a disruptive point in the lifetime of an organization and can therefore disrupt internal processes, which can also affect the process of post-merger integration and knowledge transfer. Post-merger integration either hinders or enables acquirers to use the technology (Bresman et al., 1999; Haspeslagh & Jemison, 1991). Scientists, engineers and other types of "knowledge workers" have socially embedded routines for conducting R&D. These routines can be disturbed by an acquisition, which leads to a decline in productivity (Paruchuri, Nerkar, & Hambrick, 2006). As strategically important knowledge is often tacit (Cohen & Levinthal, 1990), it is difficult to transfer it between two separate entities, as this kind of knowledge is socially embedded. There is even a risk of breaking these kind of resources (Larsson & Finkelstein, 1999).

Successful integration of large bundles of knowledge-based resources is difficult following M&A deals, sometimes even leading to a loss of knowledge-based resources (Reus, 2012). There is plenty of literature on why integration fails (see for example Capron, Dussauge, and Mitchell (1998); Haspeslagh and Jemison (1991); Jemison and Sitkin (1986); Larsson and Finkelstein (1999); Pidun (2019)).

"One of the central dilemmas in managing acquisitions — and perhaps the pivotal factor in affecting employee disruption — is the decision about whether to integrate the newly acquired firm and the acquiring firm" (Puranam et al., 2006, p. 545). A target firm that remains independent might keep a high degree of inventiveness, but the acquirer will receive no benefit for paying the high acquisition premium. On the other hand, a full integration might lead to a significant reduction of inventiveness of the target, by causing "organiza-

tional trauma" or damage of the desired resources (Zollo & Singh, 2004).

"Technologically rich acquisition targets provide opportunities for organizational learning by exposing the acquirer to new and diverse knowledge" (Makri et al., 2010, p. 603). The success of post-acquisition integration depends on the combinative capability and absorptive capacity of both firms.

An acquisition can be seen as a unification of knowledge, which can act as a trigger event for new innovations as both firms start to explore their knowledge. Furthermore, acquisitions enable firms to develop capabilities and expertise by acquiring new and unfamiliar knowledge developed by target employees (Kogut & Zander, 1992).

2.3. Previous Empirical Studies

There is a small stream of research concerning at M&A and innovation in strategic management research. Previous studies rely on different theoretical frameworks, draw their ideas from different schools of thought and use different methodologies. The results are mixed: Some studies show positive effects, while others show neutral or even negative effects. Research has mainly relied upon a couple of proxies for measuring the innovation performance, which include R&D indicators, patenting and new product introduction (Ahuja & Katila, 2001; Cassiman et al., 2005; Freeman & Soete, 1997; Stuart, 2000). Finding a unified measurement for innovation is still an unresolved challenge in the area of management research.

2.3.1. Pre 2000

The first studies in this area are based on the framework of a market for resources within the firm. The firms' managers face a trade-off between growth by acquisitions and investments in other areas of the firm, such as commitment to innovation. Managers will shift their attention away from innovation and internal R&D in favor of the process of integrating target firms or other M&A related activities, therefore affecting the innovation performance negatively (Hitt, Hoskisson, & Ireland, 1990).

Hitt, Hoskisson, Ireland, and Harrison (1991) found significant negative effects of M&A deals on R&D inputs (expenses) and R&D outputs (patents) of acquiring firms using a sample of 191 US based manufacturing firms. This indicates that managers use M&A as a substitute for internal innovation sourcing. Furthermore, the reduction in R&D output can lead to a decline in innovativeness and therefore a decline in financial performance in the long run. The decline in R&D inputs also suggests that acquirers are not fully exploiting acquired technologies, as the investments are eventually not sufficient to foster innovation.

In a subsequent study, Hitt et al. (1996) found a significant negative relationship between a high M&A frequency and the frequency of internal innovations as well as the amount of R&D spending. They attribute this effect to transaction costs and managerial attention devoted to M&A, instead of internal innovation processes. The researchers used a sample of 250 US based firms and evaluated surveys of managers and detailed firm data.

To conclude, the research of Hitt et al. suggests that firms with a M&A strategy might shift their innovation sourcing away from internal innovation towards external innovation, which is associated with a decline in post-acquisition R&D spending and lower rates of internal innovation: "Acquisitions can decrease innovation adoption by taxing resources and the managerial attention" (Barden, 2012, p. 1280).

2.3.2. Post 2000

Cassiman et al. (2005) conducted interviews with key personnel from 31 firms on 62 acquisitions to analyze the relationship between M&A, technological and market relatedness and R&D expenses. They found that firms with complementary technologies have higher R&D expenses after acquisitions and tend to increase R&D efficiency. Technological substitutive firms have lower R&D expenses following an acquisition. This might be due to the technological motive of scope M&A deals in complementary M&A. Firms then try to use synergies to become more innovative. On the other hand, R&D efficiency increases when the two firms operate in technologically complementary areas. Their findings indicate a predominant scope motive of technological M&A, rather than a scale motive (Henderson & Cockburn, 1996).

Desyllas and Hughes (2010) investigated the effect of acquisitions on R&D-intensity (R&D expenditures / total assets) and R&D productivity (patents granted / R&D expenditures) in high-tech industries using a sample of 573 firms and 2624 acquisitions. They found neutral effects in the first year of acquisitions on R&D-intensity, which turn to positive effects after that. The overall effect is positive. The effect of acquisitions on R&D productivity is negative in the first year, which diminishes to an overall neutral effect. On top of that, they analyze the effect of absorptive and financial capacity. They found a positive relationship between the size of an acquirer's knowledge base and the post-acquisition R&D productivity, supporting the hypothesis that "superior absorptive capacity will be better positioned to select appropriate targets and exploit the acquired knowledge base" (Desyllas & Hughes, 2010, p. 1118). They found a positive effect of relatedness in terms of product-relatedness on R&D productivity, supporting the findings of Cassiman et al. (2005).

Both studies show that M&A can improve the R&D efficiency, depending on the circumstances of the involved firms. Related acquisitions seem to have a positive effect on R&D efficiency and therefore have a positive effect on innovation.

Another research stream emerged from the RBV and the KBV. These studies mainly analyze the size of knowledge bases and technological relatedness of knowledge of the involved entities, using patents as a proxy for innovation.

Ahuja and Katila (2001) employed a KBV approach, viewing patents as a proxy for innovation and knowledge of firms. They analyze the innovation performance of acquiring companies of 71 firms active in the chemical industry. The dimensions studied were the absolute and relative size of the

acquired knowledge base as well as the relatedness of knowledge. They found a small positive effect of acquiring a large patent portfolio and a negative of a large relative knowledge base of the target compared to the acquirer. Furthermore, they found a curvilinear effect of the relatedness of the knowledge bases. Low and high relatedness of knowledge lead to a small positive increase of innovation performance, while a moderate amount of relatedness of knowledge leads to a bigger increase of innovation performance. Non-technological acquisitions have a negative effect on innovation output.

Cloodt et al. (2006) did an extended replication study of Ahuja and Katila (2001). They examined aerospace and defense, computers and office machinery, pharmaceuticals, and electronics and communications industry with over 347 acquiring firms and 2429 M&A deals. They reported similar findings to Ahuja and Katila (2001), besides the effect of the absolute size of acquired knowledge. The effect is slightly negative, implying that it might be challenging to integrate a large amount of knowledge.

Ahuja and Katila (2001) and Cloodt et al. (2006) used the same methodology and tested the same hypotheses, but did not find the same results. According to their research, performance is the lowest for deals in which both firms operate in similar or very unrelated technology or knowledge areas and the highest when there is a moderate degree of technology or knowledge relatedness. This indicates that there needs to be enough new knowledge, but also enough similar knowledge to generate value from M&A. Consequently, firms should choose targets that provide technological input with a degree of differentiation in knowledge and technology. This knowledge possibly enriches the innovation performance.

Building upon previous research, Makri et al. (2010) consider science similarity or complementarity as drivers of innovation in M&A. They analyzed 95 M&A deals in knowledge intensive high-technology industries. Their results suggest that complementary scientific knowledge and complementary technological knowledge contributed to enhanced post-acquisition innovation performance. Knowledge complementarity leads to a higher quality and quantity of inventions. In their study, the authors constructed different metrics using patent data. Moreover, knowledge similarity had no effect on innovation quantity and quality.

Sears and Hoetker (2014) split the knowledge relatedness into two parts: acquirer knowledge relatedness and target knowledge relatedness. Apart from this, they also used the measure of patent forward citations as a proxy for technological capabilities. These factors affect value creation from the firms' capabilities differently due to absorptive capacity, knowledge redundancy and organizational disruption. They found a negative relationship between both target relatedness and cumulative abnormal returns (CAR) and patents. As relatedness increases, less value can be generated from each unit (patent) of knowledge. Interestingly, they had similar findings using patents instead of CAR.

To conclude, Makri et al. (2010) and Sears and Hoetker (2014) add to previous research by analyzing not only knowledge relatedness, but also the quality of knowledge. They suggest that there is a "sweet spot", where the complementarity of knowledge enables firms to increase their innovation performance from M&A.

Bena and Li (2014) showed that firms with low R&D expenses and a comparatively large patent portfolio are more likely to become acquirers, while firms that have high R&D expenses and innovation are more likely to become targets. Furthermore, knowledge relatedness between firms had a positive effect on the likelihood of merger pair formation, which is reduced when firms operate in the same product markets.

Colombo and Rabbiosi (2014) analyzed the coherence of R&D restructuring activities and innovation performance. The results of their empirical analysis imply that technological similarity between firms has a large and direct negative effect on post-acquisition innovation performance. The effect was mediated by restructuring the R&D department of the target firm. To the author's knowledge, this is the only study that analyzes such activities.

In one noteworthy study, Higgins and Rodriguez (2006) focused on M&A as a means to outsource R&D in the pharmaceutical industry. Using the variables 'expected years of patent life', 'marketed products' and 'upcoming products', they construct a 'desperation index'. Firms with a high desperation index were more likely to acquire another firm. In the year following a deal, 71% of acquirers had at least maintained or even improved their product pipeline. On top of that, they report that firms which engaged in a strategic alliance with the target before the deal enjoy higher CAR. All analyzed firms formed a strategic alliance during or before the sample. This suggests that alliances might be a tool to reduce the information asymmetry between the acquirer and target.

2.3.3. Review of Previous Studies

To summarize, much of the previous research has addressed different problems in M&A and has built upon different theoretical frameworks. The author has identified a couple of research streams that build on the same frameworks and have coherent empirical findings. The overall literature, however, has many different granular findings, which are quite difficult to generalize due to the complexity of M&A, the challenge of measuring innovation and the interrelation of factors affecting innovation. To deal with this complexity, most studies focus on certain aspects and characteristics of M&A deals. On top of that, different studies have different sampling approaches, some exclude large M&A deals (e.g., Makri et al. (2010)), while others exclude small "hands-on" deals (e.g., Ahuja and Katila (2001), Cloodt et al. (2006) and Sears and Hoetker (2014)). Furthermore, research has been mainly concerned with high-tech industries.

Some trends consistently appear in literature: M&A seem to have a negative effect on R&D expenses (Cassiman & Veugelers, 2006; Hitt et al., 1996). The relatedness (complementarity or similarity) of knowledge bases is an important predictor for the post-acquisition innovation (measured by

patents) (Ahuja & Katila, 2001; Cloodt et al., 2006; Makri et al., 2010; Sears & Hoetker, 2014). As a result, acquired knowledge and technology should be complementary to the acquirer's knowledge base (Kogut & Zander, 1992), which then can lead to a "surplus" over the value that the target's and acquirer's knowledge could provide. Although previous research has provided important insights, there is still an incomplete understanding of the effect of M&A on corporate innovation.

2.4. Hypotheses

As this work intends to replicate the findings of Ahuja and Katila (2001), the first four hypothesis are based on Ahuja and Katila (2001).

There are multiple ways how acquisitions can affect the post-acquisition innovation performance. First of all, not all acquisitions are motivated by technology. Motives for acquiring other companies can be access to markets, sales channels, vertical or horizontal integration, diversification, to gain synergies or to increase market power (Cassiman & Veugelers, 2006; Schweizer, 2005b).

Acquisitions that do not involve any patents or do not have a technological motive are unlikely to improve the post-acquisition performance, as these acquisitions will likely not provide any technological input for the acquirer. The knowledge of a target provides little to none technological value to the acquiring firm (Ahuja & Katila, 2001; Reus, 2012). In this case, an acquisition should not increase the innovation performance of an acquiring firm.

Even improved routines or processes for innovation of the target are unlikely to be transferred to the acquiring firm, as post-acquisition integration decision tends to be housed in the acquiring firm. The target will likely converge to similar innovation routines as the acquiring firm (Kapoor & Lim, 2005).

Acquisitions need considerable managerial attention and consequently consume managerial resources. This can lead to a decline in innovation performance after an acquisition, because managerial attention is devoted to the acquisition instead of internal innovation projects (Haspeslagh & Jemison, 1991; Hitt et al., 1996). Moreover, acquisitions are characterized by significant disruptions of organizations, which can affect all dimensions of productivity (Bresman et al., 1999; Haspeslagh & Jemison, 1991).

Therefore, one would expect that non-technological acquisitions, that do not involve any patents, affect the innovation performance either negatively or non-significantly.

H1: *The post-acquisition innovation performance will be affected either negatively or non-significantly by non-technological M&A* (Ahuja & Katila, 2001).

Deals that are motivated by technology and include a certain amount of technological knowledge in the form of patents can have different effects on the post-acquisition innovation performance of the acquiring firm. An acquisition of a firm can be seen as an acquisition of a knowledge base. The acquired knowledge base needs to be integrated and then combined with the knowledge base of the acquiring firm, which can lead to an improved innovation performance.

On the other hand, acquisitions can also have a negative impact on innovation, as they mark a disruptive event in a firm's lifetime. To investigate whether the impact of an acquisition is positive, negative or non-significant, the following dimensions need to be considered here: the size of the acquired knowledge base, the size of acquirer knowledge base and the relatedness of the knowledge bases (Ahuja & Katila, 2001; Lubatkin, 1983). The interplay of these factors should determine the post-acquisition innovation performance.

An acquisition can improve the innovative output of the acquiring firm by three possible mechanisms: the (successful) merging of two distinct knowledge bases can lead to improved economies of scale and/or scope and improved knowledge recombination (Henderson & Cockburn, 1996): "M&A can realize economies of scale through the spreading of fixed costs over more output and the elimination of common inputs for the production of the same output" (Cassiman et al., 2005, p. 200). In the healthcare industry, for example, an acquisition allows more employees to use expensive R&D equipment for virtually no additional costs for new purposes (e.g., lab equipment). Additionally, larger R&D bases can lead to more specialization and increased economies of scope. Combination of new and existing knowledge can yield new ideas, which then lead to new technologies and innovations. Exchange between both R&D units can stimulate the further development of ideas among colleagues. With an increased size of the combined knowledge bases of target and acquirer, the extended range of possible combinations of knowledge can foster an increased patent output (Galunic & Rodan, 1998; Kogut & Zander, 1992). An acquirer has more opportunity for learning when buying a technologically rich target (Makri et al., 2010). Therefore, the absolute size of acquired knowledge gives the acquirer more opportunity to combine and recombine knowledge.

For the reasons stated above, the author expects a positive relationship between the absolute size of the acquired knowledge base and the post-acquisition patent output of the acquiring firm.

H2: *A larger absolute size of the acquired knowledge base increases the post-acquisition innovation performance* (Ahuja & Katila, 2001).

Knowledge is primarily transferred through interactions between individuals in both the acquired and acquiring entity. Resources are bound in the integration process in the form of integration teams, meetings and considerable communication between both firms. The transfer of knowledge strongly depends on this process (Haspeslagh & Jemison, 1991). If the two knowledge bases are relatively equal in size, most of the firm's knowledge resources are devoted to the task of unifying the two distinct knowledge bases. This can lead to a decrease in innovation performance, as the re-

sources for innovating are absorbed by the process of integration. If the acquiring knowledge base is much larger, however, the integration should be easier, as fewer resources of the acquiring unit are bound to the integration.

On the other hand, if the acquired knowledge base is far larger, the integration should be more difficult, as there are fewer resources on the acquirer side to handle integration and knowledge absorption. Furthermore, the entire acquiring organization needs to adapt its structures and processes to handle the integration (Haspeslagh & Jemison, 1991; Pidun, 2019).

Thus, the author expects a negative relationship between the acquired size of knowledge and the acquirer size of knowledge.

H3: *A large relative size of the acquired knowledge base will have a negative impact on the post-acquisition innovation performance* (Ahuja & Katila, 2001).

The third dimension is the relatedness of knowledge bases. The knowledge of both firms should be related, so that they can exchange knowledge and are familiar with their knowledge. However, there should also be room for new ideas. Closely related knowledge might be easier to integrate, but provides smaller room for new ideas. This kind of knowledge provides little to no value to the acquirer and should therefore not affect the patent output. Very different knowledge bases are difficult to integrate and to commercialize, since there is no connection to what is already known to the acquirer. In this case, the acquirer might not know how to commercialize the target knowledge. Therefore, a mixture of new and familiar knowledge should provide the best basis for improved post-acquisition innovation performance (Ahuja & Katila, 2001; Cloodt et al., 2006; Cohen & Levinthal, 1990; Reus, 2012).

H4: *The relatedness of the acquired knowledge base will be curvilinearly (inverted U-shape) related to the post-acquisition innovation performance of the acquiring firm* (Ahuja & Katila, 2001).

The relatedness of acquirer knowledge describes the knowledge that is part of the knowledge of the acquirer and known by the target. The higher the relatedness, the larger the share of already familiar knowledge. An increase in acquirer relatedness should have a negative effect on post-acquisition innovation performance, as the acquirer does not have the opportunity to learn anything new. In addition, acquirer employees might even retain their knowledge in the integration process, because of the risk of becoming redundant. Therefore, acquirer employees have an incentive to resist the target integration and the resulting combination of knowledge will be affected in a negative way (Sears & Hoetker, 2014). This, in turn, should have a negative effect on innovation performance.

H5: *The larger the relatedness of the acquirer knowledge, the smaller the post-acquisition innovation performance*.

The model of Ahuja and Katila (2001) falls short in capturing the effect of absorptive capacity on innovation performance. Absorptive capacity refers to the ability to recognize, assimilate and apply new external knowledge. It depends on prior knowledge and diversity of knowledge (Cohen & Levinthal, 1989, 1990). Knowledge transfer between firms depends on how easily knowledge can be communicated, interpreted and absorbed (Kogut & Zander, 1992, 1993). With more cumulative and repetitive experience in M&A, firms should be able to better leverage the acquired knowledge (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998; Zahra & George, 2002). Experience with M&A could build absorptive capacity that facilitates knowledge development. This knowledge is explicitly codified into systems, routines, and procedures of the acquirer. Thus, acquisition experience should have a positive effect on innovation performance.

H6: *Previous acquisition experience has a positive effect on post-acquisition innovation performance.*

3. Empirical Analysis

The previous chapter described and evaluated important theories and previous empirical studies on innovation performance in M&A. Six hypotheses were derived from the presented theories, four of them have been suggested by Ahuja & Katila, the other two have been suggested by the author. The following chapter contains a description of the sample, data, data processing, model, empirical methodology, limitations, and variables. Finally, the empirical results will be discussed.

3.1. Sample and Data Description

The data was drawn mainly from two sources: the Thomson Reuters Eikon Database and the PATSTAT database of the EPO. To construct a variable on cultural differences, the data provided by Geert Hofstede was used (Hofstede, 2015).

3.1.1. Sample

The sample was drawn from the Standard and Poor's (S&P) Global 1200 Health Care index (Reuters Instrument Code (RIC): SPGLOHC), which contains all healthcare firms in the S&P Global 1200.[1] The S&P Global 1200 measures the performance of large-cap stocks from all major markets and represents about 70% of world market capitalization (Standard & Poor's, 2021).

S&P uses the Global Industry Classification Scheme (GICS), which classifies firms according to their revenue to specific industries and sub-industries. The Healthcare industry is further classified in the GICS sub-industries "Health

[1]The S&P Global 1200 consists of the different component indices from all over the world: S&P 500 (US), S&P All Australian 50, S&P Europe 50, S&P Asia 50, S&P TSX 60 (Canada), S&P Latin America 40, S&P TOPIX 150 (Japan).

Care Equipment", "Health Care Technology", "Pharmaceuticals", "Life Science Tools & Services", and "Biotechnology". In this work, firms in the industry "Health Care Providers & Services" (351020) were excluded, due to the non-technological nature of this sub-industry. Firms in this industry were mainly based in the United States and active in the area of health insurance.

The distribution of the different industries in the sample can be seen in figure 1. "Pharmaceuticals" have the largest share with about 50% in the sample, followed by "Health Care Equipment", "Biotechnology" and lastly "Life Science Tools & Services".

The sample consists of 41 of the largest players in healthcare. The full list of firms can be found in the appendix in table A4.

This approach was chosen, because the author did not have a way to draw a random sample of firms. Such an approach is fairly consistent with previous research of Ahuja and Katila (2001) and Cloodt et al. (2006). However, Ahuja and Katila (2001) did not specify how they drew their sample. They identified leading players within the chemicals industry and put them together as their sample. The variance of firm size in this sample is smaller than in previous research. The range is from about 7,000 to over 130,000 employees, compared to Ahuja and Katila (2001) with 2,300 to 181,000 employees.

This study analyzes a ten year period between January/01/2006 and December/31/2017. The end of the study period on December/31/2017 was selected, so that it takes into account the time between application and grant of patents. The observation period was set to ten years, which is consistent with previous research (Ahuja & Katila, 2001; Cloodt et al., 2006). Due to the distributed lag in the regression model, the observation period reduced by four years to 2010-2017. The sample contains 41 firms and 328 (41 times per 8 years) observations. The number of M&A deals is 368.

The sample can be classified as a balanced longitudinal data set, meaning that no firm exited the sample. The data set is complete, no data is missing.

3.1.2. Data

The Thomson Reuters Eikon database was used to obtain data on M&A deals and the financial data of the sample firms (R&D expenses and revenues from 2006-2016). The database is among the leading banking databases and includes a vast amount of financial and firm data (Thomson Reuters Eikon, 2021).

The M&A deals were obtained using Deals Screener of Thomson Reuters Eikon. The deals were filtered using the following criteria: the deals had to be completed, larger than 5M$, effective between January/01/2006 and January/01/2017. Additionally, the acquirer needed to own a majority stake in the target (>50% owned after the transaction, including pre-deal shares). The M&A type was set to Disclosed Dollar Value Deal, Undisclosed Dollar Value and Stake Purchases Deal (filter codes: DI, UN, SP; the codes RE and ST are self-tenders and recapitalization and were therefore excluded). This approach is consistent with previous research (Ahuja & Katila, 2001; Cloodt et al., 2006; Hitt et al., 1996). The deals include small size acquisitions and large mergers, the deal size range was from 8M$ to 63B$.

Acquisitions of only certain assets or business units of other firms were excluded manually from the list of deals (e.g., the acquisition of Novartis AG Biologics Manufacturing Facility from Bayer Schering Pharma AG in 2007). Acquisitions of business units had to be excluded, as it was not possible for the author to correctly attribute patents to business units. Further research could address this problem, as it is common in this industry to acquire or divest business units (Ascher et al., 2020).

Not all deals were listed in the Deals Screener app. The author conducted a manual search for each firm using news reports of Thomson Reuters. This problem arose due the name change of Mylan N.V. (now: Viatris Inc.), Valeant Pharmaceuticals Inc. (now: Bausch Health Inc.) and the frequently used name of Waters Corp. Additional 19 deals were identified. Another problem occurred with the merger of "Thermo Electron" and "Fisher Scientific" to "Thermo Fisher Scientific" (TMO) in April 2006. The patents of both firms, before the merger, were retrospectively assigned to the new entity "Thermo Fisher Scientific". As the firms merged in the beginning of 2006, the firm was treated as one entity for the whole sample.

Patent data was drawn from the PATSTAT database of the European Patent Office (EPO). The PATSTAT database was specifically developed for use by government organisations or academic institutions. PATSTAT contains data from more than 100 countries and over 110 million patents. The newest version number was used (Autumn 2020). The patents of the firms were downloaded from PATSTAT using a SQL query.[2]

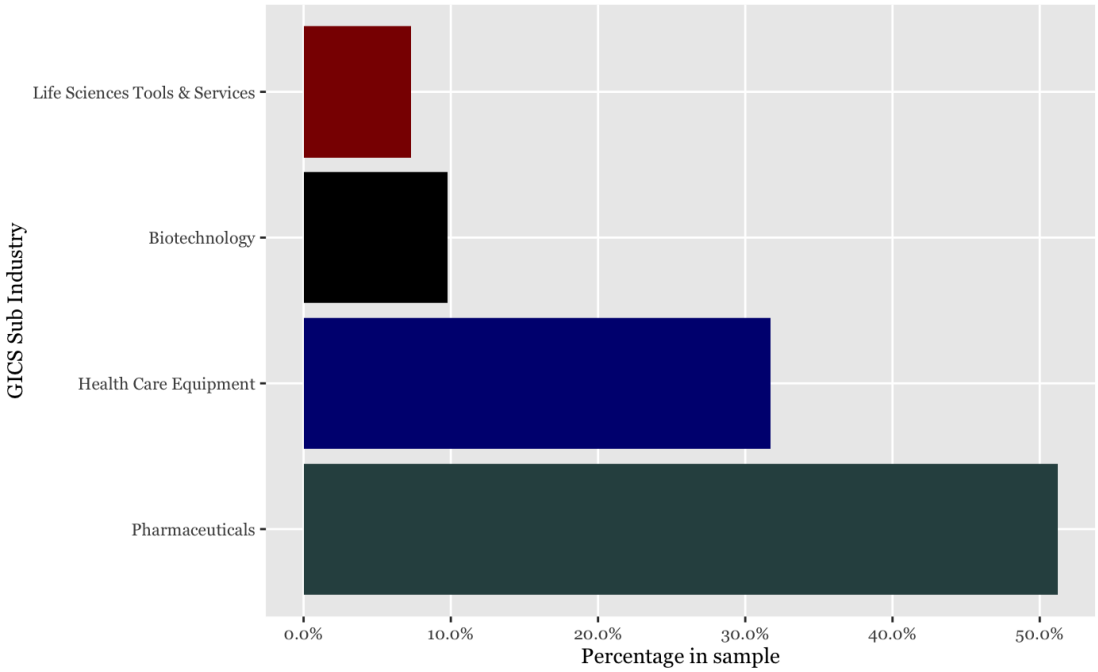
When the patent search did not specify any patents, the acquisition was marked as a non-technological acquisition. This approach is consistent with Cloodt et al. (2006), but not with Ahuja and Katila (2001), as Ahuja and Katila (2001) additionally screened news reports for the motives of the acquisition. Contrary to previous research, patent citations were not included in this research. This would have exceeded the time frame of this research.

3.1.3. Data processing and merging

Patent data of acquiring firms were obtained from January/01/2005-December/31/2017. Patent data of target firms were obtained four years preceding the date of the respective deal. The data from PATSTAT was then matched to

[2]The information included in the download were: appln_id (unique ID of the patent), appln_auth (application au thority), appln_nr (application number), appln_kind (kind of application), appln_filing_date (date of application filing), granted (selector for only granted patents), nb_applicants (number of applicants), nb_inventors (number of inventors), person_id (unique person id for the applicant), person_name, psn_name, person_ctry_code, ipc_class_symbol, ipc_version, and ipc_gener_auth. The variable appln_kind was set to "A", which means that all other document types other than patents were excluded.

Figure 1: Distribution of Global Industry Classification Standard (GICS) Sub Industries in the sample (own figure)



the firm data from Thomson Reuters Eikon using the Python libraries pandas and fuzzywuzzy (pandas development team, 2020; Van Rossum & Drake, 2009). Legal forms of the firms were removed using pandas. For each appln_id a ratio of similarity was calculated. The ratio compares the name of the firm from the list of M&A deals obtained from Thomson Reuters Eikon and from the list of patents from PATSTAT, using the Levensthein distance metric (Levenshtein et al., 1966). If the match was higher than 90%, the patents were attributed to the firm.

The dataset was constructed using the "tidyverse" package of the R programming language (R Core Team, 2019; Wickham et al., 2019). The panel data set was organized in the long format: one observation subject per row and the columns contain the variables.

3.2. Model Specification and Econometric Methodology

The empirical model follows Ahuja and Katila (2001), a random effects Poisson regression model with a distributed lag. The regression coefficients are approximated by a generalized estimating equation (GEE) (Ahuja & Katila, 2001; Liang & Zeger, 1986).

This type of model is appropriate for non-negative count values (number of patents granted per year per firm) and can handle data aggregated over multiple periods. With repeated observations, the correlation among yearly measurements in a generalized linear model would make that model useless. GEE models have been introduced to handle this deficit (Liang & Zeger, 1986; Lipsitz & Fitzmaurice, 2008).

GEE models avoid assumptions about a multivariate distribution and instead rely on a marginal distribution (a subset of random variables) at each time. It relies on the independence of different subjects (clusters) to estimate the variance of the proposed estimators (Liang & Zeger, 1986). In this research setting, each firm represents one cluster.

To account for the post-acquisition integration period, the model includes four distributed lag terms. The earliest possible application for a patent is one year after the M&A deal happened. Patent output of a given year is determined by the input of the preceding years (Ahuja & Katila, 2001). Following Ahuja and Katila (2001) four distributed lag terms are introduced, as they have found good results using four distributed lag terms. They also tested three and five lag terms respectively, but did not find significant differences. Thus, the model will have four distributed lag terms $A_{it-year}$. The regression equation has the following form:

$$P_{it} = exp(X_{it-1}\gamma + A_{it-1}\beta_1 + A_{it-2}\beta_2 + A_{it-3}\beta_3 + A_{it-4}\beta_4)$$

P_{it} is the dependent variable: the number of patents obtained by firm i in year t. X_{it-1} is a vector of control variables. $A_{it-year}$ are the vectors for independent variables (Ahuja & Katila, 2001). The variables are explained in section 3.3.

To calculate the total impact of a variable, the sum of the distributed lag coefficients can be summed up. The standard errors are then determined by the variances plus the covariances between the periods. This allows for hypothesis testing (Ahuja & Katila, 2001; Cloodt et al., 2006).

Since the observations in the longitudinal data set are cluster correlated over time, a Generalized Linear Model (GLM) is not applicable. A GLM would lead to an inaccurate estimation of coefficients and standard errors. Therefore,

Ahuja and Katila (2001) opted for a Generalized Estimating Equation (GEE). GEE models are used for population-average estimations and provide a regression approach for GLMs with longitudinal data, when the different cluster measurements are not independent. This allows for inferences about the population, accounting for the within-cluster correlation. In this research setting each firm is a cluster, with a correlation between the annual measurements. Similar to GLMs, GEE uses a link function that models the relationship between the expected value of the dependent variable to the predictors in the model (Agresti, 2003). In the case of the Poisson regression, the link function is the natural logarithm.

The GEE approach has two advantages: it is flexible and robust. Neither linearity between the predictors and the dependent variables, nor homogeneity of variance for the range of the dependent variable are assumed (Liang & Zeger, 1986).

Regression coefficients are approximated by a quasi-likelihood approach instead of a maximum likelihood algorithm. This approach uses the expected value and the variance of the dependent variables instead of a likelihood function. The quasi-likelihood approach consists of two steps: in the first step, coefficients are estimated using a specified working correlation matrix. Results of this estimate are then used in the next iteration, which then estimates the coefficients and standard errors accounting for the observed correlation of subjects and residuals (Ahuja & Katila, 2001).

To account for possible correlation between the residuals of observations for the same firm, the GEE method requires a working correlation structure to be specified. This working correlation captures the relationship between observations. Examples for such correlation structures are: independent, exchangeable or auto-regressive. In this work, the covariance structure was set to independent, as this is the most robust structure (Stokes, Davis, & Koch, 2012). This covariance structure was used by Ahuja and Katila (2001) as well. In case of a falsely assumed working correlation, GEE is still able to find robust results, by updating the working correlation matrix with each iteration (Lipsitz & Fitzmaurice, 2008).

As GEE uses a quasi-likelihood approach, typical regression fitting criteria that use likelihood functions, such as Akaike's information criterion, are not applicable to GEE models (Liang & Zeger, 1986; Pan, 2001). Thus, Pan (2001) proposed the "quasi-likelihood under the independence model criterion" (QIC). QIC uses a similar approach than Akaike's information criterion, but is based on a quasi-likelihood approach. QIC allows model comparison and model selection.

As previously mentioned, the underlying econometric model is a Poisson regression, which is an appropriate model for discrete, non-negative count variables such as patents (Agresti, 2003; Stokes et al., 2012). The dependent variable is equal to the mean of a Poisson process. The Poisson distribution requires that the variance is equal to the mean. If this assumption is violated, the standard errors can be underestimated (Agresti, 2003). The typical case is when the conditional variance exceeds the conditional mean, which is called overdispersion. There are plenty of sources for overdispersion: variability of subjects, correlation or dependence between individual sample responses, a clustered structure of the population, small sample size and more (Stokes et al., 2012). Table 3 shows the summary statistics. It can be seen that the conditional mean of the variable patents is lower than the variance. This indicates overdispersion (Cameron & Trivedi, 2013).

Furthermore, unobserved effects might lead to a serial correlation of the residuals of observations from the same firm over the years (Ahuja & Katila, 2001). This effect can also lead to an underestimation of coefficients. To solve these problems, this work uses a pre-sample approach. With this approach, unobserved heterogeneity is modeled with an additional covariate (Blundell, Griffith, & Reenen, 1995). For that reason, the *pre-sample patents* variable is included in the regression model, to account for unobserved differences in knowledge stocks between the sample firms (Ahuja & Katila, 2001). This variable is constructed from the values of the dependent variable in the period immediately preceding the observation period. The information provides the basis for controlling for unobserved heterogeneity, which then leads to an reduction in overdispersion and serial correlation (Blundell et al., 1995).

Another possibility to handle overdispersion is a Negative binomial regression. The underlying distribution of this model can be considered a generalization of the Poisson distribution. This lifts the restriction that the variance is restricted to the mean. The Negative binomial distribution has the following properties:

$$E(Y) = \mu \qquad Var(Y) = \mu + D\mu^2$$

The parameter D models the empirical variance, which corrects for overdispersion (or underdispersion). Both regression models are reported in this thesis. The replication study by Cloodt et al. (2006) uses a Negative binomial model. This study includes both models, the Poisson results are reported in this chapter, the Negative binomial results can be found in the appendix.

To find the regression parameters, the Python package "statsmodels" was used (Seabold & Perktold, 2010; Van Rossum & Drake, 2009).

3.3. Variables

Tables 1 and 2 give an overview of all variables included in the model. The following subsection will provide a comprehensive overview of the variables used in this work, as well as the underlying calculations and assumptions made to derive them. Table 4 shows the correlation matrix.

3.3.1. Dependent variable

Patents. The dependent variable is the patent output of company i in year t, which is a non-negative count value.

Researchers in management and economics have used multiple indicators to measure innovation. Typical metrics

Table 1: Overview of control variables

Variable	Description	Source
R&D Expenses	The absolute amount of R&D spending per year.	Thomson Reuters Eikon One
Natural Log. of Revenue	The natural log of firm revenue.	Thomson Reuters Eikon One
Foreign Acquisitions	Control variable for cultural differences of firms.	Homepage of Geert Hofstede
Pre-sample patents	Sum of patents in the three years prior to the entry into each period.	PATSTAT
Country dummy	Categorical dummy variable to capture different countries of origin	-
Year dummy	Categorical dummy variable to capture yearly differences.	-
GICS Industry dummy	Categorical dummy variable to capture industry differences.	-

Table 2: Overview of independent variables

Variable	Description	Source
Number of non-technological acquisitions	The absolute number of non-technological acquisitions.	PATSTAT
Absolute size of acquired knowledge	The absolute number of unique target patents numbers.	PATSTAT
Relative size of acquired knowledge	The absolute number of unique target patents numbers, divided by the absolute size of unique patents of the acquiring firm.	PATSTAT
Relatedness of target knowledge	The overlap of patent classification codes, divided by all patent classification codes of the target.	PATSTAT
Relatedness of acquirer knowledge	The overlap of patent classification codes, divided by all patent classification codes of the acquirer.	PATSTAT
Acquisition experience	Number of acquisitions from 01.01.2006 until the focal year.	Thomson Reuters Eikon One

are R&D expenditures, patents, patent citations or the introduction of new products or new product lines. Other approaches of measuring innovation performance include surveys of executives (Hagedoorn & Cloodt, 2003).

In this research setting patents are appropriate, because in the healthcare industry patents and "comprehensive patent protection is a prerequisite for subsequent commercial success" (Henderson & Cockburn, 1996, p. 38). Additionally, previous studies in the pharmaceutical sector have shown that patents are highly correlated with multiple measures of economic success (Griliches, 1998).

Patents are required to describe something novel and not obvious, and thus provide a good measure of technologically new knowledge as defined above. They have been used as a proxy for innovation in previous studies (Ahuja & Katila, 2001; Cloodt et al., 2006; B. H. Hall, Jaffe, & Trajtenberg, 2005; Sears & Hoetker, 2014). Weaknesses of using patents as a proxy for innovation will be discussed later in section 3.4.2.

3.3.2. Independent variables

The independent variables are included in the vector $A_{it-year}$ with $year \in \{1,2,3,4\}$. This vector contains the *absolute size of the acquired knowledge* base, the *relative size of the acquired knowledge* base, the *relatedness of the target and acquirer knowledge* base and the *number of technological acquisitions* where the patents were unavailable. The variable *acquisition experience* was only included with a lag of one period.

Number of non-technological acquisitions. The first independent variable *number of non-technological acquisitions* was constructed using the data from Thomson Reuters Eikon of

Table 3: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Median	Max.
Patents	264.28	284.31	0.00	178.00	1,516.00
No. non-tech. acquisitions t-1	0.17	0.44	0.00	0.00	3.00
No. non-tech. acquisitions t-2	0.18	0.45	0.00	0.00	3.00
No. non-tech. acquisitions t-3	0.18	0.46	0.00	0.00	3.00
No. non-tech. acquisitions t-4	0.19	0.48	0.00	0.00	3.00
Abs. size of acquired knowledge t-1	47.27	190.40	0.00	0.00	2,478.00
Abs. size of acquired knowledge t-2	50.10	198.98	0.00	0.00	2,478.00
Abs. size of acquired knowledge t-3	51.17	206.20	0.00	0.00	2,478.00
Abs. size of acquired knowledge t-4	54.69	217.89	0.00	0.00	2,478.00
Rel. size of acquired knowledge t-1	0.03	0.10	0.00	0.00	0.98
Rel. size of acquired knowledge t-2	0.04	0.10	0.00	0.00	0.98
Rel. size of acquired knowledge t-3	0.04	0.10	0.00	0.00	0.98
Rel. size of acquired knowledge t-4	0.04	0.11	0.00	0.00	0.98
Relatedness of target knowledge t-1	0.33	0.59	0.00	0.00	5.18
Relatedness of target knowledge t-2	0.34	0.61	0.00	0.00	5.18
Relatedness of target knowledge t-3	0.34	0.57	0.00	0.00	5.18
Relatedness of target knowledge t-4	0.34	0.57	0.00	0.00	5.18
Relatedness of target knowledge^2 t-1	0.43	1.74	0.00	0.00	26.82
Relatedness of target knowledge^2 t-2	0.40	1.94	0.00	0.00	26.82
Relatedness of target knowledge^2 t-3	0.46	1.42	0.00	0.00	26.82
Relatedness of target knowledge^2 t-4	0.45	1.37	0.00	0.00	26.82
Relatedness of acquirer knowledge t-1	0.03	0.07	0.00	0.00	0.57
Relatedness of acquirer knowledge t-2	0.03	0.07	0.00	0.00	0.57
Relatedness of acquirer knowledge t-3	0.03	0.07	0.00	0.00	0.57
Relatedness of acquirer knowledge t-4	0.03	0.07	0.00	0.00	0.57
R&D expenses t-1	2,273.05	2,594.85	47.58	1,018.53	10,740.22
Log. revenue t-1	3.99	0.47	2.88	4.00	4.87
Pre-sample patents t-1	879.53	880.94	6.00	601.50	4,420.00
Foreign acquisitions t-1	0.93	0.75	0.00	1.00	4.00
Foreign acquisitions t-2	0.93	0.78	0.00	1.00	4.00
Foreign acquisitions t-3	0.94	0.78	0.00	1.00	4.00
Foreign acquisitions t-4	0.94	0.80	0.00	1.00	4.00
Acquisition experience t-1	7.23	5.04	0.00	6.00	26.00

the M&A activity of the sample firms from 2006-2017 and combining it with the patent data from PATSTAT.

Whenever a target firm had no patenting activity in the preceding five years before the acquisition, the deal was marked as a non-technological deal (Cloodt et al., 2006). Firms therefore do not provide any significant technological input to the acquirer.

Absolute size of acquired knowledge. The second variable, *absolute size of acquired knowledge base* was obtained by summing up the number of patents of target firms of the five years preceding the acquisition (Ahuja & Katila, 2001).

Relative size of acquired knowledge. The third variable, *relative size of acquired knowledge base*, was constructed using the *absolute size of acquired knowledge base* and the number of unique patents of the acquiring firm of the five years preceding the acquisition (Ahuja & Katila, 2001). Subsequently, the variable was calculated dividing the *absolute size of acquired knowledge base* by the number of unique patents of the acquiring firm:

$$relative\_size\_of\_acquired\_knowledge = \frac{absolute\_size\_of\_acquired\_knowledge}{absolute\_size\_of\_acquirer\_patents}$$

As proposed by Ahuja and Katila (2001), when the *absolute size of acquired knowledge base* was larger than the number of patents of the acquirer, the reciprocal fraction was calculated.

Relatedness of target and acquirer knowledge. The fourth and fifth variable, are calculated using the International Patent Classification (IPC) codes. Each patent has multiple classification codes. For each patent, a list of classification codes was prepared. In order to compare the patents, the first four digits of the codes were used. The first four digits allow for a comparison of subclasses. Subclasses are the third hierarchical level of patent classification (World Intellectual Property Organisation, 2020). The use of more digits would lead to an overly granular analysis (Kogler, Rigby, & Tucker, 2013; Leydesdorff, Kogler, & Yan, 2017).

For the variable *target relatedness*, the relatedness between patent codes of both firms (redundancy of codes) was calculated and then divided by the total number of IPC codes of the target's patents, representing the target knowledge.

$$relatedness\_of\_target\_knowledge = \frac{knowledge\_overlap}{target\_knowledge}$$

The variable *acquirer relatedness* was calculated in a similar way, but using the patent codes of the acquiring firm in the denominator. Note that the target knowledge is different to the absolute size of acquired knowledge. This variable is also different from *relative size of acquired knowledge*, as one patent can have multiple IPC codes.

Acquisition experience. The variable *acquisition experience* was calculated by the sum of all acquisitions until the current observed year from the beginning of 2006. This approach is consistent with previous research (Haleblian & Finkelstein, 1999; Hayward, 2002; Zollo & Singh, 2004).

3.3.3. Control variables

To control for unobserved heterogeneity among firms, a few control variables were introduced to the model (Ahuja & Katila, 2001).

Foreign Acquisitions. Since international acquisitions have higher rates of failure than domestic mergers and involve greater integration challenges (Heimeriks, Schijven, & Gates, 2012) a control variable for acquisition involving foreign firms was introduced. The control variable for foreign acquisitions was calculated following the approach of Kogut and Singh (1988) based on the theory of cultural differences by Hofstede (1980).

The cultural dimensions were first developed by Hofstede (1980) using data on IBM-employees. They provide a metric for a quantitative comparison of cultural differences between countries. The cultural dimensions were subsequently extended by Minkov (2007) and Hofstede and Minkov (2010), to six cultural variables. As Ahuja and Katila (2001) used only the original four dimensions, the formula was adapted to fit the newest framework with six variables.

$$foreign\_acquisitions = \sum_{i=1}^{I} (I_{ij} - I_{iu})^2 / V_i / 6$$

I_i is the value of cultural dimensions, V_i is the variance of the dimension. The dimensions are Power Distance, Individualism, Masculinity, Uncertainty Avoidance, Time Orientation, and Indulgence. Each country has a value between 0 and 100 for each dimension (Hofstede, 1980; Minkov, 2007).

Firm Size. Another factor that needs to be controlled for was firm size, since larger firms tend to be less innovative. Firm size was measured as the natural log of revenue (Cloodt et al., 2006).

Ahuja and Katila (2001) use the natural log of employees. Due to missing data availability in Thomson Reuters Eikon, the author decided to discard this variable. The natural logarithm of revenue is an appropriate replacement and used in many similar studies (Cloodt et al., 2006; Sears & Hoetker, 2014).

R&D expenditures. As larger firms enjoy economies of scale and scope in R&D (Henderson & Cockburn, 1996), the control variable *R&D expenses* was introduced to the model. R&D expenses affect the patent output (Ahuja & Katila, 2001).

Pre-sample Patents. To control for firm patent output differences at the start of each period, the variable for pre-sample patents was introduced. The variable was the sum of patents by the acquiring of the last three years for each period. It also serves as a fixed-effect variable to correct for serial correlation and overdispersion (Ahuja & Katila, 2001).

Country dummy. This categorical variable controls for differences in patenting behavior of firms from different countries (Ahuja & Katila, 2001). The reference was set to "ISO Country US"

Year dummy. This categorical variable controls for differences in patenting behavior of each year in the sample, as patenting is also affected by macroeconomic trends and the current economic situation of the firms (Ahuja & Katila, 2001). The reference was set to "Year 2016".

Industry dummy. This categorical variable controls for different characteristics of the GICS Sub-Industries. The reference was set to "Pharmaceuticals".

To avoid the dummy variable trap, one-hot encoding was used (Draper & Smith, 1998).

3.4. Econometric Limitations

3.4.1. Sample

The sample only includes large firms, which are listed in the S&P 1200. Therefore, this research does not cover small or medium sized businesses. The innovation performance of small or medium sized firms in M&A might be very different. Firms were required to stay in the sample for the whole period.

Only firms that share the same name were included. Subsidiaries with different names were excluded, due to different names of patent applicants (e.g., Ethicon Inc., a subsidiary of Johnson & Johnson). In spite of a different name, knowledge transfer or spillovers could happen between those firms and are not taken into account in this study.

Acquisitions of business units were excluded, because patents could not be reliably attributed to individual business units of larger firms. Acquisitions of business units of competitors happened frequently, as it is common to restructure, divest or acquire business units (Ascher et al., 2020). Business units are often described as a bundle of strategically relevant resources and could therefore provide relevant insights (Eschen & Bresser, 2005).

Table 4: Correlation Matrix

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1	Patents	1																																
2	No. non-tech. acquisitions t-1	0.07	1																															
3	No. non-tech. acquisitions t-2	0.04	0.23	1																														
4	No. non-tech. acquisitions t-3	0.03	0.07	0.22	1																													
5	No. non-tech. acquisitions t-4	-0.01	0.01	0.07	0.21	1																												
6	Abs. size of acquired knowledge t-1	0.12	0.12	0.02	0.07	0	1																											
7	Abs. size of acquired knowledge t-2	0.27	0.09	0.08	0	0.04	0	1																										
8	Abs. size of acquired knowledge t-3	0.23	-0.03	0.07	0.09	0.02	-0.01	0	1																									
9	Abs. size of acquired knowledge t-4	0.19	0.09	-0.03	0.07	0.07	0.01	-0.01	0	1																								
10	Rel. size of acquired knowledge t-1	-0.08	0.21	0.25	0.08	0.12	0.66	0.02	0.01	0.04	1																							
11	Rel. size of acquired knowledge1 t-2	-0.01	0.15	0.2	0.25	0.08	0.06	0.62	0.02	0.01	0.1	1																						
12	Rel. size of acquired knowledge t-3	-0.01	0.07	0.14	0.2	0.22	0.04	0.04	0.62	0.01	0.16	0.09	1																					
13	Rel. size of acquired knowledge t-4	-0.04	0.09	0.06	0.12	0.16	0.07	0.01	0.03	0.61	0.22	0.15	0.05	1																				
14	Relatedness of target knowledge t-1	0.27	0.09	0.04	0.07	-0.02	0.39	0.02	0.03	-0.01	0.22	0	0.02	-0.03	1																			
15	Relatedness of target knowledge t-2	0.33	0.11	0.05	0.02	0.06	0.07	0.48	0.02	0.02	0	0.26	-0.02	0	0.15	1																		
16	Relatedness of target knowledge t-3	0.36	0.05	0.05	0.06	0.02	0.05	0.24	0.45	0.02	0.01	0.05	0.24	-0.03	0.11	0.24	1																	
17	Relatedness of target knowledge t-4	0.3	-0.02	0.06	0.04	0.06	-0.01	0.01	0.25	0.45	-0.04	0.01	0.06	0.25	0.01	0.07	0.24	1																
18	Relatedness of target knowledge^2 t-1	0.2	0.05	-0.01	0.02	-0.03	0.37	0	0	-0.02	0.16	-0.03	-0.02	-0.04	0.82	0.06	0.03	-0.03	1															
19	Relatedness of target knowledge^2 t-2	0.27	0.09	0.01	-0.02	0	0	0.53	-0.01	-0.01	-0.04	0.21	-0.04	-0.03	0.07	0.84	0.18	0	0.02	1														
20	Relatedness of target knowledge^2 t-3	0.39	0	0.01	0.03	-0.02	0	0.27	0.56	0	-0.03	0.04	0.22	-0.05	0.07	0.25	0.88	0.25	0.02	0.22	1													
21	Relatedness of target knowledge^2 t-4	0.35	0.01	0.01	0.01	0.04	-0.04	-0.01	0.28	0.57	-0.06	-0.03	0.05	0.22	0.01	0.05	0.24	0.87	-0.02	0	0.31	1												
22	Relatedness of acquirer knowledge t-1	0.04	0.21	0.23	0.22	0.09	0.71	0.02	0.09	-0.01	0.76	0.18	0.25	0.17	0.52	0.05	0.07	-0.02	0.37	-0.02	0.01	-0.05	1											
23	Relatedness of acquirer knowledge t-2	0.15	0.18	0.16	0.2	0.19	0.05	0.75	0.01	0.08	0.09	0.74	0.15	0.21	0.08	0.59	0.17	0.03	0	0.49	0.17	-0.01	0.18	1										
24	Relatedness of acquirer knowledge t-3	0.13	0.05	0.15	0.15	0.18	0.02	0.06	0.75	0.01	0.1	0.09	0.73	0.11	0.03	0.08	0.58	0.18	-0.02	0.01	0.55	0.18	0.2	0.18	1									
25	Relatedness of acquirer knowledge t-4	0.1	0.08	0.04	0.12	0.11	0	0	0.05	0.76	0.06	0.1	0.05	0.73	0	0.01	0.07	0.6	-0.04	-0.03	0.02	0.55	0.08	0.17	0.15	1								
26	R&D expenses t-1	0.49	0.02	0.01	0.01	0.01	0.15	0.21	0.23	0.22	0	0.03	0.05	0.04	0.17	0.2	0.18	0.16	0.17	0.21	0.21	0.21	0.08	0.11	0.14	0.12	1							
27	Log. revenue t-1	0.23	-0.03	-0.01	0.02	0.05	0.08	0.13	0.14	0.13	-0.02	0.02	0.05	0.04	0.13	0.18	0.19	0.16	0.09	0.13	0.16	0.13	0.02	0.08	0.1	0.09	0.37	1						
28	Pre-sample patents t-1	0.91	0.03	0.04	0.05	0.01	0.11	0.22	0.21	0.2	-0.09	-0.05	-0.04	-0.06	0.26	0.32	0.36	0.31	0.2	0.27	0.38	0.36	0.02	0.12	0.12	0.1	0.57	0.28	1					
29	Foreign acquisitions t-1	0.02	-0.01	0.09	0.11	0.11	-0.07	0.04	-0.04	-0.06	-0.1	0.07	0.05	-0.09	-0.1	-0.07	-0.04	0	-0.06	-0.08	-0.02	0	0	0.05	-0.01	-0.08	-0.05	-0.03	0.02	1				
30	Foreign acquisitions t-2	0.08	-0.05	0.01	0.09	0.12	-0.09	0.02	0.04	-0.04	-0.06	-0.08	0.06	0.03	-0.02	-0.04	-0.04	-0.03	-0.02	0	-0.01	-0.01	-0.01	0.04	0.06	-0.02	-0.03	-0.01	0.07	0.26	1			
31	Foreign acquisitions t-3	0.07	-0.02	-0.05	-0.01	0.07	0.06	-0.05	0.03	0.04	-0.03	-0.07	-0.04	0.08	-0.11	0.02	0.01	-0.03	-0.04	0.02	0.05	0	-0.03	-0.01	0.08	0.08	0.02	0	0.08	0.21	0.22	1		
32	Foreign acquisitions t-4	0.05	0.03	0	-0.05	0.02	-0.04	0.05	-0.05	0.01	-0.05	-0.03	-0.12	-0.07	-0.06	-0.08	-0.02	0.01	-0.03	-0.04	-0.01	0.04	-0.1	-0.02	-0.07	0.01	0.02	0	0.06	0.15	0.27	0.18	1	
33	Acquisition experience t-1	0.15	0.24	0.31	0.33	0.35	0.13	0.17	0.19	0.21	0.22	0.28	0.29	0.28	0.22	0.26	0.31	0.28	0.11	0.13	0.22	0.22	0.27	0.32	0.33	0.3	0.22	0.32	0.26	-0.02	-0.03	-0.06	-0.12	1

For the variable *Number of non-technological acquisitions* Ahuja and Katila (2001) analyzed newspaper reports to find the motive behind each M&A deal. In this work, a M&A deal was marked as non-technological if the target firm did not have any patenting activity in the five years preceding the deal. This may lead to different results, as some deals involving patents may not be motivated by acquiring a specific technology and, on the other hand, deals without any patents may be motivated by acquiring a technology. Following the approach of Ahuja and Katila (2001) would have exceeded the frame of this research.

For GEE, some researchers recommend at least 50 research subjects (Stokes et al., 2012), while others recommend at least more than 10, possibly 30 (Norton, Bieler, Ennett, & Zarkin, 1996). This work includes 41 firms with 368 deals. Due to the distributed lag the sample was reduced to 328 observations. More clusters and more data should lead to more robust results (Ghisletta & Spini, 2004; Stokes et al., 2012).

3.4.2. Patents as a Proxy for Innovation

Patents can be seen as a distinct set of elements of knowledge (Ahuja & Katila, 2001). This knowledge can be united in a combinational way to generate new knowledge and innovation. The larger the set of elements, the more combinations are possible and a firm can enjoy more innovation. As previously mentioned, innovations are the result of a firm's knowledge (Kogut & Zander, 1992).

Patents as a proxy for innovation performance suffer from the following weaknesses: not all inventions are patented (Henderson & Cockburn, 1996; Nagaoka, Motohashi, & Goto, 2010) and not all patents yield innovations or significant inventions. Patents can also be used strategically to block competitors from technology areas: one study found that about 40% of patents were filed to block competitors from certain technology areas (Blind, Cremers, & Mueller, 2009; Grimpe & Hussinger, 2014b). On top of that not all patents are published, especially in the US: In 2009 about 7% of the patents were not published. Patents in other countries are usually published within 18 months after the filing date. (Nagaoka et al., 2010). Therefore, patent counts can underestimate the effect of innovation activity in the US, compared to other countries.

Patents are not the only means of protection of intellectual capital. For example, pharmaceutical firms enjoy an additional protection in the United States: the Food and Drug Administration (FDA) grants exclusivity rights for new chemical entities (Higgins & Rodriguez, 2006). Firms also have explicit knowledge, such as "technical know-how", that is transferred between firms in an acquisition (Bresman et al., 1999). Patents fail to measure this effect, thus this research underestimates this effect.

Measuring innovation remains a key challenge in management research. Moreover, patents are only one possible dimension to measure innovation. The capacity to innovate is determined by multiple different factors and can be measured by multiple factors as well. Due to the nature of innovation, it is unlikely that a unified metric will be found (Adams, Bessant, & Phelps, 2006; Hagedoorn & Cloodt, 2003). Besides this, it is hard to quantify a monetary value of patents or of innovation (Griliches, 1998).

In this research approach, knowledge relatedness is measured by the overlap of patent codes. Even though two patents might share the same patent codes, the underlying knowledge is not necessarily related.

Contrary to the work of Ahuja and Katila (2001), this work does not include cited patents. This may critically affect the research. Following the idea of absorptive capacity, Ahuja and Katila (2001) write: "By creating a patent that builds on these prior patents, the firm provides evidence that the knowledge contained in those past patents is a part of the firm's knowledge set" (Ahuja & Katila, 2001, p. 202). A short discussion on patent citations will be in section 3.5.1.

3.4.3. Methodological Weaknesses

As with all econometric and statistical procedures, it cannot be ruled out that the correlation is not accompanied by a causal effect of M&A on innovation: "A convincing identification of causality will be always hindered by the fact that econometricians cannot observe most of the information that the merging firms employ in their decision" (Ornaghi, 2009, p. 78).

As M&As are hugely complex undertakings, a lot of factors affect the outcome. Not all factors can be considered in an empirical analysis. Similar to Ahuja and Katila (2001) this study ignores the acquisition management process, e.g., different degrees of integration are not controlled for. As previously mentioned, there are multiple strategies to integrate firms, each having a different impact on the innovation output of the acquirer (Pidun, 2019). For instance, if the target is left alone (preservation strategy) a non-significant impact on innovation performance of the acquirer can be expected (Haspeslagh & Jemison, 1991).

Innovation performance or the realization of resource recombination depends upon the flow of competency-related knowledge between competence areas (Cohen & Levinthal, 1990). Each deal in the sample has its unique properties and motives. Further analysis and details could provide more insights on acquisitions that involve technology.

Time series analysis allows to analyze the effects of M&A on firm performance, especially the use of distributed lags (Ahuja & Katila, 2001; Sears & Hoetker, 2014). However, as the span of the distributed lag is limited, it falls short of capturing long-term effects.

3.4.4. Poisson regression with pre-sample approach vs Negative binomial Regression

The original study by Ahuja and Katila (2001) used a Poisson regression with a pre-sample approach to control for unobserved heterogeneity, following a suggestion by Blundell et al. (1995). The Poisson regression requires the variance to be equal to the mean, which is often violated. A common cause for this is variance among subjects (Agresti, 2003).

In this case, the computed standard errors in the Poisson regression are then underestimated. The hypothesis testing can then be invalidated. For that reason, a *pre-sample patents* variable is included in the regression model, to account for unobserved differences in knowledge stocks between the sample firms (Ahuja & Katila, 2001; Blundell et al., 1995; Cameron & Trivedi, 2013).

This variable includes the values of the dependent variable in the period immediately preceding the observation period. This information provides the basis for controlling for unobserved heterogeneity, which can lead to a reduction in overdispersion and in serial correlation (Blundell et al., 1995).

An alternative to using a Poisson regression is a Negative binomial regression, which the replication study by Cloodt et al. (2006) uses. The Negative binomial distribution can be considered a generalization of the Poisson distribution, which lifts the restriction that the variance is restricted to the mean. Researchers should report both Poisson and Negative binomial models, when the software allows for it (Cameron & Trivedi, 2013). As the Negative binomial models also account for over- or underdispersion, the results should be more reliable.

3.5. Empirical Results: Estimating the impact of M&A on Innovation

Table 5 shows the results of a Poisson regression with the model, following Ahuja and Katila (2001), table 7 shows the summed model. The author's model is shown in table 6 and the sum of results in table 8. Results of both models with a Negative binomial regression can be found in the appendix, in tables A2 and A3 respectively. The results of a Poisson regression with just the control variables can be found in the appendix in table A1.

First, the results of the replication model of Ahuja and Katila (2001) are discussed, then the results of the authors adapted model.

H1 predicts a negative relationship between the *number of non-technological acquisitions* and the post-acquisition innovation performance. In the estimated model the first three coefficients are negative, followed by a positive coefficient in period four. The coefficients in the second and third period are significant. The summed coefficient, which reflects the total impact is negative as well. Overall these findings support the results of Cloodt et al. (2006) and therefore support **H1** as well. Ahuja and Katila (2001) find a negative, but non-significant effect here. This might be due to the industry nature, as the chemicals industry is less of a high-tech industry, than the healthcare industry (Cloodt et al., 2006). This also supports the idea of Hitt et al. (1996) that M&A has a negative effect on innovation as resources of the firm are consumed and bound to the M&A process, instead of innovation.

The coefficients *absolute size of acquired knowledge base* are all positive besides period four. The overall effect is positive in both models, although of small magnitude. Only the estimates for the first and third period are significant. The summed coefficient over all periods is positive. Ahuja and Katila (2001) and Cloodt et al. (2006) show different results regarding this variable. The results of this study support the findings of Ahuja and Katila (2001) and therefore support **H2**. The target firm's knowledge base will lead to increased economies of scale and scope for the acquirer and therefore an improved innovation performance.

The *relative size of acquired knowledge* has a negative and significant effect on post-acquisition patent output in the first three periods, as predicted in **H3**. This is consistent with both previous studies. **H3** is therefore also corroborated. When the acquirer has to devote a large amount of resources to the integration of a large knowledge base, the post-acquisition innovation performance will suffer (Hitt et al., 1996). The majority of deals in the sample were acquisitions of firms with a small patent portfolio. Only a handful of deals included large mergers.

H4 predicts a curvilinear relationship between innovation performance and target relatedness. This hypothesis can be supported by the results. The coefficients of *relatedness of target knowledge* are all positive, while the coefficients of the squared term are all negative. The knowledge base of both firms should be similar to some degree, but also provide enough new knowledge to fertilize post-acquisition firm learning and knowledge creation (Cloodt et al., 2006).

Unsurprisingly, *R&D expenses* have a positive effect on patent output. The control variable for firm size *Log. revenue* is negative and significant, as larger firms tend to be less innovative (Cloodt et al., 2006).

Foreign acquisitions have a mixed and non-significant effect. The first two periods are positive, while the last two periods have a negative effect. Previous research by Penner-Hahn and Shaver (2005) found that Japanese pharmaceutical firms enjoy greater international R&D productivity, when they already have some previous knowledge in a domain prior to the international expansion. This indicates that there should be a positive effect. Additional research could shed some more light on the relationship between international M&A, R&D productivity, and innovation.

The variable for the control of heterogeneity *pre-sample patents* is positive and significant as well. The "Health Care Equipment" sector seems to be more active in patenting than the other sectors, while "Biotechnology" and "Life Sciences Tools & Services" have a lower patenting activity. All control variables have a small correlation with the dependent variable, besides the pre-sample variable with a correlation of 0.91. This correlation was expected, as the pre-sample variable contains information of the dependent variable about the previous periods, although the correlation is lower than in previous research.

The author's model yields similar findings for the first four hypothesis. All of the hypotheses are supported as well. The newly introduced variables do, however, not show any significant effects.

H5 predicts a negative relationship between *relatedness of acquirer knowledge* and innovation performance. The signs of

Table 5: GEE Poisson regression based on Ahuja and Katila (2001) model

Year	Coef.	P-value	S.E.
No. non-tech. acquisitions t-1	−0.0202	0.155	0.041
No. non-tech. acquisitions t-2	−0.1356 **	0.015	0.072
No. non-tech. acquisitions t-3	−0.0822 *	0.06	0.07
No. non-tech. acquisitions t-4	0.0258	0.145	0.047
Abs. size of acquired knowledge t-1	0.0004 **	0.011	0.0
Abs. size of acquired knowledge t-2	0.0001	0.126	0.0
Abs. size of acquired knowledge t-3	0.0003 *	0.056	0.0
Abs. size of acquired knowledge t-4	−0.0001	0.139	0.0
Rel. size of acquired knowledge t-1	−1.7254 ***	0.001	0.557
Rel. size of acquired knowledge t-2	−1.0617 **	0.021	0.611
Rel. size of acquired knowledge t-3	−0.8687 **	0.042	0.626
Rel. size of acquired knowledge t-4	0.0202	0.24	0.42
Relatedness of target knowledge t-1	0.1363 ***	0.005	0.058
Relatedness of target knowledge t-2	0.1707 ***	0.003	0.069
Relatedness of target knowledge t-3	0.276 ***	0.002	0.102
Relatedness of target knowledge t-4	0.1195 **	0.037	0.083
Relatedness of target knowledge^2 t-1	−0.0174 *	0.062	0.015
Relatedness of target knowledge^2 t-2	−0.0152	0.102	0.018
Relatedness of target knowledge^2 t-3	−0.124 ***	0.0	0.039
Relatedness of target knowledge^2 t-4	−0.0352	0.103	0.043
ISO Country AU	−0.9575 ***	0.0	0.113
ISO Country BE	−0.4211 ***	0.002	0.149
ISO Country CA	−2.3768 ***	0.0	0.256
ISO Country CH	−0.6243 ***	0.002	0.214
ISO Country DE	−0.0927	0.143	0.087
ISO Country FR	−0.5504 ***	0.005	0.211
ISO Country DK	−0.3913 ***	0.004	0.144
ISO Country GB	−0.1794	0.188	0.202
ISO Country JP	−0.1177	0.326	0.26
ISO Country NL	−1.7438 ***	0.0	0.191
Biotechnology	−0.2066 **	0.04	0.117
Health Care Equipment	0.0179	0.435	0.109
Life Sciences Tools & Services	−0.6666 ***	0.001	0.202
Year 2009	1.0468 ***	0.0	0.131
Year 2010	1.1158 ***	0.0	0.143
Year 2011	0.9992 ***	0.0	0.128
Year 2012	0.8965 ***	0.0	0.115
Year 2013	0.8549 ***	0.0	0.107
Year 2014	0.6898 ***	0.0	0.1
Year 2015	0.4835 ***	0.0	0.088
R&D expenses t-1	0.00003 **	0.024	0.0
Log. revenue t-1	−0.0133	0.46	0.133
Foreign acquisitions t-1	0.0384	0.156	0.038
Foreign acquisitions t-2	0.0149	0.345	0.037
Foreign acquisitions t-3	−0.0363	0.142	0.034
Foreign acquisitions t-4	−0.0178	0.195	0.021
Pre-sample patents	0.0007 ***	0.0	0.0
Intercept	3.924 ***	0.0	0.571

P-values originate from two-sided t-test for control variables, from one-sided t-test for independent variables.
Note: *p<0.1; **p<0.05; ***p<0.01

the coefficients are all negative. However, all coefficients are non-significant. Therefore, the *relatedness of acquirer knowledge* has no significant effect on innovation performance.

Surprisingly, *acquisition experience* has a negative, but non-significant coefficient. Further analysis with a squared term indicates a curvilinear relationship, as the squared term is positive (u-shaped). Previous research, specifically on acquisition experience, has indeed found an u-shaped relationship (see Barkema and Schijven (2008); Haleblian and Finkelstein (1999)). The coefficient is non-significant. Using the acquisition experience as a proxy for absorptive capacity might not be the best approach, as the acquisition management process also determines the acquisition outcome (Pidun, 2019). Furthermore, the variable has been calculated using the sum of all acquisitions from the beginning of the sample until the focal acquisition following Haleblian and Finkelstein (1999) and Hayward (2002). Research has operationalized this variable in different ways. Other approaches could lead to different results, e.g., using a moving value of acquisition experience (Sears & Hoetker, 2014) as knowledge also faces depreciation (Sampson, 2005).

The effect of *R&D expenses* is positive and significant.

Table 6: GEE Poisson regression based on author's model

	Coef.	P-value	S.E.
No. non-tech. acquisitions t-1	−0.0224	0.132	0.036
No. non-tech. acquisitions t-2	−0.115 **	0.018	0.064
No. non-tech. acquisitions t-3	−0.0547 *	0.066	0.049
No. non-tech. acquisitions t-4	0.0418 *	0.084	0.043
Abs. size of acquired knowledge t-1	0.0003 **	0.025	0.0
Abs. size of acquired knowledge t-2	0.0001	0.152	0.0
Abs. size of acquired knowledge t-3	0.0004 **	0.017	0.0
Abs. size of acquired knowledge t-4	−0.0001	0.122	0.0
Rel. size of acquired knowledge t-1	−2.0113 ***	0.003	0.781
Rel. size of acquired knowledge t-2	−0.8634 *	0.052	0.686
Rel. size of acquired knowledge t-3	−0.4662	0.118	0.646
Rel. size of acquired knowledge t-4	0.2436	0.146	0.444
Relatedness of target knowledge t-1	0.1169 **	0.028	0.074
Relatedness of target knowledge t-2	0.2003 ***	0.001	0.069
Relatedness of target knowledge t-3	0.331 ***	0.0	0.097
Relatedness of target knowledge t-4	0.1449 **	0.019	0.081
Relatedness of target knowledge^2 t-1	−0.0172 *	0.065	0.015
Relatedness of target knowledge^2 t-2	−0.0195 *	0.078	0.019
Relatedness of target knowledge^2 t-3	−0.1191 ***	0.0	0.034
Relatedness of target knowledge^2 t-4	−0.0315 *	0.092	0.035
Relatedness of acquirer knowledge t-1	0.8929 *	0.085	0.933
Relatedness of acquirer knowledge t-2	−0.28	0.185	0.838
Relatedness of acquirer knowledge t-3	−1.2317 **	0.029	0.777
Relatedness of acquirer knowledge t-4	−0.3645	0.151	0.706
Year 2009	0.9912 ***	0.0	0.141
Year 2010	1.0641 ***	0.0	0.149
Year 2011	0.9529 ***	0.0	0.14
Year 2012	0.8571 ***	0.0	0.124
Year 2013	0.8205 ***	0.0	0.114
Year 2014	0.6689 ***	0.0	0.109
Year 2015	0.4819 ***	0.0	0.094
Biotechnology	−0.1936 *	0.05	0.117
Health Care Equipment	0.0324	0.391	0.116
Life Sciences Tools & Services	−0.6558 ***	0.001	0.207
ISO Country AU	−0.975 ***	0.0	0.113
ISO Country BE	−0.4071 ***	0.003	0.147
ISO Country CA	−2.2891 ***	0.0	0.283
ISO Country CH	−0.5651 ***	0.008	0.233
ISO Country DE	−0.1243 *	0.081	0.088
ISO Country FR	−0.3913 *	0.087	0.287
ISO Country DK	−0.3733 ***	0.005	0.142
ISO Country GB	−0.1478	0.22	0.191
ISO Country JP	−0.1294	0.313	0.266
ISO Country NL	−1.8004 ***	0.0	0.218
R&D expenses t-1	0.00003 **	0.042	0.0
Log. revenue t-1	0.0466	0.367	0.137
Foreign acquisitions t-1	0.032	0.179	0.035
Foreign acquisitions t-2	0.0151	0.347	0.038
Foreign acquisitions t-3	−0.0332	0.155	0.033
Foreign acquisitions t-4	−0.0146	0.253	0.022
Pre-sample patents	0.0007 ***	0.0	0.0
Acquisition experience t-1	−0.0112	0.183	0.012
Intercept	3.7579 ***	0.0	0.578

P-values originate from two-sided t-test for control variables, from one-sided t-test for independent variables.
Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Summed GEE regression results based on Ahuja and Katila (2001)

	Coef.	P-value	S.E.
No. non-tech. acquisitions	−0.2122	0.104	0.0284
Abs. size of acquired knowledge	0.0007	0.136	0.000
Rel. size of acquired knowledge	−3.636**	0.021	3.198
Relatedness of target knowledge	0.702***	0.001	0.0541
Relatedness of target knowledge^2	−0.191***	0.008	0.0064
Foreign acquisitions	−0.0008	0.995	0.032

P-values originate from two-sided t-test for control variables, from one-sided t-test for independent variables.
Note: *p<0.1; **p<0.05; ***p<0.01

Due to the scale of R&D expenses the coefficient is very small (0.00003742). *Log. revenue* has a negative, but non-significant effect.

A comparison of results of Ahuja and Katila (2001), Cloodt et al. (2006) and this study can be found in table 9.

To compare both models, QIC is an appropriate metric. The smaller the QIC value, the better the model fit. The QIC value of the author's model is lower (48,979.30) compared to the model after Ahuja and Katila (2001) (49,066.74).

The p-values of the models have to be regarded with caution. As the model violates the Poisson assumptions, the standard errors can be underestimated. Even though the pre-sample approach tries to correct for that, hypothesis testing can be invalidated to some extent. For this reason a Negative binomial regression was also estimated, as it yields better estimates of the standard errors and therefore more robust results of hypothesis testing. The results of the Negative binomial models can be found in the appendix in tables A2 and A3. The results and p-values are similar, indicating that the findings are robust.

3.5.1. Sensitivity analysis

To ensure validity of results, a sensitivity analysis was performed using different random sub-samples of the sample (Ahuja & Katila, 2001). The results are quite similar.

Interestingly, the number of patents granted per year per firm shows a negative trend, while the R&D expenditures continue to rise. The trend lines can be seen in figure 2. Besides, the variance of patents granted is also decreasing over time, as shown by the black dots in figure 2. This decrease is noticeable. This finding is consistent with previous research by Griliches (1998), which found that patent output gradually decreases with higher R&D expenditures.

This decrease in patenting might be also due to the increased product complexity in the medical device area or the increased challenge in finding molecules that prove to be effective (Danzon et al., 2005; Lin & Jang, 2010). However, the speed of innovation has increased in the last years, which should be mirrored in the number of patents. To further ensure the reliability of the results, the patent data should be checked again.

Also surprising is the lower correlation between R&D expenses and patents. Ahuja and Katila (2001) report a correlation of 0.89 between R&D expenses and pre-sample patents, Cloodt et al. (2006) report 0.784, while this study finds 0.57. The correlation with the dependent variable is also lower: 0.49 versus 0.89. The reduced strength of the correlation coefficient might be the result of a lower R&D expenditures to patent efficiency (Danzon et al., 2005; Ornaghi, 2009). However, the difference could be the result of a different sample and a different variance in the sample. As this idea is only based on a correlation, further analysis is required to confirm or reject it.

As this study does not include patent citations, the variable *relatedness of target knowledge* and *relatedness of acquirer knowledge* should be less interpretable. Previous research has included patent citations, e.g., Ahuja and Katila (2001); Cloodt et al. (2006); Makri et al. (2010); Sears and Hoetker (2014). Ahuja and Katila (2001) ran a sensitivity analysis, comparing patents cited by the firm and patents owned by the firm. Results indicate that own patents are reliable for measuring the *absolute* and *relative size of acquired knowledge*. However, Ahuja and Katila (2001) report that using only owned patents for measuring the *relatedness of target knowledge* does not capture the relationship well. The findings of this study are different, as the variable *relatedness of target knowledge* is significant. This difference might be a result of a different construction of the variable. Ahuja and Katila (2001) use the list of "patent numbers" to calculate the *relatedness of target knowledge*. It is unclear to the author, whether Ahuja and Katila (2001) used all digits in the "patent numbers" or only a subsection of digits. Furthermore, their analysis might be based on a different patent classification system. This work used the first four digits of the IPC system, similar to previous research on patent classification and similarity (Kogler et al., 2013; Leydesdorff et al., 2017).

4. Discussion

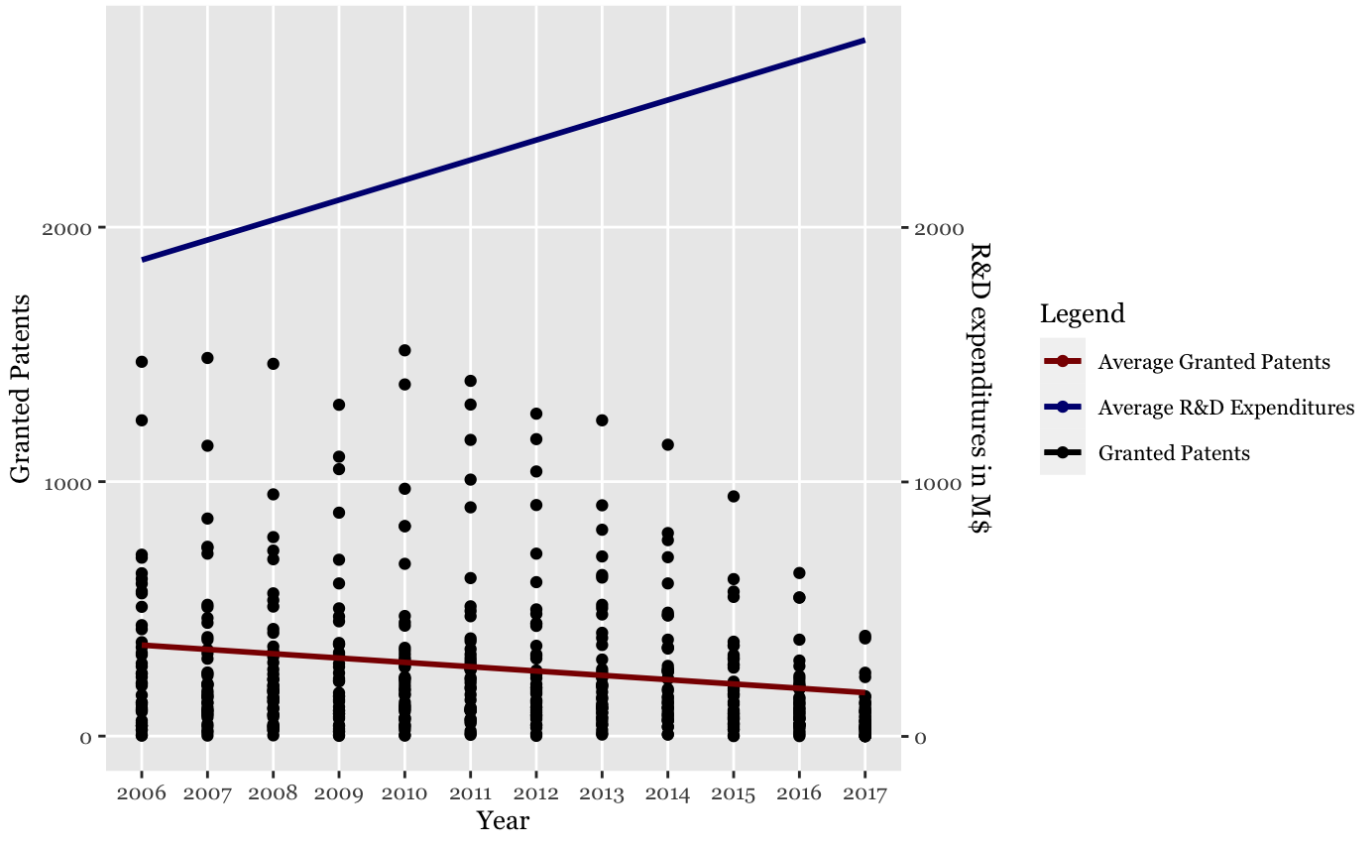
This work extends the research stream in strategic management research of M&A in several ways. First, this study focuses on an understudied post-acquisition outcome: the innovation performance of acquiring firms in high-technology (Zollo & Meier, 2008). Second, it can be seen as a replication study of Ahuja and Katila (2001) and Cloodt et al. (2006) using newer data on another high-tech industry: the healthcare industry. Third, it further extends the econometric model of Ahuja and Katila (2001) with the additional variables relatedness of acquirer knowledge, as a measurement of techno-

Table 8: Summed GEE regression results of the author's model

	Coef.	P-value	S.E.
No. non-tech. acquisitions	−0.150	0.126	0.017
Abs. size of acquired knowledge	0.0007*	0.095	0.000
Rel. size of acquired knowledge	−3.097*	0.083	5.012
Relatedness of target knowledge	0.793***	0.001	0.063
Relatedness of target knowledge^2	−0.187***	0.003	0.005
Relatedness of acquirer knowledge	−0.983	0.351	6.598
Foreign acquisitions	−0.0007	0.497	0.009

P-values originate from two-sided t-test for control variables, from one-sided t-test for independent variables.
Note: *p<0.1; **p<0.05; ***p<0.01

Figure 2: R&D expenditures vs granted patents (own figure)



logical relatedness in an acquisition and the acquisition experience of the acquirer, as a measure of absorptive capacity.

An overall description of the different sub-industries of the healthcare industry was given. Important theories of strategic management were explained, such as the knowledge-based view, absorptive capacity, and combinative capability. Previous empirical studies were described and set into context. The hypotheses draw on ideas from these theories and previous empirical research. Finally, the empirical analysis used a GEE approach for a Poisson regression and a Negative binomial regression. The findings of this work are very similar to those of Ahuja and Katila (2001) and Cloodt et al. (2006): (1) Non-technological acquisitions affect the post-acquisition innovation performance in a negative way. In the case of technological acquisitions, the following dimensions have been examined: (2) absolute size of acquired knowledge, (3) relative size of acquired knowledge, and (4) relatedness of target knowledge. The (2) absolute size of acquired knowledge has a positive effect on post-acquisition performance. Large deals provide a lot of knowledge and therefore a lot of opportunity to generate new knowledge. Firms seem to be able to successfully integrate this knowledge and benefit from it. However, a (3) large relative size of acquired knowledge has a negative effect. Integrating large knowledge bases is a challenging undertaking and therefore has a negative effect on post-acquisition innovation performance.

An inverted u-shape models the relationship between

Table 9: Comparison of Ahuja and Katila (2001), Cloodt et al. (2006), and this study

Study	Hypothesis	Results
Ahuja and Katila (2001) - Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study	**H1**: Non-technological acquisitions will affect the post-acquisition innovation output of acquiring firms either negatively or non-significantly.	(ns)
	H2: The greater the absolute size of the acquired knowledge base, the greater the subsequent innovation output of the acquiring firm.	(+)
	H3: The greater the relative size of the acquired knowledge base, the less the subsequent innovation output of the acquiring firm.	(+)
	H4: The relatedness of the acquired knowledge base will be curvilinearly (inverted U) related to the subsequent innovation output of the acquiring firm.	(+)
Cloodt et al. (2006) - Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries	**H1**: Non-technological acquisitions will affect the post-acquisition innovation output of acquiring firms either negatively or non-significantly.	(+)
	H2: The greater the absolute size of the acquired knowledge base, the greater the subsequent innovation output of the acquiring firm.	(-)
	H3: The greater the relative size of the acquired knowledge base, the less the subsequent innovation output of the acquiring firm.	(+)
	H4: The relatedness of the acquired knowledge base will be curvilinearly (inverted U) related to the subsequent innovation output of the acquiring firm.	(+)
Study	Hypothesis	Results
This study	**H1**: The post-acquisition innovation performance will be affected either negatively or non-significantly by non-technological M&A.	(+)
	H2: A larger absolute size of the acquired knowledge base increases the post-acquisition innovation performance.	(+)
	H3: A large relative size of the acquired knowledge base will have a negative impact on the post-acquisition innovation performance.	(+)
	H4: The relatedness of the acquired knowledge base will be curvilinearly (inverted U-shape) related to the post-acquisition innovation performance of the acquiring firm.	(+)
	H5: The larger the acquirer overlap, the smaller the post-acquisition innovation performance.	(ns)
	H6: Previous acquisition experience has a positive effect on post-acquisition innovation performance.	(-)

the (4) relatedness of knowledge of the target. Too similar knowledge does not spur innovation, nor does too different knowledge. Similar to the previous findings (Cloodt et al., 2006), this study suggests that there is a "sweet spot" of knowledge similarity. The overlapped knowledge serves as a baseline of absorptive capacity for handling and integrating the complexity of the target firm's high-quality knowledge.

The additional variables introduced by the author show a negative effect of (5) relatedness of acquirer knowledge and acquisition experience on post-acquisition innovation perfor-

mance. The effect of knowledge of relatedness of acquirer is negative, but non-significant. The higher the share of acquirer knowledge, that is also known by the target, the less the acquirer can learn from the target.

The effect of (6) acquisition experience is negative, contrary to expectation. Previous research has found different effects, either positive (Barkema & Schijven, 2008) or u-shaped (Barkema & Schijven, 2008; Haleblian & Finkelstein, 1999). Additional analysis with a squared term indicates a u-shaped relationship. Further research might reveal moderating effects.

Patents were used as a metric to analyze the effect of M&A on innovation performance. The knowledge of a firm can be approximated by its patent base (Ahuja & Katila, 2001). Innovations are the result of knowledge (Grant, 1996). Patents provide detailed insight into the knowledge base of a firm and they permit quantification of knowledge and thus innovation (Ahuja & Katila, 2001; Hagedoorn & Cloodt, 2003).

There are some differences in motives for M&A in the healthcare industry. As the revenue of pharmaceutical firms depends on the introduction of new drugs, M&A is often used to increase the number of potential drugs in the pipeline and to close a potential earnings gap (Danzon et al., 2007, 2005; Schweizer & zu Knyphausen-Aufseß, 2008). The healthcare equipment manufacturers are not as depended as pharmaceutical firms on M&A, as their innovations tend to be more incremental (Lin & Jang, 2010).

4.1. Theoretical Implications

M&A research has mainly been concerned with financial performance. Only a small research stream has focused on M&A and innovation performance (Zollo & Meier, 2008). This work is clearly an extension of this research stream. The most important finding is that knowledge, especially knowledge relatedness, plays an important role in technological M&A. As competition in the healthcare industry is driven by innovation and technology many firms rely on M&A as a source of innovation (Lin & Jang, 2010; Schweizer, 2005b). M&A is therefore a popular strategy and can be frequently observed in the industry. Firms rely on external knowledge to combine it with internal knowledge to compete in the respective market (Danzon et al., 2007; Grant, 1996; Kogut & Zander, 1992; Schweizer & zu Knyphausen-Aufseß, 2008).

This research shows that there is a clear difference between technological M&A and non-technological M&A, whereas non-technological M&A seems to hinder the innovative capabilities of acquiring firms. Technological M&A can have a positive impact on innovation performance. Firms can use M&A to innovate in two ways: they can leverage what the target knows or rely on the target as an independent source of innovation (Puranam & Srikanth, 2007; Schweizer, 2005a), depending on the degree of target integration (Bresman et al., 1999; Schweizer, 2005a). Regardless of the degree of integration, the ability to gain value from a transaction depends on the absorptive capacity of firms: the capability to successfully identify, assimilate and commercialize knowledge made by external entities (Cohen & Levinthal, 1990). Besides the absorptive capacity, the combinative capability plays an important role, which enables firms to combine explored knowledge with unexplored knowledge and exploit it (Kogut & Zander, 1992). Following both concepts, the knowledge of both firms should be related. The empirical results show that there is an inverted u-shape of target and acquirer knowledge relatedness. The higher the amount of "new" knowledge for the acquirer the better, until a certain tipping point, where the innovation performance starts to suffer. This indicates that both the absorptive capacity and the combinative capability of the acquirer have a limit.

Both firms should have an overlap in R&D projects (Cassiman et al., 2005) and in their patent portfolio. Based on the relationship of relatedness of knowledge and the absorptive capacity of a firm, an acquiring firm with a diversified knowledge base should be able to benefit more from acquisitions, as the firm is likely to have many similarities with the target's knowledge base. In order to improve the innovation performance by M&A, firms should aim for having a diverse R&D and patent portfolio and target firms that have complementary knowledge. However, this does not necessarily lead to an improved financial performance.

Firms that acquire regularly should benefit from an increased absorptive capacity, such as the enhanced identification and absorption of important target knowledge (Cohen & Levinthal, 1990; Desyllas & Hughes, 2010; Grant, 1996). The result of this study shows a negative effect of acquisition experience on innovation performance. To proxy the absorptive capacity with acquisition experience might not be the best approach, as the acquisition management process also determines the outcome (Bresman et al., 1999; Pidun, 2019). In addition to that, the absorptive capacity is a complex and multilayered concept (Lane et al., 2006), which cannot be easily proxied by one variable. Therefore, more research on the relationship of innovation performance, knowledge transfer, absorptive capacity, and other theories of organizational learning should be considered.

Similar to previous studies, this work has analyzed a different high-tech industry: the healthcare industry. Therefore, a generalization of these findings to low- or medium tech industries is questionable (Cloodt et al., 2006).

4.2. Managerial Implications

M&A can be a valuable tool to improve the innovation performance, as long as the target provides a moderate and right amount of technological input. A dedicated M&A strategy should help identify specific M&A themes and deal-screening criteria that support corporate innovation (Ascher et al., 2020; Pidun, 2019). Harrison, Hitt, Hoskisson, and Ireland (2001) argue that an active acquisition strategy does not necessarily reduce managerial commitment to innovation. Paying close attention when search for a complementary target with an emphasis on innovation in the integration period can enhance success (Desyllas & Hughes, 2010; Paruchuri & Eisenman, 2012). An improved due diligence process, that also considers the knowledge complementari-

ties and similarities of the firms, could have a positive impact on the innovation performance as well (Pidun, 2019).

Among pharmaceutical companies, internal R&D has often become a secondary source of drug innovation as the negative correlation between R&D cost and productivity is simply unbearable for many firms (Danzon et al., 2007; Ornaghi, 2009). For pharmaceuticals, acquiring smaller innovative firms might be a solid strategy to avoid the risk of in-house drug development and to improve the product pipeline. Of course, M&A is not the only way for firm collaboration. Strategic Alliances, Joint Ventures, or licensing agreements can be valuable alternatives as well, e.g., the case of Biontech and Pfizer (Danzon et al., 2007; Deeds & Hill, 1996; Hagedoorn & Duysters, 2002; Schweizer & zu Knyphausen-Aufseß, 2008; Thomson Reuters, 2020).

Previous research has also shown that pharmaceutical firms acquire smaller firms, when their product pipeline is empty (Danzon et al., 2007; Schweizer & zu Knyphausen-Aufseß, 2008). This study shows a positive effect of M&A on patenting, indicating that firms can revitalize their patenting activities and therefore their product pipeline and avoid inertia (Cefis & Marsili, 2015; Vermeulen & Barkema, 2001). Yet, managers tend to be biased towards more incremental innovations, as they provide short-term returns and are less risky (Hoskisson, Hitt, Johnson, & Grossman, 2002). This bias needs to be considered in an acquisition process.

4.3. Limitations

In order to not overstretch the framework of this work, this research left out multiple important deal characteristics: e.g., the motivation of acquirers, the type of deal (e.g., vertical, horizontal), the type of financing and the degree of post-acquisition integration. All of these factors can affect the post-acquisition innovation performance in various ways. The deals in the sample have a large range in terms of the monetary volume. Previous research indicates that large deals are typically not motivated only by technology and that often large deals do not lead to an improvement in innovation performance (James, Georghiou, & Metcalfe, 1998; Schweizer & zu Knyphausen-Aufseß, 2008). In this research, there is no consideration of the motivation behind the deal.

Compared to previous research (e.g., Ahuja and Katila (2001) and Cloodt et al. (2006)), the statistical power of this work is lower, with only 41 firms observed over a period of 10 years. In addition, the author did not specifically analyze the different sub-industries. As the GEE method gives population average estimators, different characteristics in the sub-industries were "canceled out".

In this study, the time frame to analyze effects of M&A was four years. This might not be enough, as the average time to develop a new drug is about 12 years and the development of medical equipment usually takes about 3-7 years (Van Norman, 2016). Research on technological deals should also observe long-term effects. These long-term effect are usually underestimated in empirical M&A research (Chakrabarti, Hauschildt, & Süverkrüp, 1994), but can play a significant role in technological M&A. Especially synergistic effects in R&D might take time to develop. Improved innovation performance eventually leads to a better financial performance in the long run. However, there is research that suggests that — depending on the circumstances — a successful integration of the target should be a comparatively fast process (Homburg & Bucerius, 2006). Thus, the effect of a short and successful period of integration should be reflected in this research.

As knowledge and innovation are very hard to quantify, this research tries to analyze it by relying on patents to measure it. Patents as a proxy are limited in several ways. First of all, "not all patents represent innovation, nor are all innovations patented" (Nagaoka et al., 2010, p. 1084). Patents are an extremely noisy indicator of innovation, since they are subject to the variance in the significance, quality, and value of individual patents (B. H. Hall et al., 2005). Using granted patents as a dependent variable, has the advantage of filtering low quality or trivial patents (Hagedoorn & Cloodt, 2003). As patents are simply used as a count variable, knowledge quality is not considered in this research (Ahuja & Katila, 2001; Han, Jo, & Kang, 2018). Knowledge relatedness is calculated by using patent classification codes. These codes were developed for other purposes and do not fully reflect knowledge overlap. Patents with the same code can still have very different underlying knowledge (Makri et al., 2010).

Additionally, patents are often used strategically. For instance, some firms patent new inventions simply to block other firms' patents or to deter entry into certain products, instead of capitalizing them. New patents often require significant novelty to existing ones and can therefore be used to block competitors (Grimpe & Hussinger, 2014a). Additionally, as there is a lot of M&A activity in the sample and many firms have multiple subsidiaries with different names, not every patent is considered (Valentini, 2012). Despite their limitation patents are used as a proxy in most empirical studies in this area (Ahuja & Katila, 2001; Cloodt et al., 2006; Desyllas & Hughes, 2010; Makri et al., 2010; Sears & Hoetker, 2014). Of course, there are also other ways to protect intellectual property in the healthcare industry, such as regulatory exclusivity and manufacturing challenges (Lakdawalla, 2018).

The variables *relatedness of target knowledge* and *relatedness of acquirer knowledge* might be constructed in a different way than in previous research of Ahuja and Katila (2001) and Cloodt et al. (2006). Hence, a direct comparison should be done carefully.

4.4. Further research

Further research could investigate if and how firms use M&A as a substitute for internal innovation programs and R&D efforts or how external and internal innovation and R&D are used. Similarly, research should investigate if and how internal and external R&D efforts are combined after M&A to enhance innovation. Especially with the involvement of highly specific knowledge in M&A, the integration process becomes a crucial part, as knowledge is not easily trans-

ferred and capitalized (Capron & Pistre, 2002; Schweizer & zu Knyphausen-Aufseß, 2008). Furthermore, different motives behind the deal require different integration strategies (Bauer, Matzler, & Wolf, 2016; Pidun, 2019).

Future work could also analyze deal outcomes and the interplay of different deal characteristics (financing, degree of integration, etc.) and the interplay with acquirer characteristics (R&D expenditures, acquisition experience, knowledge/patent portfolio). Research into the acquisition management process such as post-acquisition integration and restructuring could provide insights on additional factors that affect post-acquisition innovation performance. Additional research could also use other metrics to measure the innovation performance, as most contemporary studies have relied on patents (Ahuja & Katila, 2001; Cloodt et al., 2006; Makri et al., 2010; Sears & Hoetker, 2014). Metrics such as the rate of product introduction or productivity of inventors and R&D personnel could help understand the effect of M&A on the innovation performance better. Also, combining innovation performance with other metrics, such as financial metrics, to gain a more holistic view of M&A and M&A performance could provide new insights (King et al., 2004; Zollo & Meier, 2008).

The combinative capability and the absorptive capacity determine how firms are able to interact with new knowledge. Firms that acquire on a regular basis should have an improved absorptive capacity compared to their peers. For this reason, the variable *acquisition experience* was introduced. The results of the effects of this variable in the study are inconclusive. Previous research has found different effects of *acquisition experience*. For example, Haleblian and Finkelstein (1999) found different effects depending on the similarity of the current acquisition compared to previous acquisitions. The relation of absorptive capacity, acquisition experience and innovation performance seems to be a fruitful research direction.

Previous research has overlooked the power of preemptive patenting. Acquiring the right target firms to block competitors from entering into certain technologies might be a common strategy, especially in healthcare. Apart from this, firms might also protect themselves by acquiring targets that could block the other (potential) acquirers from capitalizing certain intellectual property (Grimpe & Hussinger, 2014b). There has been very few research on M&A and preemptive patenting in strategic management research.

Higgins and Rodriguez (2006) found that many pharmaceutical acquirers already had strategic alliances with their targets and thus avoid the "winner's curse" of paying too much for the target by having insider knowledge. Research into knowledge complementarity, insider information, target valuation, and post-acquisition performance could also be fruitful.

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