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Mergers and Acquisitions of European Healthcare Firms and Their Effects on Patenting Activity

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Keywords: M&A, innovation, patents, European healthcare, panel data, empirical study

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ABSTRACT

This thesis[1] examines the relationship between mergers & acquisitions (M&A) and innovation output in the European healthcare sector. Due to the importance of innovation in healthcare, M&A is often seen as a means to enhance productivity and research performance. To explore this relationship, we proxy innovation and firm productivity at the firm level through patent activity, using both annual patent filings and the stock of active patents.

We use a panel dataset of 1,160 European healthcare firms from 2013 to 2022 and conduct fixed-effects regressions with up to three-year lags to capture both immediate and delayed innovation outcomes. Our findings suggest that (a) target firms exhibit a short-term spike in patent filings around the acquisition year, which is indicative of signalling behaviour; (b) patent output for targets declines in the long term, which points to knowledge absorption or innovation suppression; and (c) no statistically significant innovation gains are observed for acquiring firms post-deal.

These results contribute to the literature by offering a differentiated, firm-level analysis in an underexplored regional context and challenge common assumptions about the innovative benefits of healthcare M&A in Europe.

Keywords: M&A, innovation, patents, European healthcare, panel data, empirical study

[1] Some parts of this research project were improved using AI-based language assistance tools, including ChatGPT, for stylistic and grammatical refinement. All content and analysis remain the author's original work.

Table of Contents

1. INTRODUCTION

The European healthcare sector has changed significantly over the past decade, driven by rapid technological advancements, evolving regulatory frameworks, demographic pressures, and an increasing demand for innovative therapies and medical technologies (Buertey et al., 2023; Health at a Glance: Europe 2020, 2020) [4][20]. In this context, healthcare companies, especially those in pharmaceuticals, biotechnology, and digital health, have been using M&A more and more to improve their operations, grow their markets, gain new skills, and speed up innovation (De Man & Duysters, 2004) [10]. However, even though M&A is often justified by its potential to enhance innovation output, empirical evidence about its effectiveness remains fragmented and inconclusive, especially within Europe's unique healthcare ecosystem (Cassiman et al., 2005) [6].

Innovation in healthcare is not only a key driver of long-term value creation but also a complex, uncertain, and resource-intensive process. M&A can help companies work together by creating synergies, sharing knowledge, and giving them access to intellectual property (Ahuja & Katila, 2001) [1]. But it also has risks, like interrupting research and development pipelines, cultural differences, and the possible loss of key talent, which could slow down innovation instead of speeding it up (Ahuja & Katila, 2001) [1]. As a result, there is still a lot of debate in academia and policy circles about whether M&A helps or hurts innovation.

Although considerable research has examined the relationship between M&A and innovation in general, there is a notable gap in the context of the European healthcare industry. Most existing studies focus on the United States or global conglomerates and often neglect the institutional, regulatory, and structural particularities of the EU healthcare market. Additionally, few studies use granular, firm-level data to empirically investigate how innovation output evolves in the years following a transaction. This thesis seeks to address these gaps by analysing the impact of M&A activity on innovation among European healthcare firms between 2013 and 2022, with innovation proxied by the number of patents filed and the stock of active patents owned by a firm for a certain year. The central aim of this study is to assess whether M&A transactions are associated with increased innovation output in the acquiring and target firms in the post-transaction period.

This study aims to resolve these ambiguities by addressing two core questions:

1. *How does M&A activity affect the quantity and quality of innovation (proxied by patent filings and stock of active patents) in European healthcare firms?*
2. *Is the impact of M&A on innovation immediate or lagged over several years post-transaction?*

To answer these questions, we sample 1,160 European healthcare firms in a panel dataset between 2013-2022. We use M&A activity as our independent variable and innovation output, proxied by the annual growth rate of filed patent applications and active patent stock, as our dependent variables. We include firm revenue (as a proxy for size) and macroeconomic conditions (captured by the S&P 500 total return index) as control variables. Additionally, we create lags of up to three years to capture the delayed effects of M&A activity, particularly for acquirers, as innovation synergies often materialise over time.

To test our hypotheses, we resort to a panel regression with firm and year fixed effects. Our results suggest a marginally significant increase in patent filings during the year of M&A activity, which supports the notion of pre-deal signalling behaviour. However, this effect fades in the subsequent years. For target firms, we observe a short-term rise in patent stock growth around the deal year, which is consistent with the pre-deal signalling behaviour hypothesis. However, three years after the acquisition, we see a small and non-significant drop in patent activity. This fits with the idea that knowledge is transferred to the acquiring firm and innovation is stifled.

This study contributes to the existing literature by providing a firm-level panel analysis of European healthcare companies, which is an under-represented geography in prior research that has predominantly focused on U.S. and large-cap firms (Anjani et al., 2022) [2]. Furthermore, we differentiate between acquirers and targets and capture lagged effects. By doing this, we offer a more nuanced understanding of how innovation trajectories diverge post-M&A. Our results also reinforce the value of using patent metrics as a proxy for innovation performance and support theories of absorptive capacity and signalling within the M&A context.

2. LITERATURE REVIEW

2.1. Innovation and patents in the healthcare sector

In the healthcare sector, improvements in patient outcomes, efficiency, and cost control are increasingly driven by innovation ("Health at a Glance: Europe 2020", 2020) [20]. Healthcare firms, particularly in pharmaceuticals, biotechnology, and MedTech, rely heavily on R&D to produce new therapies, devices, and diagnostics (DiMasi et al., 2016) [11]. However, this process is expensive and uncertain and is associated with long development cycles, strict regulatory barriers, and high failure rates. To maintain competitiveness, firms more and more turn to M&A as a strategic alternative to internal R&D (Higgins & Rodriguez, 2005) [21].

Patents are widely used as a proxy for innovation in empirical research, especially in healthcare, where intellectual property rights are central to business models. The granularity, public accessibility, and capacity to track technology ownership and evolution make patent data valuable. Metrics such as patent counts and active patent portfolios provide insight into both the quantity and quality of innovation output, which in the healthcare industry is a KPI for form productivity. However, not all innovation is patented, and not all patents represent valuable innovations, especially when firms file patents only to enhance perceived value before transactions (Hall & Harhoff, 2012) [16].

In addition to patent applications, this study includes the number of active patents, as in those maintained through renewal, as an alternative innovation metric. Active patents may better capture a firm's strategically preserved intellectual capital, as they exclude lapsed, expired, or abandoned filings. This distinction helps in distinguishing between permanent innovation capacity and temporary innovation signalling. Nonetheless, it is important to recognise the limitations of patent-based indicators more broadly. Not all innovation is organised through patents, especially in service-based healthcare models or early-stage biotech research. That is why patent data should be viewed as an accessible, albeit partial, proxy for innovation performance.

In the M&A context, innovation performance is often assessed through indicators that give output such as patent activity or new products, rather than solely through financial returns (Ahuja & Katila, 2001; Capron & Pistre, 2002) [1][5]. In strategic management research, this difference comes from the fact that value creation stems from long-term innovation synergies rather than immediate shareholder rewards (Zollo & Meier, 2008) [37]. Improved innovation performance post-acquisition reflects the acquiring firm's efficiency in resource transfer and knowledge integration (Voss, 2022) [34]. That is why patents serve as both a measure of innovation and a strategic tool for signalling value during acquisition processes.

Recent research has also used drug approvals as an alternative proxy for innovation and firm productivity. For example, Anjani et al. (2022) [2] study U.S.-listed healthcare giants and find that M&A leads to increased productivity and drug approvals, but those effects emerge after a two-year lag. This reinforces the view that innovation benefits from M&A activity are not always immediate. In the European context, the EUIPO (2025) [13] reports that SMEs owning patents generate 44% higher revenue per employee compared to non-patenting firms. SMEs are generally under-represented in patent filings, though, which suggests that they may have latent innovation capacity that acquisitions may tap. This supports the inclusion of medium-sized firms (above EUR 10 million in revenue) in this thesis to balance representativeness and observability of innovation activity. This study captures a broader spectrum of healthcare innovation and includes firms in biotechnology, digital health, and MedTech, unlike prior studies that focus only on pharmaceutical M&A (e.g., Harford, 2005 [18]). This comprehensive sectoral scope provides a more representative view of how consolidation affects both product and service innovation across the European healthcare ecosystem.

2.2. Theoretical frameworks for M&A and innovation

2.2.1. Schumpeterian innovation theory

The Schumpeterian view on innovation, which constitutes the central component of Joseph Schumpeter's theory (Wolfe, 1943) [35], holds that economic development is driven by the 'creative destruction' principle. This includes replacing outdated technologies and firms with new ones that are more efficient. According to this theoretical assumption, innovation is not perceived as a methodical improvement but as a revolutionary breakthrough. It is frequently stimulated by entrepreneurial action or strategic change. Schumpeter believed that large companies with financial resources and established infrastructures might be best placed to develop innovation through acquisitions.

In healthcare, M&A can be a way to create creative destruction where large companies acquire smaller innovators, integrate their technologies, and reshape product pipelines (Ahuja & Katila, 2001) [1]. This model also accounts for the risk that the more dominant firms may suppress innovation by absorbing competitors and putting on hold overlapping R&D projects. So, the Schumpeterian theory offers a dual perspective, where mergers and acquisitions can either promote or obstruct innovation, depending on the post-merger integration results.

2.2.2. Resource-based and knowledge-based views

The resource-based view (RBV) sees firms as collections of heterogeneous resources, and competitive advantage arises when firms acquire and effectively utilise valuable, rare, inimitable, and non-substitutable (VRIN) assets (Barney, 1991) [3]. The knowledge-based view (KBV) extends this by emphasising intangible resources such as expertise, organisational routines, and technological know-how as the foundation of innovation (Grant, 1996) [15].

From this perspective, M&A allows firms to access complementary knowledge bases, fill capability gaps, and recombine resources to generate innovation synergies (Grant, 1996) [15]. The success of such a process depends on knowledge relatedness, which means that while moderate overlap may facilitate learning, excessive similarity or dissimilarity may reduce potential gains (Kogut & Zander, 1992) [23]. For acquiring firms, this supports the idea of acquiring targets that have related but still distinct innovations (Kogut & Zander, 1992) [23]. For targets, the theory predicts that post-acquisition innovation varies depending on whether they retain autonomy or are fully absorbed (Kogut & Zander, 1992) [23].

From the knowledge-based view, value creation through M&A depends not only on acquiring resources but also on the firm's ability to identify, value, and integrate the knowledge embedded within the target (Teerikangas & Joseph, 2012) [33]. The intricacy of integration poses a significant barrier because if research and development units are inadequately integrated, the transfer of information may be hindered or postponed (Ranft & Lord, 2002) [31]. In some cases, even non-technological resources such as superior commercialisation capabilities from the target may contribute to innovation gains (Kaul, 2011) [22]. However, this assumes effective post-deal coordination and retention of key personnel.

2.2.3. Absorptive capacity

Cohen and Levinthal (1990) [7] introduced the concept of absorptive capacity. This is a firm's ability to recognise, assimilate, and apply external knowledge. High absorptive capacity is crucial for post-M&A innovation (Zahra & George, 2002) [36]. Acquirers with strong prior R&D capabilities are more likely to extract value from the target's intellectual assets, continue development of promising projects, and file new patents derived from integrated knowledge (Ahuja & Katila, 2001) [1].

This theory also explains why innovation outcomes are not always the same. Targets may experience declines in patenting if their R&D units are disbanded, relocated, or subordinated (Hansen & Løvås, 2004) [17]. In contrast, acquirers with high absorptive capacity may increase their innovation trajectory by internalising external ideas and refiling patents in their own name (Cohen & Levinthal, 1990) [7]. Recent empirical work (Anjani et al., 2022) [2] shows that acquirers may exploit the R&D knowledge of targets by filing subsequent patents under their own corporate entity. This is particularly relevant when acquiring smaller or IP-rich firms.

2.2.4. Signalling theory

Signalling theory suggests that firms disclose or exaggerate valuable attributes to influence stakeholders' perceptions (Spence, 1973) [32]. In M&A, targets may strategically increase patent filings shortly before a deal to boost their valuation or to signal innovative potential to the buyers. This can temporarily inflate innovation indicators and then decline once the transaction is complete. The theory supports the hypothesis that target enterprises will see a temporary surge in patent activity during the acquisition period, subsequently followed by a possible decline to inflate their innovative appearance and bargaining power during negotiations (Mcgahan & Silverman, 2006) [26]. This lends theoretical support to the hypothesis of a pre-deal spike in innovation metrics driven by signalling incentives.

2.3. Empirical evidence on M&A and innovation

2.3.1. Patent spikes pre-M&A

There is growing evidence that target firms increase patent applications before an acquisition. Voss (2022) [34] finds that patent application activity surges in the two years preceding M&A, especially in healthcare deals. This aligns with the signalling theory above, where targets patent strategically to attract buyers and improve deal value. Such pre-M&A spikes need to be carefully modelled to avoid distorting the assessment of post-M&A innovation performance. It is, therefore, necessary to distinguish between short-term spikes and long-run innovation.

2.3.2. Innovation suppression in targets post-M&A

The research suggests that targets may experience innovation stagnation or decline after acquisition. Cunningham et al. (2020) [9] describe 'killer acquisitions' where acquirers deliberately stop overlapping drug development programmes to eliminate future competition. The Publications Office of the European Union (2020) [29] found that pharmaceutical targets often show reduced Phase 2 and 3 pipeline progress post-acquisition, together with an increase in project discontinuations.

Ernst and Vitt (2000) [12] report that inventor retention declines significantly in acquired biotech firms. This supports the idea that innovation is not merely reallocated but potentially lost. The extent of suppression often depends on technological overlap, and more overlap will equal a greater likelihood of shutdown. This decline may not merely reflect innovation decay but rather a transfer of R&D capacity and IP output to the acquirer, who subsequently internalises and refiles new patents based on absorbed knowledge. The effect is even more visible when acquirers possess strong absorptive capacity and integration is deep.

2.3.3. Divergent innovation trajectories for acquirers and targets

Acquirers and targets are impacted differently by M&A, according to different studies. With successful integration and strong absorptive capacity, acquirers tend to gain by acquiring innovative capacity (Makri et al., 2010) [25]. Targets lose their incentives, autonomy, and skills, which may decrease the output of innovation (Haucap et al., 2018) [19].

Voss (2022) [34] finds that the increase in patents after an M&A is higher for the acquirers compared to the targets. This is consistent with both the KBV and absorptive capacity theories. Although it differs by case, the degree of divergence tends to be statistically significant.

In addition, recent studies have noted that the benefits or drawbacks of M&A on innovation will not be directly evident. Instead, given the knowledge integration period and frictions, as well as R&D cycle dynamics, impacts tend to last for many years (Makri et al., 2009) [25]. However, few studies use firm-level panel models to account for lagged impacts. By simulating 1–3-year lags, this thesis fills this methodological gap and captures delayed innovation synergy or suppression.

The extent to which innovation trajectories differ between acquirers and targets is also influenced by the degree of post-merger integration. The acquisition integration approaches model outlines four integration approaches: absorption, preservation, holding, and symbiosis, each of which produces distinct innovation outcomes. Deep absorption may result in decreased autonomy or decreased productivity in R&D, particularly for knowledge-intensive activities (Paruchuri & Eisenman, 2012) [28]. In contrast, preservation approaches may retain innovation at the target unit while potentially constraining the acquirer's control over resulting outputs. Therefore, the acquirer tends to be the single beneficiary of long-run innovation benefits (Puranam et al., 2006) [30].

Despite empirical recognition that innovation effects often emerge with delay, few studies apply firm-level panel models with explicit lag structures. This study addresses this methodological gap by modelling 1–3-year lags post-transaction so that both immediate and delayed innovation can be observed. These different innovation paths support the view that post-M&A outcomes are asymmetric between targets and acquirers. While the former may experience innovation decline due to autonomy loss, the latter often benefits from cumulative gains. This asymmetry forms the foundation for Hypothesis 4.

2.4. Gaps in literature

Despite substantial contributions, the literature still lacks clarity on several areas:

- Most studies focus on U.S.-based firms or global conglomerates. The European healthcare sector is under-researched, specifically for private firms.
- Few papers distinguish between pre- and post-deal effects on targets versus acquirers.
- The dynamics of active patents (vs. new filings) and ownership transitions are not well-documented.
- There is a lack of firm-level panel studies covering long post-M&A time windows (e.g., 3+ years).
- A significant limitation in existing literature is the lack of attention to endogeneity. Most studies do not fully address the possibility that firms with stronger innovation capabilities may be more likely to become acquisition targets, which is a classic case of reverse causality. Even though fixed effects and lagged specifications partially mitigate this issue, causal identification remains a challenge. Instrumental variable or event-study designs could offer more robust inference in future research (Cassiman et al., 2005) [6]. Acknowledging this limitation is crucial when interpreting the effects of M&A on innovation outcomes.

2.4.1. Geographic and institutional differences in M&A innovation effects

The European M&A environment is different from that of the United States in several important ways. EU competition policy is more conventional and entails more horizontal mergers in the biotech and pharmaceutical sectors (Favart, 2019) [14]. EU healthcare innovation is also driven, at least in part, by public funding programmes like Horizon 2020 and Horizon Europe that encourage collaborative, cross-border R&D rather than concentration (Conde, 2019) [8].

These institutional features suggest that post-M&A innovation trajectories in Europe will not mirror those seen in U.S.-focused research. The European Union's Publications Office [29], for instance, in a 2020 report, found that most post-M&A innovation slowdowns were due to regulation-induced delays and cross-border integration tensions. This thesis addresses these gaps by using panel data on European healthcare firms from 2013 to 2022 to analyse how M&A impacts patent activity for both targets and acquirers over time.

Additionally, institutional and firm-level heterogeneity plays a critical role in shaping both M&A behaviour and innovation outcomes. Prior work has shown that macroeconomic context, national regulatory environments, and firm size all influence absorptive capacity and post-merger innovation performance (Voss, 2022; Cassiman et al., 2005) [34][6]. This study accounts for these factors by controlling for firm revenue, country-year effects, and macroeconomic indicators such as the S&P 500 total return index. These controls help to isolate the innovation effects of M&A from more general cyclical or structural influences.

Cumulatively, the literature implies four empirically testable predictions about M&A and innovation: (1) M&A has both concurrent and lagged impacts on patent growth; (2) target firms experience a short-run patenting burst during acquisition, likely due to signalling; (3) targets experience innovation suppression several years following acquisition due to knowledge transfer; and (4) acquirers and targets exhibit very different innovation paths. The following section formalises these into empirical hypotheses.

3. HYPOTHESIS BUILD-UP

The objective of this paper is to try to explain the impact of M&A activity on value creation in the European healthcare sector. This chapter presents the paper's addition to existing literature and the main hypothesis tested through empirical methods.

Value creation has been largely covered by existing literature, especially from a shareholder perspective, and Nazarova, V. (2018) [27] proves M&A to lead to positive abnormal returns for acquirers in the EU and US. However, our paper aims to expand on existing literature by looking at the effect of M&A on value creation from a pure firm productivity perspective. Academic research has already explored and proved effective measuring value creation using patent activity, with Anjani, I., Suhartono, M. T., & Tjandrawinata, R. R. (2022) [2] even confirming that M&A for US-listed healthcare giants leads on average to increased productivity and sales with a 2-year lag. Most importantly, they develop the idea that value creation can be observed by studying the number of drugs approved by the FDA on a yearly basis. We aim to replicate this approach using both grants and applications given by and filed to the FDA in the US and the EMA in the EU as a proxy for value creation.

Moreover, this thesis seeks to investigate the different implications for targets and acquirers. We strongly believe that patent activity is not only a great proxy for value creation but also for innovation, thus, significant results of our empirical study could also show implications of M&A activity from a societal perspective.

Furthermore, Anjani, I., Suhartono, M. T., & Tjandrawinata, R. R. (2022) [2] limit their analysis to large, listed US enterprises, while this research paper focuses on the European market, including SMEs.

EUIPO (2025) [13] shows the effect of patenting activity on firm financial performance over a 10-year period. The study reveals that EU SMEs owning patents experience a 44% higher revenue per employee compared to their non-patent-owning counterparts, highlighting the importance of patent rights also for smaller firms. The study also confirms a lack of patenting activity from European SMEs, indicating dormant potential to be unlocked by increasing SMEs' patent filings [13]. Therefore, we include smaller European private enterprises in our sample, which contains data on European healthcare companies with revenues larger than EUR 10 million.

Accordingly, this research paper aims to prove the following hypothesis:

Hypothesis 1: M&A activity has a significant impact on active patents' growth, positive or negative, on firms engaging in M&A transactions, either in the year of the deal or with a lag of one, two, or three years.

Hypothesis 2: Target firms experience a positive and significant impact on patent growth in the year of acquisition, driven by pre-deal signalling behaviour. Specifically, such firms may enhance R&D activity and patent filings in the years preceding the transaction, aiming to increase their valuation and attract higher acquisition premiums.

Hypothesis 3: Three years post-acquisition, target firms exhibit a decline in patent filings, potentially due to R&D knowledge being transferred to the acquiring firm, which then files patents under its own name. This hypothesis is particularly relevant to this thesis, as the dataset includes smaller firms, which may be acquired solely for their intellectual property rather than their operating financial performance.

Hypothesis 4: The effect of M&A activity on active patent growth differs significantly between target and acquiring firms. It is expected that targets exhibit above-average patent growth during the acquisition year (reflecting pre-deal signalling), followed by a decline in the subsequent years.

4. DATA COLLECTION

This section covers the data collection and preparation phase performed to draft the panel data frame we use for this research paper's empirical methodology.

First, it is important to mention that one of the key challenges in preparing this thesis' data frame is gathering data from different databases and later matching them for every single firm with a high degree of confidence. We use three databases to gather information for this research paper: 1) Orbis, given its extensive coverage of financials for private enterprises; 2) LSEG, due to its deep coverage of public and private M&A activity; and PATSTAT, as this is the most comprehensive database when looking at information regarding a firm's patenting activity. Second, this section also shows how the data frame was reshaped from a cross-sectional to a panel form.

4.1. Data Sources

As introduced in the previous paragraph, the major challenge to be encountered while preparing data for a panel regression investigating the impact of M&A on firm performance proxied by the number of owned intellectual property rights ("IPR"), is to match data related to a single firm across different datasets. This is especially true for a match between a financial database (e.g., Orbis) and an IPR database (PATSTAT). This is because patent activity is shown on PATSTAT for each applicant number rather than by firm name. In fact, for very large firms this approach means trouble, as large enterprises have many subsidiaries and divisions, each with a different applicant number. Therefore, since a single firm may be associated with multiple applicant IDs, there is no one-to-one relationship between firm names and applicant IDs. Accordingly, a proper match between a firm-name-based database such as Orbis and PATSTAT (applicant-based) is tough to achieve and requires a lot of time, as each applicant ID needs to be paired with the right firm.

Fortunately, one of this paper's major sources of inspiration in terms of existing literature (EUIPO's IPRs and firm performance in the EU, 2025 study [13]) shows that the matching described above is indeed possible to achieve. However, it took almost a decade of continuous collaboration between EPO and EUIPO to collect and prepare a strong dataset linking firm performance data with patent activity. Not having enough time to come up with a high-quality matching methodology to link Orbis' firm IDs and PATSTAT's applicant IDs, we reached out to EUIPO's team based in Alicante, Spain, which proved to be very accommodating to our request and, after discussing the objective of this research paper, agreed to send us a critical piece of data: the matching between Orbis IDs and PATSTAT IDS for almost 700,000 EU corporations. This match, the most complete to be found online, allows us to reliably link patent activity with financial performance and M&A activity.

Accordingly, using SQL language, we download from PATSTAT patenting activity for the healthcare firms in our sample. First, we gather the number of active patents per year (yearly cumulative approved applications that are not yet expired) and the number of filed applications per year (the number of filings regardless of them being actually granted later on by the relevant regional drug authority), and secondly, we group the above data by the firm owning the related applicant ID based on the match provided by EUIPO.

We also screen and download legal and financial data from Orbis for approximately 16,000 healthcare firms for which we have IPR information. Orbis' data mostly contains descriptive (e.g., country ISO code and NACE number) and financial information (revenue and employees).

M&A data is then collected on LSEG (Refinitiv) once the Orbis IDs and LSEG IDs are matched using the Record Matching tool available on *'permid.org'*. To make sure the match's quality achieved through this API is excellent, we asked for the support of the HEC Learning Center data team, which gave us fundamental help in selecting the right input for the matching exercise, namely firm name, HQ address, regulatory identification numbers (e.g., LET, TIN) and NACE code. Of the almost 16,000 healthcare companies, 8,342 are matched with a high degree of confidence, representing a strong base to build a sample of firms having complete information about patents, financials, and M&A deals.

4.2. Sample composition, start and end dates

Out of these 8,342 healthcare firms, we select those that have more than EUR 10 million in revenue since we want to address the M&A impact on mature companies, leaving no space for venture capital, where innovation and patenting activity are the core of the business model by construction. In fact, Kortum, S. S., & Lerner, J. (1998) [24] reveal that increased venture capital activity in a (US) industry significantly boosts its patenting rate. Despite VC constituting less than 3% of R&D funding in recent years, it accounts for approximately 15% of industrial innovations.

Further, small enterprises have low patent activity regardless, as shown by EUIPO (2025) [3], thus, we choose not to concentrate our efforts on micro-enterprises and small enterprises, but only on firms with revenues higher than EUR 10 million.

After applying this filter, the data frame includes data for 1,160 medium and large European healthcare companies for a period of 10 years (2013-2022), for a total of 11,160 panel observations. We believe this sample size to be sufficiently large for an empirical study aimed at identifying relationships between explanatory and outcome variables through an OLS multi-regression model.

4.3. Data preparation for a panel regression

The data collection described in the previous two points yields a cross-sectional data frame with many columns showing yearly variables for each item to be regressed, as shown in [**table 1**]. This is not suitable for a panel regression, and thus we use Python3 to reshape the existing data frame into a dataset with fewer variables, expanding the number of rows such that each firm appears once for each year in the analysis period [**see table 2**]. This reshape was achieved using Python3 as follows: first, split variables in the form 'Year_Var' into Year and Variable type; second, pivot data so that each row represents a year of a firm's patenting activity.

The time horizon chosen is 2013-2022, and the choice of this period mostly falls on the following two reasons: first, the match between Orbis and PATSTAT IDs from EUIPO (2025) [3], which is related to this very specific timeframe; second, 2013-2022 represents a stable horizon for the healthcare industry since: i) 2008 and 2011 crises' effects are not present; ii) stable low interest rates throughout the period, iii) COVID-19 affected the healthcare industry to a lesser extent compared to the wider financial market, and iv) the medium-term impact of Russia's invasion of Ukraine is not yet reflected in healthcare firms' performance as of year-end 2022. The key data used for the empirical study collected for each firm is shown in [**table 3**] of each major statistic is provided in the following chapter.

4.4. Limitations of the data

The dataset we use in this thesis has several limitations that must be acknowledged. First, the quality of financial data retrieved from Orbis is not uniform across firms. Financial statements may differ based on the method of consolidation, as for some firms Orbis reports consolidated accounts, while for others the provider only shows unconsolidated reports. This lack of consistency can affect the comparability of revenue figures across firms. Additionally, Orbis contains a high volume of missing values (NaNs), particularly for SMEs' revenue data. As a result, numerous observations are dropped during the regression analysis, potentially biasing results and reducing any statistical robustness.

Second, the dataset includes 1,160 firms observed through a panel dataset over ten years. While this is suitable for a master's thesis, it objectively remains a relatively small number of observations. Ideally, a larger and more diverse dataset, including both larger firms and enterprises from additional regions or continents, would improve statistical robustness.

Third, the quality of the matching process between Orbis (financial data) and IPR data from PATSTAT represents another constraint. As there is no universal unique identifier across databases, the matching performed by EUIPO (2025) [3] relies heavily on an algorithm cleaning applicant and firm names to then ultimately make a 'best guess'. In fact, although due care is taken during the laborious matching exercise, the matching process may produce some errors, such as i) no match is found for IPR applicants or ii) the wrong company is matched. A proper match is dependent on the quality of the data available in Orbis and in IPR databanks [3].

Finally, the analysis of this research paper excludes qualitative variables, such as managerial capabilities or human resource practices, which could play a substantial role in both M&A performance and resource and development. Nevertheless, including such factors in research would prove difficult, and thus we believe that the dataset we have built is one of the more comprehensive datasets available for what concerns the linkage between firm performance, M&A, and patenting activity.

5. SUMMARY OF STATISTICS

A summary of statistics for the variables described in this section is provided in [**table 3**].

5.1. Index Variables

['BVD Id Number'] - unique Orbis ID for each firm in the dataset. This variable is exploded for the number of years available for each firm. It determines the total number of observations for the panel data frame, i.e., 11,892, for 1,160 unique companies.

['Year'] - Year within the period 2013-2022 (10 unique values) available for every firm.

5.2. Numerical variables

['Active Patents'] - number of granted patents active (stock of active patents) per firm in a specific year, based on the assumption that each patent expires after 20 years from its filing[2]. The median number of active patents for our sample is two.

['Filed applications'] - shows the number of patent applications filed by a firm per year. This does not represent the number of grants. An average of 4.93 applications was filed by a generic firm of the sample between 2013-2022, while the median value is zero.

['sp500_tr'] - the annual performance of the S&P 500, used as a proxy for macroeconomic conditions, i.e. as an indicator of periods of economic expansion or financial crisis.

['Revenue_interp'] - it is the yearly revenue for each firm. Since Orbis is incomplete in regard to revenue information, we interpolated yearly revenue linearly where possible, reducing the number of missing values ("NaNs") from approx. 21% to 19%. Revenue is used to control the size of the enterprise. The mean for this variable is approx. EUR 762.3 million, and the median is EUR 47.2 million.

5.3. Dummy (binary) variables

['MA_Activity'] - indicates whether a firm was involved in M&A activity in one year or not. 1,069 observations have experienced M&A activity throughout the sample period.

['Acquirer'] - is one if the company is an M&A buyer for a given year. The panel data contains 755 observations where this variable is equal to one.

['Target'] - is one if the company is an M&A target for a given year. We have 435 occurrences where this variable is one.

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[2] In reality, patents can be extended over 20 years in certain cases, however a 20-year expiration date is still a precise and conservative approach when calculating the stock of active patents for a firm.

Table 1 - cross-sectional dataset, sample

BVD Id Number	Permid	Name	PATSTAT_person_id	2013 Active Patents	2013 Filed applicat.	...	2020 Active Patents	2020 Filed applicat.	...
AT9010065561	4297094571	AMANN...	22113	14	4	...	22	1	...
AT9030006458	5039595692	APOMEDICA...	44982968	0	0	...	1	0	...
AT9030086963	4296813807	FRESENIUS...	1043953	4	1	...	8	2	...
...	...	...	...	...	...	...	...	...	...

Table 2 - panel dataset, sample

BVD Id Number	Permid	PATSTAT_person_id	Name	Country ISO code	NACE code	Year	Active Patents	Active_Patens_Log_Diff	Filed applications	M&A	Acqui.	Target	sp500	Revenue_interp
AT9010065561	4297094571	22113	AMANN...	AT	4774	2013	14		4	0	0	0	0.324	
AT9010065561	4297094571	22113	AMANN...	AT	4774	2014	14	0	1	0	0	0	0.137	33,739,560
AT9010065561	4297094571	22113	AMANN...	AT	4774	2015	19	0.288	5	0	0	0	0.014	37,063,419
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Table 3 - summary of statistics

Index Variables:

Variable	Count	Unique
BVD Id Number	11,892	1,160
Year	11,892	10

Numeric Variables:

Variable	Count	Mean	Std	Min	5%	50%	95%	Max
Active Patents	11,892	30.0	173.0	-	-	2.0	83.0	2,942.0
Filed Applications	11,892	4.9	50.7	-	-	-	9.0	1,293.0
Revenue (EUR M)	9,623	76.2	399.7	-	4.9	47.2	1,823.0	51,889.0
S&P500 TR	11,892	0.14	0.16	(0.18)	(0.18)	0.18	0.32	0.32

Binary Variables:

Variable	Count_0	Count_1
MA_Activity	10,823	1,069
Acquirer	11,137	755
Target	11,457	435

6. EMPIRICAL METHODS

We use the variables described above to run ordinary least squares ("OLS") regressions, while also rerunning them while replacing control variables with fixed effects and clusters, considering the data frame is a panel data. All regressions were analysed through Python3's module '*linearmodels*'.

Moreover, logarithmic differential transformation is applied to variables ['Active Patents'] and ['Filed applications'] to obtain value elasticity and facilitate the interpretation of the relationship between independent and dependent variables [2]. Specifically, considering the large number of small values (e.g., zeros and ones) in these variables, to account for skewness and normalise the distribution of innovation metrics, we apply a log-difference transformation to both the number of filed patent applications and the stock of active patents. We compute growth as the difference in the natural logarithm of one plus the variable, i.e.,

$$\Delta \boldsymbol{log}(\mathbf{1} + \boldsymbol{x_t}) = \boldsymbol{log}(\mathbf{1} + \boldsymbol{x_t}) - \boldsymbol{log}(\mathbf{1} + \boldsymbol{x_{t-1}})$$

where x_t represents the raw count of filed applications or active patents in year t. This transformation serves two main purposes: (i) it mitigates the impact of extreme values and skewed distributions often observed in patent data, and (ii) it allows for a consistent interpretation of growth rates, particularly when the underlying variables may take zero or low values. The addition of one ensures that observations with zero patents are retained in the analysis rather than dropped due to undefined logarithms. Hereafter, we will refer to the dependent variables as $\boldsymbol{Filed\_log\_dif_{it}}$ and $\boldsymbol{ActiveP\_log\_dif_{it}}$ for the annual growth rate of filed applications and stock of active patents, respectively.

Further, we create three-year lags for independent variables ['MA_Activity'], ['Acquirer'] and ['Target'] to study lagged effects of M&A, as Suhartono, M. T., & Tjandrawinata, R. R. (2022) [2] showed that in their study significance was found with a 2-year lag. From now on, the independent variables ['MA_Activity'], ['Acquirer'] and ['Target'], will be referred to as, $\boldsymbol{M\&A_{it}}$, $\boldsymbol{Acquirer_{it}}$ and $\boldsymbol{Target_{it}}$, while the control variables ['sp500_tr'] and ['Revenue_interp'] as $\boldsymbol{S\&P_t}$ and $\boldsymbol{Rev_{it}}$. The lagged variables are shown in the equations as the related independent variable followed by '*_lagn*', where n is the year lag.

We test the four hypotheses[3] described in chapter three with the following equations:

[3] We actually test for more than 20 hypotheses, however, only include those we think are most relevant to this paper.

Equation 1:

$$\boldsymbol{Filed\_log\_dif_{it} = \beta_0 + \beta_1 M\&A_{it} + \beta_2 M\&A\_lag1_{it} + \beta_3 M\&A\_lag2_{it} + \beta_4 M\&A\_lag3_{it} + \beta_5 S\&P_t + \beta_6 Rev_{it} + \varepsilon_{it}}$$

Equation 1 investigates whether M&A activity has a significant impact on the filings of new patent applications up to a 3-year lag. This equation has been controlled by firm size, proxied by the firm's revenue, and by the macroeconomic condition through the S&P 500 annual return.

Equation 2:

$$\boldsymbol{ActiveP\_log\_dif_{it} = \beta_0 + \beta_1 Target_{it} + \beta_2 Acquirer_{it} + \beta_3 S\&P_t + \beta_4 Rev_{it} + \varepsilon_{it}}$$

Equation 2 tests whether the stock of active patents is significantly impacted by M&A during the same year of the transaction. In this equation, we explore the different effects for target and acquiring firms compared to firms seeing no M&A activity. Once again, we control by revenue and macroeconomic conditions.

Equation 3:

$$\boldsymbol{Filed\_log\_dif_{it} = \beta_0 + \beta_1 Target\_lag3_{it} + \beta_2 Acquirer\_lag3_{it} + \gamma_t + \delta_t + \varepsilon_{it}}$$

Equation 3 examines the medium-term impact of M&A activity on both acquirers and targets. Specifically, we test the effect of M&A activity with a three-year lag. This time we remove control variables, and we correct the coefficients by adding firm effects (for the year) and clusters (for firm-specific results). In this specification we exclude time-varying control variables and account for unobserved heterogeneity by including firm and year fixed effects. Moreover, standard errors are clustered at the firm level to address potential autocorrelation and heteroskedasticity.

Equation 4:

$$\boldsymbol{ActiveP\_log\_dif_{it} = \beta_0 + \beta_1 M\&A_{it} + \beta_2 (M\&A_{it} \times Target_{it}) + \gamma_t + \delta_t + \varepsilon_{it}}$$

As for the previous (equation 3), equation 4 is corrected by fixed effects and clusters. This equation adds an interaction variable between M&A and Target, aiming to find a significant difference in the effect on active patent stock growth in the acquisition year between targets and acquirers.

7. EMPIRICAL FINDINGS

The empirical study described in the previous paragraph yields the following results:

Equation 1 - As shown in [**table 4**], the regression's results suggest that firms engaging in M&A experience on average a 4.6% higher growth rate in patent filings compared to firms not undergoing M&A in the year of the transaction. The effect, though, is only marginally significant, as the p-value for $\boldsymbol{\beta_1}$ is 0.052. Later time lags are statistically insignificant. This might suggest that years of M&A activity may boost innovation temporarily due to pre-deal signalling behaviour, however this effect does not last over time.

In regard to control variables, $\boldsymbol{\beta_5}$ is statistically strongly significant (p-value = 0.001), with a 1 percentage increase in the index associated with an 11.2% rise in patent filings growth, proving that periods of macroeconomic prosperity positively impact firm innovation. On the other hand, $\boldsymbol{\beta_6}$ is not statistically significant, casting doubt on its relevance for the growth of filed applications in the short term.

The model's explanatory power is limited ($R^2 = 0.003$), which can be expected when investigating innovation due to firm heterogeneity. This will be a common characteristic among all equations tested.

We would like to point out how the coefficients for M&A and its lagged effects tend to form a pattern, oscillating from positive to negative every year. Even more troublesome is the fact that coefficients $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ are equal, just with opposite signs. This could be linked to either strong multicollinearity between independent variables or a strong degree of correlation. We test this by calculating the correlation matrix between M&A's lagged variables and find a strong correlation ranging from 0.4-0.5 throughout all combinations, as shown in [**table 5**]. Again, this pattern casts doubt on the robustness of the results, and therefore we decide not to test multiple lagged variables simultaneously from now onwards.

Regardless, the analysis gives little evidence that M&A activity is strongly associated with a boost in a firm's productivity proxied by the number of patents filed. Moreover, even if coefficients were more robust, we would still reject the hypothesis since there are many omitted variables (e.g., human resources skills) which would make the OLS estimates inconsistent with the zero conditional mean assumption. Once again, this last point is applicable to all regressions performed in this paper.

Table 4 - 1st equation, regression results

Dependent Variable: Filed_log_dif				
Method: OLS (Multiple Linear Regression)				
Independent Variable	**Coefficient**	**t-Statistic**	**p-value**	**R^2**
Intercept	-0.0245	-3.141	0.002	0.003
M&A	0.0457	1.947	0.052	
M&A_lag1	-0.0457	-1.883	0.060	
M&A_lag2	0.0211	0.850	0.395	
M&A_lag3	-0.0357	-1.459	0.145	
S&P	0.1118	3.231	0.001	
Rev	0.0000	1.580	0.114	

Table 5 - correlation matrix for M&A time lags

Correlation matrix	**M&A**	**M&A_lag1**	**M&A_lag2**
M&A	1.0	0.46	0.41
M&A_lag1	0.46	1.0	0.001
M&A_lag2	0.41	0.48	1.0

Equation 2 - results suggest that M&A activity is associated with a 1.58% increase in the the growth rate of stock of active patents held by target firms in years of M&A transactions. Regardless, the coefficient is not statistically significant (p-value = 0.066). In contrast, the coefficient $\boldsymbol{\beta_2}$ for acquiring firms is statistically insignificant, suggesting that acquiring firms have no impact on their patent stock growth due to the transaction in the same year [**table 6**]. This is realistic, as the stock of active patents of a target is not formally absorbed by the buyer. Patents retain their original applicant ID and therefore are not directly held by the acquirer. As a result, PATSTAT does not aggregate the active patent stocks under the acquiring firm's profile. Further, logically a buyer might indeed experience a boost in its stock of patents following an acquisition, but only with a considerable lag. In fact, the buyer will exploit the newlyly acquired intangible resources to boost its patent applications in future years. We test this hypothesis with a 3-year lag and find no statistical significance for the firms in our sample.

Once again, among the control variables, the the S&P 500 annual return is strongly statistically significant with a p-value of 0.01, while size (proxied by revenue) is not.

Table 6 - 2nd equation, regression results

Dependent Variable: ActiveP_log_dif				
Method: OLS (Multiple Linear Regression)				
Independent Variable	**Coefficient**	**t-Statistic**	**p-value**	**R^2**
Intercept	0.0245	11.899	0.000	0.004
Target	0.0158	1.838	0.066	
Acquirer	-0.0054	-0.775	0.439	
S&P	0.0199	1.962	0.050	
Rev	0.0000	-5.108	0.000	

Equation 3 - $\boldsymbol{\beta_1}$ suggests a potential decline of approximately 6.8% in the growth of patent filings three years post-acquisition for target firms [**table 7**]. Regardless, we cannot reject the null hypothesis as the p-value is not statistically significant at 0.117. Despite the evidence not being being sufficient to prove an effect, it is interesting to speculate that, marginally, M&A activity negatively impacts patent filings for target companies in the medium term. Considering the large number of small-medium firms (with revenues less than EUR 10 million) in our sample, a stronger coefficient could prove that buyers of healthcare SMEs simply look at them as shell entities containing intangible assets and thus aim to steal their R&D knowledge rather than stimulate its growth.

$\boldsymbol{\beta_2}$ is not statistically significant ($p = 0.709$), thus no association between M&A and the the acquiring firm's patenting activity can be observed in the medium term.

Accordingly, equation 3, after controlling for fixed effects and clustering, indicates that there is no strong evidence of a medium-term impact caused by M&A activity on firm productivity proxied by patenting activity for both targets and acquirers.

Table 7 - 3rd equation, regression results

Dependent Variable: Filed_log_dif				
Method: OLS (Multiple Linear Regression) with Fixed Effects and Clustered Standard Errors				
Independent Variable	**Coefficient**	**t-Statistic**	**p-value**	**R^2**
Target_lag3	-0.0680	-1.5666	0.1172	0.0003
Acquirer_lag3	0.0155	0.3841	0.7009	

Equation 4 - Results indicate no significant effect for acquiring companies (p-value = 0.487). On the other hand, the interaction coefficient $\boldsymbol{\beta_2}$, while still not statistically significant (p-value = 0.069), points to a potential positive deviation in the growth rate of active patents stock for target firms in the transaction year relative to acquirers. If both coefficients were statistically significant, the effect of an M&A transaction

on the stock of active patents compared to firms not involved in M&A, would be interpreted as: i) $\boldsymbol{\beta_1}$ for acquirers, and ii) $\boldsymbol{\beta_1} + \boldsymbol{\beta_2}$ for targets.

Once again though, equation 4 gives little empirical evidence to prove a significant change in active patent growth for both target and acquiring firms.

Table 8 - 4th equation, regression results

Dependent Variable: ActiveP_log_dif				
Method: OLS (Multiple Linear Regression) with Fixed Effects and Clustered Standard Errors				
Independent Variable	**Coefficient**	**t-Statistic**	**p-value**	**R^2**
M&A	-0.0056	-0.6956	0.4867	0.0000
M&A×Target	0.0175	1.8189	0.0690	

8. CONCLUSIONS

This paper aims to prove a connection between M&A and immediate and lagged effects on patent activity, which we use as a proxy for innovation and firm productivity for European medium and large healthcare firms.

Running a panel regression while accounting for unobserved heterogeneity by including firm and year fixed effects, and trying to explain different effects for targets and acquirers, we find that: i) targets show increased patent filing activity in years of an acquisition, a pattern consistent with a pre-deal signalling behaviour to increase the target's valuation; ii) target companies show a negative impact on patenting activity 3 years after a transaction, possibly due to the acquirer stealing the target firm's R&D knowledge to file for new patents in its own name, and iii) results suggest no real impact for acquiring firms in terms of filed applications and stock of active patents as a result of an acquisition in the year of the transaction and up to a three-year lag. However, we cannot absolutely establish these associations, as the related coefficients are just about insignificant, having a p-value slightly above 0.05.

This paper is not only testing some existing theories such as the absorptive capacity [7] and the KBV theories [15], but it also adds to existing literature by investigating a specific geography (Europe) and by suggesting that M&A activity has no real impact on the innovation output of acquiring firms when analysing a sample including medium-sized enterprises with revenue larger than EUR 10 million. This is an interesting finding, as in practical terms, it implies a limitation of M&A for what concerns firm productivity from an innovation perspective. In fact, according to our results, M&A is not an effective strategy to improve a firm's patenting activity, while it possibly is better suited to increase market share and pursue cost synergies. Accordingly, acquiring firms would be better off concentrating their resources to develop new patents internally, rather than externally through an acquisition.

Further, despite our belief that our data is very robust, we must recognise the following limitations: 1) the sample of 1,160 unique firms, yielding approx. 11,000 panel observations, is small and could be expanded to be more thorough; 2) ideally, the panel period should be longer, up to 20 years. Moreover, for a longer period, better control variables should be proposed to correct for big macroeconomic swings; 3) the dependent variables showing the number of filed applications and the stock of active patents per firm contain numerous small values, including zeros. This complicates data interpretation and modelling. Although we apply a log-differenced transformation of the form log(1+x) to mitigate this issue, we acknowledge its limitations and recommend that further research explore alternative approaches to analyse such sparse and skewed distributions.

Recommendations for further research also include: i) add R&D as both a control variable and a dependent variable. This has been done in previous studies and could better explain the effect of M&A by looking at the problem from a broader perspective, i.e., M&A leads to more/lower R&D spending and thus to higher/lower patenting activity; ii) once further research identifies a more robust method than this paper's log(1+x) differencing to analyse the dependent variable describing patenting activity, the scope of this study should be widened to include firms with a revenue range between EUR 5 and 10 million in order to fully include SMEs in the analysis; and iii) address whether there are different effects for specific branches of the healthcare industry. For instance, we speculate that MedTech and BioTech will show more significant results, as their core business revolves much more around patent activity compared to, for instance, healthcare CDMOs.

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