The Impact of M&A on Innovation

A European Perspective

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Master's Thesis in Finance
Stockholm School of Economics
May 2017

ABSTRACT

This thesis examines the influence of M&A on corporate innovation from a European perspective. Based on a sample of 1,419 European listed firms, we find a positive impact of M&A on innovation quality for the acquirer. More precisely, conducting M&A leads to an increase in the acquirer's patent quality of up to 3.1% in the post-transaction period. That increase is even more pronounced for a subsample of the most innovative countries. We measure innovation using both patent counts and patent citations, finding significant results only with the latter. Our results convey that M&A in Europe has a supportive role to innovation activities, rather than being a key innovation driver. On average, firms acquire smaller targets with seemingly complementary technologies, which allow them to produce innovation of higher quality without materially impacting annual patent flows.

Keywords: Mergers & Acquisitions, Innovation, Patents, Research & Development
JEL Classification: G34, O31, O32
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ACKNOWLEDGMENTS

We would like to thank our supervisor Daniel Metzger, Associate Professor at the Stockholm School of Economics and Research Associate at the Swedish House of Finance for the invaluable comments and guidance over the course of writing this thesis. We are also grateful to Helen Miller, Institute for Fiscal Studies and Patrick Seidler, Middlesex University, for their time and input at different stages of the process. All errors remain our own.

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1 Introduction

Innovation is the key component behind economic growth and productivity (Solow, 1957), especially within the corporate world. Some executives even state that *"innovation is the only way to win"* (Jobs, 1999). The last decade proved that to be true, as the most successful firms found the source of their success in innovation and high technological advancements, which allowed them to constantly deliver products of the highest quality. This established innovation as a main strategic approach, rather than an expensive and risky addition to the ongoing operations (PwC, 2013).

The question of interest is how innovation is being achieved, particularly among large and listed corporations – through investments in Research and Development (R&D), through Mergers and Acquisitions (M&A), or a combination of both. For a long-time M&A, a powerful but controversial corporate activity, and R&D were perceived to be mutually exclusive (Hitt et al. 1991). Firms either followed an M&A-based strategy to grow and gain market share, which was believed to reduce R&D and subsequently innovation outputs (Pitts, 1997), or invested in R&D and grew through internal innovation. The trade-off was a consequence of the significant resources required to conduct M&A (Hitt et al. 1991). However, a fast-moving corporate environment, short-termism and shifting market perceptions, led to a change in the focus of researchers and practitioners, who started considering M&A as an alternative source of innovation, treating it as a substitute or addition to R&D, and introduced innovation-driven M&A (Sevilir and Tian, 2012).

Nevertheless, the results on the impact of M&A on innovation remain inconclusive. While in the 80s and 90s most innovation literature relied on R&D-based metrics, the increase in availability of patent data matched with financial data led to a plethora of literature focused on patent-based metrics. With this development towards measuring innovation through outputs (i.e. patent counts and citations), as opposed to inputs (i.e. R&D expenditures), results started shifting towards a positive influence of M&A on innovation. Among others, Entezarkheir and Moshiri (2016), Bena and Li (2014) and Sevilir and Tian (2012) point towards a positive effect. That stands in contrast to the previously maintained thesis, where M&A and R&D were deemed mutually exclusive.

Moreover, current literature sees an over-representation of studies conducted on data coming from firms based in the United States (U.S.). The studies that involve European peers, only assess their patenting activities in the U.S., leaving the impact of M&A on innovation in Europe uncovered and lacking a more detailed analysis.

With this thesis, we attempt to contribute by hypothesizing the positive impact of M&A on innovation for European acquirers. Moreover, we use a dual approach in our implementation, distinguishing between quantity and quality indicators for innovation. With this split, we aim to shed light on the dynamics between M&A and innovation activities, particularly in the period post acquisition. We also assess the heterogeneity of our study geography and present diverging results across European regions. The main contributions are: (1) a new analysis on the impact of M&A on innovation in the context of a contradictory research area, (2) a focus on the European region, which is underrepresented and has not been studied in this way yet, and (3) a research application of an unexplored patent dataset, which leverages on the novelty of matching between the patent holders and financial identifiers in Europe (i.e. the Amadeus Patent Database). The last was possible thanks to the recent cooperation between the OECD[1] and the EPO[2], which led to an increased harmonization of the patent applicants' names. Moreover, the findings can be further researched and developed, as well as used by practitioners.

The remaining sections of this thesis are organized as follows. In *Section 2*, we make a review of the available literature on related topics, including corporate innovation, M&A activity and motives, and innovation measures. In *Section 3*, we develop and state our research questions. In *Section 4*, we introduce our data sample and discuss different matching approaches. Further, in *Section 5* we present our research methodology. In *Section 6*, we present the regressions results for the baseline model, cross-sectional analysis, robustness tests, as well as differences-in-differences analysis. We further discuss the obtained results and present limitations and possible extensions in *Section 7*. We end the thesis with concluding remarks in *Section 8*.

[1] Organisation for Economic Co-operation and Development.
[2] European Patent Office.

2 Literature Review

Our thesis contributes to three strands of currently available academic research, including corporate innovation, innovation-driven M&A, and innovation measurements. More broadly, this thesis also relates to literature on M&A performance and corporate strategy.

2.1 Review on Related Topics

2.1.1 Corporate Innovation

There are numerous ways and strategies for CEOs to create shareholder value. Of all these, innovation presents itself as the primary driver of economic growth and productivity, as shown by Solow (1957), and later by Romer (1987, 1990) and Aghion and Howitt (1992). According to Hall et al. (2007), R&D is positively and significantly associated with Tobin's Q[3] for European companies and is rewarded by investors with a higher valuation. Griliches (1980) obtained similar results for a panel of large U.S. firms, while Bae and Kim (2003) showed that it holds not only for U.S. but also German and Japanese firms. Furthermore, even though U.S. firms invest similar amounts in R&D as its non-U.S. peers, the market attributes a higher value to those investments for German and Japanese firms.

On the other hand, it was also proven by Griliches (1992) that the social rates of return to R&D are extensively above private ones, hence returns from innovation on a firm level might lead to underinvestment when considering internal channels of innovation like R&D. Additionally, the whole process leading to innovation must be seen, as a long-term one, yielding an uncertain outcome and having a high probability of failure (Holmström, 1989). Furthermore, innovation which supposedly brings a competitive advantage, often creates an incentive to limit data disclosure and thus leads to information asymmetry (Bhattacharya and Ritter, 1983) which in theory results in undervaluation and increases the probability of hostile takeovers as shown by Stein (1989).

There is a visible difference in fostering innovation for private and public companies. According to Lerner, Sorensen and Strömberg (2011) private firms are more innovative, especially those backed by Private Equity (PE) funds. Even though the number of public-to-private transactions within their sample was limited, the biggest difference in patent quality (i.e. patent citations) was observed on them. A similar view on the topic is presented by Ferreira, Manso and Silva (2014), who show that private

[3] Defined as the ratio of market value of a firm to its replacement value.

ownership is better for innovative activities. They argue that insiders in the public markets tend to choose traditional and proven projects as the markets respond to any news instantly, leaving no space for adjustments in case of bad news. In contrast, insiders in private firms are more tolerant to long-term risky projects as they are given more space and time to pursue an early exit strategy in case of an anticipated failure. Bernstein (2015) takes the research a step further, and shows on a unique sample of firms that underwent IPO and those which withdrew their IPO application, that quality of innovation falls after the IPO. Firms that decided to withdraw their application tend to deliver better internal innovation performance. It was also shown that becoming a public company changes firms' strategy towards innovation, with M&A becoming more attractive than investments in R&D. One of the underlying reasons for such behaviour might be the short-termism exerted on management by the market and financial analysts. He and Tian (2013) analyse the influence of analyst coverage on firms' innovation activity and consider two possible mechanisms. First, they consider an information hypothesis where analysts mitigate the information asymmetry, providing a *bright side* to the analysts' work. However, they also consider a *dark side*, where analysts, through their research and target price settings, exert pressure on management to meet short-term targets, which negatively affects firms' incentive to pursue long-term innovative projects. Based on their sample, they find that the pressure hypothesis tends to outweigh the information hypothesis.

One might conclude that growth is highly dependent on the innovation activities of the company. The question that remains is how it is achieved – through investments in R&D (internal innovation), which, as shown above, become complicated when the company decides to go public; through innovation-driven M&A (external innovation), which, as will be shown below, remains inconclusive when considered as a source of innovation; or through the combination of both. Our study aims to shed some light on this discussion in a European context.

2.1.2 Internal Innovation or M&A

As early stated by Burgelman (1985), firms grow and develop through either acquisitions or internal innovation, very often having to choose between those two mutually exclusive strategies (Hitt et al., 1991), which are frequently seen as equally attractive options. Both strategies should lead to a firm's growth and strengthen its competitive position. In this subsection, we view M&A more broadly, and not exclusively as an innovation targeted strategy.

Firms following an M&A-based growth strategy tend to invest less in R&D and vice versa (Pitts, 1997). Furthermore, M&A leading to considerable market consolidation tends to discourage innovation, as it often results in lower competition, allowing for a higher cost structure and lower production efficiency (Arrow, 1962). Following these findings, researchers started considering the influence of M&A on firms' R&D expenditures. Hall (1990) delved into a sample of manufacturing companies, which on average tend to have lower levels of R&D compared to other, more technological industries. However, she still found a negative impact of acquisitions on R&D spending in the years after acquisitions. Her research was expanded by Hitt et al. (1991, 1996) who reported similar results for both R&D expenditures and R&D outputs (alternatively referred to as innovation outputs), noting that there are no positive R&D economies of scale following M&A. Following this discussion, we also assess the impact of M&A on R&D expenditures for our panel of European firms.

2.1.3 Innovation-driven M&A

In theory, motives for M&A can be divided into strategic, financial and managerial (Johnson et al., 2011). Among the key strategic motivations one can highlight: gaining market power (Baker and Bresnahan, 1985), existence of complementary assets (Coase, 1937; Grossman and Hart, 1986), redeployment of assets (Capron, 1999; Jensen and Ruback 1983), cost synergies (Damodaran, 2005), or agency issues (Mock, Shleifer and Vishny, 1990). For a long time, innovation and M&A were treated as substitutes, and only recently innovation as a key strategic driver of M&A became of interest to researchers. Technological companies, especially those listed, were assumed to forgo investments in R&D and instead pursue acquisitions of companies with high R&D levels, strong know-how and patents of high quality, thus innovation-driven acquisitions could encourage and strengthen innovation (Huck, 2000). Research has proven it is not the case that M&A merely complements R&D expenditures, but that in some cases it is used as an external source of innovation that substitutes for the lack of internal innovation channels or failed innovation attempts in order to catch up with the leading industry innovators (Bena and Li, 2014).

Recent research mostly covers the U.S. market due to data quality and availability, especially on reported R&D figures, which are not mandatory in all European countries. In addition, the publication of the NBER Patent Citations Data File strongly facilitated matching patent data with financial data, which led researchers to focus even further on the U.S. market.

One strand of research focuses on the characteristics of M&A, its participants, and their influence on innovation. Among the most researched M&A characteristics are: size of the knowledge base, market relatedness, firm size, timing, and technological components of both target and acquirer. For instance, large companies are more likely to improve their innovative performance after the acquisitions if they acquire small targets (Ahuja and Katila, 2001). Furthermore, firms with complementary technologies prior to the merger tend to have more efficient R&D activities after the transaction. The same is not true for firms with substitutive technologies prior to M&A (Cassiman et al., 2005). The size of the target's knowledge base negatively influences the innovation output of the acquirer after the merger in high-tech industries, additionally in case the transaction does not involve any technological components there are no expectations to see any positive effects on the innovation activity of the acquirer (Cloodt et al., 2006). Firms tend to have a different level of innovative activity around the transaction, higher levels in the pre-merger phase and lower levels post-merger (Stahl, 2010). Hagedoorn and Duyster (2002), discussing firms' external sources of innovative capabilities, look at the size of firms involved in M&A, finding that deals yield better innovation results if the merging companies are of similar size. Higgins and Rodriguez (2006) considered the pharmaceutical industry and found that the deterioration of internal productivity encourages acquisitions as an alternative to mitigate weak internal research work streams, yielding positive post-merger innovation performance.

There are several examples showing either positive, negative or inconclusive results on the impact of M&A on innovation activities, as shown in Table 1. Also, as mentioned in *Section 1*, the shift in researchers focus to patent-based metrics has brought more positive results. Furthermore, different results depend, among other things, on factors such as data sample coverage, unbalanced data, limited geographical setting (Bertrand and Zuniga, 2006) time horizon, specific industries (Ornaghi, 2009; Haucap and Stiebale, 2016), and use innovation measurements.

On one side, negative results were obtained by Szücs (2014) who finds a significant reduction of R&D by both merger participants in the post-merger period, where a decline in the incentive to innovate is pointed out as a main reason. Stahl (2010) also reports a post-merger decrease in innovation, concluding that motivations for mergers might not be as connected to innovation growth as originally assumed, but rather be more competition-driven. Schulz (2007) argued in his literature review that, on aggregate, mergers have a negative impact on post-merger innovation. However, that changes in certain situations (e.g. when economies of scale are achieved on R&D expenditures). Apart from showing that the overall industry innovation activity declines after the merger, Haucap and Stiebale (2016) also show that post-merger innovation output of the acquirer is lower than prior to the merger.

Contrary results are presented by Gantumur and Stephan (2007), who highlight that a decline in the technological capabilities and in the success rate of R&D of the acquirer lead to a positive influence of M&A on the post-transaction innovation activity. Furthermore, according to Rhodes-Kropf and Robinson (2008) the combination of acquirer's and target's innovation activities is a key reason for the recorded positive impact of M&A on post-deal innovation performance. Sevilir and Tian (2012), whose paper closely relates to our thesis, also record a positive effect of M&A on innovation output. A very recent research performed on a panel of U.S. firms suggests a positive correlation between M&A activity and firms' innovative performance, where the time span of the correlation differs, as M&A tends to have larger effects on innovation in the longer term compared to other sources of innovation (Entezarkheir and Moshiri, 2016).

Finally, several studies obtain inconclusive results. Capron (1999), using surveys on manufacturing U.S. and European firms, and Bertrand and Zuniga (2006) using a sample of OECD countries do not find one-sided results. Also, as previously mentioned, Ahuja and Katila (2001) obtain inconclusive results for their sample of firms from the chemical industry in non-technological mergers.

Table 1: Literature Results

This table reports the results found by related literature on the impact of M&A on innovation activities. The table is segmented based on the measure used for innovation activity. We refer to literature using R&D, patent counts and patent citations based metrics. Further details on these measures can be found in *Section 2.2.2*. An extended version of this table including details on focus region, industry and database can be found in the *Appendix* (see Table 6).

		Patent-based			Citations-based			R&D-based		
Authors	**Year**	**Positive**	**Neutral**	**Negative**	**Positive**	**Neutral**	**Negative**	**Positive**	**Neutral**	**Negative**
Entezarkheir, Moshiri	2016				x					
Haucap, Stiebale	2016			x			x			x
Bena, Li	2014	x			x					
Szücs	2014									x
Sevilir, Tian	2012	x			x					
Stahl	2010						x			
Gantumur, Stephan	2007	x						x		
Hagedoorn, Duysters	2006	x						x		
Cloodt et al.	2006			x						
Bertand, Zuniga	2006								x	
Ahuja, Katila	2001		x							
Hall et al.	1999								x	
Hitt et al.	1991			x						x
Hall et al.	1990									x
Ravenscraft, Scherer	1987									x
	Total	**4**	**1**	**3**	**3**	**0**	**2**	**2**	**2**	**5**

When trying to aggregate research results on the direct influence of M&A on the post-deal innovation activities of the acquirer, we come across diverging results. Hence, it remains unclear whether there is a positive or negative influence on innovation *per se*, highlighting the need for further research on the topic. Furthermore, very few, from the above-mentioned studies, focus on innovation and M&A activities in a European context. This paper aims to contribute to this line of research by providing a European perspective to the topic.

2.2 Review on Variable Measures

In this section, we review relevant literature on different approaches to measure both, our study variable (i.e. M&A) and our outcome variables (i.e. innovation outputs). *Section 2.2.1* covers related literature on M&A measures, while *Section 2.2.2* refers to literature on innovation measures, namely patent counts and citations.

2.2.1 Measuring M&A

One of the key reasons why different studies achieve different results is linked to the way M&A is measured and implemented in different models. It is worth highlighting four most commonly used approaches in the literature, which are: time dummies, deal value, variable indicators, and more broadly, other economic models.

An M&A time dummy is the simplest way of including the merger or acquisition as a control variable, where one stands for the occurrence of an M&A event for a certain firm-year observation and zero stands for no M&A activity. Considering the common data limitations on M&A deals, which will be discussed below, time dummies seem to tackle most of them and present themselves as a simple and strong explanatory variable. This measure was implemented, among others, by Cloodt et al. (2006).

A natural extension of the simple time dummies for M&A periods is transaction value measured as M&A deal value divided by a firm size metric (e.g. total assets or total revenue). Among others, Sevilir and Tian (2012) use this measure. It provides a better understanding of the acquisition expenditures and their influence on innovation. It also creates the possibility to estimate the marginal utility of a currency unit spent on R&D versus M&A, as measured by innovation outputs. Unfortunately, there are strong limitations to this measure, as very often deal values are not public information, leaving researchers with a sizable portion of missing data. In this context, the geographical span of research does not support using different variables, as U.S. data is not much better than European. Sevilir and Tian (2012) mention that due to c. 40% missing deal values in their dataset, the obtained results are to be considered as significantly underestimated.

Another alternative to the simple time dummy is the so-called variable indicator, which was used by Hitt et al. (1991), Ashenfelter et al. (2009) and recently by Entezarkheir and Moshiri (2016). It is a dummy variable which assigns one to the merging firms in post-merger period, which often assumes different lengths in different papers, and zero otherwise. One of the issues with this measure is how to distinguish the effect of a single year M&A activity, for the firms that conduct M&A in consecutive years, creating the overlap within the post-M&A period. All these measures also force researchers to include multiple controls in the model to address the issue of simultaneity and omitted variable biases. Those can include market share, firm size, Tobin's Q, firm age or R&D intensity, among others.

There are also multiple economic models, which in different ways include the influence of M&A on innovation, and which depend highly on the characteristics of the tested hypotheses. For instance, Haucap and Stiebale (2016) check the influence of M&A on innovation not only on a single firm level, but also on the overall industry, using a Cournot oligopoly model. A different model to measure M&A influence on innovation was implemented by Phillips and Zhdanov (2011). The model was based on a simple utility function, where consumers can choose between offered products and where firms can introduce new products (i.e. innovate) or acquire other competitors.

2.2.2 Measuring Innovation

Innovation measures can be divided into input and output variables. Among input variables, the most important one is R&D (Keller, 2010), among the output variables patent counts and citations[4] are regarded by literature as some of the most prominent ones (Hagedoorn and Cloodt, 2003). The impact of different market events on companies' innovation were at the beginning measured using R&D exclusively. For instance, Hall (1990) used R&D intensity[5] to check the influence of restructuring on R&D levels of industrial firms. Hitt et al. (1991) analysed the impact of acquisitions on R&D, as well as on patents. Later, a similar approach was used by Blonigen and Taylor (2000), who used R&D intensity to test the influence of acquisitions on the innovation output of high-tech industries in the U.S. Thereafter, many studies have argued that innovation output variables measure changes in innovation performance more accurately compared to traditional metrics such as R&D expenditures.

Firstly, the period of data availability for patents is much longer than for other metrics. Secondly, in many countries, especially in Europe, R&D reporting is not mandatory, which makes research much harder and possibly leads to partially biased and inconclusive results.

The introduction of patents as research metrics can be traced back to Schmookler and Griliches (1963) who pioneered patent statistics and Scherer (1959) who worked

[4] Patent citations are mentions included in a patent application document referring to other patents upon which inventors have built on.
[5] R&D intensity is here defined as R&D expenditures to sales.

with patents in chemical, steel and oil industries. The first big data sample used in digital form, based on the USPTO[6] database, was introduced by Griliches et al. (1980), who argued that patents present themselves as a good indicator for the differences in innovation activities among firms. They also pointed out that there is a strong relation between R&D and patents across firms. This research was taken further by Carpenter et al. (1981) and Narin et al. (1987), who focused on patent citations instead of raw patent counts, showing their strength and added value. Then Pavitt (1988) delved deeper and summarized the uses and abuses of the patent statistics, once again highlighting the strength of patent citations. Similar conclusions were presented by Albert et al. (1991), who argued that citations are a good indicator, allowing to distinguish between important and regular patents. Karki (1997) also contributed to the discussion, with a slightly different perspective on the topic, namely as a policy analysis tool, he further reinforces the validity of patent citations. Further, Harhoff et al. (1999) checked the relation between the estimated patent value three years after the filing date and the number of citations it obtained. Through the survey of German patent owners, a single citation was found to reflect an increase in patent value of as much as USD 1.0 million, supporting the strength of patent citations as a good quality measure.

Ever since, there is an ongoing discussion whether one should focus on just one indicator, as well as whether patent counts are better than patent citations or vice-versa. Among others, patent counts as a dependent variable were used by Ahuja and Katila (2001) and Hall and Trajtenberg (2004), however they used multiple indicators in their research. Furthermore, Cloodt et al. (2006) who, a few years earlier, discussed the usage of multiple indicators outlining their advantages and disadvantages, used patent counts as a core dependent variable, while conducting their research on the influence of M&A on innovation activity. Recently, a similar approach was used by He and Tian (2013), who used both patent counts and patent citations while addressing the influence of financial analysts on the innovation performance of public firms.

The latest strand of research gives credit to patent citations[7], as raw patent counts are argued to miss the important differences between ground breaking patents and less valuable ones (Hall and Trajtenberg, 2004). First to introduce such measures were Jaffe and Trajtenberg (2002), who treated each patent as the number of its citations. A similar solution was used by Hall et al. (2005) when they show the influence of innovation activity on the firm's market value. They, among others, also largely contributed, to the construction of the NBER Patent Citations Data File (Hall, Jaffe

[6] United States Patent and Trademark Office
[7] Sometimes referred to as citation-weighted patents.

and Trajtenberg, 2001), which has been a fundamental tool, fostering research progress in this field. Further, patent citations were also used by Aghion et al. (2005) who proved that the relationship between competition and innovation is U-inverted, meaning that starting from a monopoly market, introducing competition fosters innovation, however there is a peak where any marginal increase in competition will lead to a decrease in innovation. Aghion also used the same measure in his next paper (Aghion et al., 2009), where institutional ownership was proven to positively influence the innovation activity of firms, as institutional investors are believed to be more patient, due to their long-term scope of investments. Recent research, including Stahl (2010), who tested the impact of mergers on innovation, as well as Bena and Li (2013) who worked on the relation between M&A and innovation changes post-M&A, also used citation-weighted patents as the key measure of innovation. Finally, Entezarkheir and Moshiri (2016) tested the influence of mergers on innovation using a panel of public U.S. firms, with citation-weighted patent stocks.

In this study, we follow the latest trend in research and use both patent counts and citations as innovation measures. This allows us to get a more comprehensive view on the topic and distinguish between different effects of M&A on innovation outputs.

3 Hypotheses Development

Within our literature review, we present the latest findings and theory on the link between M&A and innovation. On aggregate, the available results are diverging, however the most recent literature, using patent-based metrics, supports a positive relation. That research is also mostly based on U.S. data and, to our best knowledge, the relation has been limitedly explored in a European context. The different geographic setup could itself lead to different results. Thus, we must consider opposing hypotheses. In *Section 3.1*, we build on these premises and on the existing literature to establish and support our hypotheses. We further consider additional hypotheses in *Section 3.2* contingent on splitting European regions and imposing restrictions on firms' characteristics.

3.1 Key Research Questions

Following the existing theory, we identify several reasons why one could expect a positive influence of M&A on innovation. Firstly, the mere combination of the acquirer's and the target's innovation capabilities could lead to an increase in the level of innovation activities (Rhodes-Kropf and Robinson, 2008). In other words, the merger of innovation competences could generate economies of scale, as theorised by Cassiman et al. (2005).

Further, if M&A is a strategic move triggered by a perceived decrease in the level of innovative performance, as verified by Bena and Li (2014), one could also expect it to have a positive effect on innovation. The acquirers will presumably look for options to move towards the market technological frontier[8] and M&A could be one of them. Although, this requires that M&A presents itself not only as an option, but as a fruitful one. In our framework, this dynamic would be reflected by a decline in innovation outputs prior to M&A and a subsequent increase.

Whether M&A is a successful tool to achieve innovation could also be related to the technological components involved in the acquisition (Cloodt et al., 2006). Previous literature denotes a more pronounced positive impact when looking at acquisitions of smaller targets with complementary research capabilities (Ahuja and Katila, 2001). This last argument is strongly linked to the characteristics of the panel of firms studied and must be kept in mind throughout the development of this study.

[8] Market technological frontier, in this context, reflects the forefront of technological advancement (i.e. innovation) within an industry.

All the arguments presented above can explain the positive results obtained by Sevilir and Tian (2012) or Entezarkheir and Moshiri (2016). In line with the above premises, we address the following baseline hypothesis:

Hypothesis 1: *M&A has a positive and significant impact on innovation outputs*

Nonetheless, those results were put forward in the context of U.S. firms. Hence, to establish this hypothesis one must assume that the differences between Europe and the U.S. are marginal and that the same dynamics would be observed in Europe. However, there are numerous reasons that could lead to diverging results in different regions (i.e. one could find multiple arguments against *Hypothesis 1*).

One of those reasons lies in the different levels of financial markets' development. Historically, financial markets have played a key role on the innovation activities of a country. Hsu et al. (2014) highlight that the development of equity markets is closely tied with the innovation levels of the different European countries, especially in high-tech intensive industries that are more reliant on external financing. Nevertheless, the role of financial markets is not limited to equity financing. Also, credit financing is of utmost importance to the risk appetite of small innovative entrepreneurial companies. For example, Hsu et al. (2014) show that between 1976 and 2006 countries with strong credit markets (e.g. Germany and France), as compared to equity market, exhibit higher levels of R&D intensity, whereas countries with comparatively more developed equity markets (e.g. UK and Sweden) evidence lower levels of R&D intensity. In our framework, this potentially suggests that firms based in countries with more developed credit markets (a major part of the firms in our sample) are rather breeding innovation internally via R&D, instead of acquiring it via M&A.

Public markets do not stand only for financing, but also carry other important characteristics. For instance, with more developed equity markets typically analyst coverage increases and that, as evidenced by He and Tian (2012), has a negative impact on average on the level of innovation outputs and inputs. Therefore, it will influence large and well-developed firms more, as they are on the spotlight of analysts and investors, thus to meet quarterly targets, they might forgo long-term projects including R&D investments (Morck, Shleifer and Vishny, 1990; Holden and Lundstrum, 2008) and instead focus on growth through an M&A-based strategy.

We must also question whether the European target base of innovative firms is big enough, during the period covered by our research, to support a significant level of innovation-driven M&A or at least whether it allows to balance the firms with acquisitions of high quality innovations. To understand these issues, one should consider the late formation of start-up clusters in Europe (Forge et al., 2013), as compared to the U.S., and the delayed regulatory adjustments to stimulate innovation within young companies that have limited access to financing. Such facts give arguments for higher levels of internal innovation as opposed to innovation-driven M&A. Under this scenario, M&A would be expected to be a less important or even insignificant driver of innovation compared to what it is in the United States. Furthermore, if the above holds, and Europe is not an ideal region to conduct innovation-driven M&A, then the ongoing acquisitions must have other motivations and prove not to be compatible with investments in innovation (Hitt et al., 1991). In this case, we would expect the relation between M&A and innovation to be negative.

Finally, just by looking at the distribution of patents across European countries, we find that, between 1995 and 2010, Germany was responsible for 42.5% of all granted patents, but stood behind with only a 13.9% share of the total M&A activity in Europe. Meanwhile, the U.K. accounted for 5.3% of all granted patents and stood ahead in respect to M&A activity with a share of 32.8%[9]. This showcases a strong heterogeneity across countries and will also have a big influence on the outcome of any research conducted at the aggregate level on European firms. Potentially, firms based in less innovative countries could drive negative results. Geographical heterogeneity is, however, not exclusive to Europe. Similarly, in the U.S., California and Massachusetts drive the results of innovative activity within the country (Jamrisko and Lu, 2016). Nevertheless, it must be considered as an additional driving force on aggregate results.

Based on the above arguments, we introduce the following alternative hypothesis:

Alternative Hypothesis: *M&A has a negative and significant impact on innovation outputs*

3.2 Additional Hypotheses

3.2.1 Quality vs Quantity

Going further, we must emphasise again the difference between patent counts and patent citations. One should highlight that citations allow to differentiate patents of diversely perceived quality and importance. Why are not all the patents equally important? One of the reasons concerns the continuous patenting of even very small innovations, just to safeguard competitive and regulatory issues, commonly referred to as *defensive patenting* (Hall and Ziedonis, 2001). Sometimes we also observe *patents*

[9] Percentages were calculated based on PATSTAT/Amadeus data for patents and SDC Platinum data for M&A activity. M&A data includes only changing control deals as incorporated in our broadest M&A dataset.

floods[10] (Meurer, 2002) or have to deal with *patent trolls*[11] (Lemley and Melamed, 2013), which also affect the quality and quantity of patents. Keeping that in mind and knowing that prior to the acquisition, the acquirer has a comprehensive knowledge of the target's patent stock and its potential value as measured by patent quality indicators (e.g. patent citations) and possibly its knowledge base[12] as well as the current state of R&D projects in the pipeline, we might assume that acquisitions should have a more significant impact on patents' quality, rather than quantity. In other words, acquirers have to some extent a cherry-picking ability when conducting M&A that they cannot achieve while using internal innovation channels, and can recur to M&A to find complementary technologies which could improve the quality of future innovations. That can be the case especially in Europe, where equity markets are not as developed as in the U.S. (excluding the U.K. and the Nordics[13]), hence M&A levels are not as high as in the U.S. Such reasoning also brings us to the distinction between acquiring innovation outputs or acquiring innovators (i.e. human capital/researchers). The latter would influence patent quality in the mid- to long-term, but not certainly their quantity. In other words, different M&A dynamics could generate a scope or scale economy effect of M&A (Cassiman et al. 2005), depending on the target characteristics sought-after in acquisitions. Following these premises, we introduce an additional hypothesis:

Hypothesis 2: *M&A has a positive and significant impact on patent quality, but not on their quantity*

3.2.2 Innovation-friendliness and M&A

There are also visible differences between countries, when it comes to innovation, which can already be seen on the level of distribution of patents across Europe as shown by Abramovksy et al. (2008) or within the country statistics of our sample (see Table 9 in the *Appendix*). Among other reasons, we point out the economic and financial development of a country, but also its innovation-friendliness. In the *Bloomberg Innovation Index* (2017), among the top 10 most innovative economies in the world one can find Sweden, Germany, Finland and Denmark, while Czech Republic, Hungary, Italy or Poland are in the 3rd tenth of the index, highlighting the differences across European countries, which were even bigger between 1995 and 2010 (*Global Innovation Index,* 2010). Building on that, one might expect the results to be

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[10] Sudden and striking growth in filed patents within certain classes of inventions.
[11] Patent owners who profit from patent misuse, for example, by suing firms that allegedly infringe their patent rights or by just holding them without ongoing related activities merely to keep competitors away from that invention.
[12] Knowledge base here refers to the quality of innovators, in other words, human capital.
[13] Denmark, Finland, Norway and Sweden.

heterogenous across the countries. Hence, we test our baseline hypothesis on a subsample including Sweden, Germany, Finland and Denmark and compare it with the rest of the countries within the sample, leading to the following hypotheses:

Hypothesis 3a: *M&A has a positive and significant impact on innovation outputs in Innovative Countries*

Hypothesis 3b: *M&A has a negative and significant impact on innovation outputs in Other Countries*

3.2.3 R&D Intensiveness and M&A

Further, we expect corporate strategy to have some degree of influence on the way innovation outcome is produced at the firm level. To shed light on this side of corporate innovation and to further assess our sample, we test an additional hypothesis on a delimited subsample based on the R&D intensiveness of the covered firms. The goal of this premise is to further understand whether firms that focus on internal channels of innovation, also achieve better results when seeking innovation through external channels (i.e. M&A). In other words, we test whether the relation exists or becomes stronger when firms pursue innovation through both channels. Hence, we hypothesise the following:

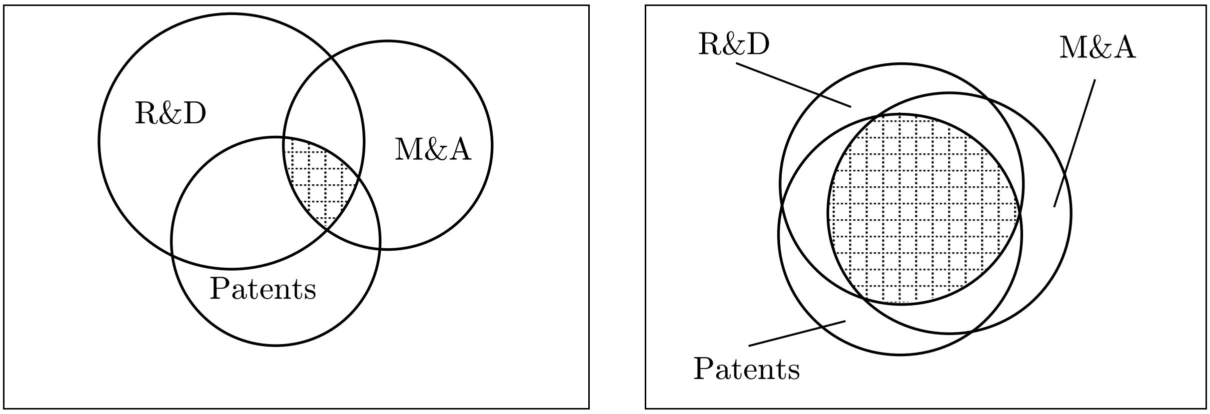
Hypothesis 4*: M&A has a positive and significant impact on innovation output for R&D intensive firms*[14]

The motivation for this sample split arises from a suspicion that our results can be underestimated by firms that do not pursue any type of innovation activity, neither via internal nor via external channels. Hence, ensuring a certain level of R&D intensity allows us to analyse the behaviour of our study variable on firms with a persistent level of innovation input. This distinction can be more easily understood by the means of an illustration as portrayed by Hagedoorn and Cloodt (2003) in the context of new product announcements. Similarly, our understanding for the different types of approaches firms take on M&A and its linkages to innovation activities is represented by Figure 1 below.

[14] R&D intensive firms are defined as firms with above-median R&D intensity in a sample context.

Figure 1: Innovation Channels

Venn diagrams highlighting two possible relationships between R&D, M&A and Patents for two firms (A and B) in two hypothetical industries with different technological setups (see also Hagedoorn and Cloodt, 2003). These are two extreme scenarios that aim to help the reader visualize different innovation dynamics for companies possibly covered by our sample.



These different interactions between M&A, patents (both counts and citations) and R&D become particularly interesting when trying to understand whether M&A works as a substitute for failed R&D projects carried out internally within each firm. If that is the case, we would expect stronger coefficients in our subsample analysis when using both patent counts and patent citations as dependent variables.

4 Sample Selection and Summary Statistics

The sample examined in this paper covers 1,419 European[15] listed firms, which recorded some degree of patenting activity[16] between 1995 and 2010. The choice of period reflects mostly the availability and quality of European patent data via the EPO's database PATSTAT. Recent efforts by the EPO and the OECD led to an improved and harmonized patent database provided by Amadeus that matches PATSTAT patent data with financial identifiers[17]. This thesis leverages on the uniqueness and novelty of this database, which remains largely unexplored by researchers.

To this date, the clear majority of literature on corporate innovation including patent data has been conducted using the NBER Patent Citations Data File. This paper attempts to contribute to this line of research by also exploring a different patent database and provide a European perspective on the topic. M&A transaction data was gathered from the SDC Platinum database ranging from 1993 to 2010. The broader period in our M&A dataset allows for a lagged analysis of our models' independent variables. Finally, we collect financial data for control purposes from three different databases Datastream, Amadeus and Compustat, which have been prioritized in the same order. Hereafter, we detail the data collection process for all data types used and provide descriptive statistics for selected variables.

4.1 Patent Data Collection

4.1.1 Measuring Innovation Output

Our measures of innovation output are based on firm-year patent counts and citations. We consider application year, instead of grant year, as Griliches, Pakes and Hall (1988) have shown application year captures the time of innovation better than grant year.

We first collect firm-year observations on the total number of patents filed in a given year (i.e. patent flows) that are eventually granted from the Amadeus patent universe. As this measure on its own does not provide any information about the quality and the importance of the innovation included in each patent application, we also collect information on the total number of forward citations[18] given to a certain patent. As previously discussed (see *Section 2.2.2*), patent citations are generally

[15] Our target country group is EU-28. However, our final dataset does not cover any listed firm from Cyprus and Malta.
[16] Firms which were granted at least one patent.
[17] This dataset remains an ongoing project with continuous inputs from the OECD, EPO and Amadeus, hence data quality will likely improve further in future versions. The database relies on BvD ID numbers, which are BvD's unique firm identifiers.
[18] A patent's forward citations are those contained in another's patent application referring back to that same patent, whereas backwards citations are those included in a patent's application referring back to other patents.

accepted as one of the best measures to assess a patent's quality and the degree of its innovativeness as shown by Jaffe and Trajtenberg (2002) and Hall et al. (2005). Given a firm's dimension and the level of its innovation inputs, the number of granted patents together with its citations provides a sound measure of the firm's innovation outputs.

4.1.2 Patent Counts Data Collection

Patent data compiled from Amadeus covers patent applications between 1995 to 2010 for patents that have eventually been granted (i.e. we do not consider applications still in review or rejected). The choice of period is mainly driven by the characteristics of our two main patent variables (patent counts and patent citations – see *Section 4.1.1*). Broadening our period would expose our sample to poor data availability prior to 1995 and to truncation issues after 2010, both on patent counts, as it can take several years until a patent is granted and on citations (see *Section 4.1.3* for a detailed description). Our data compilation leverages on the recent efforts of the OECD in harmonizing company names in the OECD HAN[19] database, which serves as a basis for the Bureau van Dijk's Amadeus Patent Database. The initial patent sample consists of 2,622,016 patents granted to private and public companies headquartered in Europe. One must highlight that the majority of these patent applications are owned by private firms, which will be disregarded in our analysis. However, in order to capture patents granted to subsidiaries of listed firms we use the broadest dataset possible as a starting point.

4.1.3 Patent Citations and Truncation Exposure

Patent citations available on Amadeus consider all forward citations given to a patent following its application date. Whereas this provides the highest number of citations possible (a total number of 709,777 for the c. 2.6 million patents downloaded from Amadeus), it seriously exposes our dataset to truncation issues. This happens because recently granted patents have a shorter citing period compared to older patents. Thus, we observe a monotonous decrease in patent citations over time, which raises a truncation issue.

There are three most common ways to address that issue as discussed by Lerner and Seru (2015), namely estimating the distribution function for citations and projecting forward citations based on the available historical data (Jaffe and Trajtenberg, 1996), scaling citations within the technology class and year it belongs to (Hall, Jaffe and Trajtenberg, 2001), or using citations for a limited number of years after a patent was granted (Lerner, Sorensen and Strömberg, 2011).

[19] Harmonised Applicants' Names.

Firstly, we gathered the latest available citations dataset from PATSTAT released in the Autumn 2016 (it increased the total number of citations from 709,777 to 726,087), however as suspected it was not sufficient to correct the strong truncation but provides with the latest version available (see Table 2). Hence, we decided to follow the approach firstly implemented by Lerner, Sorensen and Strömberg (2011), who counted citations only within the first three years after application year. We expand this approach, by accounting for five years of citations following a granted patent's application year. A five-year period captures the peak in patent citations, which according to Lerner and Seru (2015) is achieved, on average, five years after the patent application. It is important to note that by using such approach, even though we correct the truncation exposure, we discard a high amount of valuable information (the total number of citations drops from 726,087 to 271,816), as most patents receive citations even up to 50 years after its publication. Nevertheless, this approach ensures our patent citations data is truncation-free (see Figure 2).

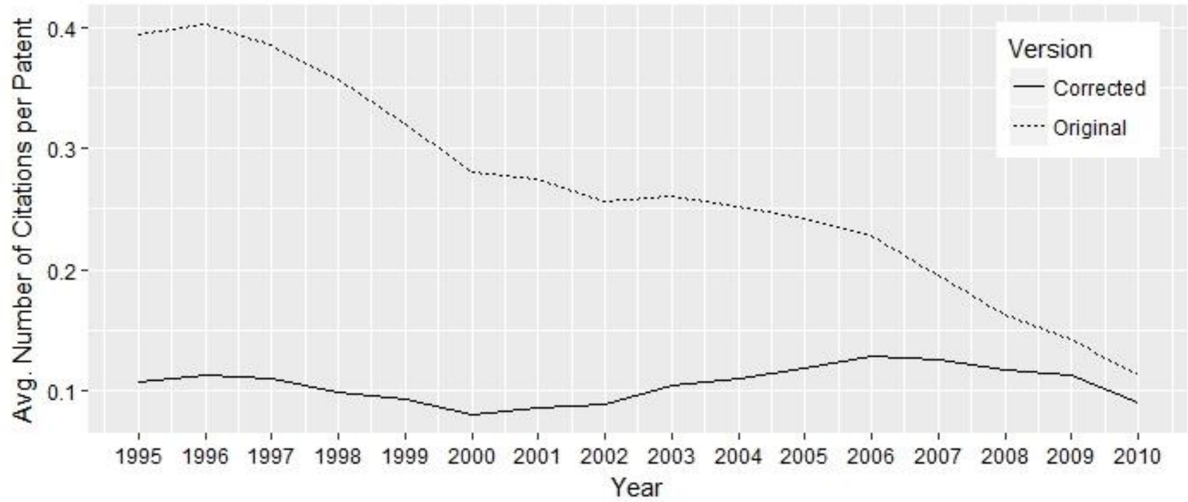
Table 2: Total Number of Patents and Citations per Year

This table reports the breakdown of the number of patents and patent citations on a yearly basis. This breakdown covers the complete patent sample as downloaded from the Amadeus Patent Database. Patent citation data is based on the PATSTAT Autumn 2016 version. The original version refers to all forward citations available in PATSTAT for the patents covered in the Amadeus Patent Database. Corrected figures are adjusted for truncation exposure. We follow Lerner et al. (2011) approach to correct patent citation truncation accounting only for citations given in the first five years following a patent's application year.

Year	**No. Patents**	**No. Citations**	
		Original	*Corrected*
1995	158,546	62,539	16,996
1996	167,611	67,469	18,906
1997	178,267	68,640	19,541
1998	182,857	65,257	17,958
1999	195,489	62,637	18,130
2000	207,262	58,145	16,557
2001	198,209	54,476	16,890
2002	185,034	47,517	16,245
2003	179,038	46,749	18,576
2004	171,445	43,141	18,784
2005	159,988	38,720	18,915
2006	151,336	34,482	19,379
2007	139,795	27,320	17,521
2008	132,461	21,436	15,524
2009	114,884	16,283	12,968
2010	99,794	11,276	8,926
TOTAL	2,622,016	726,087	271,816

Figure 2: Citations per Patent Over Time – Truncation Correction

This figure shows the yearly development of the number of citations per patent for the complete patent sample downloaded from the Amadeus Patent Database. Patent citation data is based on the PATSTAT Autumn 2016 version. The original version refers to all forward citations available in PATSTAT for the patents covered in the Amadeus Patent Database. Corrected figures are adjusted for truncation exposure. We base our approach on Lerner et al. (2011) and correct patent citations truncation accounting only citations given in the first five years following a patent's application year.



4.1.4 Consolidation Process

Following the compilation of our broad patent dataset including the truncation-corrected forward citations, we proceed with the consolidation of our firm-level observations to GUO-level[20] observations as defined by Amadeus. At this stage, we filter out all private parent companies (i.e. GUO entities) and narrow our dataset to parent companies headquartered in the EU-28[21]. These steps bring our sample down to c. 2,199 parent companies with ISIN identifiers[22] and their almost 6,000 subsidiaries. The remaining reduction in the number of companies covered by our dataset is explained by the lack of good quality financial data including the lack of R&D figures (see *Section 4.2* for details on financial data used).

4.1.5 Comment on Different Matching Attempts

One of the main challenges in using PATSTAT data is matching the single patent entries with firms' financial identifiers. After an extensive research on available datasets matched with financial identifiers, we decided to design and conduct also our

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[20] Global Ultimate Owner is the highest level of ownership of a company/subsidiary that is not necessarily located in the same country as the subject entity.
[21] European Union 28 member countries: Austria, Belgium, Bulgaria, Cyprus, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, United Kingdom, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden.
[22] ISIN financial identifiers are used for cross-database data merging.

own matching process to be able to compare the outcome and use the latest available data (i.e. Autumn 2016). We initialized our matching process by downloading identifiers for all EU-28 companies from Amadeus, the database used by the OECD in its harmonization efforts. The Amadeus universe covers a total of 116,225 of private and public companies. We ran a series of automated matching steps that attempted to match company names from PATSTAT with BvD IDs[23]. Whereas false matches are possible, they are rather unlikely considering we avoided using matching algorithms that use other matching techniques beyond an exact name matching. Ultimately, we consider only listed firms or subsidiaries of a listed firm, which comprised a total of 54,477 patent observations for 881 listed firms. Previously, researchers tried various matching algorithms, notable mentions include Hall et al. (2007) and Abramovsky et al. (2008). However, their results were obtained relatively long ago, thus were not perfect for purposes of our thesis, and would also require truncation treatments. In conclusion, we deemed the version available on Amadeus to create a better patent dataset for our purposes, as ultimately, we cover a significantly higher number of listed firms (i.e. 1,419 as mentioned before) and patents.

4.2 Financial Data

The financial dataset consists of a series of control variables regarded by the literature as the most relevant when studying innovation output as measured by patent counts and citations. Naturally, one of the key control variables concerns what is regarded by the literature as the core measure for innovation input: R&D Expenditures[24]. Other considered variables are: Net Income, Total Assets, Total Equity, Capital Expenditures (CAPEX), Net Property, Plant and Equipment (Net PPE), Total Debt[25] and Market Capitalization[26]. All financials were collected for the period between 1993 and 2010 to allow for a lagged analysis of innovation output. The data was compiled using three databases – Datastream, Amadeus and Compustat – prioritized in the same order. Data was linked across databases recurring to the list ISIN codes retrieved from Amadeus. To avoid measure inconsistencies across databases, we downloaded exclusively raw measures included in the companies' financial statements and computed all ratios ourselves.

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[23] BvD IDs are Bureau van Dijk's unique firm identifiers used across several databases.
[24] By leveraging on the financials available in three databases we avoid assuming zero R&D expenditures due to missing data, which is a relatively common approach in the existing literature. Hence, we avoid that additional level of bias without losing many observations.
[25] For consistency across databases, we compiled information on long-term debt and the current portion of long-term debt; later used to compute a leverage ratio.
[26] Market Capitalization is used to compute a firm's Tobin's Q.

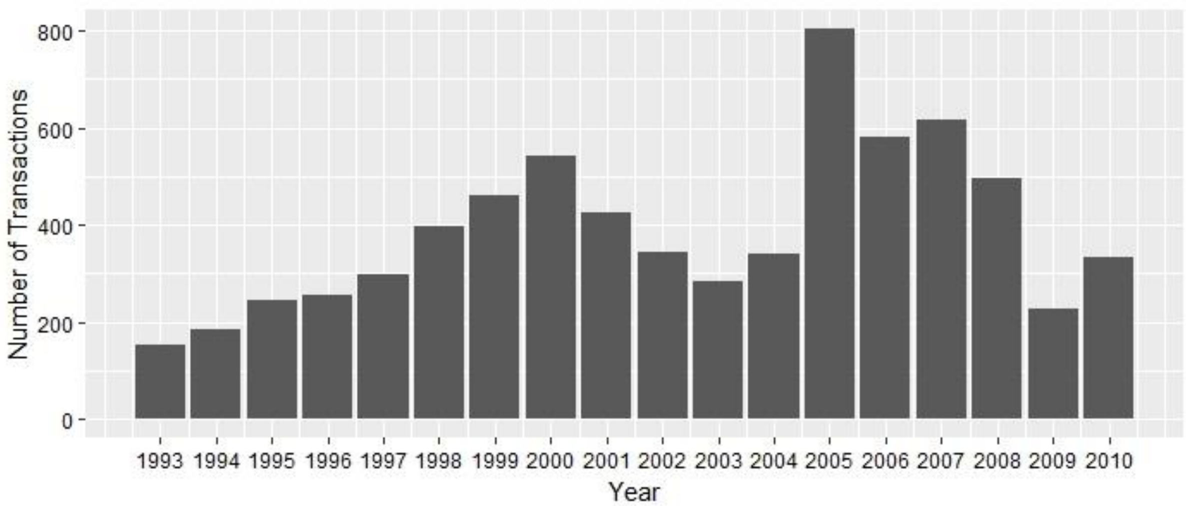
4.3 M&A Transactions Data

To compile the M&A transactions sample, we used the SDC Platinum database. We begin with all the deals specified as a merger or an acquisition, with non-US targets and acquirers. We restrict on the initial percentage stake being lower or equal to 50% and the final percentage stake at least 50%, where the acquirer or the ultimate parent of the acquirer is a listed company. In order to match the M&A dataset with our patent dataset we had to recur to Datastream identifiers (*DSCD*), available both in Datastream and SDC Platinum. The downloaded data is for the period between 1993 and 2015 and the initial dataset consists of 38,716 transactions conducted by 8,334 companies. As a next step, we matched the M&A data with our patent dataset, yielding a total of 6,991 transactions for 972 companies present in our final sample of 1,419 companies (i.e. about 68% of the firms covered in our sample display some degree of M&A activity, which is deemed as balanced). In our sample, we do not distinguish between technological and non-technological acquisitions due to data limitations. On one hand, it restricts the possible interpretations we can infer. On the other hand, focusing on technological deals only could be a bias source, undermining the significance of our results on the relation between M&A and innovation outputs.

An overview of yearly M&A activity can be seen in Figure 3. An additional breakdown per country is included in Table 9 of the *Appendix*. Our time window can be divided into three key time periods, based on economic and financial crises (1995 – 2000, 2001 – 2007 and 2008 – 2010). Hence, we cover two peaks (2000, 2005) and two low points (2003, 2009) of European M&A activity. The time also has an influence on firms' innovation activities as shown in Table 2.

Figure 3: M&A Transactions Over Time

This figure shows the yearly development of the number of M&A transactions for the final set of 1,419 firms covered in our sample. From all firms only 972 display some degree of M&A activity, those are the ones depicted in the plot below.



4.4 Industry Codes

For descriptive purposes, we compiled NACE Rev. 2 classifications[27] for all sample firms to gain a better understanding of our sample. Table 10 in the *Appendix* shows a breakdown of firms, patent counts and citations per NACE classification. One must point out that our sample covers mainly two industry groups – Manufacturing[28] (accounting for 41% of the total number of firms, 50% of patents and 75% of citations) and Professional Scientific and Technical Activities[29] (accounting for 27% of the total number of firms, 35% of patents and 21% of citations).

4.5 Summary Statistics

Ultimately, our sample comprises a total of 17,551 firm-year observations used for different implementations. Following the innovation literature, we set the number of patent counts and citations to zero when there is no available information in Amadeus or PATSTAT. Moreover, we use the natural logarithm of patent counts (*LnPatents*) and the natural logarithm of patent citations (*LnCites*), due to right-skewed distributions of patent counts and patent citations. To avoid losing firm-year observations with zero patents or zero patent citations, we add one to the actual values when computing the natural logarithm. We also consider R&D intensity (measured as the natural logarithm of R&D expenditures divided by total assets – *LnR&DIntensity*), capital expenditures intensity (measured as the natural logarithm of capital expenditures divided by total assets – *LnCAPEXIntensity*), total assets (measured as the natural logarithm of total assets – *LnAssets*), leverage (measured as total debt[30] divided by total assets), profitability (measured by *ROA*[31], which is defined as net income divided by total assets), asset tangibility (measured by net PPE[32] divided by total assets) and growth opportunities (measured by Tobin's Q, which is defined as total market capitalization divided by total assets). To reduce the noise introduced by

[27] Statistical classification of economic activities in the European Community compiled by the Eurostat.

[28] Manufacturing covers manufacture of food products, beverages, tobacco products, textiles, wearing apparel, leather and related products, wood and of products of wood and cork, furniture, articles of straw and plaiting materials, paper and paper products, coke and refined petroleum products, chemicals and chemical products, basic pharmaceutical products and pharmaceutical preparations, rubber and plastic products, other non-metallic mineral products, basic metals, fabricated metal products, except machinery and equipment, computer, electronic and optical products, electrical equipment, machinery and equipment, motor vehicles, trailers and semi-trailers and other transport equipment; printing and reproduction of recorded media and repair and installation of machinery and equipment.

[29] Professional Scientific and Technical Activities cover legal and accounting activities, activities of head offices; management consultancy activities, architectural and engineering activities; technical testing and analysis, scientific research and development, advertising and market research, other professional, scientific and technical activities and veterinary activities.

[30] Total debt is calculated by compiling raw data on total long-term debt and the current portion of long-term debt from the different databases used for financial data.

[31] Return on assets.

[32] Property, plant & equipment.

outliers or potential database-level inaccuracies, we winsorize all dependent and independent variables at the 1st and 99th percentiles, following He and Tian (2013) with this approach. Table 7 describes all variables used in our sample and Table 3 below provides descriptive statistics for selected variables.

Table 3: Summary Statistics

This table reports the summary statistics for variables constructed based on the European firms sample from 1995 to 2010 for patents data and from 1993 to 2010 for all other variables. All empirical analyses are conducted on subsets of this broader sample. See Table 7 included in the *Appendix* for variables definitions.

Statistic	N	Min	Pctl(25)	Median	Mean	Pctl(75)	Max	SD
Patents	17,551	0.000	0.000	1.000	25.746	7.000	3,201	132.418
Cites	17,551	0.000	0.000	0.000	2.777	0.000	1,921	37.826
M&A last 3Y	17,551	0.000	0.000	0.000	0.412	1.000	1.000	0.492
R&DIntensity	17,551	0.000	0.000	0.001	0.030	0.030	0.382	0.062
CAPEXIntensity	17,551	0.000	0.022	0.042	0.054	0.072	0.253	0.046
LnR&DIntensity	17,551	0.000	0.000	0.001	0.028	0.030	0.323	0.055
LnCAPEXIntensity	17,551	0.000	0.022	0.042	0.051	0.069	0.225	0.042
LnAssets	17,551	7.656	11.123	12.540	12.763	14.302	18.115	2.256
Leverage	17,551	0.000	0.076	0.196	0.211	0.318	0.703	0.161
ROA	17,551	-0.811	0.007	0.039	0.011	0.073	0.238	0.147
PPEAssets	17,551	0.001	0.119	0.249	0.276	0.393	0.857	0.195
TobinsQ	17,551	0.081	0.420	0.747	1.200	1.329	9.799	1.482

The statistics above highlight the right-skewness of both patent counts and patent citations. One should also mention that only c. 4.0% of all patents receive any citation, with the total number of citations amounting to about 11.0% of the total number of patents. In addition, it is also important to highlight the characteristics of the average firm represented in our sample, as it will significantly impact our interpretations. Our sample consists mostly of large European firms with an average size of total assets amounting to EUR 3.7 billion. Further, the average firm has an R&D intensity of 3.0% and a CAPEX intensity of 5.4%. ROA is the only variable assuming negative values, which is explained by firms running on losses in certain years. However, on average, firms exhibit a positive profitability of about 1.1%. The average firm also has a leverage ratio of c. 21.0%.

When comparing the patent statistics with the ones obtained on related studies conducted on U.S. data, we observe two main differences. Firstly, the average number of patents is higher as the average firm represented in our sample is relatively larger. Secondly, the average number of citations is lower mainly due to regulatory reasons. While in the U.S. the patent applicant is legally liable to provide patent citations, that is not the case in Europe where most citations are added by the patent examiner.

5 Methodology

In this section, we establish our methodology to study the link between innovation outputs and M&A. To do so, we define a panel data model used to test our previously defined hypotheses. Hereafter, we discuss how our dependent variables and main study variable are defined and measured. We also discuss which control variables are implemented in the model and fundament them based on related literature. In *Section 5.1*, we define our baseline specification and discuss the different metrics used. We then discuss the set of control variables used in the baseline model in *Section 5.2*. In *Section 5.3*, we describe the different regressions implemented as robustness checks. Further, we explore different cross-sectional and subsample variations in *Section 5.4*. Lastly, we introduce a differences-in-differences (DiD) identification strategy in *Section 5.5* to analyse the development of innovation activities over time around the occurrence of M&A.

5.1 Baseline Specification

Our baseline specification explores the effect of the occurrence of M&A on the level of innovation output achieved by a firm. Our empirical design relies on an OLS regression, following Sevilir and Tian (2012) and He and Tian (2013), performed on the previously described panel data. The equation for our baseline model is the following:

$$Ln(Innovation_{i,t+n}) = \alpha + \beta \times M\&A\ last\ 3Y + \delta Z_{i,t} + Year_t + Firm_i + \mu_{i,t} \qquad (1)$$

where i indexes firms, t indexes time and $n \in \{1,2\}$.

Ln(Innovation) can take the form of two different dependent variables, namely the natural logarithm of patent counts for firm i and year $t+n$ or the natural logarithm of forward patent citations in the five years following a patent application[33] for firm i and year $t+n$. As previously mentioned in *Section 4.1*, to avoid losing firm-year observations with zero patents or zero patent citations, we add one to the actual values when computing the natural logarithm. The same approach has been used by Sevilir and Tian (2012), He and Tian (2013), Haucap and Stiebale (2016) and Entezarkheir and Moshiri (2016) among others.

M&A last 3Y represents a binary variable for which one is taken if an M&A transaction fitting our criteria for firm i occurred in the three years between t and t-*2,* zero is taken otherwise. M&A occurrence as a dummy was used among others by

[33] As described in *Section 4.1.3*, we correct our citations measure to account only for citations in the first five years following a patent application year.

Cloodt et al. (2006) as mentioned in *Section 2.2.1,* although we expand their approach of accounting only for the previous year and instead look three years back (see Figure 4). Such expansion allows us to better capture M&A activity, considering the heterogeneity of M&A activity and patent regulations across different European countries. We expect different lags in terms of M&A integration, thus this dummy allows us to capture more information in a single variable.

Figure 4: Graphical Presentation of M&A Variable Design

This figure illustrates the setup of our study and dependent variables in our baseline specification given by Equation 1. *M&A last 3Y* stands for a binary indicator for the occurrence of changing control M&A deal for firm *i* in the three years between *t* and *t-2*. *Patents* stands for total number of patents filed (and eventually granted) by firm *i* in year *t* and *Cites* for total number of forward citations received in the five years following the patent application year by firm *i*'s granted patents applied for in year *t*.

Illustration A: *MA last 3Y* study variable on two-year lead innovation outputs

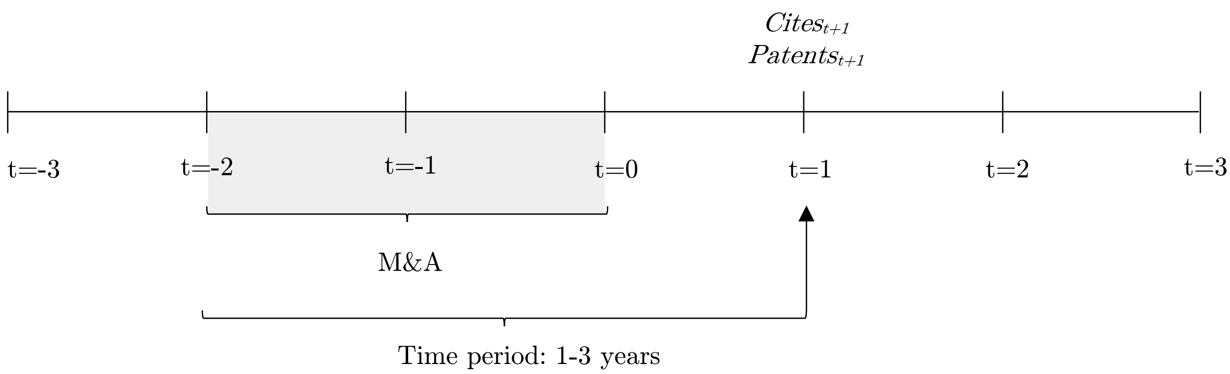
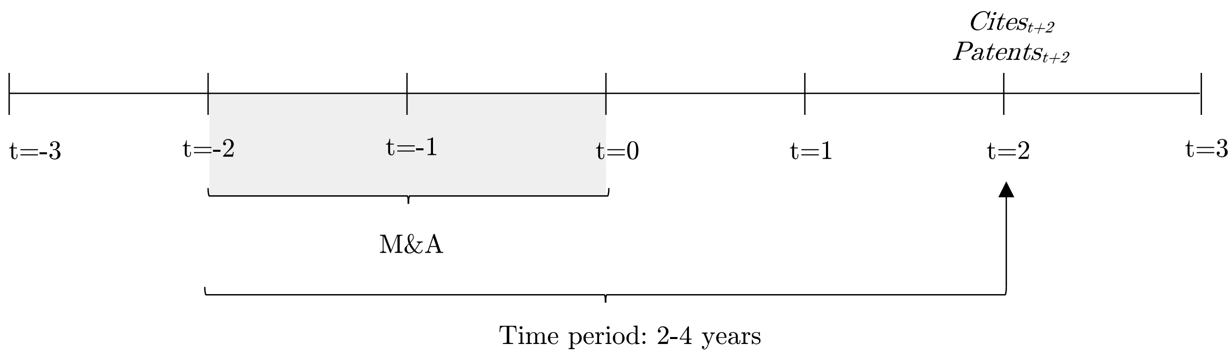


Illustration B: *MA last 3Y* study variable on two-year lead innovation outputs



Z represents a vector of firm characteristics, which, according to literature, may affect the level of a firm's innovation output. Those controls are introduced and discussed in the following section. *Year* captures time fixed effects, whereas *Firm* captures time-invariant unobservable firm characteristics. The inclusion of fixed effects in our specification is done on a step-by-step approach to capture coefficient variation and analyse the potential impact of omitted variable bias in our model formulations. As suggested by Petersen (2009), heteroskedasticity-robust standard errors are clustered at the firm level.

There are several reasons to include firm fixed effects in the baseline specification. Most corporate finance studies face an endogeneity issue, as it is likely that omitted variables may affect both dependent and independent variables alike leading to spurious results. Having as a main objective to analyse the impact of M&A on innovation outputs, we must be concerned with unobservable omitted variables that affect both innovation outputs and the occurrence of M&A transactions for a certain firm *i*. As an example, a firm may be particularly efficient at achieving strong innovation outputs through both internal and external channels of innovation. In this scenario, the unobservable firm's efficiency may not be captured by other control variables and since correlation with both our innovation output metrics and M&A is possible, it could bias the M&A coefficient estimate. Moreover, including firm fixed effects alleviates the bias arising from unobserved time-invariant heterogeneity across firms. Hence, it allows us to interpret the β coefficient as the impact of a firm's M&A activity on its subsequent innovation outputs.

5.2 Control Variables

When designing the set of firm characteristics to be used as control variables in our model specification, we refer to related literature and compile a set of controls that is generally deemed as significant when analysing innovation outputs at a firm-level. In our most simple specification we exclusively control for two dimensions: innovation inputs and firm size. As a measure of innovation input we control for the relative level of R&D expenditures for each firm-year observation, which is widely regarded by literature as the main measure for innovation input. We define innovation input as R&D intensity and measure it as the natural logarithm of R&D expenditures divided by total assets (*LnR&DIntensity*), whereas for firm size we use the natural logarithm of total assets (*LnAssets*). In our most comprehensive specification, we control for a wider set of firm's characteristics namely: *Leverage*, *ROA*, *LnCAPEXIntensity*, *PPEAssets* and *TobinsQ*. Further details on these variables can be found in *Section 4.5* and all definitions are included in Table 7 of the *Appendix*. All control variables are winsorized at the 1st and 99th percentiles.

There are also other control variables which are sometimes used in related literature, but which were not used in our analysis. The first of them is *Firm Age,* used among others by He and Tian (2013), which presents good control as young firms tend to have higher R&D intensities and focus on internal innovation. However, as they pointed out, it tends to be strongly correlated with *Firm Size*. Next is *Institutional Ownership* used by Sevilir and Tian (2012) and Aghion et al. (2009), which is considered important due to long-term investment horizon of such investors, who are assumed to be more positive when it comes to long-term, uncertain and risky projects involving high R&D expenditures. Another of such controls is *Herfindahl Index*, which was incorporated by Sevilir and Tian (2012), He and Tian (2013) and Aghion et al. (2005), and is supposed to capture the probable non-linear relation of product market competition and innovation. We forgo those controls due to data limitations and due to possible inconsistencies across the firms within our sample, which might lead to biased results. Nonetheless, the lack of these controls is alleviated by the inclusion of firm fixed effects in the model specification.

The interpretation of coefficient estimates on control variables is included under *Section 6.1*.

5.3 Robustness

We conduct a comprehensive set of robustness tests on our baseline specification. In this section, we will describe the implementation of those tests, whereas test results are briefly discussed under *Section 6.2* and reported in Table 12 to Table 16 in the *Appendix*.

Firstly, we adopt an alternative measure for M&A. As described in *Section 2.2.1*, there are several possible approaches to measure M&A previously adopted in related literature. In our baseline specification, we use a binary variable measure, however as a robustness check we replace our study variable by *Ln(M&A Deal Volume)* – defined as the natural logarithm of total M&A volume a firm undertakes in a given year, i.e. if a firm acquires more than one firm/asset this will capture the total acquisition value when available. There are drawbacks to this measure, which have been previously identified by the scholars. As data on transaction volume is often not available, it underestimates the magnitude of the M&A coefficient. This arises from the fact that the emphasis is on the effect of an extra currency unit spent in acquisitions on the level of innovation outcome following those transactions. Ex-ante we expect the coefficient to be smaller and less significant than with our baseline regression, however with the same direction.

Secondly, one valid concern that relates to our dependent variable measurements relies on the fact that patenting volumes vary greatly across the firms represented in our sample. This concern is mostly grounded on the high levels of patenting activity in top 10 firms represented in our sample (see Table 11 in the *Appendix*). To address this concern, we replace our dependent variable by a dummy variable defined as one if a firm has a patent granted in that year and zero otherwise. This specification allows us to remove the effects arising from different patenting volumes and rather focus on the patenting event *per se*.

Moreover, to address the possibility that our results may be biased by firms which do not rely heavily on innovation patenting, and only sporadically obtain patents, we run our baseline specification on a subsample of patent intensive firms (defined as firms with at least three patents granted in the analysed period 1995-2010). We expect the results to remain as significant as in our baseline specification.

Furthermore, we analyse another channel for M&A to ultimately impact innovation, which is through the increase of the innovation inputs (i.e. R&D expenditures measured through R&D intensity). We do so by replacing our dependent variable by the natural logarithm of R&D intensity. Ex-ante we expect to see a lower or even negative impact on R&D intensity arising from M&A, due to their potentially incompatible characteristics.

Finally, considering our main study variable is given by a binary variable covering three years in its baseline definition we assess its soundness by splitting it into three separate dummies, one for each year covered. This additional check allows us to test that our results are not biased by the study variable design and provides additional insight into the timing effect of M&A on innovation outputs.

5.4 Cross-Sectional and Subsample Analyses

Based on our baseline specification we perform a cross-sectional analysis to better understand the reactions of our model under different restricted conditions. We explore the impact of different geographical setups, where the sample is divided into two subsamples, *Innovative Countries* and *Other Countries* as described in *Section 3.2.2*. Furthermore, we delve into an above median R&D intensity subsample, where we check whether firms innovate through both channels, internal and external. Results for the analyses are presented and discussed in *Section 6.3*.

5.5 Development of Patent Counts and Citations Over Time

In this section, we describe an additional identification strategy to assess the possibility that M&A active firms might exhibit different innovation activity behaviours in the period pre- and post-M&A. We are particularly interested in understanding how this behaviour differs for patent quantity and quality indicators. For that purpose, we design an identification method for treated firms described in *Section 5.5.1*. In *Section 5.5.2*, we outline our procedure to create a matched sample and showcase differences in innovation activity between treated and control group around the M&A occurrence recurring to DiD plots.

5.5.1 Identification of the Treatment Group

To analyse the trends in innovation activity in the treatment group, we impose several restrictions on our sample to ensure we cover a period long enough for the treated firms leading our analysis to be meaningful. Treated firms are those with at least one M&A occurrence in the analysed time period. To analyse the patterns in innovation activity leading to and following the deal, we refer to the year when an M&A deal has been completed as year 0.

M&A is potentially a repetitive event for each firm, hence to establish robustness of our findings we implement a twofold approach. Firstly, when a firm completes several deals in the analysed period, we centre our analysis around the first M&A occurrence. This identification strategy allows us to isolate a period without any acquisitions prior to year 0. We also restrict our sample to firms active for eight consecutive years and conduct our analysis for a total of eight years around the occurrence of an M&A deal. Secondly, we repeat the process stacking time series around every deal irrespectively of being the first deal conducted by a firm. We are aware that both approaches have their drawbacks, as with the first approach the levels of innovation activity following the first M&A deal can be further impacted by successive acquisitions, and the second approach adds additional noise to both sides of the plot. However, this comparison aims to visually assess the robustness of our findings and help in deriving conclusions. The results of these implementations are presented and discussed in *Section 6.4*.

5.5.2 Matched Sample Design based on Propensity Scores

Following the identification of the treatment group, we proceed with the creation of a matched sample. We match treated and control firms using a propensity score matching approach described below.

Propensity score matching (PSM) is a statistical tool that relies on a score computation used to approximate similarities between treatment and control cases as described by Randolph et al. (2014). By implementing this quasi-experiment, we aim to provide an alternative view on our OLS results that reduces selection bias by matching treatment and control cases based on similarities prior to the treatment event. In other words, it aims to make treatment and control more comparable. We use a nearest-neighbour matching technique, which recurs to a logit estimation to compute scores and match the closest control case with the treated one[34]. In our case, treatment and control cases entail different firms and treatment is given by the

[34] We conduct our matching without replacement (i.e. control cases are only allowed to be matched with treatment cases once).

completion of an M&A deal as described in the previous section. We compute propensity scores using the following metrics: firm size (measured by the natural logarithm of total assets) and R&D intensity (measured by the natural logarithm of R&D expenditures divided by total assets) in the two years prior to treatment. Previous studies using PSM highlight the merits of including only variables that predict the outcome (i.e. innovation outputs) but are unrelated to the treatment (i.e. M&A) in the scores calculations (Brookhart et al., 2006). That makes us limit our score calculations to these two variables. Algebraically, the propensity scores ($p_{i,t}$) are given by the following conditional probability:

$$p_{i,t} = \Pr[\mathrm{T}{=}1 | LnR\&DIntensity_{i,t-n},\ LnAssets_{i,t-n}] \tag{2}$$

where i indexes firms, t indexes time, $n \in \{1,2\}$ and T stands for treatment (i.e. M&A).

We refrain from constraining our matched pairs on any innovation output metric to ensure that any trends captured in our analysis are not biased by time-specific restrictions on the level of innovation activities. We also include an exact matching restriction on industry classification and year on all our matching runs. Treated cases follow the identification strategy described in *Section 5.5.1* and potential control cases are limited on the level of M&A activity carried out by the firm to two deals in the analysed period besides the matching year.

For robustness, we implement two different approaches: 1-to-1 and 1-to-3[35] nearest-neighbour matching. The implementation of the latter does not restrict the sample to pairs with three controls but rather up to three when the computed propensity score allows that. Moreover, we conduct the same comparisons using only R&D intensity as a covariate in the propensity score calculations.

Results of these comparisons are presented and discussed in *Section 6.4.2*.

[35] The first number refers to the number of treated cases and the second to the number of control cases allowed in the matching process.

6 Results and Analysis

In this section, we present and discuss all obtained results for the specifications described in *Section 5*. We begin with the results of our baseline regression on the impact of M&A on innovation outputs as measured by patent counts (see *Section 6.1.1*) and patent citations (see *Section 6.1.2*), both with different leads. We also discuss the results using different control variables. Additionally, we present the outcome of our robustness tests in *Section 6.2* and the outcome of the cross-sectional and subsample analyses in *Section 6.3*. Each of the previous sections is structured in a similar manner, firstly introducing a statistical interpretation and then proceeding with an economic interpretation of all variables of interest. Finally, we show and discuss the development of innovation activities over time as obtained through the DiD analysis in *Section 6.4*.

6.1 Main Results: Panel Data Regression

6.1.1 M&A Impact on Patent Counts

The first regression, addressing *Hypothesis 1*, is performed on patent counts. Columns (1) and (4) in Table 4 present results for a OLS regression including year fixed effects with *LnR&DIntensity* and *LnAssets* as control variables, and *M&A last 3Y* as a study variable. Column (1) is with one-year lead on the dependent variable, while column (4) is with two-year lead. Within those models, the M&A coefficient is negative (-0.109 and -0.115). *LnR&DIntensity* (7.587 and 7.805) as well as *LnAssets* (0.370 and 0.376) have a positive influence on innovation output. All variables are significant at the 1% level.

Columns (2) and (5) show results for a model introducing additional control variables, as results from columns (1) and (4) are believed to be influenced by omitted variable bias. Within those models the M&A coefficient is higher, but also negative and significant in both (-0.133 and -0.140), again showing stronger influence with two-year lead. *LnR&DIntensity* coefficients (6.641 and 6.879) still exhibit a positive influence on innovation outputs, however the explanatory power is lower as more variation is explained by the newly introduced controls. *LnAssets* (0.400 and 0.405) gains in power and remains positive. Those key control variables are significant at the 1% level. From the newly introduced controls *PPEAssets* (-1.319 and -1.410) as well as *Leverage* (-0.466 and -0.428) have a negative influence on innovation as measured by patent counts. *ROA* (0.332 and 0.414), *LnCAPEXIntensity* (3.648 and 3.929) and *TobinsQ* (0.040 and 0.038) have a positive influence on innovation. All the newly introduced controls are significant at the 1% level.

Finally, we introduce firm fixed effects controlling for time-invariant unobservable omitted variables and report the results in columns (3) and (6). The M&A coefficient remains negative (-0.010 and -0.023), however it is no longer significant. These results already suggest that the occurrence of M&A is not firm-irrelevant as controlling for time-invariant covariates materially influences the significance of our study variable's coefficient. Hereafter, we must analyse the most simplified versions of our model cautiously as the lack of control for time-invariant unobservable variables can lead our M&A coefficient spurious. *LnR&DIntensity* (1.021 and 0.423) with one-year lead is visibly lower, but still significant at the 1% level, however with two-year lead it becomes insignificant, which implies that R&D has a higher influence on patents in the short-term. *LnAssets* (0.098 and 0.081) show lower influence on innovation and stay significant at the 1% level. *PPEAssets* (-0.026 and -0.068) becomes insignificant. *Leverage* (-0.211 and -0.143) and *LnCAPEXIntensity* (0.486 and 0.519) keep their signs and significance at the 1% level. *ROA* (0.162 and 0.156) with two-year lead is significant at the 5% level. *TobinsQ* (0.009 and 0.015) loses significance with one-year lead and is significant with two-year lead at the 5% level.

R&D has a higher effect on patents with one year lead, whereby with a 10% change in R&D intensity we expect the firm to obtain 10% more patents the year after. Conducting M&A suggests a to 13.3% to 14.0% decline in the number of obtained patents in the next one to four years, however upon the introduction of firm fixed effects M&A keeps the negative sign, but becomes insignificant. As mentioned above, we conclude that the firm conducting M&A has an important weight in the relevance of the variable and its impact on innovation activities post-acquisition. Clearly, European firms mainly breed their innovation in-house, investing heavily in R&D projects, and on aggregate, even if the M&A are innovation-driven, they are not motivated by the number of patents or, in other words, by innovation quantity. It is worth mentioning that the sample consists of both technological and non-technological M&A, thus the inclusion of the latter might drive the coefficient downward or make it insignificant (Ahuja and Katila, 2001). As expected, we also observe a positive relation between patent counts and firm size, profitability, CAPEX intensity and Tobin's Q, while leverage exhibits a negative relation.

Due to lack of significance we cannot address the *Hypothesis 1* using patent counts, and state that M&A have a positive and significant impact on innovation output. However, we test the same hypothesis using an alternative measure for innovation output (i.e. patent citations). Hence, we must take a more informed view on *Hypothesis 1* by analysing all results together.

Table 4: Regression Results of Patent Counts on M&A

This table reports regressions of patent counts (with a lead from one to two years) on the occurrence of M&A in the three-year period between *t* and *t-2* and other control variables. The dependent variable, *LnPatents,* is defined as the natural logarithm of one plus firm *i*'s total number of patents filed (and eventually granted) in year *t*. *M&A last 3Y*, the study variable, is a binary indicator for the occurrence of a changing control M&A deal for firm *i* in the three years between to *t* and *t-2*. *LnR&DIntensity* is the natural logarithm of R&D expenditures divided by book value of total assets for firm *i* measured at the end of fiscal year *t*. *LnAssets* is the natural logarithm of book value of total assets for firm *i* measured at the end of fiscal year *t*. *Leverage* is defined as book value of debt divided by book value of total assets measured at the end of fiscal year *t*. *ROA* stands for return on assets and is defined as net income divided by book value of total assets for firm *i*, measured at the end of fiscal year *t*. *LnCAPEXIntensity* is the natural logarithm of capital expenditures divided by book value of total assets for firm *i* measured at the end of fiscal year *t*. *PPEAssets* is defined as net property, plant & equipment divided by book value of total assets for firm *i* measured at the end of fiscal year *t*. *TobinsQ* is a market-to-book ratio for firm *i* during fiscal year *t*, calculated as market capitalization divided by book value of total assets. Each regression includes a separate intercept not displayed.

	Dependent variable:					
	LnPatents $_{t+1}$			*LnPatents* $_{t+2}$		
	(1)	(2)	(3)	(4)	(5)	(6)
M&A last 3Y	-0.109***	-0.133***	-0.010	-0.115***	-0.140***	-0.023
	(0.023)	(0.023)	(0.015)	(0.024)	(0.023)	(0.015)
LnR&DIntensity	7.587***	6.641***	1.021***	7.805***	6.879***	0.423
	(0.215)	(0.235)	(0.266)	(0.232)	(0.252)	(0.279)
LnAssets	0.370***	0.400***	0.098***	0.376***	0.405***	0.081***
	(0.006)	(0.006)	(0.013)	(0.006)	(0.007)	(0.014)
Leverage		-0.466***	-0.211***		-0.428***	-0.143**
		(0.068)	(0.058)		(0.071)	(0.061)
ROA		0.332***	0.162***		0.414***	0.156**
		(0.075)	(0.060)		(0.080)	(0.067)
LnCAPEXIntensity		3.648***	0.486***		3.929***	0.519***
		(0.281)	(0.175)		(0.286)	(0.186)
PPEAssets		-1.319***	-0.026		-1.410***	-0.068
		(0.066)	(0.078)		(0.068)	(0.084)
TobinsQ		0.040***	0.009		0.038***	0.015**
		(0.008)	(0.006)		(0.008)	(0.006)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	No	No	Yes	No	No	Yes
No. Firms	1,419	1,419	1,419	1,409	1,409	1,409
Observations	15,672	15,672	15,672	14,713	14,713	14,713
R^2	0.286	0.313	0.858	0.288	0.317	0.863
Adjusted R^2	0.286	0.312	0.843	0.287	0.315	0.848
F Statistic	349.018***	310.460***	59.513***	329.744***	295.813***	58.417***
Note:	***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in the parentheses are the cluster-robust standard errors (clustered at the firm-level).					

6.1.2 M&A Impact on Patent Citations

The second regression, testing *Hypothesis 1*, is performed on patent citations and enables us to get a more detailed picture of M&A influence on innovation outputs, particularly on the quality of those outputs.

Columns (1) and (4) in Table 5 present a OLS regression including year fixed effects with *LnR&DIntensity* and *LnAssets* as control variables, while *M&A last 3Y* remains our study variable as in the previous section. Column (1) is with one-year lead on our dependent variable, while column (4) is with two-year lead. Within those models, M&A is negative and significant in both, -0.077 and -0.084. *LnR&DIntensity* (1.730 and 1.837) is positive and much lower than in the regression with patent counts as a dependent variable. *LnAssets* (0.122 and 0.125) also have a positive influence on innovation outputs. All variables are significant at the 1% level.

Similarly, to the model with patent counts, columns (2) and (5) show results for a model with a more comprehensive set of control variables. Those specifications show a higher, negative and significant coefficient for M&A (-0.086 and -0.092). *LnR&DIntensity* (1.567 and 1.689) keeps the positive influence on innovation outputs, however its explanatory power is lower highlighting the possible presence of omitted variable bias in the more simplistic specifications. *LnAssets* (0.132 and 0.135) gains in power and remains positive. Those key control variables are significant at the 1% level. From the newly introduced controls *PPEAssets* (-0.548 and -0.572) as well as *Leverage* (-0.211 and -0.225) have a negative influence on innovation similar to the results obtained with patents counts. *LnCAPEXIntensity* (2.035 and 2.161) remains positive and significant at the 1% level. There are observable changes to *TobinsQ* (-0.016 and -0.019), which becomes negative as opposed to the regression with patent counts, but still significant at the 1% level, and to *ROA* (0.021 and 0.029), which remains positive, however not significant.

Finally, we introduce firm fixed effects for the reasons previously established. The results are reported in columns (3) and (6). Interestingly, we observe a flip in the M&A coefficient sign (0.031 and 0.024) which becomes positive for both one-year and two-year leads, and significant at the 1% level. This confirms our previous suspicion that time-invariant omitted variables drive our study variable coefficient downward. With this result, we acknowledge the results obtained with our more simplistic specifications must be interpreted cautiously and a greater emphasis should be put on the year and firm fixed effects models when making any conclusions. Furthermore, *LnR&DIntensity* with a coefficient of 0.219 on one-year lead is visibly lower, but still significant at the 1% level, however for two-year lead (0.056) it becomes insignificant, just like in the regression with patent counts. *LnAssets* (0.022 and 0.017) show a lower influence on innovation and stay significant at the 1% level. *PPEAssets* (0.034 and 0.052) becomes insignificant and switches sign to positive. *Leverage* (-0.092 and -0.138) and *LnCAPEXIntensity* (0.257 and 0.238) keep their signs and significance at the 1% level with one-year lead, and at the 5% level in the two-year lead setup. *ROA* (0.073 and 0.032) loses its significance in two-year lead model, while *TobinsQ* (0.005 and 0.005) becomes insignificant in both cases.

R&D has a positive effect on patent citations only within one year, however it is much lower than for patent counts, as with a 10% change in R&D intensity we expect the firm to obtain 2.2% more patent citations the year after. A possible explanation is that when investing in R&D the firm cannot assure the quality of innovation output when the R&D project is concluded. Moreover, usually too many irrelevant innovations are being patented[36] as suggested by Hall and Ziedonis (2001). As a result of their low quality, they achieve a minimal number or no forward citations.

Without controlling for firm fixed effects, M&A has a negative impact on innovation, as measured by patent citations, of -8.6% on patent citations with one-year lead and -9.2% with two-year lead. However, we suspect these results might be driven spurious by unobservable time-invariant omitted variables. Upon introduction of firm fixed effects, we observe a flip in sign of the M&A coefficient, which suggests omitted variables not only bias the coefficient downward but also lead us to biased interpretations. Our most comprehensive specification suggests a 2.4% to 3.1% growth in patent citations, or innovation output quality, following the occurrence of an M&A deal in any of the previous three years. Such results show that M&A, for European listed firms, is rather an additional innovation tool or source, than a key innovation driver. It might be interpreted as a firm's ability to cherry-pick high quality innovation targets either due to complementary technologies, which allow to improve soon-to-be patented projects in the R&D pipeline, or as per Bena and Li (2014), Zhao (2009) or Higgins and Rodriquez (2006) is used as an external source of innovation that substitutes for the lack of internal innovation channels or failed innovative attempts allowing to catch up with the leading industry innovators. The time trend obtained by differences-in-differences analysis, as well as a robustness check on the influence of M&A on R&D intensity, both discussed below, will allow us to get a better view on those interpretations. Moreover, the integration of the target's innovators (i.e. research teams) in the acquirer's knowledge base is also a possibility, which could enrich the quality of innovation in the mid-term. Firm size, profitability and CAPEX intensity also reveal a positive relation with patent citations. On the other hand, leverage shows

[36] This practice is typically referred to as *defensive patenting* (see *Section 3.2.1* for further details).

a negative relation. All control variables' coefficients are consistent with prior literature results adding robustness to our model.

The results and interpretations presented above are in line with *Hypothesis 1*, thus we can accept it and state that M&A have a positive and significant impact on innovation outputs, as measured by patent citations. Further, based on the above, we also reject the *Alternative Hypothesis*.

That also allows us to address the additional *Hypothesis 2*, which is strongly supported by the evidence shown above, as M&A indeed has a positive and significant influence on patent quality. Due to insignificance on patent counts we cannot economically infer any impact on patent quantity, however our robustness tests point towards a negative relation, if any, allowing us to accept *Hypothesis 2*. Theoretically, these findings are supported by the previous literature suggestions as outlined in *Section 3.2.1*. Prior to the acquisition, the acquirer can screen the quality of the target's patent stock and to some extent assess the quality of the R&D projects in the pipeline, depending on the information available during the due diligence process. Hence, acquirers focused on improving their innovation outputs through acquisitions can focus on a specific complementary technology, which can improve the quality of its innovation outputs, and/or on innovators included in the target's human capital base (i.e. cherry-picking ability).

Table 5: Regression Results of Patent Citations on M&A

This table reports regressions of patent citations (with a lead from one to two years) on the occurrence of M&A in the three-year period between *t* and *t-2* and other control variables. The dependent variable, *LnCites*, *is* defined as the natural logarithm of one plus the number of forward citations received in the five years following the patent application year by firm *i*'s granted patents applied for in year *t*. *M&A last 3Y*, the study variable, is a binary indicator for the occurrence of changing control M&A deal for firm *i* in the three years between to *t* and *t-2*. *LnR&DIntensity* is the natural logarithm of R&D expenditures divided by book value of total assets for firm *i* measured at the end of fiscal year *t*. *LnAssets* is the natural logarithm of book value of total assets for firm *i* measured at the end of fiscal year *t*. *Leverage* is defined as book value of debt divided by book value of total assets measured at the end of fiscal year *t*. *ROA* stands for return on assets and is defined as net income divided by book value of total assets for firm *i*, measured at the end of fiscal year *t*. *LnCAPEXIntensity* is the natural logarithm of capital expenditures divided by book value of total assets for firm *i* measured at the end of fiscal year *t*. *PPEAssets* is defined as net property, plant & equipment divided by book value of total assets for firm *i* measured at the end of fiscal year *t*. *TobinsQ* is a market-to-book ratio for firm *i* during fiscal year *t*, calculated as market capitalization divided by book value of total assets. Each regression includes a separate intercept not displayed.

	Dependent variable:					
	LnCites $_{t+1}$			*LnCites* $_{t+2}$		
	(1)	(2)	(3)	(4)	(5)	(6)
M&A last 3Y	-0.077***	-0.086***	0.031***	-0.084***	-0.092***	0.024***
	(0.012)	(0.012)	(0.009)	(0.013)	(0.013)	(0.009)
LnR&DIntensity	1.730***	1.567***	0.219**	1.837***	1.689***	0.056
	(0.091)	(0.105)	(0.109)	(0.100)	(0.115)	(0.119)
LnAssets	0.122***	0.132***	0.022***	0.125***	0.135***	0.017**
	(0.004)	(0.004)	(0.007)	(0.004)	(0.004)	(0.007)
Leverage		-0.211***	-0.092***		-0.225***	-0.138***
		(0.035)	(0.033)		(0.036)	(0.035)
ROA		0.021	0.073***		0.029	0.032
		(0.032)	(0.025)		(0.033)	(0.029)
LnCAPEXIntensity		2.035***	0.257***		2.161***	0.238**
		(0.153)	(0.096)		(0.155)	(0.098)
PPEAssets		-0.548***	0.034		-0.572***	0.052
		(0.030)	(0.039)		(0.031)	(0.044)
TobinsQ		-0.016***	0.005		-0.019***	0.005
		(0.004)	(0.003)		(0.004)	(0.003)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	No	No	Yes	No	No	Yes
No. Firms	1,419	1,419	1,419	1,409	1,409	1,409
Observations	15,672	15,672	15,672	14,713	14,713	14,713
R^2	0.132	0.151	0.744	0.135	0.156	0.747
Adjusted R^2	0.131	0.150	0.718	0.134	0.154	0.720
F Statistic	132.030***	121.080***	28.632***	127.184***	117.693***	27.469***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in the parentheses are the cluster-robust standard errors (clustered at the firm-level).

6.2 Robustness

We conduct a comprehensive number of robustness tests for our baseline hypothesis, as introduced in *Section 5.3*. The results can be found in Table 12 to Table 16 included in the *Appendix*. While analysing the results we only focus on *M&A last 3Y* coefficients as our key study variable.

Firstly, we check whether our results are robust to another proxy for M&A and substitute the *M&A last 3Y* dummy by *Ln(M&A Deal Volume)* in the full model. This measure was also used by Sevilir and Tian (2012). For this setup, we obtain coefficients with the same signs as for *M&A last 3Y*, which are negative for patent counts and positive for patent citations. With *LnPatents* as a dependent variable, *Ln(M&A Deal Volume)* is significant at the 5% level in the two-year lead model, while with *LnCites* it is significant at the 5% level in the one-year lead model. Results (see Table 12 in the *Appendix*) remain robust with the alternative measure of M&A activity, however we must be aware that the coefficient can be biased downward due to the large number of missing deal values (c. 50%). Under this specification, the M&A coefficient reflects the impact on patent counts and citations of an extra currency unit spent on acquisitions. Intuitively, one would expect patent counts not to be materially impacted by larger amounts spent on acquisitions, while the reverse would be expected for citations as acquiring, for example, a better research team could entail a higher acquisition premium. Our results are in line with this reasoning.

Secondly, to address the differences in patenting volumes across the firms, we run our full specification using a dummy for patents as a dependent variable. The obtained coefficients (see Table 13 in the *Appendix*) have similar signs (-0.0001 and -0.010) and remain insignificant as in our baseline model.

Furthermore, to address the possible bias coming from firms that are not heavily reliant on patenting activity, we rerun the regression on a subsample of patent-intensive firms and present the results in Table 14. Those are also robust to this change, as the influence of M&A on patent counts proves to be negative and on patent citations positive.

At this stage, one might highlight that the majority of our robustness checks suggest that, if any, the impact on M&A on patent counts is negative.

Additionally, we regress on R&D as a measure of innovation to check whether the results are robust to different proxies of innovation. As mentioned before, R&D is an innovation input measure, as opposed to patent counts and citations, which are innovation outputs. The M&A coefficient is positive and significant at the 1% level. The results suggest that the R&D intensity of the targets might be superior to the one of acquirers, which could be related to the effect of size as well as higher focus from targets on internal innovation as opposed to acquirers. It is also an argument that supports the proposition of innovation as a rationale for conducting M&A. Moreover, this result provides support to the view that M&A can affect innovation quality without a major change on innovation quantity by affecting internal channels of innovation (e.g. through the integration of more qualified innovators in the acquirer's teams).

Finally, we split our *M&A last 3Y* study variable into three separate dummies – $M\&ADummy_t$, $M\&ADummy_{t-1}$ and $M\&ADummy_{t-2}$ – to test the robustness of our main study variable design and to get a better insight into which time periods have a real influence on innovation outputs. Overall, the results (see Table 16) are robust to the change, as patent counts are insignificant and close to zero, while patent citations are positive and significant for two- and three-year periods. Looking at the results, we might say that one year is not enough for the results of an M&A deal to significantly impact innovation outputs. The effects are visible in two- and three-year periods, where conducting M&A two years ago would yield 2.6% more patent citations today, and conducting M&A three years ago would yield 2.1% more patent citations today. In a four-year period, we do not record a significant influence of M&A on patent citations.

6.3 Cross-Sectional and Subsample Results

As introduced in *Section 3*, we consider the innovation heterogeneity across different European countries and based on their innovation-friendliness split the sample into *Innovative* and *Other Countries* [37]. The results obtained for these cross-sectional regressions are reported in Table 17 and discussed in *Section 6.3.1* and *Section 6.3.2*. Furthermore, we also analyse the results for a subsample of R&D intensive firms, to assess, on a very specific group, whether firms use one or multiple channels of innovation. Results are reported in Table 18 and discussed in *Section 6.3.3*.

6.3.1 Impact of M&A on Patents in Innovative and Other Countries

All results are obtained for the full model, the panel data OLS regression with year and firm fixed effects including the most comprehensive set of control variables, with one-year and two-years leads on innovation outputs. Columns (1) and (2), in Table 17, show results on patent counts for *Innovative Countries*, where *M&A last 3Y* (0.034 and 0.020) is insignificant and *LnR&DIntensity* (0.750) is significant only for the one-year lead model at the 10% level. Same regression results, but for *Other Countries* are reported in columns (3) and (4). *M&A last 3Y (-0.032 and -0.043)* is negative and

[37] *Innovative Countries* for the purpose of this cross-sectional analysis are given by the European countries included in the top 10 of the *Bloomberg 2017 Innovation Index* (i.e. Sweden, Germany, Finland and Denmark). While *Other Countries* include all other countries represented in our sample.

significant at the 10% and 5% levels, respectively. *LnR&DIntensity* (1.128) is significant only for the one-year lead at the 1% level.

There are visible differences between *Innovative* and *Other Countries* when compared using patent counts. Firstly, conducting M&A in *Other Countries* leads to a decline in the number of granted patents one to four years after the M&A activity of 3.2% to 4.3% patents, while it has no significant effect on *Innovative Countries.* Furthermore, R&D intensity is much more important for *Other Countries*, as a 10% growth in R&D intensity leads to c. 11.3% growth in number of patents the year after. For *Innovative Countries,* that increase equals 7.5%. One might conclude that firms from *Other Countries* pursue innovation-driven M&A to a lesser extent, and have greater emphasis in breeding their innovation in-house. Hence, any M&A has more of substitutive role to R&D, making firms forgo long-term investments if they decide to pursue M&A. Another possible explanation to the divergence in results across the two country groups is linked to the industry breakdown within each subsample. While the *Innovative Countries* group has a total of c. 97% of patents in typically patent-intensive industries[38], this number drops to c. 72% in the *Other Countries* group.

6.3.2 Impact of M&A on Citations in Innovative and Other Countries

Columns (5) and (6), in Table 17, present the results on the patent citations regressions for *Innovative Countries*, where the M&A coefficient (0.063 and 0.050) is significant at the 1% level on the one-year lead model and at the 5% level with two-year lead. *LnR&DIntensity* (0.216) is insignificant for both lags. Same regression results, but for *Other Countries*, are shown in columns (7) and (8). *M&A last 3Y* (0.015 and 0.012) is positive and significant at the 10% level only with one-year lead. *LnR&DIntensity* (0.211) is significant only for one-year lead at the 10% level.

The differences between *Innovative* and *Other Countries* are not as large when regressed using patent citations, as compared to the ones measured by patent counts. To begin with, conducting M&A is positive for both subgroups, however stronger for *Innovative Countries*, where conducting M&A leads to an increase in the number of obtained citations one to four years after the M&A transaction of 5.0% to 6.3%, and only 1.5% in *Other Countries.* Furthermore, R&D intensity is very similar for both groups, with 10% growth leading to c. 2.1% growth in number of citations the year after. M&A proves to be a tool for boosting the quality of patents, that possibly allows firms to move towards the market technological frontier, and this relation is stronger for the leading innovators (as per country innovation-friendliness index).

[38] Patent-intensive industries refer to the following NACE classifications: C. Manufacturing and M. Professional scientific and technical activities.

Based on patent citations, we accept *Hypothesis 3a* and claim that M&A has a positive and significant impact on innovation outputs in *Innovative Countries*. The same cannot be said about *Other Countries* where patent citations are positive and patent counts are negative, being both significant. Hence, we reject *Hypothesis 3b* as we cannot claim M&A has a negative and significant impact on innovation outputs in *Other Countries*. We see once again that in Europe there are significant differences between acquiring innovation as per quantity and acquiring high quality innovations. We must mention that the two subsamples were of different size, and the results might be slightly biased. On the other hand, we must also point out that the subgroup of *Innovative Countries* provides the same results as the whole sample results, thus it seems our results are mostly driven by these countries' innovation activities.

6.3.3 R&D Intensive Subsample

The regressions on a subsample of R&D intensive firms, similarly to the countries cross-sectional analysis, were performed with the full model specification, the OLS regression with year and firm fixed effects including all the control variables, with one-year and two-year leads on innovation outputs (see Table 18 in the *Appendix*).

Ex-ante, we set a hypothesis that M&A has a positive and significant impact on innovation outputs for R&D intensive firms, in other words, we assumed that European firms use both innovation channels. When we look at columns (1) and (2), which cover the results for patent counts as a dependent variable, we see that they are negative and insignificant (-0.021 and -0.021). Columns (3) and (4) show results for the regression on patent citations, which are positive and significant for both lags (0.056 and 0.036), meaning that conducting M&A leads to an increase of 3.6% to 5.6% in patent citations between one and four years after the event. The results allow us to accept *Hypothesis 4*, and show that European firms indeed pursue innovation through both channels, internal and external, while M&A serves rather as an additional tool than the key innovation driver.

6.4 The DiD Estimation

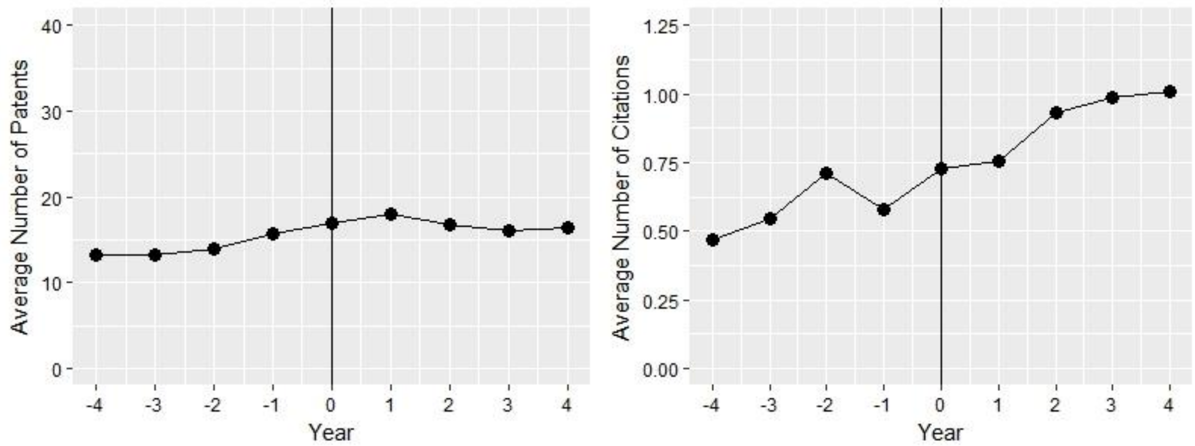
6.4.1 Development of Innovation Activity for Treated Firms

Following the implementation of our identification strategy outlined in *Section 5.5*, we achieve a subsample of 972 firms carrying M&A activities. To analyse the results, we plot the development of our innovation indicators over time for the treatment group for a total of eight consecutive years. As mentioned, our approach is twofold. Firstly, we plot the time series around the occurrence of the first M&A deal. In this section, the focus is on the analysis of the output of this approach (see Figure 5). For robustness, we also create the same plots but instead stack each series of observations multiple times around every deal a firm has completed (see Figure 7).

Figure 5: Innovation Activities Over Time for Treated Firms

The plots below show the development of innovation activities for the treatment group (i.e. firms engaging in M&A activities). The average number of patent counts is shown in A.1 and the average number of patent citation in A.2. Year 0 represents the occurrence of M&A. These plots cover 286 firms which remained active for eight consecutive years during the analysed period and displaying some degree of M&A activity from year 0 and no M&A activity in the four years before.

A.1: Development in Number of Patents **A.2**: Development in Number of Citations



The plots in Figure 5 highlight the impact of M&A on innovation activities in the period before and after the acquisitions for treated firms. Moreover, alongside our regression results, they also shed light on the potential motives behind M&A, as firstly suggested by Sevilir and Tian (2012). If we focus on the period prior to M&A, we observe a slight drop in patent citations a year prior to M&A, whereas patent counts remain relatively stable. The visible trend suggests one of the underlying motives to conduct M&A could rely on a reduction in the perceived quality of the acquirer's innovation outputs in the period prior to the acquisition (i.e. this supports the idea that firms look at M&A as an option to fill the gap created by either a lack of internal innovation activities or unsuccessful ones). Following the drop, we observe a progressive increase in patent citations from the M&A completion year onwards. One must also highlight that since year 0 stands for deal completion year, rather than announcement year, the increase between year -1 and year 0 might already incorporate some of the acquisition's impact, more so if the deal was completed earlier in the year. The observed increase in citations presents M&A as a successful tool to boost innovation outputs, not necessarily in terms of quantity of patents but in quality. Importantly, one must emphasise the different magnitudes of these changes and its relevance in statistical terms. Patents have, by nature, much higher volumes compared to citations, thus the larger fluctuations in absolute numbers. Contrarily, a minor change in the average number of citations can be of much greater statistical and economic relevance as pointed out by our regression analyses. In summa, one must look at the figures bearing in mind the concept of variation.

Once again, we point out the ability of acquirers to cherry-pick among available acquisition targets, choosing those that can mostly improve the quality of their innovation outputs. Moreover, the level of innovation activities either keeps increasing following the deal or remains at a sustained higher level. This aspect turns our discussion to the possible ways an acquisition can impact innovation activities. The sustained higher level of citations following the acquisition hints that the integration of the target's human capital, or in other words target's innovators leads to patents of higher quality after the target integration.

Meanwhile, the flow of patent counts slightly increases after the acquisition, but remains close to 15. As a caution note, we must emphasize that our results are centred around the first deal completed by each firm. We estimate that c. 35% of the firms covered complete an additional acquisition in the year after the first one. Hence, the trend after year 0 is further boosted by consecutive acquisitions. Thus, a marginal increase in patent counts in some instances assumes a multiplication effect when plotted this way, which justifies the slight increase. Nonetheless, this approach ensures that the trend prior to year 0 is not impacted by any significant M&A activity[39]. If this is the case, we would expect the line to look flatter when the analysis is centred around all deals as the period prior to a deal could also be impacted by other acquisitions. At the same time, citations should reflect a smoother continuous increase for the same reasons. These are indeed the results we achieve, as shown in Figure 7 included in the *Appendix*.

6.4.2 Comparison Between Treatment and Control Groups

As discussed in *Section 5.5.2*, we match our treatment group with control cases by recurring to a propensity score. Including both, total assets and R&D intensity as scoring criteria, the 1-to-1 matching produces 496 unique pairs, while the 1-to-3 matching leads to 564 unique pairs covering 1,234 firms. Including only R&D intensity as a score calculation criteria, the 1-to-1 matching produces 490 unique pairs and the 1-to-3 matching 557 unique pairs covering 1,219 firms. In this section, we focus our analysis on the plots presented in Figure 6 based on the 1-to-3 matching with both scoring metrics. We plot the development of patent counts and citations for both, treated and control cases for a total of two years prior to the occurrence of M&A and

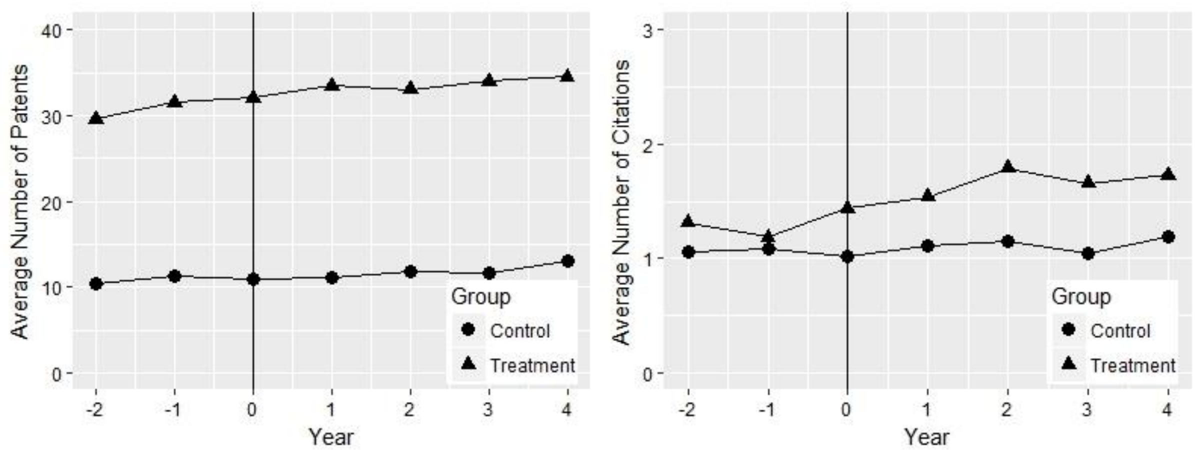
[39] It is important to note that we only consider control-changing acquisitions or asset acquisitions in our analyses. Hypothetically, smaller acquisitions of a minority share or further increases in existing minority holding could also lead to a marginal impact on the level of innovation activities.

four years after. The output of alternative matching versions is included in Figure 8 of the *Appendix*. The conclusions remain largely the same.

Figure 6: The DiD Plot

The plots below show the development of innovation activities in our matched sample. Treatment group is shown with triangles and control group with circles. Year 0 represents the occurrence of M&A. Treatment control cases are matched based on a propensity score calculated using total assets and R&D intensity as matching criteria. Both plots reflect a 1-to-3 matching and include 564 unique pairs covering 1,234 firms. The plots show the development of patent counts (see A.1) and patent citations (see A.2), two years prior to the occurrence of an M&A transaction for the treated firm and four years following the transaction.

A.1: Development in Number of Patents **A.2**: Development in Number of Citations



Due to sample size restrictions, we were unable to match all treated cases with control cases with satisfactory propensity scores. We acknowledge that matched treated firms have a higher average patent number than when looking at the whole treatment group (see Figure 5). Nevertheless, the comparison remains interesting in terms of the development post-M&A for treated and control cases and the plots provide a clear visualisation of the results achieved through our regression analysis. When analysing the pattern in patent counts, the DiD plot suggests a flat development of the average number of patents for treatment and control group. This conclusion goes in line with our OLS regression findings using patent counts as a dependent variable. More interestingly, looking at patent citations we observe a much greater divergence between the averages for treatment and control groups, especially after the M&A occurrence. Our findings suggest that firms engaging in M&A have a similar level of patent citations in the periods immediately prior to M&A, yet in the period following the completion of the acquisition they distant themselves from the level observed for the control group. Also, one must note that the observed increase seems to start already one period prior to year 0. This could be due to timing differences in terms of deal completion date across the year generating some time spillover effects in our analysis. These findings strongly support our prior acceptance of *Hypothesis 2* suggesting that M&A activities lead to improved innovation outputs for the acquiring firms.

7 Limitations and Future Research

We are aware of the limitations and possible extensions to our research. In this section, we list the main ones and discuss them, lining the ground for future research, particularly the one with a European focus. Further, we also briefly discuss the potential practical applications of our results in *Section 7.1*.

Due to the novelty of our dataset, we face a limited number of firms within our sample compared to the samples obtained for the U.S. market. That could potentially lead to biased results as we expect the firms with a bigger patent stock to be matched with financial identifiers before other firms. However, this remains a suspicion and cannot be tested statistically. Increased accuracy and coverage in databases matching patent data with financial identifiers could lead to more robust results in the future. Additionally, constrained by the truncated data, we conduct the research on a period that ended more than five years ago, while it would be interesting to see how corporate innovation strategies changed in more recent years that remains a drawback of using patent data. Finally, our sample size is further lowered by missing R&D values, as not all the European countries had mandatory R&D reporting between 1995 and 2010.

As described in *Section 4.1.3*, there are several ways to deal with truncations. By using our approach and accounting only for citations for five years after patent application date, we have disregarded a large amount of data. There is a possibility, depending on data availability, to use one of the other mentioned approaches, including projecting forward citations based on historical data as per Jaffe and Trajtenberg (1996), or scaling citations within the technology class and year it belongs to as proposed by Hall, Jaffe and Trajtenberg (2001). Getting more data would give a more precise view on the discussed topic and probably strengthen the coefficients, however we do not believe it would affect the direction in which M&A influences innovation as measured by patent citations.

As for possible extensions, firstly, we do not cover an important distinction on characteristics of the M&A deal – technological vs non-technological. Data limitations did not allow us to incorporate such distinction, which could shed more light on the differences between those acquisitions. Technological acquisitions were several times shown by researchers (Cloodt et al., 2006 or Ahuja and Katila, 2001) to be more significant than non-technological when it comes to positive impact on innovation outputs and that could strengthen the coefficients. Furthermore, having more information on targets would allow to estimate the size of their knowledge base, as well as potentially check the changes to research teams and elaborate on acquiring human capital. Hence, further investigating acquisition targets' characteristics could boost the general understanding of M&A and innovation dynamics in Europe.

There would be a possibility to implement additional control variables including market share and institutional ownership. Market share would allow to differentiate between mergers and acquisitions and observe how do they affect innovation within a certain industry prior and post the event. Whereas, by introducing data on institutional ownership, one could evaluate whether it is correlated with higher R&D expenditures and lower innovation-driven M&A, or vice-versa.

We also acknowledge two possible extensions of the dataset, which would allow for testing hypotheses comparing the U.S. market to the European one, as well as innovation strategies of private firms as compared to public firms. The first extension would involve adding U.S. firms and patents to the dataset and the second would involve adding private firms to the sample.

It would also be interesting to look at the price performance following the analysed deals, which goes beyond the scope of our research. In addition to technological and non-technological deals, analysing the differences in price performance of firms involved in the covered deals would allow to understand how these deals affect post-acquisition returns, and whether innovation-driven M&A are favourably priced by the market.

7.1 Practical Application

Results of our research can be used not only by academics and researchers, but also by practitioners and executives. We deem our findings useful within the scope of work conducted by financial advisors. Our research proves the usability of patent data as a form to assess the innovation outputs produced by different firms. Hence, financial advisors can leverage on our results, by preparing more informed add-on assessments for clients, where one of the used characteristics could be the possible complementarity of innovation activities, as well as the quality of past innovation outputs produced by potential targets. They could also include a new bidding rationale behind M&A, providing their clients with more likely value-creating opportunities.

Furthermore, the results can be used also by institutional owners (e.g. PE firms). We highlight the capability created by M&A to boost innovation quality, something that would likely be a lengthier process if attempted merely through internal R&D processes. If we combine that with the typical holding period of PE-owned firms, we advocate acquisitions, particularly add-on acquisitions, could be an effective tool to faster achieve certain innovation targets established for portfolio companies. In addition, by knowing what acquirers are looking for in an innovation-driven acquisition process, institutional owners could better position their portfolio firms for an exit through a sale to a strategic player.

8 Conclusion

In this thesis, we analysed the impact of M&A on innovation from a European perspective, based on a panel of 1,419 listed firms, displaying some degree of patenting activity from a wide-range of industries. Our study spans from 1995 to 2010, including two European M&A peaks and lows, as well as two financial and economic crises, hence it is deemed as balanced.

Research using patent data remains challenging despite its prolonged availability, especially when focusing on European data. Thus, we compared all the available, to our best knowledge, matches between patent applicants and financial identifiers, for European firms, including our own. We then chose the one yielding the biggest sample with lowest possible matching mistake rate, besides allowing us to use the latest available data.

We follow the methods widely used in the literature, implementing a two-way fixed effects OLS regression with patent counts and patent citations as dependent variables. In addition, we use a differences-in-differences identification strategy to compare the development of innovation activities over time based on the degree of M&A activity conducted by different European firms. We further introduce a new way of measuring the study variable, by suggesting a three-year time dummy, when accounting for M&A, which proves robust to other traditional measures. Further, we expand the truncation correction method suggested by Lerner et al. (2011) and account for the first five years of citations, instead of three, following a patent's application year. With this approach, we cover more data and capture the average peak in citations achieved by a certain patent, thus reducing the bias of our results.

We find a positive relation between M&A and innovation outputs, when measured with patent citations and no significant results when using patent counts. Yet, two of our robustness tests, first using M&A volume as a study variable and, second on a subsample of patent-intensive firms, suggest a negative and significant coefficient for M&A. Hence, if any, there is a negative influence of M&A on patent flows. Furthermore, we observe a positive influence of M&A on R&D intensity, which shows that M&A activity is not incompatible with R&D. In fact, our results suggest firms achieve innovation through both channels.

Moreover, we find that the targets are rather small, as the average target size in our sample is 7.5% to 13.1% of the acquirer's size[40], thus we can assume those are more likely add-on acquisitions than mergers of equals. These findings are further supported by the DiD analysis. Our visuals suggest a potential decline in the perceived quality of

[40] Measured as deal value divided by acquirer's total assets.

innovation outputs of the acquirer prior to M&A could be one of the motives to engage in M&A as suggested by Bena and Li (2014).

Combining all the above, we suggest that the positive impact of M&A on innovation quality arises from acquisitions of relatively small targets with seemingly complementary technologies, which enable the acquirers to enhance the outcome of their current projects, and produce patents of a higher quality in the future. Furthermore, the mid-term growth in innovation quality might be obtained through the integration of the target's research teams in the acquirer's R&D processes. The results are more pronounced for the subsamples of patent-intensive firms and innovative countries. Whereas growth in patent counts following the acquisition would seem intuitive if we would think of a typical merger of equals, it unsurprisingly does not occur in our sample. On a simple example, one could say the integration of the target's research capabilities into the acquirer's knowledge base generates one patent of a better quality, rather than two patents of a lower quality, leaving patent flows following the acquisition unchanged or lower.

These findings partly diverge from the most recent results reported in a U.S. context, where a positive relationship is suggested, not only between M&A and innovation quality, but also between M&A and innovation quantity in the post-acquisition period. However, one must point out that innovation dynamics are different in Europe compared to the U.S. Hence, European firms seem to use M&A more as an additional channel to boost innovation, possibly a tool focused on complementary technologies, rather than a key innovation driver. Moreover, R&D intensity is much higher in Europe, and as per our sample, and it has a positive relation with M&A. That is also different from the results reported for U.S. firms.

Today, due to the data restrictions, we can only assess whether M&A conducted by European firms led to innovation improvements between 1995 and 2010. However, bearing in mind, the continuously changing economic and financial landscape, regulatory changes within the European Union, as well as the newly introduced initiatives to boost innovation in the region, it would be interesting to conduct a similar research in a few years' time.

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Appendix

Table 6: Extended Literature Results

This table reports the results found by related literature about the impact of M&A on post-acquisition innovation activities. The table is segmented based on the measure used for innovation. We refer to literature using R&D, patent counts and patent citations based metrics.

					Patent-based			Citations-based			R&D-based		
Authors	**Year**	**Region**	**Industry**	**Database[41]**	**Positive**	**Neutral**	**Negative**	**Positive**	**Neutral**	**Negative**	**Positive**	**Neutral**	**Negative**
Entezarkheir, Moshiri	2016	U.S.	Manufacturing	NBER				x					
Haucap, Stiebale	2016	Germany	Pharmaceutical	PATSTAT			x			x			x
Bena, Li	2014	U.S.	-	PATSTAT	x			x					
Szucs	2014	International	-	-									x
Sevilir, Tian	2012	U.S.	-	NBER	x			x					
Stahl	2010	U.S.	-	NBER						x			
Ganturum, Stephan	2007	International	-	NBER	x						x		
Hagedoorn, Duysters	2006	International	-	USPTO	x						x		
Cloodt et al.	2006	International	High-Tech	NBER			x						
Bertand, Zuniga	2006	OECD	-	-								x	
Ahuja, Katila	2001	International	Chemical	NBER		x							
Hall et al.	1999	U.S.	Semiconductors	-								x	
Hitt et al.	1991	U.S.	-	USPTO			x						x
Hall et al.	1990	U.S.	Manufacturing	-									x
Ravenscraft, Scherer	1987	U.S.	-	-									x
				Total	**4**	**1**	**3**	**3**	**0**	**2**	**2**	**2**	**5**

[41] Database or source.

Table 7: Variable Definitions

The table below presents the definitions of all variables used in this paper. Variables are segmented based on data type and the data source is provided for each of the data sources. For summary statistics on Financial Variables see Table 3.

Variable	Definition
Innovation Variables (Source: Amadeus Patent Database and PATSTAT Autumn 2016)	
$Patents_{i,t}$	Number of patents filed (and eventually granted) by firm i in year t
$Cites_{i,t}$	Number of forward citations received in the five years following the patent application year by firm i's granted patents applied for in year t
$LnPatents_{i,t}$	Natural logarithm of one plus $Patents_{i,t}$
$PatentDummy_{i,t}$	Binary indicator for the grant of at least a patent to firm i year t
$LnCites_{i,t}$	Natural logarithm of one plus $Cites_{i,t}$
M&A Variables (Source: SDC Platinum Database)	
M&A last 3Y $_{i,t}$	Binary indicator for the occurrence of changing control M&A deal for firm i in the three years between to t and t-2
M&ADummy $_{t}$	Binary indicator for the occurrence of changing control M&A deal for firm i in year t
LnM&AVol last 3Y $_{i,t}$	Natural logarithm of total deal volume for firm i in the three years between t and t-2
Financial Variables (Source: Datastream, Amadeus and Compustat)	
R&DIntensity $_{i,t}$	Research and development (R&D) expenditures divided by book value of total assets for firm i measured at the end of fiscal year t
$CAPEXIntensity_{i,t}$	Capital expenditures divided by book value of total assets for firm i measured at the end of fiscal year t
LnR&DIntensity $_{i,t}$	Natural logarithm of *R&DIntensity* $_{i,t}$
$LnCAPEXIntensity_{i,t}$	Natural logarithm of $CAPEXIntensity_{i,t}$
$Assets_{i,t}$	Book value of total assets for firm i measured at the end of fiscal year t
$LnAssets_{i,t}$	Natural logarithm of $Assets_{i,t}$
$Leverage_{i,t}$	Leverage ratio for firm i, defined as book value of debt divided by book value of total assets measured at the end of fiscal year t
$ROA_{i,t}$	Return on assets ratio defined as net income divided by book value of total assets for firm i, measured at the end of fiscal year t
$PPEAssets_{i,t}$	Net property, plant & equipment divided by book value of total assets for firm i measured at the end of fiscal year t
$TobinsQ_{i,t}$	Market-to-book ratio for firm i during fiscal year t, calculated as market capitalization divided by book value of total assets

Table 8: Correlation Matrix

This table reports correlation coefficients between all variables employed in our baseline analysis. All variables are defined in Table 7. The correlation coefficients are calculated based on the full dataset of 17,551 firm-year observations covering 1,419 firms between 1995 and 2010.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LnPatents	(1)	1.00									
LnCites	(2)	0.67	1.00								
M&Alast3Y	(3)	0.09	0.04	1.00							
LnR&DIntensity	(4)	0.14	0.04	-0.12	1.00						
LnAssets	(5)	0.46	0.33	0.29	-0.23	1.00					
Leverage	(6)	0.00	0.01	0.12	-0.20	0.27	1.00				
ROA	(7)	0.09	0.07	0.13	-0.42	0.31	-0.01	1.00			
LnCAPEXIntensity	(8)	0.05	0.07	0.02	-0.10	0.08	0.10	0.14	1.00		
PPEAssets	(9)	-0.02	-0.01	0.02	-0.25	0.26	0.29	0.15	0.52	1.00	
TobinsQ	(10)	0.02	-0.04	-0.09	0.40	-0.27	-0.27	-0.17	0.03	-0.20	1.00

Table 9: No. Firms, Patents, Citations and M&A Transactions per Country

This table provides a breakdown of the number of firms, patent counts, patent citations and M&A deals on a country basis, for all countries covered in our sample. The number of citations reported in this table are the truncation-corrected ones (for details on the original number of citations refer to Table 7). These statistics are computed based on the full sample of 17,551 firm-year observations.

Country	No. Firms	No. Patents	No. Citations	No. M&A Deals
Austria	38	3,463	454	221
Belgium	38	10,091	346	180
Bulgaria	2	21	1	4
Croatia	1	2	0	0
Czech Republic	5	74	0	0
Denmark	49	7,700	299	147
Estonia	1	1	0	0
Finland	70	32,165	738	614
France	223	109,560	3,591	1,039
Germany	245	147,034	37,328	628
Greece	6	36	2	12
Hungary	7	872	3	31
Ireland	20	3,447	332	183
Italy	85	7,328	137	222
Latvia	4	17	0	2
Lithuania	1	2	0	1
Luxembourg	5	177	17	8
Netherlands	47	47,668	1,954	459
Poland	53	508	12	54
Portugal	9	17	0	18
Romania	6	32	0	1
Slovakia	1	11	0	0
Slovenia	5	268	1	10
Spain	61	2,277	90	320
Sweden	126	36,547	1,871	832
United Kingdom	311	42,551	1,571	2,001
TOTAL	1,419	451,869	48,747	6,987

Table 10: No. Firms, Patents and Citations per NACE Industry Classification

This table provides a breakdown of the number of firms, patent counts and patent citations per NACE Industry Classification. We use NACE Rev. 2 Statistical Classification of Economic Activities in the European Community compiled and published by the Eurostat. The number of citations reported in this table are the truncation-corrected ones (for details on the original number of citations refer to Table 2). These statistics are computed based on the full sample of 17,551 firm-year observations.

NACE Group	No. Firms	No. Patents	No. Citations
A. Agriculture forestry and fishing	3	106	3
B. Mining and quarrying	17	6,549	101
C. Manufacturing	583	225,463	36,527
D. Electricity gas steam and air conditioning supply	17	1,479	78
E. Water supply; sewerage waste management and remediation activities	14	168	11
F. Construction	38	1,167	86
G. Wholesale and retail trade; repair of motor vehicles and motorcycles	90	6,107	300
H. Transportation and storage	19	583	111
I. Accommodation and food service activities	6	102	0
J. Information and communication	83	10,359	247
K. Financial and insurance activities	107	40,642	1,078
L. Real estate activities	12	138	6
M. Professional scientific and technical activities	381	156,753	10,141
N. Administrative and support service activities	29	1,965	57
O. Public administration and defence; compulsory social security	4	214	0
P. Education	1	10	0
Q. Human health and social work activities	4	24	0
R. Arts entertainment and recreation	4	7	0
S. Other service activities	7	33	1
TOTAL	1,419	451,869	48,747

Table 11: No. Patents and Citations per Company – Top 10

This table provides an overview of the number of patents and patent citations per company for the 10 firms with the highest number of patents in our sample of 1,419 companies. The number of patents refer to granted patents between 1995 and 2010 for each mentioned company. The number of citations reported in this table is corrected for truncation.

	Company	No. Patents	No. Citations
1	Siemens AG	41,755	16,053
2	Nokia Oyj	23,740	429
3	BASF SE	23,463	548
4	Koninklijke Philips NV	18,724	425
5	L'Oreal SA	15,691	409
6	Telefonaktiebolaget LM Ericsson	14,338	192
7	Peugeot SA	14,223	1,085
8	Renault SA	9,074	151
9	Daimler AG	8,185	5,222
10	Unilever NV	8,170	181
TOTAL		177,363	24,695

Table 12: Regression Results of Innovation Outputs on M&A Deals Volume

This table reports regressions of innovation outputs (with a lead from one to two years) on the occurrence of M&A in the three-year period between *t* and *t-2* and other control variables. The dependent variables are: *LnPatents* defined as the natural logarithm of one plus firm *i*'s total number of patents filed (and eventually granted) in year *t+1* and *LnCites* defined as the natural logarithm of one plus the number of forward citations received in the five years following the patent application year by firm *i*'s granted patents applied for in year *t*. The study variable, *LnM&A Vol last 3Y*, is defined as a natural logarithm of total deal volume for firm *i* in the three years between *t* and *t-2.* Definitions of control variables are in Table 7. Each regression includes a separate intercept not displayed.

	Dependent variable:			
	LnPatents $_{t+1}$	*LnPatents* $_{t+2}$	*LnCites* $_{t+1}$	*LnCites* $_{t+2}$
	(1)	(2)	(3)	(4)
LnM&A Vol last 3Y	-0.002	-0.004**	0.002**	0.002
	(0.002)	(0.002)	(0.001)	(0.001)
LnR&DIntensity	1.020***	0.420	0.225**	0.061
	(0.265)	(0.279)	(0.109)	(0.119)
LnAssets	0.100***	0.084***	0.022***	0.018**
	(0.013)	(0.014)	(0.007)	(0.008)
Leverage	-0.209***	-0.139**	-0.092***	-0.138***
	(0.059)	(0.061)	(0.033)	(0.035)
ROA	0.161***	0.154**	0.073***	0.033
	(0.060)	(0.067)	(0.025)	(0.029)
LnCAPEXIntensity	0.487***	0.522***	0.263***	0.243**
	(0.175)	(0.186)	(0.096)	(0.098)
PPEAssets	-0.029	-0.075	0.035	0.053
	(0.078)	(0.084)	(0.039)	(0.044)
TobinsQ	0.009	0.015**	0.005	0.004
	(0.006)	(0.006)	(0.003)	(0.003)
Year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
No. Firms	1,419	1,409	1,419	1,409
Observations	15,672	14,713	15,672	14,713
R^2	0.858	0.863	0.743	0.747
Adjusted R^2	0.843	0.848	0.717	0.720
F Statistic	59.519***	58.435***	28.620***	27.458***
Note:	***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in the parentheses are the cluster-robust standard errors (clustered at the firm-level).			

Table 13: Regression Results of Patent Dummy on M&A

This table reports regressions of the innovation output, measured by a patent dummy (with a lead from one to two years) on the occurrence of M&A in the three-year period between *t* and *t-2* and other control variables. The dependant variable, *Patent Dummy* is defined as a binary indicator for the grant of at least a patent to firm *i* year *t+1. M&Alast3Y*, the study variable, is a binary indicator for the occurrence of changing control M&A deal for firm *i* in the three years between to *t* and *t-2.* Definitions of control variables are in Table 7. Each regression includes a separate intercept not displayed.

	Dependent variable:					
	Patent Dummy $_{t+1}$			*Patent Dummy* $_{t+2}$		
	(1)	(2)	(3)	(4)	(5)	(6)
M&A last 3Y	-0.025***	-0.033***	-0.0001	-0.029***	-0.037***	-0.010
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
LnR&DIntensity	1.776***	1.699***	0.351***	1.817***	1.767***	0.278**
	(0.073)	(0.084)	(0.128)	(0.077)	(0.089)	(0.136)
LnAssets	0.071***	0.075***	0.035***	0.071***	0.075***	0.026***
	(0.002)	(0.002)	(0.007)	(0.002)	(0.002)	(0.008)
Leverage		-0.052**	-0.026		-0.028	0.015
		(0.026)	(0.034)		(0.027)	(0.035)
ROA		0.201***	0.080**		0.244***	0.094**
		(0.030)	(0.034)		(0.032)	(0.037)
LnCAPEXIntensity		0.774***	0.142		0.922***	0.326***
		(0.108)	(0.108)		(0.109)	(0.117)
PPEAssets		-0.300***	-0.112**		-0.334***	-0.125**
		(0.025)	(0.045)		(0.026)	(0.049)
TobinsQ		0.009***	0.004		0.009***	0.008**
		(0.003)	(0.003)		(0.003)	(0.003)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	No	No	Yes	No	No	Yes
No. Firms	1,419	1,419	1,419	1,409	1,409	1,409
Observations	15,672	15,672	15,672	14,713	14,713	14,713
R^2	0.110	0.125	0.536	0.111	0.128	0.550
Adjusted R^2	0.109	0.123	0.490	0.110	0.127	0.502
F Statistic	107.387***	96.919***	11.430***	101.608***	94.046***	11.354***
Note:	***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in the parentheses are the cluster-robust standard errors (clustered at the firm-level).					

Table 14: Regression Results – Subsample of Patent-Intensive Firms

This table reports regressions of the innovation outputs (with a lead from one to two years) on the occurrence of M&A in the three-year period between *t* and *t-2* and other control variables, performed on a subsample of Patent-Intensive firms (own three or more patents). The dependent variables are: *LnPatents* defined as a natural logarithm of one plus firm *i*'s total number of patents filed (and eventually granted) in year *t+1* and *LnCites* defined as the natural logarithm of one plus the number of forward citations received in the five years following the patent application year by firm *i*'s granted patents applied for in year *t*. *M&Alast3Y*, the study variable, is a binary indicator for the occurrence of changing control M&A deal for firm *i* in the three years between to *t* and *t-2*. Definitions of control variables are in Table 7. Each regression includes a separate intercept not displayed.

	Dependent variable:			
	LnPatents t+1	*LnPatents t+2*	*LnCites t+1*	*LnCites t+2*
	(1)	(2)	(3)	(4)
M&A last 3Y	-0.024	-0.030*	0.033***	0.025**
	(0.017)	(0.018)	(0.010)	(0.011)
LnR&DIntensity	1.317***	0.576*	0.270**	0.074
	(0.302)	(0.314)	(0.126)	(0.136)
LnAssets	0.132***	0.106***	0.031***	0.024**
	(0.018)	(0.019)	(0.010)	(0.010)
Leverage	-0.289***	-0.203***	-0.114***	-0.173***
	(0.074)	(0.077)	(0.043)	(0.045)
ROA	0.225***	0.210***	0.090***	0.042
	(0.074)	(0.082)	(0.032)	(0.036)
LnCAPEXIntensity	0.531**	0.564**	0.332***	0.305**
	(0.222)	(0.231)	(0.123)	(0.124)
PPEAssets	-0.020	-0.053	0.043	0.073
	(0.104)	(0.110)	(0.052)	(0.058)
TobinsQ	0.010	0.016**	0.005	0.005
	(0.007)	(0.007)	(0.003)	(0.004)
Year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
No. Firms	1,100	1,098	1,100	1,098
Observations	12,715	12,008	12,715	12,008
R2	0.843	0.849	0.738	0.742
Adjusted R2	0.828	0.833	0.713	0.715
F Statistic	55.466***	54.513***	29.106***	27.899***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in the parentheses are the cluster-robust standard errors (clustered at the firm-level).

Table 15: Regression Results of R&D Intensity on M&A

This table reports regressions of the innovation input in *t*, *t+1* and *t+2* (R&D intensity) on the occurrence of M&A in the three-year period between *t* and *t-2* and other control variables. *LnR&DIntensity* is defined as the natural logarithm of research and development (R&D) expenditures divided by book value of total assets for firm *i* measured at the end of fiscal year *t*. *M&Alast3Y*, the study variable, is a binary indicator for the occurrence of changing control M&A deal for firm *i* in the three years between to *t* and *t-2.* Definitions of control variables are in Table 7. Each regression includes a separate intercept not displayed.

	Dependent variable:		
	LnR&DIntensity $_t$	*LnR&DIntensity* $_{t+1}$	*LnR&DIntensity* $_{t+2}$
	(1)	(2)	(3)
M&A last 3Y	0.001***	0.001**	0.001
	(0.0005)	(0.001)	(0.001)
LnAssets	-0.007***	-0.002***	0.0005
	(0.001)	(0.001)	(0.001)
Leverage	-0.010***	-0.018***	-0.019***
	(0.003)	(0.003)	(0.003)
ROA	-0.066***	-0.039***	-0.031***
	(0.005)	(0.005)	(0.005)
LnCAPEXIntensity	0.006	-0.001	-0.006
	(0.007)	(0.007)	(0.007)
PPEAssets	0.013***	0.006*	0.002
	(0.003)	(0.003)	(0.003)
TobinsQ	0.002***	0.001	0.001*
	(0.0004)	(0.0004)	(0.0005)
Year FEs	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes
No. Firms	1419	1419	1409
Observations	17,551	16,132	14,713
R^2	0.822	0.829	0.840
Adjusted R^2	0.806	0.812	0.822
F Statistic	51.529***	49.269***	48.585***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in the parentheses are the cluster-robust standard errors (clustered at the firm-level).

Table 16: Regression Results of Innovation Outputs on M&A Dummies

This table reports regressions of the innovation outcome, measured by patent counts and patent citations (with a lead from one to two years), on the occurrence of M&A in the three-year period between *t* and *t-2,* measured separately by a yearly M&A dummy reflecting the occurrence of an M&A deal for each firm. The dependent variables are: *LnPatents* defined as the natural logarithm of one plus firm *i*'s total number of patents filed (and eventually granted) in year *t+1* and *LnCites* defined as the natural logarithm of one plus the number of forward citations received in the five years following the patent application year by firm *i*'s granted patents applied for in year *t*. The study variable, *M&ADummy* is defined as a binary indicator for the occurrence of changing control M&A deal for firm *i* in year *t*. Definitions of control variables are in Table 7. Each regression includes a separate intercept not displayed.

	Dependent variable:							
	LnPatents $_{t+1}$	*LnPatents* $_{t+2}$			*LnCites* $_{t+1}$	*LnCites* $_{t+2}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
M&ADummy $_t$	0.009	-0.007			0.015	0.026***		
	(0.014)	(0.015)			(0.009)	(0.009)		
M&ADummy $_{t-1}$			0.008				0.021**	
			(0.015)				(0.010)	
M&ADummy $_{t-2}$				-0.016				0.003
				(0.016)				(0.010)
LnR&DIntensity	1.018***	0.418	0.446	0.481	0.226**	0.061	-0.070	-0.056
	(0.266)	(0.279)	(0.303)	(0.325)	(0.109)	(0.119)	(0.131)	(0.147)
LnAssets	0.096***	0.079***	0.080***	0.083***	0.025***	0.019**	0.017**	0.022**
	(0.013)	(0.014)	(0.015)	(0.016)	(0.007)	(0.007)	(0.008)	(0.009)
Leverage	-0.213***	-0.146**	-0.155**	-0.161**	-0.088***	-0.136***	-0.127***	-0.120***
	(0.058)	(0.061)	(0.065)	(0.069)	(0.033)	(0.035)	(0.038)	(0.039)
ROA	0.161***	0.157**	0.138**	0.122*	0.070***	0.029	0.012	0.010
	(0.060)	(0.067)	(0.070)	(0.074)	(0.025)	(0.029)	(0.031)	(0.033)
LnCAPEXIntensity	0.477***	0.513***	0.447**	0.328	0.263***	0.235**	0.202*	0.249**
	(0.175)	(0.186)	(0.199)	(0.213)	(0.096)	(0.098)	(0.106)	(0.122)
PPEAssets	-0.023	-0.066	0.045	0.058	0.031	0.053	0.075*	0.061
	(0.078)	(0.084)	(0.092)	(0.097)	(0.039)	(0.044)	(0.045)	(0.047)
TobinsQ	0.009	0.015**	0.020***	0.028***	0.005	0.004	0.004	0.003
	(0.006)	(0.006)	(0.007)	(0.008)	(0.003)	(0.003)	(0.003)	(0.004)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Firms	1,419	1,409	1,375	1,296	1,419	1,409	1,375	1,296
Observations	15,672	14,713	13,304	11,929	15,672	14,713	13,304	11,929
R^2	0.858	0.863	0.870	0.876	0.743	0.747	0.754	0.760
Adjusted R^2	0.843	0.848	0.854	0.861	0.717	0.720	0.725	0.730
F Statistic	59.513***	58.405***	56.917***	57.144***	28.608***	27.472***	26.172***	25.559***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in the parentheses are the cluster-robust standard errors (clustered at the firm-level).

Table 17: Regression Results – Geographical Cross-Sectional Analysis

This table reports regressions of the innovation outcome, measured by patent counts and patent citations (with a lead from one to two years) on the occurrence of M&A in the three-year period between *t* and *t-2* and other control variables, performed on a two subsample, Innovative Countries and Other Countries. The dependent variables are: *LnPatents* defined as the natural logarithm of one plus firm *i*'s total number of patents filed (and eventually granted) in year *t+1* and *LnCites* defined as the natural logarithm of one plus the number of forward citations received in the five years following the patent application year by firm *i*'s granted patents applied for in year *t*. *M&Alast3Y*, the study variable, is a binary indicator for the occurrence of changing control M&A deal for firm *i* in the three years between to *t* and *t-2*. Definitions of control variables are in Table 7. Each regression includes a separate intercept not displayed.

	Dependent variable:							
	Innovative Countries		*Other Countries*		*Innovative Countries*		*Other Countries*	
	LnPatents *t+1*	*LnPatents* *t+2*	*LnPatents* *t+1*	*LnPatents* *t+2*	*LnCites* *t+1*	*LnCites* *t+2*	*LnCites* *t+1*	*LnCites* *t+2*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
M&A last 3Y	0.034	0.020	-0.032*	-0.043**	0.063***	0.050**	0.015*	0.012
	(0.027)	(0.027)	(0.017)	(0.018)	(0.020)	(0.020)	(0.009)	(0.009)
LnR&DIntensity	0.750*	0.302	1.128***	0.410	0.216	0.010	0.211*	0.074
	(0.401)	(0.433)	(0.352)	(0.364)	(0.199)	(0.216)	(0.119)	(0.133)
LnAssets	0.098***	0.091***	0.107***	0.082***	0.015	0.002	0.025***	0.025***
	(0.023)	(0.026)	(0.017)	(0.017)	(0.016)	(0.017)	(0.007)	(0.008)
Leverage	-0.333***	-0.266***	-0.139*	-0.065	-0.084	-0.231***	-0.083**	-0.082**
	(0.099)	(0.102)	(0.073)	(0.076)	(0.070)	(0.073)	(0.035)	(0.037)
ROA	0.137	0.200**	0.186**	0.138	0.114**	0.087	0.047*	0.008
	(0.099)	(0.100)	(0.075)	(0.089)	(0.048)	(0.062)	(0.028)	(0.026)
LnCAPEXIntensity	0.934***	0.853***	0.188	0.275	0.618***	0.386**	0.026	0.135
	(0.265)	(0.289)	(0.235)	(0.244)	(0.193)	(0.185)	(0.089)	(0.103)
PPEAssets	-0.393***	-0.495***	0.169*	0.171	-0.120	-0.065	0.120***	0.121**
	(0.129)	(0.135)	(0.098)	(0.108)	(0.079)	(0.081)	(0.042)	(0.050)
TobinsQ	-0.023**	-0.006	0.027***	0.025***	0.012*	0.005	0.002	0.004
	(0.011)	(0.011)	(0.008)	(0.008)	(0.006)	(0.006)	(0.003)	(0.003)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Firms	490	484	929	925	490	484	929	925
Observations	5,465	5,113	10,207	9,600	5,465	5,113	10,207	9,600
R^2	0.876	0.881	0.845	0.850	0.769	0.774	0.680	0.683
Adjusted R^2	0.863	0.868	0.830	0.834	0.745	0.749	0.647	0.649
F Statistic	68.267***	67.626***	53.224***	51.975***	32.152***	31.114***	20.685***	19.710***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in the parentheses are the cluster-robust standard errors (clustered at the firm-level).

Table 18: Regression Results – Subsample of R&D-Intensive Firms

This table reports regressions of the innovation outputs (with a lead from one to two years) on the occurrence of M&A in the three-year period between *t* and *t-2* and other control variables, performed on a subsample of R&D-Intensive firms (R&D intensity above the full sample median). The dependent variables are: *LnPatents* defined as a natural logarithm of one plus firm *i*'s total number of patents filed (and eventually granted) in year *t+1* and *LnCites* defined as the natural logarithm of one plus the number of forward citations received in the five years following the patent application year by firm *i*'s granted patents applied for in year *t*. *M&Alast3Y*, the study variable, is a binary indicator for the occurrence of changing control M&A deal for firm *i* in the three years between to *t* and *t-2.* Definitions of control variables are in Table 7. Each regression includes a separate intercept not displayed.

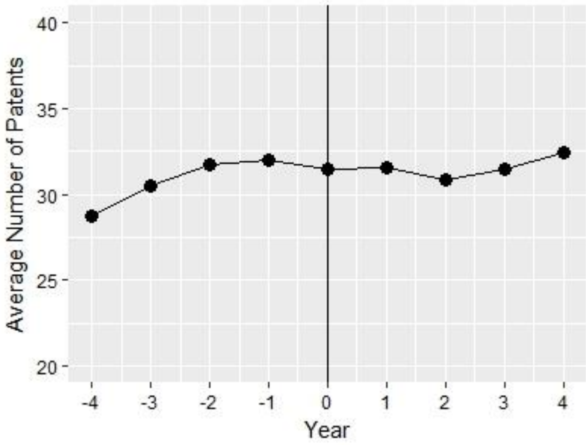
	Dependent variable:			
	LnPatents $_{t+1}$	*LnPatents* $_{t+2}$	*LnCites* $_{t+1}$	*LnCites* $_{t+2}$
	(1)	(2)	(3)	(4)
M&A last 3Y	-0.021	-0.021	0.056***	0.036**
	(0.022)	(0.023)	(0.014)	(0.015)
LnR&DIntensity	1.320***	0.596*	0.430***	0.211
	(0.302)	(0.316)	(0.134)	(0.144)
LnAssets	0.148***	0.095***	0.042***	0.025*
	(0.023)	(0.025)	(0.013)	(0.013)
Leverage	-0.489***	-0.400***	-0.103*	-0.161***
	(0.093)	(0.098)	(0.058)	(0.062)
ROA	0.254***	0.272***	0.140***	0.086**
	(0.085)	(0.093)	(0.036)	(0.044)
LnCAPEXIntensity	0.978***	0.711**	0.360**	0.358**
	(0.303)	(0.320)	(0.171)	(0.181)
PPEAssets	0.231	0.281*	0.075	0.069
	(0.148)	(0.155)	(0.085)	(0.092)
TobinsQ	0.020**	0.018**	0.007*	0.007
	(0.008)	(0.008)	(0.004)	(0.004)
Year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
No. Firms	709	705	709	705
Observations	7,892	7,425	7,892	7,425
R^2	0.871	0.875	0.767	0.769
Adjusted R^2	0.858	0.861	0.743	0.744
F Statistic	66.151***	64.266***	32.229***	30.646***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The numbers in the parentheses are the cluster-robust standard errors (clustered at the firm-level).

Figure 7: Innovation Activities Over Time for Treated Firms – Robustness

The plots below show the development of innovation activities for the treatment group (i.e. firms engaging in M&A activities). The average number of patent counts is shown in A.1 and the average number of patent citation in A.2. Year 0 represents the occurrence of M&A. These plots cover all 972 firms displaying some degree of M&A activity in year 0, despite conducting other acquisitions in the years before and after year 0.

A.1: Development in Number of Patents



A.2: Development in Number of Citations

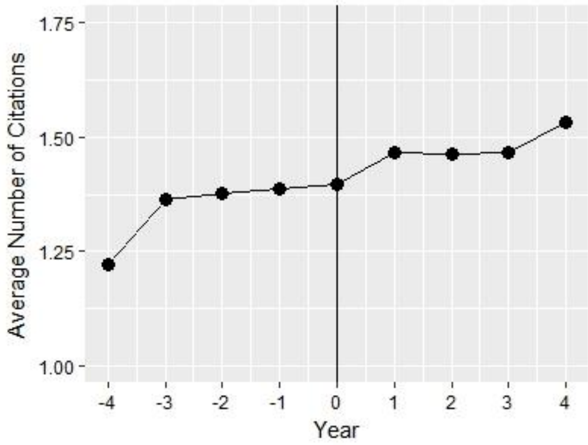
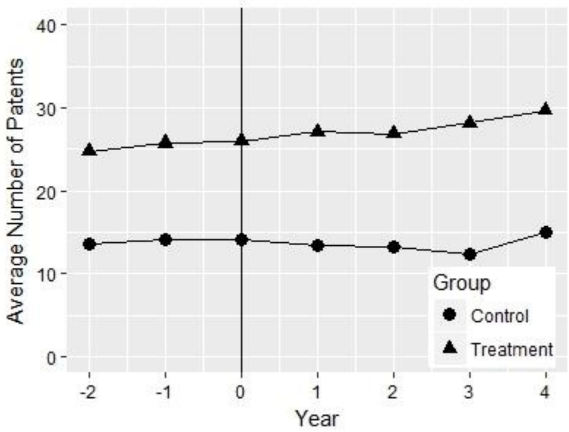


Figure 8: The DiD Plot – Robustness

The plots below show the development of innovation activities in our matched sample. Treatment group is shown with triangles and control group with circles. Year 0 represents the occurrence of M&A. Treatment can control cases are matched based on a propensity score calculated using R&D intensity and total assets as matching criteria and a 1-to-1 matching in Panel A, R&D intensity as matching criteria and a 1-to-3 matching in Panel B and R&D intensity as matching criteria and a 1-to-1 matching in Panel C. Version 1 of each panel shows the development of patent counts and version 2 shows the development of patent citations, two years prior to the occurrence of an M&A transaction for the treated firm and four years following the transaction. Panel A, B and C report 496, 557 and 490 unique pairs, respectively.

<u>Panel A</u>: 1-to-1 matching based on propensity scores using R&D intensity and total assets

A.1: Development in Number of Patents



A.2: Development in Number of Citations

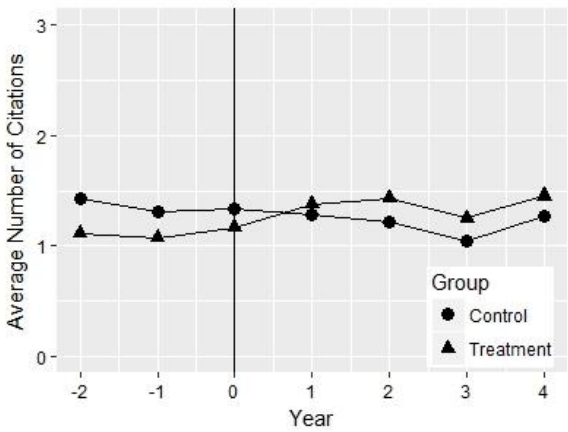
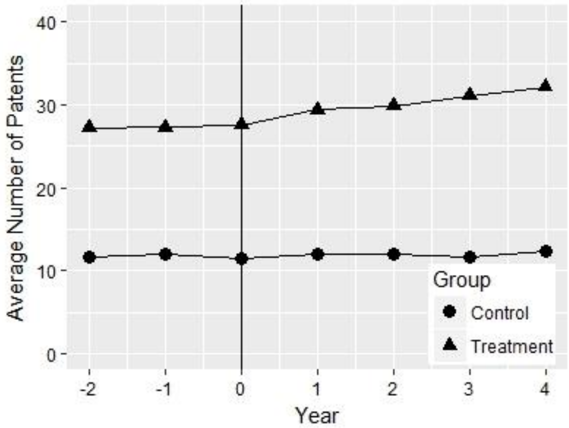


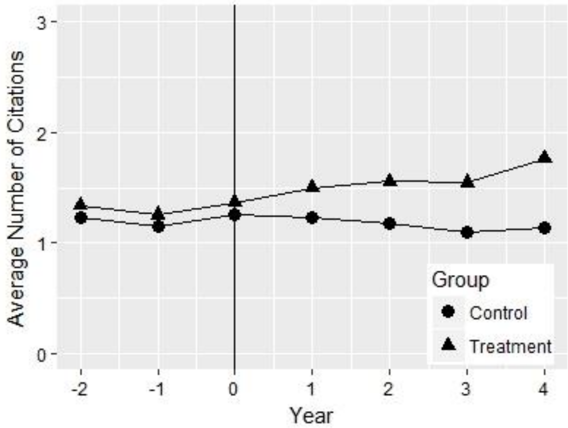
Figure 8: The DiD Plot – Robustness *(continued)*

Panel B: 1-to-3 matching based on propensity scores using R&D intensity

B.1: Development in Number of Patents

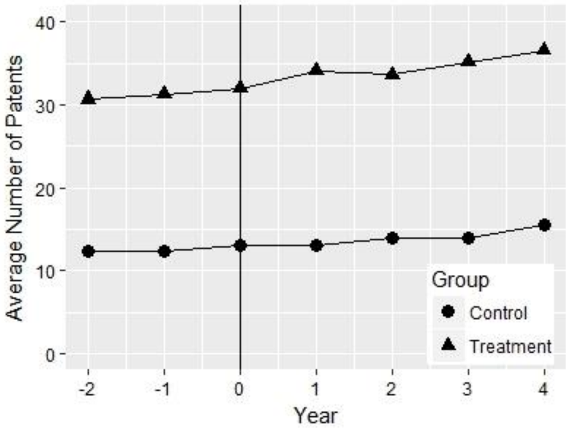


B.2: Development in Number of Citations



Panel C: 1-to-1 matching based on propensity scores using R&D intensity

C.1: Development in Number of Patents



C.2: Development in Number of Citations