MERGING MINDS

EXAMINING THE IMPACT OF M&A ON CORPORATE INNOVATION

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Abstract

This study examines the impact of M&A on corporate innovation for U.S. public acquirers in the period 2010-2023. Using a panel dataset where we combine financial, patent and M&A data, we assess changes in innovation input (R&D intensity), innovation output (patent counts and citations), and innovation productivity (patents per dollar R&D), following acquisitions. Employing OLS regressions, we find M&A to have a negative insignificant impact on innovation inputs, particularly among R&D intensive and high-tech acquirers. On the contrary, we observe that M&A has a positive and statistically significant impact on innovation output, as evidenced by an increase in patent and citation counts in the years following M&A. The observed effects on innovation productivity are inconclusive, reflecting signs of the complexity of post-M&A integration and knowledge absorption. The findings of this study contribute to the existing body of research in the area by offering a contemporary view on the innovative capabilities of acquirers in the modern M&A landscape, suggesting a successful integration of organizational capabilities to yield innovation success in respect to output, while simultaneously strengthening the notion of M&A's non-linear effect on innovation input and productivity.

Keywords:

M&A, Corporate Innovation, Research and Development, Patents, Innovation Productivity

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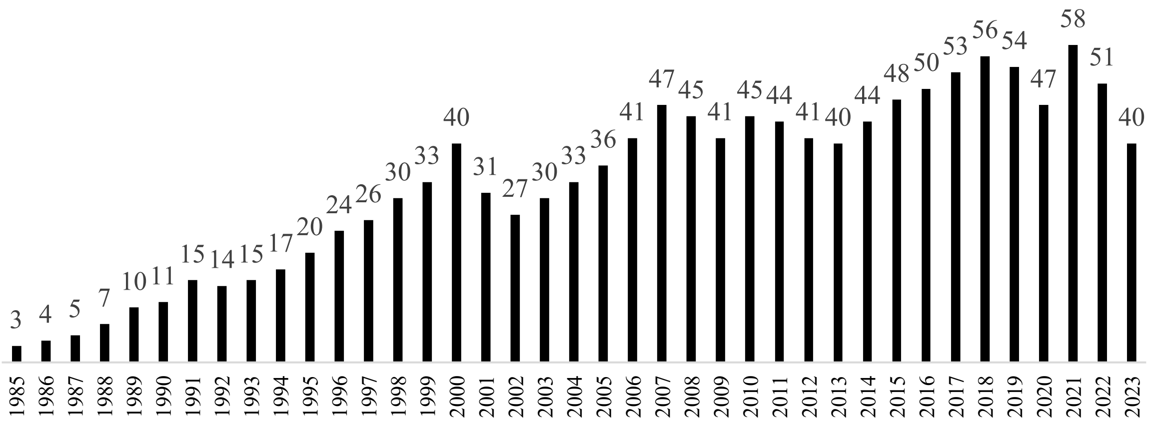
1. Introduction

Technological innovation is widely recognized as a cornerstone of long-term economic growth, based on Schumpeterian theory, where innovation drives productivity gains and structural transformation (Schumpeter, 1912). In further classical and endogenous growth theory, accumulating knowledge and developing novel production processes are central to explaining cross-country productivity differences and firm-level competitive advantages (Aghion and Howitt, 1992; Romer, 1990). The private sector plays a central role in conducting R&D, as it serves as a vital engine of technological innovation, producing spillovers that yield substantial benefits for society, as firms are seen as the engine of innovation (Schumpeter, 1912). However, innovation does not arise in isolation. It is shaped and constrained by the firm's governance structure, capital composition, operational efficiency, and overarching strategic direction, positioning it as an integral component of corporate strategy.

In this context, firms must decide whether to pursue innovation by internal development, i.e. through internal R&D, or externally acquired via M&A. M&A provides a strategic pathway to acquire knowledge, market access or technological capabilities in an efficient manner. As noted by Ikeda and Doi (1983), firms engage in M&A to increase market share, improve efficiencies through synergies, achieve growth, and ultimately enhance technological capabilities, or a combination of both.

Importantly, M&A activity itself has been argued to not occur at random, rather, M&A is commonly expressed in terms of waves throughout history, where such waves occur in consequence of specific market conditions, most prominently by negative demand shocks. Mitchell and Mulherin (1996) argue that mergers and acquisitions tend to occur in clusters, primarily triggered by structural transformations such as innovation and deregulation. They emphasize that M&A waves are not solely the result of firm-specific developments, but are also shaped by broader macroeconomic forces, including technological change. The visual development of M&A waves, in sheer transaction quantity, is shown in Graph 1, while characteristics and time-periods for each wave are shown in Table 1.

Graph 1: Number of global M&A transactions per year (in thousands) (1985-2023)



Note: The graph shows the number of M&A transactions per year (1985-2023), in thousands. (Institute for Mergers, Acquisitions and Alliances, 2025)

Table 1. Overview of Historical M&A Waves

Period	Wave	Characteristics
1893-1904	First Wave	Horizontal mergers
1919-1929	Second Wave	Vertical mergers
1955-1970	Third Wave	Diversified conglomerate mergers
1974-1989	Fourth Wave	Co-generic mergers; Hostile takeovers; Corporate Raiding
1993-2000	Fifth Wave	Cross-border mergers, mega mergers
2003-2008	Sixth Wave	Globalization, Shareholder Activism, Private Equity
2014-	Seventh Wave	Horizontal mergers of Western Companies, SPAC Mergers, Increased technological development

Note: The table shows the historical M&A waves throughout history (1893-today) and its characteristics. (Martynova and Renneboog, 2008)

Building on this foundation, this study aims to investigate how acquiring firms' innovation performance is affected following M&A transactions. Given that innovation serves as a fundamental driver of both societal advancement and economic growth, we analyze its role by examining innovation inputs and outputs, as well as a composite measure of innovation efficiency that evaluates the relationship between these measures, for the acquirers solely.

Within the field of M&A and corporate innovation, prior literature is extensive, though mixed in terms of scope, research design, and results. Some study the intersection (M&A and corporate innovation) through the lens of innovation inputs (R&D Intensity), whereas others study innovation output (Patents and Citations), and some have assessed them both in conjunction. In terms of innovation inputs, findings are divergent. Several researchers find a negative relationship between M&A and subsequent innovation-input levels, partially attributable to a conflicting increase in focus on short-term benefits as well as the process of commercializing the acquired knowledge, as opposed to investing further in operating expenditures (Hitt et al., 1991, 1996; Szücs, 2014). On the contrary, other studies find that acquiring firms tend to increase their R&D efforts post-M&A, particularly prominent when the targets possess weak technological capabilities or that the acquirer wish to continue building on prior innovation success (Cefis, 2010; Gantumur and Stephan, 2010, 2012). For outputs, the evidence leans more consistently toward a positive relationship between M&A, and patent and citation count. Emphasizing that M&A may allow firms to achieve synergies through integrating complementary capabilities (Bena and Li, 2014; Hagedoorn and Duysters, 2002). Other studies, however, identify a negative relationship, frequently attributing this outcome to disruption of organizational processes and organizational inertia following M&A (Cassiman et al., 2005; Cloodt et al., 2006; Haucap et al., 2019). What becomes evident is that prior literature offers no consensus on the topic, arguing for substantial context dependencies. Moreover, since much of the existing work is set in earlier periods, under market and technological conditions that are substantially different compared to today's rapidly evolving market landscape, there is a growing need for an updated study on the effects of M&A on innovation performance. Such a study would capture the influence of M&A, in a contemporary setting, characterized by increased complexity, globalization, and heightened competition in technological positioning. Accordingly, this paper seeks to contribute to the existing literature in three distinct ways, with a particular focus on areas that have thus far received limited attention.

Firstly, this study compiles a modern dataset in a new competitive landscape, covering the period 2010-2023. A key driver of M&A activity, which is commonly agreed upon in the extant literature, is synergies in terms of both revenues and costs. However, there is little direct evidence of whether, and how, synergies in the technology space drive firms' individual decisions to participate in M&A (Bena and Li, 2014). This mainly stems from previous literature with older datasets, often ending in 2010, failing to capture the seventh wave of M&A and the impact of the last decade's technological development, renewal of accounting standards and the competitive environment. From 2010 to today, society has experienced significant technological development with a shifting focus from technological hardware to software, data-driven services, and intangible assets more broadly, making research on M&A's impact on innovation increasingly relevant.

Secondly, this study analyzes innovation inputs (R&D investments) and outputs (patents) both independently and jointly, thereby contributing to a literature that has traditionally examined these dimensions in isolation, or in parallel, but rarely in an integrated manner. Inspired by studies such as Desyllas and Hughes (2010), we seek to contribute to past literature by looking at both sides of the innovation spectrum as well as joint measures, proxying for efficiency by incorporating the two.

Thirdly, this study seeks to enrich the existing body of evidence by offering additional insights in terms of results, acknowledging that prior research has produced a range of findings, both positive and negative, regarding the impact of M&A on acquirers' innovation performance (as summarized in Table 2). Given the lack of consensus and evolving environment, this study may offer valuable new insights to the academic discussion. Additionally, as a large proportion of the existing body of research within the topic is in strategic management journals, we seek to contribute to the existing gap in accounting and finance literature, where evidence on the impact of M&A on corporate innovation is scarce.

This paper proceeds as follows. Section 2 reviews the relevant literature and develops our hypotheses. Section 3 outlines the data collection and sample construction process. In Section 4, we present the empirical methodology, define key variables, and provide descriptive statistics. Section 5 reports the results of the effect of M&A activity on acquirers' innovation, including our main specifications and further robustness tests, followed by a discussion of the implications in relation to our hypotheses and prior research, in Section 6. We conclude in Section 7, and provide limitations and suggestions for future research in Section 8.

2. Literature and Theory

2.1. Literature Review

This section is structured as follows. Firstly we assess past literature relating to corporate innovation (see section 2.1.1. Corporate Innovation), we proceed by studying prior literature in M&A (see section 2.1.2. Mergers & Acquisitions), and conclusively we review the body of literature situated in the intersection of M&A, and corporate innovation, specifically focusing on studies that examine how M&A activity influences firms' innovation performance (see section 2.1.3. M&A and Corporate Innovation).

2.1.1. Corporate Innovation

Innovation has become an increasingly defining element in modern corporate strategies, more evidently so given the extent of digital technologies, such as AI, reshaping traditional business models and daily operations. Babina et al. (2024) highlight this shift in a cross-sector empirical study on AI adoption. Their results highlight a significant increase in AI investments across sectors where the firm adopting it, in turn, experiences higher growth in sales, employment, and market valuations. The authors witness that these growth factors are mainly attributable to product innovation. These results are more significant across larger firms in highly competitive industries. The results emphasize that new technologies like AI have the potential to contribute to growth and highly successful firms through innovations, suggesting that innovation is a catalyst for growth and a key response to external market pressures, an effect which is likely to continue to rise over time. This finding raises broader questions about how firms obtain and apply the knowledge necessary to drive such innovation. Grant (1996) offers a useful lens, through the knowledge-based view of a firm, focusing on knowledge integration as opposed to knowledge creation, arguing that firms serve as institutions for integrating and applying specialized knowledge, rather than merely creating it. By emphasizing the knowledge-based view, the author highlights coordination mechanisms that enable firms to leverage individual expertise, shape organizational design, and establish firm boundaries. Highlighting how firms apply knowledge to enhance capabilities, this perspective underscores the strategic role of innovation in maintaining competitiveness and adapting to evolving management practices. This view substantiates the notion that in today's high-tech context, the ability to incorporate technology-related capabilities is becoming a hygiene factor for competitive participation.

Yet, this pursuit of further innovation is highly complex. As noted by Haucap et al. (2019), R&D is a fundamental driver of competitive advantage and economic growth. High R&D intensity (defined as R&D expenses normalized to sales, or assets) is naturally a more pronounced characteristic of technology-intensive industries. Firms invest in R&D to develop new sets of products as well as improve processes. However, R&D outcomes are inherently uncertain, a point emphasized by (Cloodt et al., 2006). The processes are noisy and significantly influenced by firm-specific factors such as existing knowledge base, size, prior experience, and external factors such as competition and technological opportunities. This complexity fuels a long-standing debate on the relationship between competition and innovation. Aghion et al. (2005) argue that the effect of competition on innovation can be ambiguous, on the one hand, intense rivalry in a high-substitutable market may force firms to innovate to ensure survival, firms in less competitive (or even monopolistic) environments may innovate due to their greater resource slack. The duality of this phenomenon suggests that innovation strategies may differ across industries but are nonetheless shaped by the surrounding competitive environment. Building on this, Hitt et al. (1998) further suggests that globalization and technological change have made strategic flexibility a necessity. Developing strategic flexibility is essential to cope with rising competitive pressures, and innovation then becomes a mechanism for adaptability. This implies that firms must build dynamic capabilities, leverage new technologies, and adopt learning-oriented structures to sustain a competitive advantage. Consequently, competition catalyzes innovation, pushing firms to adapt and evolve, which would imply that firms, by different means, try to either internally develop or externally acquire innovative capabilities. In sum, a firm's capacity to innovate constitutes a critical determinant of its sustained success and thus, serves as a fundamental driver of shareholder value.

In this context, establishing a link between R&D investments and subsequent innovation outcomes becomes especially relevant. Pakes and Griliches (1980) provide evidence, confirming a link between R&D spending and innovative output, proxied by patent count. Their study of 121 U.S. firms over eight years finds that patent counts serve as a reliable indicator of inventive activity, particularly in cross-sectional comparisons. They estimate that a long-term increase in R&D spending leads to a proportional rise in patenting. While the relationship is weaker at the individual firm level due to randomness in innovation timing and patenting decisions, the findings suggest that sustained R&D investment contributes to firm growth, profitability, and market value. However, how firms would translate this investment into capability varies significantly. Where some rely on organic development, others pursue M&A in order to absorb external knowledge. Regardless, the growing role of sourcing for external innovation serve as implications to a broader shift to ecosystems of innovation where firms do not innovate in isolation, but rather use strategic acquisitions and integration of knowledge-intensive firms to cope with rising competition across industries. The dual strategy of internal development and external sourcing essentially becomes a necessity to maintain a sustainable competitive edge.

2.1.2. Mergers and Acquisitions

In light of this shift toward external innovation sourcing, M&A activity has been proven to occur in waves, spurred by outside factors such as globalization, technological shifts, and financial market dynamics (Cefis and Triguero, 2016). Qiu and Zhou (2007) discuss the concept where mergers occur in waves, due to specific market conditions, most prominently negative demand shocks, which in turn, triggers a wave of M&A across sectors as companies tend to follow their competitors. These waves often exhibit a sense of synchronicity, unfolding over time with similar thematic patterns and shared structural characteristics. Much of the evidence obtained from contemporary market research suggests that there is currently a new wave which is about to commence, looking at positive market sentiment and growing extent of mega-deals, defined as deals where the deal value is greater than USD 1 billion (Levy, 2025).

Andrade and Strafford (2004) contributed to the research on M&A, as they investigated the economic role of M&A. They distinguish between expansionary mergers, which add assets and capacity, and contractionary mergers, which facilitate industry consolidation. Through this, they compare M&A activity to internal corporate investments. They find that mergers have two distinct roles: (1) expansionary M&A occurs in growth industries with high profitability and capacity utilization, and (2) contractionary M&A helps industries rationalize excess capacity in times of economic prosperity, and high growth. Additionally, they find that M&A and internal investment serve different roles. When capacity is near peak, firms prefer internal investment, while excess capacity leads to M&A-driven consolidation. Ultimately, the study highlights capacity utilization as a key determinant for M&A, and shows that M&A is driven both by growth opportunities and industry pressures, rather than just firm-level financials. Ahuja and Katila (2001) contribute to the discussion by providing additional nuance to the M&A drivers, which include: i) increasing market share, ii) improving efficiency, iii) accelerating growth, and iv) enhancing technological capabilities. The fourth point has gained less attention in prior literature, but is growing increasingly relevant in today, given the fast-evolving technological evolution. However, synergies are broadly researched and acknowledged as key drivers of M&A, both in terms of revenues, but also costs. Despite the extensive research on the topic of synergies, there remains limited amount of direct evidence regarding how, and to what extent, synergies within the technology landscape influence firms' decisions to engage in M&A (Bena and Li, 2014). From a theoretical perspective there are contrasting views on the topic, where the resource-based theory view M&A as a way to acquire valuable resources and capabilities that otherwise are difficult to obtain. Organization learning theory suggests that acquisitions enable knowledge transfer where the acquiring firm can internalize external expertise (Teece, 1986). In contrast, agency theory posits that managers may initiate acquisitions to advance personal interests, rather than to enhance firm performance and thus, serve in the shareholders' best interest (Ikeda and Doi, 1983; Morck et al., 1990). Overall, such theories provide useful frameworks to understand how M&A works as a means to extend internal capabilities in the modern context. One such interpretation could thus be that the prevalence of M&A could be argued to increase, from the perspective of the resource-based view, where the technology is growing ever more complex and difficult to internally develop to meet the standards of the competitive landscape.

2.1.3. M&A and Corporate Innovation

The effects of M&A on innovation have been widely studied in previous literature, focusing on various areas of explanations, though with positive and negative outcomes. Cassiman et al (2005) explain the effect of M&A on corporate innovation by referring to factors of technology- and market-relatedness; studies focusing on scale and scope economies argue for efficiencies stemming from M&A activity (Henderson and Cockburn, 1996); cultural, size-related, and other organizational differences as key determinants of post-acquisition innovation outcomes, as the strategic and organizational fit between acquirer and target plays a critical role in the impact of M&A activity on acquirers' corporate innovation (Ahuja and Katila, 2001; Chakrabarti et al., 1994; Ernst and Vitt, 2000; Hagedoorn and Duysters, 2002; Seth, 1990); integration of acquired firm technology post-acquisition (Ahuja and Katila, 2001; Cloodt et al., 2006). Hence, Transaction Cost Economics, Resource Based and Knowledge-Based Views, Agency theory and perspectives from Financial Economics form multiple theoretical frameworks that may explain how M&A activities influence innovation. A key determinant in most prior studies, is the acquiror's absorptive capacity of external acquired knowledge, which Cohen and Levinthal (1989, 1990) define as a firm's ability to recognize the value of new, external information, and assimilate it. Fundamentally they argue that absorptive capacity is related to prior knowledge, as it relates to recognition: identifying valuable external knowledge, assimilation: understanding and processing such knowledge, and application: leveraging it to improve products. Thus, R&D serves as a dual purpose: it produces innovation but also enhances absorptive capacity which is key in successfully integrating externally acquired knowledge. Drawing on these theoretical foundations, the literature examining the impact of M&A on corporate innovation typically follows one of three approaches: it focuses either on innovation inputs (R&D expenditure), on innovation outputs (patenting activity), or on both in parallel, though still treated separately, finding both positive and negative effects. Studies that integrate innovation input and outputs into a unified measure of innovation productivity remain limited, and also them with ambiguous findings.

Parts of the research focusing on the effect of acquisitions on R&D expenses find a negative relationship between the two. One explanation of the negative relationship between R&D intensity (R&D expenses / sales raito), is a de-emphasis of financial controls, implying less internal innovation as firms seeks short-term benefits (Hitt et al., 1991, 1996). Further, Cefis and Triguero (2016) separate in-house and external R&D post-acquisition, in the Spanish manufacturing sector, and find that the negative impact of M&A on innovation, is on average more negative on external R&D, due to rationing of R&D capacity, but still negative for internal in-house R&D to a lesser extent. Separating the effect on acquiror and target, Szücs (2014), for a European sample, also found that R&D decreased post-merger for both type of firms as acquirers, opposed to expanding R&D efforts, commercializes the acquired innovative efforts, thus explaining the decrease in R&D intensity through a sharp increase in sales. In line with this, but contrary to conventional expectations that innovation capabilities are drivers of acquisition success, Ochirova and Dranev (2021), find that it may in fact undermine post-M&A efficiency through a technology substitution effect, wherein internally developed innovation-efforts are crowded out by external technological acquisitions, resulting in the observed negative relationship.

Other studies, on the contrary, find both neutral and positive effects of M&A on innovation input performance, as proxied by R&D. Hall (1987; 1990) finds that R&D spending did not decrease following acquisitions, as R&D spending in fact remained in line pre-merger R&D-performance. However, the R&D which was acquired, was valued more highly at the margin by the firms which take it over, potentially indicating that mainly successful innovations are taken over in acquisitions, in which acquiring firms generated larger gains. Cefis (2010) finds that M&A has a positive and significant impact on innovation investments, in particular focusing on R&D intensity and total expenditure on innovation. However, the post-M&A phase favors in-house R&D, versus externally acquired technologies, as firms invest more heavily in internal R&D in the post-acquisition phase. Further, the author finds that M&A has a 3-5 year impact period on the acquirer's total innovation expenditure, indicating a longer horizon compared to the horizon chosen in extant literature. In line with this, Gantumur and Stephan (2010, 2012) further observe a positive relationship between M&A and R&D, which is found to be driven by both prior success of in-house R&D, and from weakness of technological capabilities in acquiring firms prior to the deal, as scale and scope in R&D strengthens both firms' innovation capabilities. Building on this, Bertrand (2009) identifies a strong increase in R&D post-acquisition, stemming from a greater innovation budget, applying both to internal and external R&D expenditures. A less clear relationship is found by Miller (1990), who through an interview-based study finds some R&D cutbacks following takeovers, in other cases he finds a positive result, indicating that M&A's impact on R&D is not a single simple matter to predict. However, he deems the impact to be substantial in terms of effect, and level, but overall, M&A's impact is deemed neutral, in line with Ikeda and Doi (1983). In line with this, looking at the pharmaceutical industry, Danzon et al. (2005), find that initial innovation in early product development phases is positively affected by acquisitions, however, in later stages that involve more complexity, the effect diminishes and turns negative, indicating a varying effect based on firm and project maturity. Partly in line with this Healy et al. (1992), find that merged firms experience significant improvement in productivity, higher operating cash flow, and maintained Capex and R&D rates, post-merger, indicating that firms do not reduce their long-term investments as a result of M&A, concluding the various results of papers observing M&A activity's impact on innovation output.

Similar to the literature that examines innovation input in isolation, studies focusing solely on innovation output, typically proxied by patent counts and citation data, report mixed results in terms of direction, magnitude, and statistical significance, although the overall evidence tends to suggest a negative relationship. Some studies find that technological acquisitions may entail a disruption in organizational routines and other factors, resulting in decreased innovation performance post-acquisitions, thus reducing R&D efforts and patenting output (Cassiman et al., 2005; Cloodt et al., 2006; Haucap et al., 2019; Hitt et al., 1991; Stahl, 2010). Adopting a broad industry perspective, Haucap et al. (2019) demonstrate that M&A activity not only affects the innovation performance of the merging firms but also exerts negative spillover effects on competitors, leading to a general decline in both innovation output and R&D expenditures across the industry, consistent with the notion that reduced competition suppresses sector-wide innovative effort. Taking a firm-level perspective, Hitt et al. (1996) find that both innovation input and output decline following acquisitions, a pattern they attribute to agency theory, whereby managerial commitment to internal innovation diminishes, ultimately fostering an increasing reliance on externally sourced innovation. In contrast, a positive relationship for post-acquisition innovation performance, proxied by patents and citations, is found by Bena and Li (2014), who suggest that acquirers produce more patents in the post-M&A period, referring to the synergies of combining innovation capabilities as a key determinant of this effect, in line with Hagedoorn and Duysters (2002), and Gantumur and Stephan (2010). Thus, in line with aforementioned theories, the acquirer's innovation output can improve, by economies of scale and scope in research, and through enhancement of inventive and complementary combinations (Fleming, 2001; Henderson and Cockburn, 1996). A non-uniform, but overall neutral, relationship is found by Ahuja and Katila (2001), as non-technological acquisitions (i.e., acquisitions whose primary aim is not transfer technology) do not have a significant impact on subsequent innovation output, while in technological acquisitions' knowledge base, and relative size of acquired knowledge base, has a positive and negative impact, respectively, on innovation output, respectively, proving that accounting for characteristics of acquisitions is important when determining the impact of M&A on innovation performance.

Several studies measure the impact of M&A on R&D input and output separately and in parallel, as a scarce area in the previous literature is those that simultaneously study the impact of innovation performance in terms of input, output and further combining them into productivity-related measures. Desyllas and Hughes (2010) sample U.S. high-technology firms, over a 3-year post-acquisition window and studies the impact of acquisition on R&D intensity (R&D expenses/assets) and R&D productivity (successful patent applications/R&D expenditure), to find positive R&D-intensity changes, but insignificant R&D productivity changes. However, upon distinguishing between related and unrelated firms, they find that related acquisitions exhibit a positive relationship between acquisitions and R&D productivity as the absorptive capacity is enhanced, as opposed to unrelated acquisitions where the relationship becomes increasingly negative. By controlling for endogeneity and deal-specific effects, in line with prior literature, the authors find that acquirer-specific characteristics significantly shape the impact of M&A on post-acquisition innovation performance.

Overall, there is no single narrative regarding the effect of M&A on innovation, and previous literature highlights many contradicting views, results, and conclusions. Pharmaceutical mergers, for instance, imply R&D decline due to reduced competition (Cloodt et al., 2006), whereas high technology acquisitions experience temporary R&D dips, followed by rebounds (Desyllas and Hughes, 2010; Haucap et al., 2019), highlighting the effect of heterogeneity across deals and moderating factors.

Said heterogeneity, and its interplay with the effect of acquisition on innovation performance, making it contingent on external factors is a common ground for most previous literature. Hagendoorn and Duysters (2002) find that overall organizational and strategic fit, including related product markets, between the firms involved in the transaction, is what significantly affects the post-acquisition innovation performance. Further, in addition to the realized positive significant growth in R&D performance post-M&A, they find that the firm size of targets and acquirers showcases a positive impact on the R&D performance, indicating that the prevalence of larger firms positively influences the R&D performance. Moreover, Phillips and Zhdanov (2013) show that smaller firms are more likely to become acquisition targets, while larger firms predominantly act as acquirers, suggesting that the observed positive relationship between firm size and acquirer status may naturally arise from underlying industry dynamics, as larger firms primary acquire external M&A. Lee and Lieberman (2010) take an overarching perspective and argue that firms are likely to use internal development if targets possess resources and technologies close to their own. In contrast, they acquire the knowledge externally if the target possesses distinct resources from own knowledge and technology base.

In line with the observed societal technological development, Cassiman et al. (2005) argue that technology-relatedness and market-relatedness between the target and acquirer are core determinants of the effect. Similarly, Ahuja and Katila (2001) find that technological acquisitions boost innovations, however, contingent upon that the acquired knowledge base is not too large, relative to the acquirer's own pre-acquisition base. Additionally, the authors show that knowledge base relatedness has a nonlinear effect, with where acquisitions of firms with high levels of relatedness and unrelatedness both prove inferior to acquisition of firms with modest levels of relatedness, within technological acquisitions. In contrast, non-technological acquisition shows no significant impact on innovation. Cloodt et al. (2006) present a similar take, separating on what is argued to be high-tech and low-tech industries, finding that non-technological firms witness a negative effect from acquisitions on the firm's innovation output, while technological firms only witness a positive effect in the initial years. These results highlight the complexity of post-merger knowledge assimilation, emphasizing that successful innovation outcomes depend on the size and compatibility of acquired technological assets and organizations. A further explanation of this is found by Hitt et al. (1996) as they argue that organizational learning opportunities expand when firms acquire diverse technological capabilities, fostering knowledge integration and innovation, meaning that effective utilization of external knowledge is crucial for enhancing post-M&A innovation performance. Important to have in mind are Ornaghi's (2009) findings, showing that firms with higher innovation levels and technological similarities are more likely to engage in mergers, indicating that the improved R&D performance from technological relatedness in prior literature, might be due to successful pre-acquisition innovation in the acquirer, and overrepresentation of such firms in technology-driven M&A transactions. Overall, the literature, despite various directions, agrees that heterogeneity in deals is important to examine, when studying interplay between firm characteristics, technological alignment, and industry context when assessing the innovation outcomes of M&A activity, as no universal effect can be assumed across different acquisition settings.

While previous literature has extensively covered the effect of M&A on innovation, we contribute to existing body of research by studying a contemporary sample, essential given the change in market dynamics both relating to competition as well as technology. Furthermore, as M&A activity typically unfolds in distinct waves influenced by shifting macroeconomic conditions and strategic priorities, it is plausible that a recent wave (7th wave) has passed without receiving adequate attention in the existing literature. As recent data suggest that we are now entering what is considered the eighth wave of M&A activity, this naturally suggests an end to the seventh wave. This observation aligns with Warf (2003), who identifies technological change and the pursuit of economies of scale and scope as key drivers of merger activity, suggesting that the emergence and growing adoption of generative AI may signal the beginning of a new M&A wave, fueled by rising transactions in this space (Levy, 2025). Lastly, with some prior research studying innovation input and output in parallel, but still separately, their joint integrated analysis remains relatively unexplored. We thus seek to investigate a U.S.-based sample in a modern context, where acquirers' innovation input, output and productivity are analyzed following acquisitions.

Table 2. Overview of results from a selection of prior literature

Authors	Input / Output	Result
Bertrand (2009)	Input	Positive
Bertrand and Zuniga (2006)	Input	Neutral
Blonigen and Taylor (2000)	Input	Negative
Cassiman et al. (2005)	Input	Negative
Cefis (2010)	Input	Positive
Cefis & Triguero (2016)	Input	Negative
Cefis et al. (2009)	Input	Mixed
Hall et al. (1990)	Input	Negative
Healy et al. (1992)	Input	Neutral
Hitt et al. (1996)	Input	Negative
Ikeda and Doi (1983)	Input	Neutral
Ochirova & Dranev (2021)	Input	Negative
Ornaghi (2009)	Input	Negative
Stiebale (2013)	Input	Positive
Szücs (2014)	Input	Negative
Desyllas and Hughes (2010)	Input / Output	Positive
Haucap & Stiebale (2016)	Input / Output	Negative
Hitt et al. (1991)	Input / Output	Negative
Gantumur and Stephan (2010)	Input / Output	Positive
Gantumur and Stephan (2012)	Input / Output	Positive
Stiebale and Reize (2011)	Input / Output	Negative
Ahuja and Katila (2001)	Output	Neutral / Positive
Cloodt, Hagedoorn, and Van Kranenburg (2006)	Output	Mixed
Hagedoorn and Duysters (2002)	Output	Positive
Makri et al. (2010)	Output	Positive
Sevilir, Tian (2012)	Output	Positive

Note: The table shows a aggregated list of the results obtained in prior literature as well as their core measure of innovation. A more detailed summary in Appendix A Table A1.

2.2. Hypothesis Development

In this section, we theorize based on previous literature across several fields to develop arguments about the impact of M&A on acquirers' innovation, as well as the factors that might impact this potential relationship. Overall, the previous literature presents inconclusive and contradictory results, in terms of (i) magnitude, (ii) significance, and (iii) direction of M&A activity's impact (positive, negative, or neutral), making it difficult to predict such an outcome in our thesis.

Hypothesis I: *M&A has a negative impact on innovation input (R&D intensity) with diminishing effects in the post-acquisition years, predominantly in cross-industry acquisitions.*

The relationship between M&A and innovation input, as proxied by R&D expenses normalized by total sales, we hypothesize to be negative, in line with the results in a majority of found previous literature. Overarching this, is the findings in Ahuja and Katila (2001), who contend that M&A activity is predominantly motivated by a sales-growth oriented logic; prioritizing market share and inorganic expansion in the short-term, or improving operational efficiency through cost-reducing synergies. Hence, we argue that acquirers, in general, are not looking at targets based on their innovation performance, but rather their market share and potential top-line, or profitability synergies. Prior literature relies on more narrowly defined samples, wherein the strategic rationale for M&A is more readily identifiable. In contrast, by focusing on the broader U.S. market, our analysis does not assume that M&A activity is primarily driven by R&D considerations. Instead, we adopt the prevailing view that such transactions are largely motivated by objectives related to market share expansion, top-line growth, or improvements in operational efficiency. Further, such short-term focus, we argue in line with Hitt et al. (1991, 1996), would lead to weaker internal financial control, as firm's would disregard long-term competitive advantages, which Haucap et al. (2019) find is an outcome of having sufficient R&D capabilities, thus de-emphasizing long-term innovation. However, in related acquisitions, we predict a weaker negative and potentially neutral, or even positive relationship, in line with Cohen and Levinthal (1989, 1990), as absorptive capacity is key for the innovation outcome and is significant, path-dependent, and domain-specific meaning it develops within particular industries, making it more efficient and easier for firms to innovate in existing areas of expertise. This aligns with the findings of Hagedoorn and Duysters (2002), who show that overall fit between acquirer and target is a key determinant of post-acquisition innovation performance, resulting in firms operating in the same or adjacent industries, more likely to experience higher R&D input performance, stemming from more efficient absorption and understanding of the acquired knowledge. Hence, we predict a negative relationship between M&A activity on acquirers post-acquisition R&D input, more noticeable in cross-industry acquisitions.

Hypothesis II: *M&A has a positive impact on innovation output in terms of patent counts and citations.*

Although a substantial fraction of past literature has found a positive impact of M&A on innovation output, the evidence remains mixed, with studies also documenting neutral, as well as negative effects. We hypothesize the relationship between M&A and subsequent innovation output performance, as proxied by patents and citations, to be positive, grounded in the notion that acquirers are argued to produce a greater number of patents following an acquisition as the synergies from combining knowledge bases between acquirers and targets yield more output than the two in isolation (Bena and Li, 2014; Gantumur and Stephan, 2010; Hagedoorn and Duysters, 2002). The integration of diverse capabilities between two firms strengthens the potential of the combined firm to yield innovation output, either by acquiring a substantial amount of innovative capabilities, or by gaining the necessary capabilities to capitalize on the pre-existing internal innovative capabilities. Additionally, the suggested positive effect of an acquired knowledge base on innovation output is more prominent in high-technology acquisitions (Ahuja and Katila, 2001). Thus, given the increasingly technology-centric nature of modern businesses across industries, this would allow the hypothesis to gain traction in our chosen setting. The synergies in innovation-oriented acquisitions are argued to be more attainable compared to 20 years ago, given the horizontal application of advanced technologies in contemporary markets. Consequently, innovation output should increase, despite a theorized decrease in innovation inputs, as we argue that firms are keen on commercializing and capitalizing on innovation in the post-acquisition period, this will be further assessed in Hypothesis III as we cover Innovation Productivity post-M&A.

Hypothesis III: *M&A has a positive impact on innovation productivity in the immediate post-acquisition period.*

In relation to Hypotheses I and II, a natural inference is that innovation productivity should increase when innovation output rises while innovation input declines, as productivity is inherently determined by the relationship between these two innovation proxies, with caution in relation to factors such as integration challenges which could interfere with the logic supporting a rise in innovation in the post-M&A period. Desyllas and Hughes (2010) find a positive relationship between acquisitions and R&D productivity, however, solely for related acquisitions, as the acquirer has enhanced absorptive capacity to select and absorb targets. This is suggested to not hold for unrelated acquisitions where the relationship becomes increasingly negative. Following our main idea, that our dataset is derived from a more technologically developed setting, we argue that the overall technological development among firms, especially those classified as non-technological has led to an improved absorptive capacity.

Examples of such technological development among firms include usage of ERP systems, CRM software, accounting and financial software, productivity suites, business intelligence and analytics tools, and cloud infrastructure, which allows for a greater knowledge base, strengthening the notion of a different context than the one prior literature has researched. Building on Cassiman et al. (2005), who emphasize technological relatedness as a key driver of acquisition synergies, we propose a positive link between acquisitions and R&D productivity, given that the firms in our sample exhibit greater technological homogeneity within the applied setting, allowing for greater absorptive capacity and more efficient use of innovation input.

3. Data

3.1. Sample and Data Collection

We construct a large, unbalanced panel of U.S. publicly traded firms for the period 2010-2023 for all firms that conducted at least one acquisition. The dataset contains information on firms' acquisition activity from Thomsons Financial's SDC Platinum, R&D data and financial data from Standard and Poor's Capital IQ, and patenting activity from Wharton Research Data Services database, which includes all utility patents granted by the U.S. Patent and Trade Office.

3.1.1. Financial Data

The dataset we built for our study is mainly determined by the availability of standardized financial data for publicly traded companies in the U.S. To construct our dataset, we obtained market, and financial data, through Standard and Poor's Capital IQ for firms listed at any point on NASDAQ, NYSE and AMEX markets, resulting in 9,364 unique firms, serving as the reference group for publicly listed companies.[1] To ensure validity, we extracted only firms where a market cap during the period 2009-2023 could be obtained, resulting in 5,544 being listed at some point during our sample period.[2] To complete the dataset we augment the market data with R&D and standardized financial data for all the firms included in our sample on a calendar-year basis.[3] To ensure validity, a common approach in existing literature, we replace all missing R&D values with 0 (assuming that missing R&D observations imply zero R&D expenditure); see section 5.2.2. Excluding missing R&D observations for the validity of this impact.

Table 3. Sample selection from CapitalIQ

Sample	**No. of firms**
Total number of publicly traded firms in the U.S. over time	9,364
No capital market data available for 2007-2023	*3,820*
Publicly traded companies 2007-2023	5,544
Cleaning[4]	*27*
Total number of firms in the sample	**5,517**

Note: The table shows our sample selection from CapitalIQ, collected during the spring of 2025 for U.S. publicly traded firms.

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[1] Includes firms listed at any time on NASDAQ Capital Market (NASDAQCM), NASDAQ Global Market (NASDAQGM), NASDAQ Global Select Market (NASDAQGS), New York Stock Exchange (NYSE), or NYSE American (NYSEAM).
[2] CY2009 included as there are several control variables which are constructed t-1 (original sample period 2010-2023).
[3] To account for distortions arising from non-calendar (broken) fiscal years.
[4] Firms were excluded due to de-listing and subsequent relisting events, or because firm names or tickers contained non-standard or special characters that could not be reliably matched.

3.1.2. M&A Data

Data on the composition of M&A transactions was retrieved from SDC Platinum, a database from Refinitiv which compiles data on all M&A transactions in the U.S since the beginning of the 1980s. Our starting point is to compile all M&A transactions for the period 2010-2023, where the acquirer is a publicly listed company in the U.S at the time of the acquisition, and our final dataset yields 6,451 transactions, including mergers and acquisitions for majority interest, spin-offs, leveraged buyouts and recapitalizations where the target was either private or public.[5] The total number of announced M&A transactions amounted to 49,579 during the period 2010-2023, but to ensure empirical validity, only completed transactions were kept, which amounted to 47,910, with the total number of firms that carried out at least one M&A transaction for the years 2010-2023 amounting to 10,203.[6] Regarding the number of deals, 4,011 firms were involved in one M&A transaction, 1,800 were involved in two M&A transactions, 994 in 3 M&A transactions and 3,398 firms were involved in four, or more, transactions, with 88.37% of firms having conducted 1-9 M&A transactions during the sample period. To accurately measure the impact on firm-level we only choose the first completed transaction for each year for firms that conducted more than 1 transaction each year, a common approach in existing literature. This approach sacrifices some information attributable to high-frequency acquirers but avoids mixing overlapping post-M&A periods.

Table 4. M&A transaction sample selection from SDC platinum

No. of announced transactions with publicly traded acquiror (2010-2023)[7]	**49,579**
Withdrawn transactions	*1,669*
Completed transactions	47,910
Multiple transactions	*20,446*
Number of transactions	**27,464**
Number of unique acquirers	**10,203**

Note: M&A transactions, with publicly traded U.S. acquiror for the period 2010-2023, collected from SDC Platinum during the spring of 2025.

3.1.3. Innovation Output Data

Patent data was collected from the WRDS patent database, which compiles all granted patents for U.S. companies from 2011-01-01 until 2019-12-31. It sources data directly from United States Patent and Trademark Office XML files. Patent granted and forward citations for private and public companies were extracted, lacking data for 2020 and onwards, creating an acknowledged limitation to our dataset.

Upon collecting patent data, we merged all separate patents pertaining to the same company for one year, i.e. creating unique firm-year observations which included all accumulated patents and citations for the whole year. Unlike R&D expenses, missing values in patent and citation

[5] No definition of which exchanges that are included in the criteria of being publicly listed on SDC Platinum.
[6] Transactions that lacked completion date was assumed to be withdrawn and excluded.
[7] Based on announcement date

data are not imputed with zeros, as this would risk misclassification due to the reliance on fuzzy name-matching and the frequent reporting of intellectual property under alternative legal entities, such as subsidiaries.

Table 5. Patent data overview

Year	Original Dataset		Reduced dataset	
	Patents	Forward Citations	Patents	Forward Citations
2011	235,004	1,983,879	8,094	112,300
2012	263,931	1,908,201	6,830	71,913
2013	289,677	1,742,505	14,351	111,886
2014	312,797	1,491,752	8,628	59,710
2015	313,295	1,133,035	8,165	34,752
2016	321,647	868,448	7,879	24,965
2017	339,648	639,863	8,280	16,049
2018	328,732	336,748	8,434	8,343
2019	360,805	115,276	9,928	3,007

Note: number of patents and forward citations for the original dataset collected from WRDS, and the reduced dataset used in this thesis.

3.1.4. Combining Data

Combining different data from various databases and imposing data requirements impose certain restrictions and difficulties. The reference point of publicly traded companies in the U.S. for our sample period of 2010-2023 is the dataset from Capital IQ where our dataset from SDC Platinum was merged using an unique match based on year and ticker, which yielded 12,755 transactions over 2,853 unique acquirers; thereafter, for transactions where no unique match could be found, we conducted strict fuzzy matching, generating an additional 1,670 observations over 528 firms.[8] The dataset was thereafter completed by merging patent data through a strict fuzzy matching routine, due to a lack of common identifiers. Finally, we arrive at a sample of 46,815 observations on 5,517 firms (including 14,425 deal observations across 3,381 acquirers). The remaining 2,136 firms did not conduct at least one transaction during the period of 2010-2023 and serve as comparison group.

[8] Fuzzy Matching is a process where you match data based on a vast majority of the firm name or title, in this setting, we conducted matching on company names, we complemented this with exact matching on year.

Table 6. Matching selection

Sample	No. of transactions	No. of unique acquirers
Exact ticker & year match	12,755	2,853
Fuzzy matching	1,670	528
Total in final sample	**14,425**	**3,381**

Note: Firm-level matches based on exact ticker identifiers. Only observations with a one-to-one correspondence were retained. For the remaining cases, including duplicates and instances without a unique match, an additional round of stringent fuzzy matching on name (with exact match on year) was applied to ensure accurate alignment.

Table 7. Year distribution of acquisition activity in the sample, U.S. acquirers 2010-2023

Year	Full sample				Reduced Sample
	No. of deals	No. of acquirers	No. of acquirers in single deals	No. of acquirers in multiple deals	No. of deals
2010	3,840	2,228	1,434	794	745
2011	4,099	2,269	1,403	866	814
2012	3,675	2,010	1,252	758	821
2013	3,438	1,961	1,268	693	846
2014	4,046	2,231	1,410	821	989
2015	3,907	2,186	1,418	768	1,058
2016	3,287	1,892	1,226	666	958
2017	3,497	1,942	1,247	695	1,042
2018	3,461	1,885	1,164	721	1,115
2019	2,661	1,543	1,013	530	980
2020	2,424	1,500	1,064	436	964
2021	3,808	2,163	1,402	761	1,430
2022	3,227	1,998	1,361	637	1,452
2023	2,540	1,656	1,222	434	1,211
Total	**47,910**	**10,230**	**17,884**	**9,580**	**14,425**

Note: Acquirers are U.S. publicly traded firms

4. Methodology

Here we present the methodology employed to study the effect of acquisition on innovation, both input and output, on acquiring firms in the U.S. for the period 2010-2023. We construct an unbalanced panel dataset of publicly listed U.S. firms to test our hypotheses. The section will be structured as follows: We begin by describing our dependent variables (4.1. Measures of Innovation – Dependent Variables), independent variables (4.2 Measures of M&A – Independent Variables), and control variables (4.3. Control Variables), followed by our baseline model specification (4.4. Model Specification). We conclude this section by providing some descriptive statistics (4.5. Descriptive Statistics).

4.1. Measures of Innovation - Dependent Variables

Prior empirical work on M&A and innovation focuses on either innovation input or innovation output. Literature looking at input as the main dependent variable employs various measures of R&D expenditures (Bertrand, 2009; Cassiman et al., 2005; Cefis, 2010; B. H. Hall et al., 1990; Hitt et al., 1996). Literature focusing on innovation output focuses on patent grants or citations (Ahuja and Katila, 2001; Cloodt et al., 2006; Gantumur and Stephan, 2010; Hagedoorn and Duysters, 2002). To be comparable with existing literature, we will demonstrate how M&A transactions impact innovation performance on acquirers, which is measured using both innovation output and innovation input, thereby overcoming the limitations of looking at one or the other in isolation (Desyllas and Hughes, 2010; Hagedoorn and Cloodt, 2003; Pakes and Griliches, 1980). Looking at innovation input and output in tandem helps not only to determine the extent of effort put into innovation, but also to what ends such efforts are successful. Our dependent variables are further specified below.

4.1.1. Innovation Input - R&D Intensity

Δ_*R&D_Intensity* serves as a dependent variable, which we calculate as the normalized change in R&D intensity (R&D expenses to sales).[9] The change, in line with Desyllas and Hughes (2010), is derived from the latest year-end financials prior to the transaction (t-1), to three post-acquisition years (t+3). A four-year window allows for us to capture both possible immediate consolidation effects in the financial statements in the year-end that follows the transaction, as well as possible effects that materialize over time following an acquisition. In addition, we include the three-year average. The dependent variables related to innovation output are calculated as following:

$$(1)\ \Delta\text{R\&D Intensity}_{\,it+T} = \frac{R\&D\ expenses_{it+T}}{Total\ Sales_{it+T}} - \frac{R\&D\ expenses_{it-1}}{Total\ Sales_{it-1}}\ T \in \{1,2,3\}$$

[9] Total revenues and total sales are used interchangeably.

$$(2)\ \text{Avg.}\,\Delta\text{R\&D Intensity}_{it+T} = \frac{1}{3}\sum_{T=1}^{3}\frac{R\&D\ expenses_{it+T}}{Total\ Sales_{it+T}} - \frac{R\&D\ expenses_{it-1}}{Total\ Sales_{it-1}}$$

4.1.2. Innovation Output – Patents and Citations

Patents as a proxy for innovation are advantageous and relevant for a plethora of reasons, among those are that they are less affected by accounting manipulations and varying reporting rules, compared to e.g. R&D expenditures as argued by Haucap et al. (2019). For patents, we assign them to years by looking at the grant date rather than the application date, whilst the application date reflects when the patent was filed, grant date more accurately reflects when the innovation becomes officially recognized and legally protected, this also aligns better with timing of potential commercial impact for the firm producing the patent. We match all patents generated in a year by a specific firm to one total which then becomes our variable *Patents*. We construct a set of dependent variables, with each reflecting a different proxy for innovation output.

Ln_Patents_ t+1 and *Ln_Patents_t+2 are* defined as the natural logarithm of (1 + total number of granted patents per firm annually) in the two subsequent years after an acquisition has occurred. *Ln_Citations_t+1* and *t+2* are constructed in a similar manner to the patent variables, where we use the forward citation count for a firm-year observation, i.e. combining all the forward citations, which are attributable to new patents in each year (Sevilir and Tian, 2012). We then take the natural logarithm of 1 + total number of yearly forward citations. We normalize by using natural logarithm for both of these variables, and 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 (Haucap et al., 2019).

4.1.3. Innovation Productivity

Both measures relating to innovation productivity are proxies which should provide a reference of the amount of innovation outputs generated in respect to the amount of innovation inputs. *Innovation_Productivity* is defined as patent count divided by growth of R&D expenses on a year-on-year basis. *%_Change_Patents_to_LnR&D* is defined as the percentage change in patent count divided by the natural logarithm of R&D expenses, which was initially used by Ornaghi (2009). The variables are calculated as following:

$$(3)\ \text{Innovation\_Productivity} = \frac{Patent\ Count_{t+1}}{\frac{R\&D_{t+1}}{R\&D_{t-1}} - 1}$$

$$(4)\ \text{\%\_Change\_Patents\_to\_LnR\&D}_{it+1} = \frac{\frac{LnPatents_{t+1}}{LnR\&D_{t+1}}}{\frac{LnPatent_{t-1}}{LnR\&D_{t-1}}} - 1$$

4.2. Measure of M&A - Independent Variables

To identify the effect of M&A activity, we construct a treatment indicator at the firm-year level, *M&A_Last_3_Years*. The dummy variable takes the value 1 if the firm engaged in a merger or acquisition in the current year or in any of the three preceding calendar years, and 0 otherwise. Desyllas and Hughes (2010), and Hagendoorn and Cloodt (2003) only look at the current year, which we define as *M&A_Current_*Year, but is only used in section 5.2.5 Replacing M&A_Last_3_Years with M&A_Current_Year. However, we adopt a more conservative approach and consider a firm as treated if it has completed an acquisition in the current year (t = 0) or in any of the three preceding years (t-1, t-2, or t-3).

4.3. Control Variables

Following the extant literature, we control for a vector of firm characteristics and deal characteristics that could confound the relation between M&A transactions and a firm's innovative efforts and success. All variables are computed for firm i over calendar year t. We control for firm size, leverage, revenue growth, profitability, liquidity, cross-border transactions, and cross-industry transactions, which are elaborated further below.

We include one measure on firm size, *Ln_Total_Assets*, in line with Cohen and Klepper (1996); equal to the natural logarithm of a company's total assets (in USD), which acts as a proxy for a firm's resource base and absorptive capacity, as larger firms are presumed to possess superior internal financing capabilities, more diversified R&D portfolios, and deeper organizational structures and governance that may facilitate knowledge integration post-merger (Hagedoorn and Duysters, 2002). We refrain from using market cap, due to the that impact investor sentiment, market dynamics, and behavioral biases have on this measure, beyond a firm's control.

We also control for leverage through the change in leverage in the year leading up to an acquisition through *Leverage_growth*, (long-term debt over assets from year t-2 to t-1). Changed capital structure, through increased debt, is often part of acquisition financing strategies (Kaplan and Stein, 1993).

Ln_Sales_Growth, as defined by natural logarithm of the change in revenue during the calendar year preceding the M&A transaction (t-2 to t-1), accounts for underlying firm expansion dynamics and strategies that may capture growth incentives, which influences both a firm's acquisition strategies and underlying innovation outcomes as R&D may play a crucial part in organic growth. Additionally, key strategic and operational decisions are often guided by growth trajectories, laying a foundation for a potential increase in operational expenses for scaling the business, including increased investments in intangible assets, such as R&D. Controlling for this also accounts for changes in R&D intensity that are solely driven by fluctuations in sales, as found by Szücs (2014), and Coad and Rao (2010).

EBIT_Margin, as defined by operating profit margin (operating profit over total revenues) and liquidity, proxied by the *Current_Ratio* (current assets over current liabilities), in the year preceding the M&A transaction (t-1) controls for the firm's financial health and operational efficiency, which both may impact a firm's ability and capacity to engage in M&A activities, and more specifically innovation enhancing ones (Szücs, 2014).[10] Controlling for these variables may help mitigate bias from endogenous differences in financial capacity, for instance, as firms with stronger liquidity positions and higher margins might be able to absorb integration costs and potential margin impacts following acquisitions.

In line with Desyllas and Hughes (2010), we control for deal characteristics; *Same_Nation* and *Same_Industry*. *Same_Nation* captures whether the target is headquartered outside the U.S., possibly accounting for cross-border frictions, as such transactions involve cultural, regulatory and institutional distance factors that complicate post-merger integration and impact the acquirer's absorptive capacity (Desyllas and Hughes, 2010). The *Same_Industry* dummy captures whether the target operates in the same macro-industry (based on two-digit SIC codes), as cross-industry deals may entail greater technological and organizational dissimilarity, which potentially limits knowledge transferability and R&D synergies, yet again, stemming from potential absorptive capacity (Ahuja and Katila, 2001; Hagedoorn and Duysters, 2002).

Certain control variables, used in previous literature, but are not used in our analysis, including *Firm Age* (Balsmeier et al., 2017)*, Institutional Ownership* (Sevilir and Tian, 2012)*, Herinfindahl Index* (captures the non-linear relation of product market competition and innovation) (Aghion et al., 2005), *Tobin's Q* (Balsmeier et al., 2017), *pre-merger patent-stock* (Cloodt et al., 2006; Haucap et al., 2019), and *Capex* (Balsmeier et al., 2017). Due to data limitations, heteroscedasticity and inconsistencies across the firms in our sample we do not include them but alleviate the excursion by including industry fixed effects to capture larger differences, as opposed to firm fixed effects. One notable omission is a direct measure of the acquirers pre-existing innovative capacity, as proxied by either *Patent Stock* (Haucap et al., 2019) or *Knowledge base* (Desyllas and Hughes, 2010), we acknowledge this could affect our results and discuss it further in section 8.1. Limitations.

[10] Earnings before interest and taxes

Table 8. Variable Overview

Variable	Definition
Dependent variables	
Δ_R&D_Intensity	**Innovation input:** Post-acquisition innovation input measured as delta R&D expenditures scaled by total sales, compared to t-1, computed for t+1, t+2, t+3, and as a three-year post-acquisition average. Computed as difference in percentage points. (shown in %)
Ln_Patents	**Innovation output:** Natural logarithm of the total number of patents granted in the first and second year following the acquisition (t+1 and t+2).
Ln_Citations	**Innovation output:** Natural logarithm of the total number of forward citations to granted patents in years t+1 and t+2; proxies for the technological impact of innovations.
Innovation_Productivity	**Innovation output:** Ratio of patent count to the year-over-year change in R&D expenditures; captures the efficiency of converting R&D input into patentable output.
%_Change_Patents_to_LnR&D	**Innovation output:** Percentage change in the number of patents divided by the natural logarithm of R&D expenditures, reflecting innovation yield per R&D investment (Ornaghi, 2009).
Independent variables	
M&A_Last_3_Years	Treatment: Binary indicator equal to 1 if a firm has completed at least one M&A transaction in year t (current year), or in any of the preceding three years (t–1, t–2, t–3); 0 otherwise (Desyllas and Hughes, 2010).
M&A_Current_Year	Treatment: Binary indicator equal to 1 if a firm has completed at least one M&A transaction in year t (current year), 0 otherwise.
Control Variables	
Ln_Total_Assets	**Control (firm specific):** Natural logarithm of total assets, serving as a proxy for firm size to control for scale-related effects (Cohen and Klepper, 1996; Hagedoorn and Duysters, 2002).

Leverage_Growth	**Control (firm specific)**:Change in financial leverage (in %), measured as the year-over-year percentage change in the ratio of total debt to total assets; captures dynamics in capital structure.
Ln_Sales_Growth	**Control (firm specific)**: Natural logarithm of the year-over-year growth in net sales; captures revenue dynamics in a scale-invariant form.
EBIT_Margin	**Control (firm specific):** Operating profitability (in %), defined as earnings before interest and taxes (EBIT) scaled by total revenues; controls for operational efficiency.
Current_Ratio	**Control (firm specific):** Measure of short-term liquidity, calculated as total current assets divided by total current liabilities.
Same_Nation	**Control (deal specific):** Binary indicator equal to 1 if the acquirer and target firms are headquartered in the same country (e.g., both in the U.S.); 0 otherwise (Desyllas and Hughes, 2010).
Same_Industry	**Control (deal specific):** Binary indicator equal to 1 if the acquirer and target operate within the same broad industry classification (macro-industry); 0 otherwise (Ahuja and Katila, 2001).

4.4. Model Specification

To test our hypothesizes specified in section 2.2 Hypothesis Development (H1, H2, and H3) i.e., the relationship between acquirers' M&A activity and innovation input, output and productivity, we estimate the following model

$$\Upsilon_{it+n} = \beta_0 + \beta_1 M\&A\ L3Y_{it} + \beta_2 \mathrm{X}_{it-1} + \beta_3 \mathrm{Z}_{it} + \delta_j + \delta_t + \epsilon_{it}$$

Where: Υ_{it} equals dependent innovation input, and output variable(s) (as seen in Table 8) t indexes time and $n \in \{1,2,3\}$, for firm i. $\mathrm{X}_{it-1}$is equal firm-level financial controls for firm *i* at time *t-1* and Z_{it} is deal-specific controls for firm *I* and time *t-1.* δ_j and δ_t is industry fixed effects based on two digit SIC-codes and year-fixed effects, respectively. The model uses firm-level and deal-specific controls (as seen in Table 8) and clustered standard errors by firm, to control for heteroscedasticity and autocorrelation in the error term. We utilize industry and year fixed effect to account for cross-sectional variation, which the model fails to capture in the explanatory variables.

4.5. Descriptive Statistics

4.5.1. Summary Statistics

To address the influence of extreme values, we winsorize the entire sample at the 1st and 99th percentiles.

Table 9. Descriptive Statistics

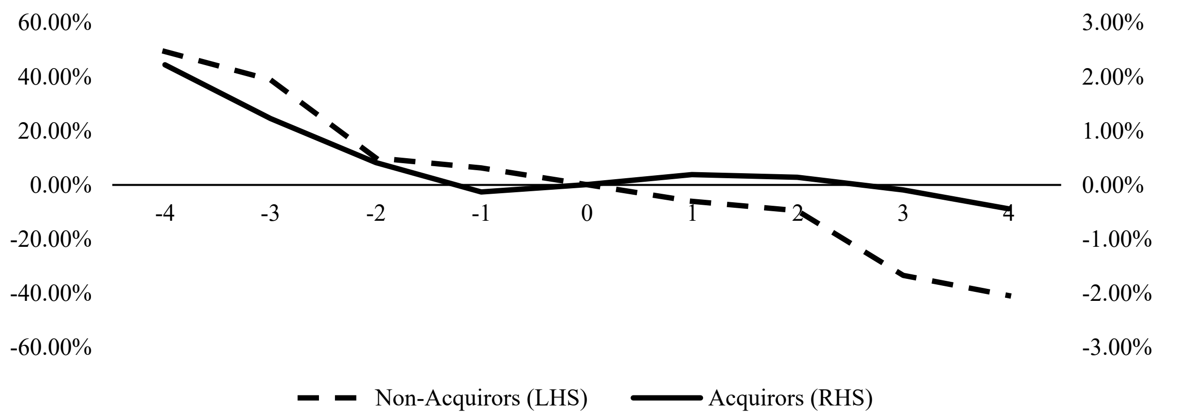
Variables	Obs	Mean	Std. Dev.	Min	Max
M&A_Current_Year	46,815	0.308	0.462	0.000	1.000
M&A_Last_3_Years	46,815	0.515	0.500	0.000	1.000
R&D_Intensity_t-1	40,870	27.715	164.32	0.000	1,463.813
R&D_Intensity_t-0	43,131	35.565	215.365	0.000	1,916.561
R&D_Intensity_t+1	41,743	31.895	194.116	0.000	1,743.591
R&D_Intensity_t+2	37,406	25.992	153.607	0.000	1,363.198
R&D_Intensity_t+3	33,239	21.419	124.759	0.000	1,115.538
Patent_Count_t+1	7,276	8.502	22.995	1.000	167.000
Patent_Count_t+2	6,315	8.488	22.587	1.000	162.000
Citations_Count_t+1	7,276	34.169	116.745	0.000	898.000
Citations_Count_t+2	6,315	28.365	93.370	0.000	698.000
Total_Assets	43,306	8.803	26.682	0.001	198.825
EBIT_Margin	46,815	-130.135	827.668	-7,059.033	94.517
Leverage_Growth	46,815	0.538	9.298	-39.483	43.143
Current_Ratio	41,538	03.75	5.471	0.084	37.065
Sales_Growth	38,399	18.142	65.072	-74.752	486.376
Same_Industry	46,815	0.226	0.418	0.000	1.000
Same_Nation	46,815	0.252	0.434	0.000	1.000

Note: Descriptive statistics (N, mean, SD, min, max). *R&D_intensity* is defined as R&D-to-sales in years t–1 to t+3. *Patent_Count* and *Citations_Count* reflect total firm-level counts in t+1 and t+2. *Total_Assets* are in USD million. *Sales_Growth* denotes percentage revenue growth from t–2 to t–1. All controls are measured at t–1 (pre-acquisition).

Table 8 reports descriptive statistics for the sample. Approximately 31% of firm-year observations involve an M&A transaction in the current year (*M&A_Current_Year*), while just over half (52%) have engaged in at least one transaction in the current or prior three years (*M&A_Last_3_*Years). R&D intensity, peaks in the current year with a mean of 35.6% (*R&D_Intensity_t-0),* declining steadily in the subsequent three years, suggesting either front-loaded investment post-acquisition or diminishing innovation effort over time. Backward-looking R&D intensity (*R&D_Intensity_t-1*) averages 27.7%, indicating that firms engaging in M&A are, on average, already investing significantly in innovation ex ante. Patent and citation counts in the years following a transaction are modest on average but highly skewed, with mean granted patents just above 8 and citations ranging from 28 to 34, reflecting substantial heterogeneity in innovative output. The average firm in the sample reports total assets of USD 8.8 million, though dispersion is considerable. Financial controls further reflect variability in firm fundamentals: mean *EBIT_Margin* is negative, reflecting the presence of loss-making firms, while current ratio and leverage growth show wide variation, indicating diverse liquidity positions and capital structure dynamics. Finally, only a minority of transactions involve firms in the same industry (23%) or the same nation (25%), underscoring a heterogeneous set of deal types spanning cross-border and cross-industry contexts. Full correlation table for the exact variables used in the main regression can be found in Appendix B, Table B2.

Table 10 displays the evolution of R&D intensity from four years before to four years (t-4 to t+4) after an M&A transaction for acquirers and non-acquirers, based on the variable M&A_Last_3_Years. The results indicate a stable post-acquisition R&D intensity for acquirers, while non-acquirers exhibit a decline.

Table 10. Average change R&D intensity development



Note: Average R&D intensity trajectory for acquirers and non-acquirers from t–4 to t+4, based on the indicator *M&A_Last_3_years.* Values are indexed such that R&D intensity at t=0 equals 0.

4.5.2. Correlation

The Pearson correlation matrix (Appendix B Table B2) shows moderate correlations among the regression variables. No signs of problematic multicollinearity are observed, with all coefficients below 0.8. The strongest correlation appears between *Same_Nation* and *Same_Macro_Industry* ($r = 0.745$, $p < 0.01$), which is expected due to the structural likelihood that cross-border acquisitions are more diversified across sectors. All other relationships are modest, supporting the reliability of the regression estimates.

5. Results

5.1. Main Specification

In this section of the paper, we present and discuss the results obtained from employing the methodology outlined in the previous section. We begin by examining a set of OLS regressions in which innovation inputs, i.e., R&D-based metrics, serve as the dependent variables. We proceed to examine innovation outputs, where patent-based metrics and innovation efficiency measures serve as the dependent variables. Thereafter, we present a section on robustness, introducing the propensity score matching principle to simulate the effects after matching each firm-year conducting M&A (treatment) observation to a comparable non-treatment one, followed by a set of other remedies (robustness tests) to effectively control for any limitations of our methodology. These tests include, among others, looking at high-tech vs non-high-tech firms as well as the results from a procedure where all the firm-year observations whose R&D values were missing upon collecting the data (which were originally replaced with zero and included in the sample), are excluded from the sample.

5.1.1. The Acquisition Effect on Acquirer R&D Intensity

Table 11 presents OLS regression results using Δ_*R&D_Intensity* as the dependent variable, measured as both annual and averaged post-acquisition outcomes.[11] Including industry-fixed effects entails a decrease in magnitude for the impact of *M&A_Last_3_Years* (*p>0.1).* However, including industry-fixed effects is natural, due to the varying approaches to innovation across industries, and mitigates heterogeneity in the model, stemming from this. Across the models focusing on individual yearly developments (t-1 to t+1, t+2, t+3), the coefficient on the M&A dummy, *M&A_Last_3_Years*, is strictly negative, though statistically insignificant for t+1, and t+2 (-0.379%, p>0.1for t+1; -0.198% p>0.1 for t+3), indicating that the negative effect is stronger in the first year following acquisitions, and subsequently diminishes in the third. However, the coefficient is positive in year t+2 (0.718%, p<0.1). The negative effect suggest a decrease in R&D intensity following acquisitions initially and then a positive impact in year 2, but ultimately a negative impact beyond that. However, high standard errors (around 0.4-0.5) as well as lack of statistical significance limits the quantitative findings, though this is expected given the inherent noisiness of the studied environment. Altogether, the regression shows that acquisitions have a negative but statistically insignificant effect on acquirers' innovation input, in the post-acquisition years. It is important to note, however, that the observed R^2 values are relatively low (ranging from 0.01-0.11), which is expected given the inherently noisy nature of our studied setting.

Control variables are generally consistent across years in their treatment effect, with *Ln_Total_Assets* having a negative and statistical significant impact on Δ_*R&D_Intensity* in

[11] By using outcome variables that capture year-over-year changes (Δ_*R&D_Intensity*), our research design implicitly controls for time-invariant firm-level characteristics mirroring firm-fixed effects. Thus, a substantial amount of the industry-fixed effects are absorbed since industry-fixed effects are a subset of firm-fixed effects.

the post-acquisition year with industry-fixed effects (-0.387, p<0.01 for t+1; -0.347, p<0.01 for t+2; -0.273, p<0.01 for t+3), indicating that smaller firms' showcases a higher R&D intensity in the post-M&A period. *Leverage_Growth* is negatively associated with R&D intensity, however at a small impact (-0.07%, p<0.05 for t+1; -0.115%, p<0.01 for t+2; -0.096%, p<0.01), suggesting that firms experience lower R&D intensity following increases in debt to capital ratio, by 7 basis points in the first year for a one percent increase in leverage growth. Additionally, *EBIT_Margin* has a consistent positive effect on R&D impact, at 0.5 to 1 basis points, indicating the more profitable firms experience a higher R&D intensity. Notably, looking at deal specific control variables, *Same_Industry* has an initial negative, yet small impact one year beyond the acquisition, thereafter a positive impact in the two-years to follow, but statistically insignificant impact, on R&D performance (p>0.1), indicating that acquisitions within the same industry positively impacts the R&D performance in later post-acquisition stages. *Same_Nation* has an initial positive, and statistically insignificant (p>0.1) impact on innovation input for the first two post-acquisitions years, and then turns negative, indicating contrasting results to our cross-industry variable, as domestic acquisitions in the U.S. initially boosts R&D intensity post-acquisitions and thereafter has a negative impact.

Table 11. Regression Results for M&A's impact on R&D Intensity

	Dependent Variable							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	ΔR&D intensity avg		ΔR&D intensity t+1		ΔR&D intensity t+2		ΔR&D intensity t+3	
M&A_Last_3_Years	-0.822	-0.441	-0.608	-0.379	-0.579	0.718*	-0.383	-0.198
	(0.521)	(0.538)	(0.391)	(0.402)	(0.369)	(0.412)	(0.362)	(0.375)
Ln_Total_Assets	-0.899***	-0.955***	-0.343***	-0.387***	-0.277***	-0.395***	-0.191**	-0.273***
	(0.128)	(0.137)	(0.0959)	(0.102)	(0.0929)	(0.0998)	(0.0929)	(0.0979)
Leverage_Growth	-0.0606	-0.0658	-0.0682**	-0.0704**	-0.113***	-0.116***	-0.0947***	-0.0962***
	(0.0426)	(0.0425)	(0.0335)	(0.0336)	(0.0325)	(0.0326)	(0.0329)	(0.0330)
Ln_Sales_Growth	0.0258*	0.0192	-0.0000989	-0.00275	0.0122	0.00989	0.00849	0.00745
	(0.0145)	(0.0145)	(0.0112)	(0.0113)	(0.0111)	(0.0112)	(0.0116)	(0.0117)
EBIT_Margin	0.00429***	0.00538***	0.0104***	0.0109***	0.0122***	0.0126***	0.0126***	0.0129***
	(0.00116)	(0.00118)	(0.000977)	(0.000998)	(0.000968)	(0.000983)	(0.000997)	(0.00101)
Current_Ratio	0.175**	0.154*	0.310***	0.327***	0.192***	0.196***	0.0814	0.0769
	(0.0762)	(0.0839)	(0.0641)	(0.0725)	(0.0599)	(0.0678)	(0.0579)	(0.0653)
Same_Nation	0.374	0.653	0.280	0.388	-0.0827	-0.481	-0.0962	-0.0176
	(0.496)	(0.501)	(0.335)	(0.341)	(0.308)	(0.358)	(0.289)	(0.296)
Same_Industry	-0.451	-0.752	0.0633	-0.0196	0.524*	0.425	0.456*	0.413
	(0.488)	(0.493)	(0.321)	(0.327)	(0.293)	(0.370)	(0.274)	(0.280)
Constant	13.02***	10.10***	1.880	0.340	2.568*	3.462**	2.105	3.487**
	(2.047)	(2.039)	(1.542)	(2.113)	(1.541)	(1.609)	(1.508)	(1.607)
Obs.	31,036	31,036	34,361	34,361	30,593	30,593	27,133	27,133
Firms	3,422	3,422	3,817	3,817	3,521	3,521	3,170	3,170
R^2	0.01	0.02	0.06	0.06	0.09	0.09	0.11	0.11
Adj. R^2	0.01	0.02	0.06	0.06	0.09	0.09	0.11	0.11
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Note: OLS regression with Δ*R&D Intensity* (R&D/Sales) for year t-1 to t+1, t+2, t+3 and the 3-year average as the dependent variable. See Table 8 for variable definitions. Regression (2), (4), (6), (8) include industry dummies, but not shown. All regressions include year dummies, but not shown. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

5.1.2. The Acquisition Effect on Acquirer Innovation Output

Shifting focus to patent-based dependent variables, i.e., output-based measures, we present regression result in Table 12 Looking at the output variable defined as 1 + natural logarithm of patents, following acquisitions (*Ln_Patents_t+1*) we find that the *M&A_Last_3_Years* exhibits a positive and significant effect on innovation outcomes (0.082, $p<0.01$), indicating that the occurrence of M&A has a positive impact on the subsequent patent count. This positive effect persists into the second year, as shown by the effect of *M&A_Last_3_Years* when assessing *Ln_Patents_t+2*, (0.10, $p<0.01$). Larger coefficients for the treatment variable are observed when excluding industry-fixed effects, though only marginally, while the explanatory value of the model is higher upon including them, as shown by consistently higher R^2 across all regressions, which suggests that there are industry-level differences that account for a part of the variation in the dependent variable. This points towards a certain degree of unobserved heterogeneity that the non-FE model fails to capture.[12] Standard errors of coefficients are small (~0.03)., indicating no issues with the robustness of these results. Upon looking at quality-related dependent variables, i.e., *Ln_Citations*, the results show positive effects for *M&A_Last_3_Years* in t+1 (0.12; $p>0.01$) and t+2 (0.11; $p>0.05$), when including industry-fixed effects, indicating that an increase in *Ln_Citations* (a proxy for the quality of patents) following acquisitions is diminishing over time in magnitude, suggesting a slight gradual decrease of the positive effects. The difference is limited compared to excluding industry-fixed effects, as evidenced by the coefficients for the acquisition dummy *M&A_Last_3_Years* (t+1: 0.15, $p<0.01$; t+2: 0.14, $p<0.01$). However, the explanatory value (R^2) is superior when including FE (0.25 compared to 0.20). *Innovation_Producitivty* exhibits a negative but statistically insignificant effect for *M&A_Last_3_Years* (-2.36, $p>0.1$), suggesting that acquirers are granted fewer patents relative to R&D expenses, compared to non-acquirers. This is essentially a proxy for the firm-year observation's efficiency in generating outputs, which is shown to decrease in the post-M&A period. Additionally, looking at the number of new patents in relation to the growth of relevant inputs (*%_change_Patents_to_LnR&D)*, we witness a negative, but statistically insignificant, effect when assessing *M&A_last_3_years* (-28.78%, $p>0.1$). This indicates a 29% decrease in output in relation to inputs (a proxy for efficiency) following an acquisition.

Taken together, all variables relating to output (*Ln_Patents_t+1, Ln_Patents_t+2, Ln_Citations_t+1,* and *Ln_Citations t+2)* consistently exhibits positive and statistically significant effects across regressions, indicating that acquisitions positively impact innovation output, in the short-to-medium-term. While all measures related to innovation productivity (*Innovation_Productivity* and *%_Change_Patents_to_LnR&D*), show a negative and insignificant relationship with acquisitions.

Control variables suggest that larger firms are more prevalent in the above discussions, as we witness a significant and positive impact of *Ln_Total_Assets* on all output- and efficiency-

[12] Non-industry fixed effects

based measures (p<0.01), except for *Innovation_Productivity*. Conversely to the R&D-based dependent variable regressions, where results in Table 12 suggest the opposite effect of *Ln_Total_Assets*. *EBIT_Margin* exhibits a consistent positive impact for pure patent-based variables (*Ln_Patents & Ln_Citations*), but negative for productivity variables (*Innovation_Productivity* and *%_change_Patents_to_LnR&D)*, significant only for patent-based dependent variables, albeit small impact (0.0001, p<0.01), suggesting that more profitable firms produces more patents, whereas the inverse holds in relation to productivity (with limited reassurance). Conversely, *Current_Ratio* shows mixed results with both positively and negatively association of liquidity with various measures of innovation output and efficiency (e.g. -0.005, p<0.05 for *Ln_Patents_t+1* whereas for *Innovation_Productivity* it is positive at 0.821, p>0.1). Domestic acquisitions, as suggested by *Same_Nation*, show negative impact on patent and citations, suggesting the prevalence of a negative effects on innovation output following such acquisitions. *Same_Industry* exhibits a positive and statistically significant effect for the efficiency-based measure *%_change_Patents_to_LnR&D* (190%, p<0.01), indicating a more potent effect if the target and acquirer operate in the same industry, however it has an insignificant impact on *Innovation_Productivity* (21.33, p>0.1).

Table 12. Regression Results for M&A's impact on innovation output

	Dependent Variable											
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Ln Patents t+1		Ln Patents t+2		Ln Citations t+1		Ln Citations t+2		Innovation Productivity		% Ch. Pat / LnR&D	
M&A_Last_3_Years	0.110***	0.0823***	0.133***	0.102***	0.146***	0.115**	0.136***	0.105**	-2.719	-2.256	-8.175	-28.78
	(0.0307)	(0.0302)	(0.0333)	(0.0328)	(0.0477)	(0.0471)	(0.0503)	(0.0498)	(12.94)	(13.44)	(38.64)	(41.19)
Ln_Total_Assets	0.0349***	0.0434***	0.0339***	0.0425***	0.0277***	0.0375***	0.0237***	0.0323***	2.242	3.852	47.28***	49.94***
	(0.00339)	(0.00364)	(0.00362)	(0.00391)	(0.00528)	(0.00550)	(0.00548)	(0.00577)	(2.961)	(3.079)	(9.413)	(10.00)
Leverage_Growth	0.00324***	0.00278**	0.00115	0.000540	0.00434**	0.00405**	0.00472**	0.00431**	0.0468	-0.0120	2.860	2.771
	(0.00111)	(0.00110)	(0.00122)	(0.00120)	(0.00183)	(0.00183)	(0.00208)	(0.00208)	(0.354)	(0.358)	(1.788)	(1.795)
Ln_Sales_Growth	0.000529*	0.000214	0.000122	-0.0000322	0.00126**	0.000810	0.000801	0.000576	0.0822	0.0481	-0.312	-0.211
	(0.000281)	(0.000279)	(0.000312)	(0.000311)	(0.000496)	(0.000492)	(0.000530)	(0.000531)	(0.110)	(0.114)	(0.279)	(0.271)
EBIT_Margin	0.00003***	0.00003***	0.00003***	0.00003***	0.000018	0.000016	0.000016	0.000012	0.000265	-0.000396	-0.000484	-0.00694
	(0.000008)	(0.000008)	(0.000008)	(0.000009)	(0.000015)	(0.000015)	(0.000015)	(0.000016)	(0.00154)	(0.00172)	(0.00498)	(0.00592)
Current_Ratio	-0.000414	-0.00460**	0.00285	-0.00177	0.00374	0.00121	0.00754*	0.00453	0.735	0.821	1.147	1.934
	(0.00213)	(0.00221)	(0.00256)	(0.00266)	(0.00374)	(0.00388)	(0.00440)	(0.00460)	(0.639)	(0.758)	(2.588)	(2.665)
Same_Nation	-0.0966**	-0.0615	-0.0950**	-0.0442	-0.0989	-0.0575	-0.0705	-0.00512	10.52	12.54	-13.27	-22.37
	(0.0412)	(0.0405)	(0.0449)	(0.0444)	(0.0611)	(0.0604)	(0.0635)	(0.0631)	(21.78)	(21.96)	(58.57)	(59.48)
Same_Industry	0.124***	0.115***	0.0920**	0.0789*	0.0832	0.0792	0.0864	0.0783	25.71	21.33	184.1***	190.3***
	(0.0415)	(0.0406)	(0.0450)	(0.0440)	(0.0614)	(0.0607)	(0.0638)	(0.0629)	(22.33)	(22.68)	(57.37)	(58.90)
Constant	0.936***	0.990***	0.979***	0.848***	2.320***	1.685***	2.203***	1.632***	30.76	0.181	-447.9***	-916.4***
	(0.0594)	(0.220)	(0.0606)	(0.215)	(0.101)	(0.361)	(0.0998)	(0.390)	(37.66)	(41.31)	(125.9)	(191.6)
Obs.	7,082	7,082	6,146	6,146	7,082	7,082	6,146	6,146	3,810	3,810	2,450	2,450
Firms	1,546	1,546	1,419	1,419	1,546	1,546	1,419	1,419	806	806	578	578
R^2	0.04	0.11	0.03	0.10	0.20	0.25	0.18	0.23	0.01	0.02	0.03	0.04
Adj. R^2	0.04	0.10	0.03	0.09	0.20	0.24	0.18	0.22	0.00	0.00	0.03	0.02
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: OLS regression with innovation output-, and productivity-based dependent variables: *Ln_Patents_t+1* & t+2, *Ln_Citations_t+1 & t+2*, *Innovation_Productivity*, and *%_change_Patents_to_LnR&D*. See Table 8 for variable definitions. Regression (2), (4), (6), (8), (10), and (12) include industry dummies, but not shown. All regressions include year dummies, but not shown. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

5.2. Robustness

To verify the results obtained in the main specification, a set of additional tests and variations of the original specification and sample is compiled. To approximate a counterfactual control group, analogous to the identifying strategy in a difference-in-differences framework, we implement a propensity score matching (PSM) procedure (see section 5.2.1. Propensity Score Matching). Thereafter, we perform additional robustness tests to address some inherent limitations of our study, starting with the removal of all observations that had missing R&D expenses, while running the original specification on this sample (see section 5.2.2. Excluding Missing R&D Observations). Upon trying to determine if there is a noticeable difference based on technological development, we perform OLS regressions on high-tech and low-tech samples separately (see section 5.2.3. High-Tech vs Non-High-Tech). We proceed to conduct separate regressions across various industries, where we expect to observe the effect previously discussed, with some industries exhibiting more pronounced effects (see section 5.2.4. Industry Comparison). In addition to this, we use a different treatment variable: a one-year M&A dummy, opposed to a three-year lag dummy (see section 5.2.5. Replacing M&A_Last_3_Years with M&A_Current_Year). Lastly, we run an OLS regression on a sample which we winzorise at the 2nd and 98th percentile (compared to 1st and 99th in our original sample), to reassure that outliers do not drive the results (see section 5.2.6. Additional Winzorising (2n and 98th percentile)).

5.2.1. Propensity Score Matching

To account for selection biases of observable characteristics, we utilize a propensity score matching procedure, based on our firm characteristic control variables (*Ln_Total_Assets*, *Leverage_Growth*, *Ln_Sales_Growth,* and *EBIT_Margin)* and find the nearest neighbor of each treated firm, which have conducted M&A in last three years, for firms in which *M&A_Last_3_Years* is equal to zero (no M&A activity in past-three years), thereby constructing a control group that is more statistically comparable in terms of pre-treatment characteristics, reducing endogeneity issues and ex-ante observable firm characteristics. In this procedure we find matches for 2,944 firms, i.e., dropping 4,437 acquiring firm, due to lacking a match. Table 13 and 14 shows the results from the OLS regression, where the PSM method has been applied to create a more comparable sample, in terms of control firms.

Table 13. PSM OLS Regression Innovation Input

	Dependent Variable							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	ΔR&D intensity avg		*ΔR&D intensity t+1*		*ΔR&D intensity t+2*		*ΔR&D intensity t+3*	
M&A_Last_3_Years	-0.146	-0.262	-0.973*	-1.042*	-0.729	-0.781	-0.178	-0.208
	(0.760)	(0.799)	(0.530)	(0.578)	(0.483)	(0.526)	(0.468)	(0.509)
Ln_Total_Assets	-0.319**	-0.341**	-0.219**	-0.246**	-0.142	-0.159	-0.0997	-0.109
	(0.141)	(0.157)	(0.110)	(0.119)	(0.107)	(0.116)	(0.0984)	(0.107)
Leverage_Growth	-0.0228	-0.0208	-0.0727*	-0.0740*	-0.0424	-0.0424	-0.0377	-0.0364
	(0.0478)	(0.0480)	(0.0391)	(0.0392)	(0.0366)	(0.0368)	(0.0354)	(0.0357)
Ln_Sales_Growth	0.00594	0.00429	-0.00310	-0.00440	-0.00181	-0.00326	-0.00149	-0.00191
	(0.0174)	(0.0174)	(0.0129)	(0.0129)	(0.0126)	(0.0126)	(0.0127)	(0.0128)
EBIT_Margin	0.00400	0.00447	0.00746***	0.00771***	0.0118***	0.0121***	0.0108***	0.0111***
	(0.00305)	(0.00306)	(0.00244)	(0.00247)	(0.00261)	(0.00262)	(0.00269)	(0.00270)
Current_Ratio	0.182	0.167	0.234**	0.248**	0.171*	0.173*	0.161*	0.157
	(0.129)	(0.142)	(0.102)	(0.115)	(0.0879)	(0.1000)	(0.0876)	(0.0993)
Same_Nation	0.516	0.731	0.325	0.395	0.0167	0.0913	-0.355	-0.260
	(0.562)	(0.584)	(0.366)	(0.383)	(0.321)	(0.335)	(0.314)	(0.330)
Same_Industry	-0.576	-0.602	0.0183	0.0281	0.471	0.477	0.274	0.253
	(0.571)	(0.576)	(0.371)	(0.384)	(0.343)	(0.356)	(0.320)	(0.331)
Constant	4.444*	3.284	2.216	-2.188	1.201	1.941	0.424	1.251
	(2.326)	(2.324)	(1.761)	(4.751)	(1.753)	(1.784)	(1.655)	(1.736)
Obs.	16,259	16,259	17,618	17,618	15,891	15,891	14,134	14,134
Firms	30,70	3,070	3,383	3,383	3,111	3,111	2,814	2,814
R^2	0.01	0.02	0.03	0.03	0.07	0.07	0.07	0.07
Adj. R^2	0.01	0.01	0.03	0.03	0.07	0.07	0.07	0.06
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Note: OLS regression on innovation input-based dependent variables, with propensity score matching methodology. Δ*R&D Intensity* (R&D/Sales) for year t-1 to t+1, t+2, t+3 and the 3-year average as the dependent variable. See Table 8 for variable definitions. Regression (2), (4), (6), and (8) include industry dummies, but not shown. All regressions include year dummies, but not shown. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 14. PSM OLS Regression Innovation Output

	Dependent Variable											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Ln Patents t+1		Ln Patents t+2		Ln Citations t+1		Ln Citations t+2		Innovation Productivity		% Ch. Pat / LnR&D	
M&A_Last_3_Years	0.208***	0.117*	0.183***	0.0837	0.240**	0.114	0.167*	0.0633	-3.082	-3.102	-81.87	-94.09
	(0.0623)	(0.0625)	(0.0655)	(0.0664)	(0.0934)	(0.0939)	(0.0946)	(0.0957)	(31.31)	(32.95)	(104.0)	(111.1)
Ln_Total_Assets	0.0497***	0.0614***	0.0429***	0.0554***	0.0407***	0.0570***	0.0258***	0.0386***	5.534	8.254	76.98***	81.79***
	(0.00571)	(0.00636)	(0.00620)	(0.00692)	(0.00884)	(0.00959)	(0.00854)	(0.00948)	(4.875)	(5.066)	(16.95)	(18.18)
Leverage_Growth	0.00609***	0.00509**	0.00317	0.00179	0.00819**	0.00727**	0.00563	0.00453	0.997	0.965	8.849**	8.825**
	(0.00216)	(0.00215)	(0.00243)	(0.00246)	(0.00329)	(0.00332)	(0.00364)	(0.00367)	(0.889)	(0.908)	(4.392)	(4.414)
Ln_Sales_Growth	0.000318	-0.000356	0.000125	-0.000249	0.00131	0.000721	0.00128	0.000972	0.133	0.0866	-1.591**	-1.492*
	(0.000549)	(0.000550)	(0.000619)	(0.000623)	(0.000898)	(0.000897)	(0.000978)	(0.000983)	(0.272)	(0.291)	(0.806)	(0.822)
EBIT_Margin	0.0000212	0.0000336	0.0000348	0.0000427	0.00000268	-0.0000130	0.0000260	0.0000113	0.00895	0.00369	-0.0228	-0.0441*
	(0.0000239)	(0.0000261)	(0.0000243)	(0.0000262)	(0.0000359)	(0.0000375)	(0.0000351)	(0.0000365)	(0.00745)	(0.00782)	(0.0215)	(0.0253)
Current_Ratio	0.00848*	-0.00377	0.00938	0.00191	0.00835	-0.00147	0.00856	0.000162	4.905***	4.548**	1.987	2.605
	(0.00515)	(0.00505)	(0.00595)	(0.00562)	(0.00861)	(0.00877)	(0.00876)	(0.00894)	(1.836)	(2.085)	(6.871)	(7.193)
Same_Nation	-0.161***	-0.0866*	-0.141**	-0.0495	-0.176**	-0.0851	-0.111	-0.000713	8.860	12.51	12.45	-10.61
	(0.0516)	(0.0512)	(0.0548)	(0.0548)	(0.0756)	(0.0754)	(0.0773)	(0.0773)	(25.02)	(25.14)	(83.34)	(86.62)
Same_Industry	0.0629	0.0642	0.0494	0.0586	0.00837	0.0290	0.0443	0.0684	22.45	17.88	209.1***	203.5***
	(0.0475)	(0.0471)	(0.0510)	(0.0510)	(0.0697)	(0.0699)	(0.0720)	(0.0724)	(28.52)	(29.66)	(69.76)	(73.51)
Constant	0.700***	1.018***	0.852***	0.411***	2.170***	0.618***	2.177***	0.986***	-4.862	-43.55	-843.7***	-1442.6***
	(0.0988)	(0.116)	(0.105)	(0.126)	(0.157)	(0.179)	(0.155)	(0.181)	(68.03)	(74.98)	(248.1)	(335.1)
Obs.	3,661	3,661	3,212	3,212	3,661	3,661	3,212	3,212	1,850	1,850	1,234	1,234
Firms	1,157	1,157	1,078	1,078	1,157	1,157	1,078	1,078	583	583	414	414
R^2	0.04	0.12	0.03	0.11	0.19	0.25	0.17	0.23	0.01	0.03	0.04	0.05
Adj. R^2	0.03	0.10	0.02	0.08	0.19	0.24	0.17	0.21	0.00	0.00	0.02	0.02
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: OLS regression on innovation output- and productivity-based dependent variables, with a reduced sample obtained utilizing propensity score matching methodology. *Ln_Patents_t+1* & t+2, *Ln_Citations_t+1 & t+2*, *Innovation_Productivity*, and %*_change_Patents_to_LnR&D*. See Table 8 for variable definitions. Regression (2), (4), (6), (8), (10), and (12) include industry dummies, but not shown. All regressions include year dummies, but not shown. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Acquisitions' effect on R&D intensity (as seen in Table 13) remains negative, similar to the original specification, with strengthened statistical significance in the first acquisition year ($p<0.1$). However, the statistical significance is not sustained for years t+2, and t+3. Further, the magnitude of the coefficient for *M&A_Last_3_Years* is 0.66 percentage points smaller, in absolute terms (-1.04%), indicating a greater negative impact in the first acquisition year, while the two-to-three acquisition years' impact remain similar, indicating a decrease in R&D intensity in the short term. The explanatory value of the models decrease, as shown by a lower R^2. Overall, the control variables' impact remains similar, with statistical significances dropping for *Ln_Total_Assets, Leverage_Growth,* and *Current_Ratio.* Surprisingly, the impact of acquiring within the U.S. generates a positive impact on R&D intensity, still statistically insignificant, for the first two-acquisition years, in addition to the three-year average, and a greater negative impact on R&D intensity in t+3.

Additionally, for output-based dependent variables (as seen in Table 14) the statistical significance drops for *M&A L3Y* for patent and citation-based variables, and impact becomes greater, yet still statistically insignificant, for *Innovation_Productivity*, and *%_Change_Patents_to_LnR&D,* indicating that the effect of acquisitions on innovation efficiency is more substantial when looking at comparable firms. The effect of all other variables remains similar to the main specification, further showing a positive impact of acquisition on innovation output, but a greater decrease in innovation efficiency.

5.2.2. Excluding Missing R&D Observations

In this section, all observations with missing R&D data are removed, previously imputed as zero, to avoid distorting the input-based regressions. This restriction ensures that the sample includes only firms that explicitly report R&D expenditures, which likely indicates a business model in which R&D plays a substantive operational role, rather than being subsumed under broader operating expense categories. Regressions are conducted using this restricted sample and focus solely on dependent variables in which R&D is a factor in constructing the them (*R&D_Intensity, Innovation_Productivity,* and *%_Change_Patents_to_LnR&D*).

Table 15. Removing missing R&D observations

	Dependent Variable					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	ΔR&D intensity avg	ΔR&D intensity t+1	ΔR&D intensity t+2	ΔR&D intensity t+3	Innovation Productivit y	% Ch. Pat / LnR&D
M&A_Last_3_Year s	-7.502	-19.74**	-18.44**	-12.02*	-2.275	-28.75
	(8.588)	(9.031)	(7.970)	(6.400)	(13.92)	(41.33)
Ln_Total_Assets	-16.95***	-13.56***	-15.53***	-14.27***	4.371	50.39***
	(2.119)	(2.180)	(1.975)	(1.837)	(3.176)	(9.972)
Leverage_Growth	8.567	8.029	3.193	7.790	13.82	-22.10
	(7.385)	(7.174)	(5.938)	(5.555)	(22.66)	(59.54)
Ln_Sales_Growth	-6.203	1.413	2.611	0.206	20.77	189.7***
	(6.846)	(6.729)	(5.648)	(5.251)	(23.44)	(58.98)
EBIT_Margin	-0.197	-0.141	-0.147	-0.563	0.0106	1.961
	(0.543)	(0.560)	(0.514)	(0.500)	(0.285)	(1.443)
Current_Ratio	0.0989	0.256	0.146	0.0616	0.0444	-0.184
	(0.265)	(0.266)	(0.252)	(0.220)	(0.110)	(0.249)
Same_Nation	0.149***	0.0783***	0.133***	0.140***	-0.000322	-0.00421
	(0.0117)	(0.0127)	(0.0112)	(0.0104)	(0.000906)	(0.00274)
Same_Industry	3.064	8.640***	6.488***	1.877	0.904	1.920
	(2.245)	(2.581)	(2.275)	(2.164)	(0.829)	(2.814)
Constant	208.1***	142.6***	182.1***	176.8***	-4.888	-922.8***
	(32.43)	(32.26)	(29.74)	(27.61)	(42.61)	(190.9)
Obs.	10,559	11,784	10,192	8,794	3,763	2,446
Firms	1,410	1,615	1,427	1,200	786	577
R^2	0.28	0.09	0.26	0.37	0.02	0.04
Adj. R^2	0.27	0.08	0.25	0.36	0.00	0.02
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS regression with Δ*R&D_Intensity* (R&D/Sales) for year t-1 to t+1, t+2, t+3 and the 3-year average, as well as *Innovation_Productivity*, and *%_change_patents_to_LnR&D* as the dependent variable(s). See Table 8 for variable definitions. Missing R&D observations are removed, instead of assumed to 0. Standard errors are in parenthesis. Industry and year dummies are included, but not shown. *** p<0.01, ** p<0.05, * p<0.1

Table 15 shows consistently negative coefficients for input-based measures, i.e. Δ_*R&D_Intensity* t+1, t+2 as well as t+3, indicating a post-M&A decline in R&D intensity. This effect differs in magnitude compared to the main specification, and consistently more negative coefficients with a diminishing effect over time are observed (-19.7%, p<0.05 for t+1; -18.4%, p<0.05 for t+2; -12.0% p<0.1 for t+3). The effects that are statistically significant, suggest substantiated indications of a decrease in R&D intensity following acquisitions. The stronger coefficients suggest that excluding missing R&D expenses has a diluting effect on the results in the main regression (as seen in section 5.1.1 The Acquisition Effect on Acquiror R&D Intensity). These results may be a truer depiction of the effects, and including all negligible observations in the main specification is what might drive the results closer to zero (as witnessed in Table 11). The explanatory value of the model is raised and showcased by R^2

values at 0.09-0.37 for the R&D-based regressions (compared to 0.06-0.11 in the main specification).

Upon assessing regressions where efficiency-based dependent variables are used, a similar negative effect of *M&A_Last_3_Years* on *Innovation_Productivity* is observed, in line with the main specification. The same goes for *%_Change_Patents_to_LnR&D,* which remains negative. Both regressions remain statistically insignificant for *M&A_Last_3_Years* (p>0.1). We witness an overall coherency with the main specification in regards to magnitude, statistical significance, as well as explanatory value of the model.

The control variables display more potent effects in this specification. *Ln_Total_Assets* exhibits an evident negative effect on the input-based regressions (-13 to -17, p<0.01), suggesting that larger firms show lower R&D Intensity. We witness a consistent effect for efficiency-based regressions with the one from the main specification relating to *Ln_Total_Assets* (4.37, p>0.1 for *Innovation_Productivity*; 50.4, p<0.01 for *%_Change_Patents_to_LnR&D*).

Notably, the variable *Same_Nation* becomes coherently positive for input-based variables (Δ*R&D Intensity)* and statistical significance improves, though negative, but still statistically insignificant for productivity-based variables, compared to the main specification (0.133%, p<0.01 compared to -0.02%, p>0.1 for Δ_*R&D_Intensity_t+3*). This may suggest a more positive effect of domestic deals on innovation inputs in this restricted sample.

5.2.3. High-Tech vs Non-High-Tech

Using the definitions of Desyllas and Hughes (2010), the panel classify a set of companies as *High-Tech*, basing it on a set of primary SIC codes, whereas the residuals thus, becomes *Non-High-Tech*.[13] We then ran the regression on these two samples to observe any differences, in innovation input (Δ_*R&D_Intensity_t+3*), innovation output *Ln_Patents_t+2,* and Innovation efficiency (*Innovation_Productivity).*

As seen by Appendix C, Table C1 Looking at the innovation input-based regressions, various results are found, contrasting with the results in section 5.1. Main Specification. For *Non-High-Tech* firms, there is a positive effect, though statistically insignificant (0.14%, p>0.1), whereas *High-Tech Firms*, in line with the our original sample, show an insignificant negative effect (-0.56%, p>0.1). For innovation output (Appendix C Table C2), both group of firms show a positive impact in number of patents produced following an acquisition, however only *High-Tech* firms show a statistically significant relationship (0.094, p<0.05), indicating that high-tech acquirers are able to produce more patents following an acquisition, compared to non-high-tech acquirers. The explanatory model for R&D intensity based dependent variables

[13] Firms categorized as *High-Tech* is based on the following primary SIC industry codes: 28 (Chemicals and Allied Products), 35 (Industrial and Commercial Machinery and Computer Equipment), 36 (Electronics and Electrical Equipment), 37 (Transportation Equipment), 38 (Measuring, Analyzing and Controlling Instruments; Photographic, Medical and Optical Goods), and 48 (Communications), we define those without a match (the inverse) as *Non-high-tech*.

among *Non-High-Tech* firms diverges from the regression results in the main specification, suggesting the presence of unobserved heterogeneity or omitted factors influencing R&D intensity beyond the effect of M&A activity. These results suggest that firms within inherently more technological advanced industries show a decrease in R&D intensity following acquisition, combined with an increase in the number of patents granted. Looking at the results for innovation productivity (Appendix C Table C3), the results are in line with the main specification, with no significances across all control variables.

In respect to control variables for input- and output-based regressions, the effects are relatively consistent with what is seen in the main specification. *Ln_Total_Assets* is negatively related to to innovation input (Δ*R&D_Intensity*: -0.24, p>0.1 *High-Tech*; -0.145, p<0.1 *Non-Tigh-Tech*), with the same for *Leverage_Growth*, a more potent effect for high-tech firms (-0.15, p<0.01) is witnessed, with positive effects for innovation output. Additionally, whether the acquisition is intra-industry plays a statistically significant role for high-tech firms as the effect is coherently positive for innovation input (0.82, p<0.1 *High-Tech*; -0.15, p>0.1 *Non-High-Tech*), as suggested by *Same_Industry*, indicating a strong positive impact of the target and acquirer being in the same industry on the innovation input levels, potentially attributable to the role of technological and strategic relatedness in R&D efforts. C*urrent_Ratio*, a proxy for liquidity, is negligible for *Non-High-Tech* firms. In contrast, it is positively associated with innovation inputs for *High-Tech* firms, suggesting that liquidity positively influence R&D intensity for such firms.

5.2.4. Industry Comparison

Upon dividing the original sample into industry segments, based on macro SIC codes (two-digit SIC-codes), we witness highly varying effects across the different industries for innovation input dependent variables. Similar to the high-tech vs non-high-tech comparison, we proxy innovation input by the three-year Δ*_R&D_Intensity* (Appendix C Table C5). Here, the effects of M&A on innovation input levels are the most prominent and significant in *Services* (-1.623%, p<0.01), but an overall insignificant impact (p>0.1) and varying signs for the other industries. These varying results suggest that industry context plays a role in acquisitions' impact on innovation input performance in, but not to a meaningful level. Notably, the impact of *Ln_Total_Assets* on R&D intensity varies across industries, with *Retail Trade* showing the greatest absolute impact, where larger firms showcase higher relative innovation input. Further, domestic acquisitions (*Same_Nation)* in the *Transport & Utilities* industry statistically insignificant and negatively impact R&D intensity (-1.037%, p<0.05), surprisingly showing that cross-border acquisitions result in higher R&D intensity. Overall, looking at *Same_Industry*, which has a positive, yet statistically insignificant impact (p>0.1), our results suggests that acquisitions within similar industries have the potential of yielding higher R&D intensity, for the acquirers.

Comparable results, with varying levels of statistical significance, are observed when employing innovation output-based dependent variables across different industries (see Appendix C Table C5). The most pronounced positive effects of *M&A_Last_3_Years* are found in *Mining* (0.604, $p < 0.01$), *Manufacturing* (0.128, $p < 0.01$), and *Retail Trade* (0.362, $p < 0.05$), suggesting that recent acquisitions are associated with an increase in the number of granted patents for acquirers in these sectors. In contrast, the *Services* sector exhibits a negative and statistically significant relationship ($p < 0.1$), though the heterogeneity of firms within this broad category limits the interpretability of the result and calls for more granular industry-level analysis. Notably, intra-industry acquisitions are only statistically significant for acquirers in selective industries (*Mining, Finance & Real Estate,* and *Services)* at $p<0.05$. However, the effect varies, as acquirers in *Mining*, opposed to *Finance & Real Estate*, and *Services* are granted less patents after acquisitions.

5.2.5. Replacing M&A_Last_3_Years with M&A_Current_Year

Replacing the M&A dummy looking at the current, and three pre-acquisition years with *M&A_Current_Year*, which equals 1 only if an acquisition has been conducted in the current year (t-1 to t), which test whether results are more sensitive to the choice of exposure window and can isolate for more immediate effects directly upon acquisition. As seen in Appendix C Table C6, the explanatory power of the model, as seen by R^2 remains similar, indicating a low impact of selection window. Noticeably, the impact of acquisitions on R&D intensity turns positive with limited magnitude coefficients, still with statistical insignificance ($p>0.1$), indicating that, presuming a short, immediate effect of M&A on acquisitions, similar to the direct consolidation effect of the financial statements in the year-end to follow, the impact is positive. The effects show that the immediate effect of M&A on R&D intensity is positive. Noticeably, the impact of acquisitions on acquirers' output becomes less statistically significant for *Ln_Patents* and *Ln_Citations* for t+2, indicating that the effect is less systematically immediate. In line with previous robustness tests, but contrasting to the OLS regression utilizing the three-year M&A dummy, the *%_Change_Patents_to_LnR&D* shows a negative relationship with acquisitions. Overall, patents and citations act relatively coherent to the main OLS regression results (as seen in Table 12), with consistent positive and similar economical magnitudes coefficients, with lower statistical significance in terms of p-values, as well as explanatory power. Contrastingly, innovation productivity measures do not act accordingly to the main OLS regression results (results shown in table Table 12), and show a larger negative impact on both variables (*Innovation_Productivity* & *%_Change_Patents_to_LnR&D*). Overall, a potential bias in these results arises from the influence of acquisitions conducted more than two years prior to the current year, whose effects are assumed to be negligible.

5.2.6. Additional Winzorising (2nd and 98th percentile)

To further control for extreme outliers, given the inherent noisiness of innovation inputs and outputs, we winzorise all variables in the dataset to the 2nd and 98th percentiles (compared to 1^{st} and 99^{th} in the original sample). This partially ensure that, a few highly innovative firms or other type of outliers, do not drive the observed effects. The results obtained in Appendix C, Table C7 from winzorising at the 2^{nd} and 98^{th} percentile exhibits a decrease in magnitude for both input and output-based regressions. For *Δ_R&D_Intensity*, the impact of *M&A_Last_3_Years*' magnitude decreases to about 0.0% (0.03%, $p>0.1$ for t+1; -0.03%, $p>0.1$

for t+2; 0.03% p>0.1 for t+3), compared to -0.2% to -0.3% in the original sample (-0.379%, p>0.1 for t+1; -0.360%, p>0.10 for t+2; -0.198% p>0.10 for t+3); lower magnitude of coefficients as well as switched signs for some treatment variables, and with an decrease in statistical significance across tests, are observed. The output-based dependent variables exhibits similar results to the *Main* Specification (Table 11) upon applying a more cautious approach in the treatment of outliers (winzorise 2nd and 98th), the observable difference are more substantial upon assessing the input-based regressions (comparing to Table 11). In contrast to the findings reported in Table 12, the productivity-based outcome measures yield a markedly different pattern (Appendix C Table C7). Specifically, both *Innovation_Productivity* and *%_Change_Patents_to_LnR&D* exhibit a positive and statistically significant association with *M&A_Last_3Y_Years* (4.645%, p<0.01 for *Innovation_Productivity*; 27.58%, p<0.01*%_Change_Patents_to_LnR&D*), reversing prior results in the main specification. The inconsistency between results of the original sample (1st and 99th percentile) and the sample which is winzorised at the 2nd and 98th percentile provides implications in relation to the noisiness of the sample, as expected, that outliers could, to some extent, drive a notable fraction of the results, primarily concerning innovation inputs and productivity.

5.2.7. Summary of Robustness Findings

Altogether, the robustness results above suggest that our main specification is robust in principle, while some notable results are worthwhile highlighting. Among those are the results obtained from removing those observations which originally showed missing R&D values, as removing these from the sample significantly alters the results for the input-based regression results, from coefficients close to zero (in the main specification) to a negative impact on innovation inputs with statistical significance across years (t+1 – t+3). This effect is limited to input variables only. Taken together, in our chosen setting, M&A is observed to negatively affect innovation input components, as proxied by R&D intensity when including a more accurate sample. In contrast, innovation output, i.e. patents and citations, are positively influenced by the occurrence of M&A, regardless of model or chosen sample (with slight variations in statistical significance). These effects are more potent in high-tech industries, consistent with much of the previous literature. Additionally, results are deemed to be relatively sensitive to outliers (winzorising at the 2nd and 98th percentile) but timing assumptions (altering the M&A treatment variable to 1-year impact) does not impact results substantially, if anything, the original model is superior to some its alternatives (e.g. using 3-year lag M&A treatment variable compared to using 1-year M&A variable), indicating robustness of the original model.

6. Discussion

In this paper we address the question of whether acquisitions impact innovation performance, examined through innovation input (R&D intensity), innovation output (patent-based measures), and innovation productivity (R&D expenses in conjunction with patents) on a sample of around 14,000 transactions conducted by c. 3,400 publicly traded U.S. acquirers. Further we explore what underlying factors might be at play, looking at high-tech and non-high-tech firms. Looking at our sample and analysis at an aggregate level over the three post-acquisitions years, we find neutral to negative effects on R&D intensity, positive effects on patents, and negative effects on productivity. The results of our study indicate partial support for our theoretical predictions, showcasing disparity between R&D inputs, patent counts and citations, and R&D productivity.

Table 16: Results' implication for hypotheses

H1.	*M&A has a negative impact on innovation input (R&D intensity) with diminishing effects in the post-acquisition years, predominantly in cross-industry acquisitions.*	Partly supported
H2.	*M&A has a positive impact on innovation output in terms of patent counts and citations.*	Supported
H3.	*M&A has a positive impact on innovation productivity, in the immediate post-acquisition period*	Partly rejected

6.1. Innovation input

Our findings suggest that acquisitions impact innovation input. We observe a negative but inconsistent effect on innovation input which diminishes over time in the post-acquisition years, in line with parts of the results found in the previous literature (Cefis and Triguero, 2016; Hitt et al., 1991, 1996; Ochirova and Dranev, 2021; Szücs, 2014). The interpretations and underlying fundamentals of decreased R&D intensity post-acquisitions include a decreased amount of R&D investments, as explained by internal R&D being phased out, and external sourcing strategies are weakened (Cefis and Triguero, 2016). Similarly, the results, which are in line with our hypothesis (**HI**), stemming from an absolute decrease in in R&D expenses be further explained by increased commercialization of acquired external knowledge, instead of increasing or holding R&D spending constant (Szücs, 2014), as targets are likely to spend less on R&D following an acquisition (Stiebale and Reize, 2011). In line with this, our findings may be also be explained by change in sales, given the innovation output proxy, and the theorization of M&A, in general, being sales-driven, which naturally would result in a decline in relative R&D input (Ahuja and Katila, 2001; Szücs, 2014). Additionally, consistent with the authors, acquirers frequently engage in M&A with cost-reduction motives, particularly targeting operating expenditures such as R&D. Thus, a post-acquisition decline in R&D intensity may be attributable to the centralization of innovation-related activities and reduction in decentralized R&D spending across the combined entity. The negative, yet insignificant, relationship between acquisitions and innovation input, could show that acquirers internalize external acquired knowledge poorly, and lack absorptive capacity for targets, which is partly explained by the positive impact of acquiring targets within similar industries (Cohen and Levinthal, 1989, 1990). Instead, looking at explanations stemming from pre-existing internal innovation capabilities, the findings may suggest that acquirers internal R&D is reduced, or poorly leveraged post-acquisitions, as acquisitions may result in disruption of established organizational R&D activities (Ranft and Lord, 2002). On aggregate, our findings are on average less negative than previous literature (B. H. Hall, 1994; Hitt et al., 1991), and in line with Desyllas and Hughes (2010). Regarding organizational and strategic fit, our results indicate that cross-industry acquisitions do not exhibit a more pronounced negative impact on R&D intensity. The findings are generally ambiguous and contradict prior literature, which suggests that intra-industry acquisitions should positively affect R&D intensity (Hagedoorn and Duysters, 2002). Given the inconsistent findings, we find neither support for nor rejection of Hypothesis I on this matter. Further our analysis on a sample where acquirers and non-acquirers share similar observed firm characteristics, the findings become ambiguous. On one hand, the improved effect on acquisitions in the near term on R&D intensity is in line with theories, and supports Hypothesis I, that organizational fit and technological relatedness play a crucial role in post-acquisitions innovation success (Hagedoorn and Cloodt, 2003; Szücs, 2014). However, the drop in explanatory value of the model, points to the opposite, potentially indicating that such characteristics may not play as important a role. When restricting the sample to firms that explicitly disclose R&D expenditures as a separate line item, arguably indicative of R&D being a central element of the firm's business model and potentially a strategic consideration in target selection, we observe a more robust and temporally declining post-acquisition effect on R&D intensity. These findings may explain the negative relationship through changes in R&D (e.g. poor absorptive capacity, or diminishing internal R&D, poor sourcing strategies) instead of increased sales. The observed diminishing effect is consistent with theoretical perspectives suggesting that acquired innovation may function as a substitute rather than a complement to internal R&D, serving primarily as a mechanism for firms to compensate for innovation deficits or to close technological gaps (Bena and Li, 2014). When segmenting firms by technological orientation, proxied through SIC-based industry classifications, the results show that high-tech firms, in contrast to their non-high-tech counterparts, exhibit a decline in R&D intensity following acquisitions. This divergence from our primary hypothesis may reflect that, in the context of our more recent and globally integrated sample, both high-tech and non-high-tech firms operate at higher absolute levels of technological sophistication than those examined in prior studies. As a result, the complexity of innovation in high-tech firms may hinder the integration of externally sourced knowledge, due to technological complexity. However, non-high-tech acquirers may possess complementary and similar technology as targets, resulting in improved innovation performance (Cassiman et al., 2005).

Overall, our results are inconclusive due to a lack of statistical significance, which limits the explanatory power of the analysis, potentially reflecting the noisy and heterogeneous nature of post-acquisition innovation activity. Accordingly, we conclude that Hypothesis I (**H1**) is only partially supported by our findings.

6.2. Innovation Output

The results obtained when using output-based dependent variables consistently indicate a positive, statistically significant relationship between M&A activity and innovation output for acquirers. These results align with a large extent of previous literature that suggests an increase in patent-stock following acquisitions (Bena and Li, 2014; Hagedoorn and Duysters, 2002). Two primary mechanisms may explain this positive impact. Firstly, firms may successfully internalize valuable knowledge embedded in target firms. Secondly, the acquisitions may help unlock underutilized internal capabilities for the acquirer by providing new resources, scale, or complementary assets, which makes it more feasible to commercialize the existing innovative capabilities. Said mechanisms align with prior research highlighting M&A as a mechanism of realizing economies of scale and scope in innovation, thus enabling a more efficient recombination of existing knowledge bases (Fleming, 2001; Henderson and Cockburn, 1996). The positive and statistically significant relationship found by the results based on the sample constructed with a more closely matched control group aligns with previous research that financial and strategic alignment facilitates post-M&A innovation performance, particularly in high-tech industries (Ahuja and Katila, 2001). However, the coherence with the results in the main specifications limits the extent of this impact. The positive relationship, contrasts the findings of previous literature who observe a negative relationship between M&A and innovation output performance. This negative relationship is explained by researchers as acquisitions disrupting organizational routines and other internal processes, thereby diminishing post-acquisition innovation performance through reduced R&D investments and lower patenting activity (Cassiman et al., 2005; Cloodt et al., 2006; Haucap et al., 2019; Hitt et al., 1991; Stahl, 2010). By yielding a positive result, our analysis implies the inverse relationship, supporting the notion that such acquisitions can generate positive synergies through the effective recombination of knowledge bases between acquirer and target. The idea of relatedness is further reinforced by the coherence of the observed effect of intra-industry acquisitions, as this remains positive across tests. This could be explained by the fact that firms may be better at choosing targets that synergize better with the acquirer, if they already operate the same industry, i.e. companies are better at picking suitable patent-intensive companies (Hagedoorn and Duysters, 2002). Additionally, the role of firm size emerges as an important determinant, as suggested by the results, where larger firms are more likely to generate substantial numbers of patents, likely due to greater scale, infrastructure, and risk tolerance, consistent with prior literature which suggests the importance of scale in innovation processes (Henderson and Cockburn, 1996). Meanwhile, the counterintuitive negative relationship with liquidity could reflect the investment-heavy nature of R&D, where firms that actively are pursuing innovation may appear less liquid but are now seeing their investment bear fruit, as shown by the increase in innovation output. In accordance with Hypothesis II (**H2**.), our findings provide empirical support for the proposition finds M&A exerts a positive and statistically significant effect on innovation output for acquirers.

6.3. Innovation Productivity

Overall, the relationship between acquisitions and innovation productivity of acquiring firms is coherently insignificant, and predominantly negative in general. This is not in line with our hypothesis (**H3.**), but partly in line with the findings in Desyllas and Hughes (2010). Such decrease in efficiency may be explained through two possible mechanisms. First, viewing the acquisition as the target's knowledge base being absorbed into the acquirers. In this case, such absorption results in weakened economics of scale and scope in research, where the acquired patent output stemming from the combined knowledge base, does not compensate for increased R&D expenses (Fleming, 2001; Henderson and Cockburn, 1996). Secondly, as discussed above, that the acquisition disrupts established routines and reduces productivity, as managerial attention and disruptive transaction-cost cast attention away from R&D (Hitt et al., 1991, 1996; Jemison and Sitkin, 1986). However, as theorized, in related acquisitions M&A has a large positive and statistically significant impact on innovation productivity, indicating that the knowledge base increases post-acquisition, in addition to an enhanced capacity to select and absorb targets (Cohen and Levinthal, 1989; Desyllas and Hughes, 2010). However, it is difficult to determine whether this stems from greater efficiency in the exploitation of internal R&D or the infusion of new knowledge base or from an increased number of patents, as observed in our results. As theorized in past literature, outcomes of R&D processes are uncertain and significantly influenced by firm-specific factors such as existing knowledge base, size, and prior experience as well as external factors such as competition and technological opportunities which could provide nuance to why a direct increase in innovation efficiency isn't observed in the results (Cloodt et al., 2006). Overall, our analysis exhibits an insignificant relationship between acquisitions and innovation productivity, providing us substance to partly reject our hypothesis (**H3.)**

7. Conclusion

This thesis sets out to examine whether mergers and acquisitions (M&As) influence corporate innovation for the acquirers, using a comprehensive panel of transactions from U.S. public firms 2010-2023. We analyzed innovation from multiple angles; R&D expenses (innovation input), patent-based outcomes (innovation output), and a combined efficiency measure, to capture the nuanced ways an acquisition might bolster or hinder a firm's innovative activity. Our findings present a nuanced picture: in general, acquisitions are associated with a reduction in R&D intensity, increase in patent output, while the effect on R&D productivity remains ambiguous.

In terms of innovation inputs, we observed a slight post-merger decline in innovation input (R&D intensity) among acquiring firms, though this effect was not consistently significant. The evidence suggests that while some firms may cut R&D spending following an acquisition, potentially to eliminate redundancies, others maintain or reallocate innovation budgets, resulting in a varied pattern. Notably, among R&D-active firms, this reduction was more apparent, indicating that M&A may lead to real shifts in how internal innovation is resourced. A surprising insight is that the distinction between related and unrelated acquisitions was not as significant as expected, suggesting that deal-specific factors may play a larger role than industry similarity. Furthermore, concluding the analysis around innovation outputs, our analysis found a consistent and positive post-acquisition increase in both granted patents and citations, which supports the view that acquisitions can enhance a firm's innovative output by leveraging newly acquired knowledge, technologies, and ongoing development pipelines. The gains appeared early and persisted over several years, particularly within more technology-driven industries. Importantly, the increase in patent activity does not necessarily reflect organic patent growth alone but captures the absorption of the target's innovation pipeline. Lastly, innovation productivity, as measured by the efficiency of converting R&D expenses into output, shows a negative, yet insignificant, association with acquisitions. The productivity effect varied across firms, and neither consistently improved, nor decreased post-M&A. This suggests that integration complexities, cultural differences, or disrupted R&D workflows may limit short-term efficiency gains, even when innovation output rises.

Overall, the thesis demonstrates that M&A is neither inherently detrimental nor uniformly beneficial for innovation, and that M&A can serve as a reallocation mechanism for innovation efforts, rather than a straightforward boost or reduction. Instead, outcomes depend on how well firms integrate their innovation capabilities post-deal, as our findings contribute to the existing literature by offering a contemporary understanding of how M&A affects corporate innovation for acquirers. By examining innovation input, output, and their interaction, our study contributes to the understanding of the complex trade-offs and integration challenges that characterize contemporary M&A activity.

For practitioners, this highlights the importance of thoughtful target selection, integration strategies that preserve and activate acquired knowledge assets. For researches, our findings emphasize the need to further explore the deal- and firm-level conditions under which M&A

can drive, not dilute, innovation performance, which will be further elaborated in section 8.2 Suggestions for future research.

8. Limitations and Future Research

8.1. Limitations

Our empirical analysis enables an investigation into whether corporate acquisitions affect the innovation performance of acquiring firms. Nonetheless, the chosen empirical design is subject to several limitations that should be acknowledged.

The data collection process presented a set of limitations. Firstly, by collecting data limited to U.S. public companies, we fail to capture the dynamics of private markets and other global markets, subject to different regulatory, cultural or market environments, limiting the generalizability we can draw from our sample. Secondly, underlying our financial data, we acknowledge that there exist inherent limitations with respect to the U.S. GAAP treatment of capitalization of Research & Development, which generally treats expenses as incurred. However, there exists exceptions, especially relating to software development costs. In relation to software development costs, firms are allowed to capitalize certain ones as intangible assets. This accounting flexibility could introduce inconsistencies in how R&D intensity is reported across different firms. Similarly, our analysis may be affected by biases inherent in patent counts and citation dynamics. Not all innovation is patented, particularly in industries such as services and finance, where firms often rely on process innovations or trade secrets. As a result, patent-based metrics may understate the true level of innovative output in these sectors. Additionally, patent citations accumulate gradually and often take several years to reflect the full impact of an invention. This citation lag, combined with the relatively short observation window discussed below, presents a further limitation to capturing innovation output comprehensively.

Additionally, we observe an inherent limitation in our patent data collection process by using grant date as the time marker for patents. While the grant date is at the point in time when the patent becomes legally viable and has the potential to become commercialized, it could just as well be argued that this on the other hand fails to acknowledge when the actual innovation process occur as the application date is a more accurate depiction of that, provided that it reflects the point in time which the patent is filed. We argue that both time markers presents limitations, ultimately, we argue grant date to be a more logical choice (despite inherent limitations).

Furthermore, the lack of deal-specific information, most notably deal value, constrains the depth of our analysis given that such variables may represent important moderators of the observed relationship between acquisitions and subsequent innovation outcomes. Due to data limitations, patent information beyond January 1, 2020, was unavailable, thereby constraining the analysis to an earlier period. This restricts the study's ability to capture more recent technological developments, particularly those related to advancements in artificial intelligence over the past four years.

The design of our empirical methodology entails several limitations. Most notably, we acknowledge the potential presence of endogeneity stemming from omitted variable bias, as outlined in Section 4.3 on Control Variables. This limitation constrains our capacity to draw strong causal inferences. While our control variables account for financial firm-specific and deal-specific characteristics, they do not capture qualitative dimensions such as board composition, product portfolios, or strategic motives, all of which are likely to influence post-M&A outcomes. Due to data availability constraints, these qualitative factors were excluded, despite their potential to offer valuable context, particularly in assessing the similarity of firm-year observations. This limitation also affects the construction of a more realistic control group through propensity score matching, as the matching procedure is restricted to a limited set of financial ratios.

Moreover, we permit matches between treated and non-treated firm-year observations originating from the same firm but in different years. Although this approach enhances financial comparability, it introduces potential bias arising from firm-specific, time-varying effects. Additionally, to construct a consistent panel of firm-year observations and facilitate matching with both patent data and M&A information, we restricted the dataset to unique firm-year pairs. In instances where firms engaged in multiple acquisitions within a given calendar year, only the first transaction was retained. This exclusion limits our ability to capture the behavior and innovation dynamics of serial acquirers, whose cumulative deal activity may significantly influence both innovation input and output measures.

We limit our analysis to a three-year post-acquisition window. However, innovation outcomes often materialize over longer horizons, meaning that potential benefits or drawbacks of M&A activity on innovation may not be fully captured within our observation period. By truncating the window at three years, we risk omitting delayed effects that could provide a more comprehensive understanding of the relationship.

8.2. Suggestions for Future Research

We suggest that future research separate the analysis of acquirers and targets to better understand how innovation evolves on both sides of the transactions. This could clarify how internal and acquired knowledge interact post-deal and offer a more detailed view of absorptive capacity, especially whether acquirers leverage or lose the target’s innovation potential.

Another key area is the role of emerging technologies, particularly artificial intelligence, in shaping post-M&A innovation outcomes. Studying AI-intensive industries, or regions, could reveal whether AI enhances integration and innovation performance, or introduces new challenges. This could offer timely insights into how technology reshapes M&A agendas, strategies, and outcomes, as AI continues to evolve as both a catalyst and consequence of innovation; its full impact still unfolding in ways no one can yet predict.

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Appendix

Appendix A

Table A1. Overview of results from previous literature

Authors	Sample	Input / Output	Measure of innovation	Sample Period	Result	No. of Firms
Bertrand (2009)	French high-tech firms	Input	R&D expenditure	1994-2004	Positive	123
Bertrand and Zuniga (2006)	Global manufacturing sample	Input	Industry-level R&D investment	1990-1999	Neutral	+50,000 (obs)
Blonigen and Taylor (2000)	U.S. Electronic and electric equipment	Input	R&D intensity (assets)	1985–1993	Negative	217
Cassiman et al. (2005)	EU Medium- and high-tech industries	Input	R&D input/output	1987–2002	Negative	62
Cefis (2010)	Dutch manufacturing industry	Input	R&D expenditure	1994–2002	Positive	2,913
Cefis and Triguero (2016)	Spanish Manufacturing sector.	Input	R&D	1990-2008	Negative	4,629
Cefis et al. (2009)	Dutch general sample	Input	R&D expenditure and efficiency	1994-2004	Mixed	3,696
Hall et al. (1990)	U.S. manufacturing industry	Input	R&D intensity (sales)	1959–1987	Negative	25
Healy et al. (1992)	U.S. manufacturing industry	Input	R&D intensity (over market value of assets)	1979–1984	Neutral	100
Hitt et al. (1996)	U.S. manufacturing industry	Input	R&D intensity (sales), new product intensity	1985–1991	Negative	776
Ikeda and Doi (1983)	Japan manufacturing industry	Input	R&D intensity (sales)	1964–1975	Neutral	44
Ochirova and Dranev (2021)	Global technology	Input	R&D expenditure, Intangible assets	2010-2019	Negative	322
Ornaghi (2009)	Pharmaceuticals	Input	R&D performance	1988-2004	Negative	27
Stiebale (2013)	German firms	Input	R&D intensity	2002-2007	Positive	324
Szücs (2014)	Global	Inputs	R&D expenditure	1990-2009	Negative	388
Desyllas and Hughes (2010)	U.S. High-Tech acquisitions	Input / Output	R&D intensity/Patents & Productivity	1984-1998	Positive	2,624

Haucap and Stiebale (2016)	Pharmaceutical firms in Europe	Input / Output	Patents, citations, R&D	1991-2007	Negative	381
Hitt et al. (1991)	U.S. acquisitions	Input / Output	R&D and patent intensity	1970-1986	Negative	191
Gantumur and Stephan (2010)	German Manufacturing	Input / Output	Productivity Index	1992-2004	Positive	412
Gantumur and Stephan (2012)	U.S. Telecommunication equipment	Input / Output	R&D intensity & Patents	1988–2002	Positive	208
Stiebale and Reize (2011)	German high-technology firms	Input / Output	R&D expenditure	2000-2008	Negative	304
Ahuja and Katila (2001)	U.S. Global chemicals industry	Output	Patents	1980–1991	Neutral / Positive	72
Cloodt, Hagedoorn, and Van Kranenburg (2006)	U.S., Europe and Asia high tech industries	Output	Patents granted	1994–1996	Mixed	347
Hagedoorn and Duysters (2002)	U.S, computer industry (US, EU and Canada)	Output	Patent intensity growth	1986-1992	Positive	135
Makri et al. (2010)	U.S. Drug, chemical, and electronics industry	Output	Patents	1999–2001	Positive	95
Sevilir, Tian (2012)	Cross-industry U.S. Sample	Output	Patents, citations	1990-2006	Positive	105,314 (obs.)

Table A2. Distribution of number of transactions from firms

Number of transactions	**Number of firms**	**% of sample**
1	4,011	39.31%
2	1,800	17.64%
3	994	9.74%
4	684	6.70%
5	453	4.44%
6	368	3.61%
7	312	3.06%
8	209	2.05%
9	185	1.81%
10–19	820	8.04%
20–29	205	2.01%
30–39	81	0.79%
40–49	17	0.17%
50–59	25	0.25%
60–69	13	0.13%
70–79	5	0.05%
80–89	6	0.06%
90–99	2	0.02%
100+	13	0.13%
Total	**10,230**	**100%**

Note: M&A Transactions per firm, and its distribution in final sample.

Appendix B

Table B1. Descriptive Statistics for variables in main regression

Variables	Obs	Mean	Std. Dev.	Min	Max
M&A_Last_3_Years	46,815	0.515	0.500	0.000	1.000
ΔR&D_Intensity_avg	35,575	2.223	38.543	-165.626	306.846
ΔR&D_Intensity_t+1	39,002	-.753	32.378	-224.459	188.829
ΔR&D_Intensity_t+2	34,802	-.951	29.435	-216.029	156.437
ΔR&D_Intensity_t+3	30,918	-1.156	27.552	-213.192	131.112
Ln_Patents_t+1	7,276	1.410	1.006	0.693	5.124
Ln_Patents_t+2	6,315	1.416	1.007	0.693	5.094
Ln_Citations_t+1	7,276	1.650	1.701	0.000	6.801
Ln_Citations_t+2	6,315	1.557	1.653	0.000	6.550
Innovation_Productivity	3,812	13.832	336.592	-1,871.933	1,812.000
%_Change_Patents_to_LnR&D	2,452	220.445	937.646	-98.604	7,324.917
Ln_Total_Assets	46,815	12.647	4.319	0.000	19.043
Leverage_Growth	46,815	0.538	9.298	-39.483	43.143
Ln_Sales_Growth	46,815	6.987	32.463	-119.845	155.966
EBIT_Margin	46,815	-130.135	827.668	-7,059.033	94.517
Current_Ratio	41,538	3.750	5.471	0.084	37.065
Same_Nation	46,815	0.252	0.4340	0.000	1.000
Same_Industry	46,815	0.226	0.4180	0.000	1.000

Note: Summary statistics for variables using in main specification (*5.1 Main Specification*) OLS regressions (see section 4. Methodology Table 8. Variable Overview for definitions).

The descriptive statistics reveal several noteworthy patterns that underscore both heterogeneity and skewness in the firm-level innovation and financial characteristics in the sample. The treatment variable *M&A_Last_3_Years* indicates that 52% of firm-year observations involved a firm active in M&A within the past three years, suggesting a substantial level of acquisition activity. The average change in R&D intensity (*ΔR&D_Intensity*$_{avg}$) is modest at 2.2%, but the high standard deviation (39%) and wide range (-166% to 307%) indicate considerable dispersion, suggesting sensitivity to outliers and a high degree of heterogeneity in firms' innovation responses. This pattern persists across the future R&D change measures (*ΔR&D_intensity* t+1 to t+3), all of which display negative means and substantial variability, pointing to declining R&D trajectories on average post-M&A, albeit with large firm-level differences. Innovation output variables also exhibit significant skewness and outlier sensitivity. The variables *Ln_Patents*$_{(t+1)}$ and *Ln_Patents*$_{(t+2)}$ have similar means around 1.41, while *Ln_Citations*$_{(t+1)}$ and *Ln_Citations*$_{(t+2)}$ average 1.65 and 1.56, respectively, indicating modest citation levels but with considerable variation, particularly in the right tail. *Innovation_Productivity* has a mean of 13.83 and a standard deviation of 336.6, with extreme minimum and maximum values (-1,871to 1,812), reflecting large disparities in innovative output relative to input. Likewise, *%_change_Patents_to_LnR&D* shows a mean of 220% and a standard deviation of 938%, again suggesting that a few firms exhibit disproportionately high innovation efficiency while others show severe declines. The control variables similarly reflect non-normal distributions and firm-level volatility. *EBIT_Margin* is notably negative on average (-130%) with a very large standard deviation (828%) and minimum value (-7,059), indicating the presence of distressed or highly unprofitable firms. *Ln_Assets, Leverage_Growth, Ln_Sales_growth*, and *Current_Ratio* also exhibit substantial variation across observations, although within more expected ranges for firm-level financial data. Lastly, the deal-specific controls *Same_Nation* and *Same_Industry* indicate that only 25% and 23% of acquisitions, respectively, occur within national or industry boundaries. This suggests that cross-border and cross-sector M&A dominates the sample, consistent with a strategy of acquiring external capabilities or accessing new markets.

Table B2. Correlation matrix

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	M&A_Last_3_Years	1.000										
(2)	R&D_intensity_t+1	-0.023***	1.000									
(3)	Patent_count_t+1	0.084***	-0.007	1.000								
(4)	Citation_count_t+1	0.044***	-0.004	0.648***	1.000							
(5)	Ln_Total_assets	0.369***	-0.025***	0.120***	0.068***	1.000						
(6)	Leverage_Growth	0.010**	0.007	0.003	-0.003	0.001	1.000					
(7)	Ln_Sales_Growth	0.050***	0.011**	0.002	0.019	0.055***	-0.035***	1.000				
(8)	EBIT_Margin	0.123***	-0.087***	0.028**	0.017	0.096***	-0.035***	0.129***	1.000			
(9)	Current_Ratio	-0.146***	0.024***	-0.046***	-0.026**	-0.195***	-0.034***	-0.014***	-0.091***	1.000		
(10)	Same_Nation	0.563***	-0.015***	0.055***	0.029**	0.202***	-0.033***	0.032***	0.078***	-0.087***	1.000	
(11)	Same_Industry	0.524***	-0.014***	0.053***	0.044***	0.214***	-0.032***	0.029***	0.074***	-0.084***	0.745***	1.000

Note: Correlation matrix. *** p<0.01, ** p<0.05, * p<0.1

Appendix C

Table C1: High-Tech vs Non-High-Tech OLS Regression Innovation Input (R&D intensity)

	Dependent Variable ΔR&D intensity t+3	
	(1)	**(2)**
	High-Tech	Non-High-Tech
M&A_Last_3_Years	-0.560	0.144
	(0.657)	(0.171)
Ln_Total_Assets	-0.236	-0.145*
	(0.159)	(0.0800)
Leverage_Growth	-0.0218	0.0745
	(0.483)	(0.256)
Ln_Sales_Growth	0.822*	-0.152
	(0.466)	(0.219)
EBIT_Margin	-0.149***	-0.00338
	(0.0482)	(0.0218)
Current_Ratio	0.0135	-0.000370
	(0.0184)	(0.00387)
Same_Nation	0.0138***	0.00269
	(0.00108)	(0.00168)
Same_Industry	0.258	-0.0163
	(0.157)	(0.0104)
Constant	2.576	2.029
	(3.023)	(1.253)
Obs.	15,168	11,965
Firms	1,811	1,359
R^2	0.12	0.03
Adj. R^2	0.12	0.02
Year FE	Yes	Yes
Industry FE	Yes	Yes

Note: OLS regression with Δ*R&D Intensity_t+3* (R&D/Sales). See Table 8 for variable definitions. Classification of firms into *High-Tech* (Two-Digit SIC Codes: 28, 35, 36, 37, 38, 48) and *Non-High-Tech* (residuals). Standard errors are in parenthesis. Industry and year dummies are included, but not shown. *** p<0.01, ** p<0.05, * p<0.1

Table C2: High-Tech vs Non-High-Tech OLS regression innovation output (Patents)

	Dependent Variable Ln Patents t+2	
	(1)	**(2)**
	High-Tech	Non-High-Tech
M&A_Last_3_Years	0.0936**	0.0957
	(0.0381)	(0.0620)
Ln_Total_Assets	0.0501***	0.00364
	(0.00442)	(0.00838)
Leverage_Growth	-0.00719	-0.112*
	(0.0540)	(0.0617)
Ln_Sales_Growth	0.0643	0.102*
	(0.0541)	(0.0582)
EBIT_Margin	0.000600	0.000466
	(0.00131)	(0.00275)
Current_Ratio	-0.0000578	-0.000125
	(0.000336)	(0.000756)
Same_Nation	0.0000312***	-0.0000342
	(0.00000908)	(0.0000825)
Same_Industry	-0.000313	-0.0126**
	(0.00288)	(0.00511)
Constant	0.906***	1.249***
	(0.309)	(0.230)
Obs.	4,989	1,157
Firms	1,072	347
R^2	0.09	0.08
Adj. R^2	0.08	0.03
Year FE	Yes	Yes
Industry FE	Yes	Yes

Note: OLS regression with *Ln_Patents_t+2* as dependent variables. See Table 8 for variable definitions. Classification of firms into *High-Tech* (Two-Digit SIC Codes: 28, 35, 36, 37, 38, 48) and *Non-High-Tech* (residuals). Standard errors are in parenthesis. Industry and year dummies are included, but not shown. *** p<0.01, ** p<0.05, * p<0.1

Table C3: High-Tech vs Non-High-Tech OLS regression innovation productivity (Productivity)

	Dependent Variable Innovation Productivity	
	(1)	**(2)**
	High-Tech	Non-High-Tech
M&A_Last_3_Years	-1.746	-52.16
	(13.92)	(39.55)
Ln_Total_Assets	3.702	12.25
	(3.191)	(8.248)
Leverage_Growth	4.317	132.8
	(22.83)	(93.39)
Ln_Sales_Growth	31.13	-148.9
	(23.24)	(118.5)
EBIT_Margin	0.0126	-2.953
	(0.365)	(2.538)
Current_Ratio	0.0717	-0.410
	(0.113)	(1.171)
Same_Nation	-0.000451	-0.213
	(0.00174)	(0.189)
Same_Industry	0.907	1.488
	(0.790)	(2.952)
Constant	-80.55	1.472
	(115.2)	(102.8)
Obs.	3,666	144
Firms	769	37
R^2	0.02	0.16
Adj. R^2	0.01	-0.10
Year FE	Yes	Yes
Industry FE	Yes	Yes

Note: Table shows OLS regression with *Innovation_Productivity* as dependent variable. See Table 8 for variable definitions. Classification of firms into *High-Tech* (Two-Digit SIC Codes: 28, 35, 36, 37, 38, 48) and *Non-High-Tech* (residuals). Standard errors are in parenthesis. Industry and year dummies are included, but not shown. *** p<0.01, ** p<0.05, * p<0.1

Table C4: Industry comparison OLS regression innovation input (R&D intensity)

	Dependent Variable ΔR&D intensity t+3									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Agriculture	Mining	Construction	Manufacturing	Transport & Utilities	Wholesale Trade	Retail Trade	Finance & Real Estate	Services	Public Admin
M&A_Last_3_Years	0.126	-0.0156	-0.0391	0.0397	-0.108	0.0597	0.0448	-0.0830	-1.623**	-0.0603
	(2.347)	(0.332)	(0.0883)	(0.810)	(0.575)	(0.0436)	(0.0344)	(0.195)	(0.758)	(0.269)
Ln_Total_Assets	0.544	-0.182	0.0674*	-0.323	-0.528*	0.00614	0.0344***	0.0614	-0.252	-0.0238
	(0.557)	(0.115)	(0.0392)	(0.199)	(0.284)	(0.0109)	(0.0111)	(0.0801)	(0.200)	(0.0450)
Leverage_Growth	-0.736	0.717	0.0933	0.274	-1.037**	0.00111	0.125*	-0.371	-0.0223	0.461
	(1.698)	(0.874)	(0.0648)	(0.583)	(0.419)	(0.0129)	(0.0644)	(0.320)	(0.733)	(0.279)
Ln_Sales_Growth	1.193	-0.701	0.00508	0.681	0.0214	0.00301	-0.164**	0.199	0.701	0.0423
	(1.257)	(0.845)	(0.0426)	(0.566)	(0.442)	(0.0119)	(0.0641)	(0.294)	(0.658)	(0.261)
EBIT_Margin	-0.0458	-0.00186	-0.00151	-0.183***	-0.0522	0.0000587	0.000347	-0.0386	-0.0192	0.00488
	(0.0601)	(0.0268)	(0.00302)	(0.0573)	(0.0815)	(0.00112)	(0.00144)	(0.0328)	(0.0710)	(0.0293)
Current_Ratio	-0.0146	-0.00199	0.00245	0.0120	0.0369*	-0.000212	0.00135*	0.000597	-0.000335	-0.00962**
	(0.0199)	(0.00238)	(0.00160)	(0.0215)	(0.0188)	(0.000567)	(0.000720)	(0.00170)	(0.0242)	(0.00477)
Same_Nation	-0.00260	0.000164	0.00120	0.0127***	0.00233	-0.00146	-0.000618	0.000407	0.0206***	0.0300***
	(0.00250)	(0.000151)	(0.00261)	(0.00115)	(0.00467)	(0.00357)	(0.00137)	(0.000435)	(0.00296)	(0.000205)
Same_Industry	-0.0836	-0.0790	0.0157**	0.402**	0.160	0.00626	-0.00125	0.00492	-0.503*	-0.177*
	(0.143)	(0.0552)	(0.00624)	(0.180)	(0.351)	(0.00546)	(0.00464)	(0.00373)	(0.278)	(0.102)
Constant	-6.070	2.543	-1.234*	2.394	9.693**	-0.110	-0.514***	-0.966	5.678	0.151
	(7.670)	(1.631)	(0.662)	(3.127)	(4.875)	(0.169)	(0.178)	(1.068)	(3.464)	(0.734)
Obs.	97	992	435	11,551	2,450	941	1,531	4,387	4,669	80
Firms	11	132	46	1,338	259	94	169	499	612	10
R^2	0.15	0.05	0.09	0.10	0.04	0.02	0.04	0.02	0.26	1.00
Adj. R^2	-0.09	0.03	0.04	0.10	0.03	-0.00	0.03	0.01	0.26	1.00
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS regression with Δ*R&D_Intensity_t+3* as dependent variable. See Table 8 for variable definitions. Comparison across industries, based on two-digit SIC-codes (*Agriculture*: 01-09; *Mining*: 10-14; *Construction*: 15-17; *Manufacturing*: 20-39; *Transport & Utilities*: 40-49; *Wholesale Trade*: 50-51; *Retail Trade*: 52-59; *Finance & Real Estate*: 60-67; *Services*: 70-89; *Public Admin*: 91-99). Standard errors are in parenthesis. Industry and year dummies are included, but not shown. *** p<0.01, ** p<0.05, * p<0.1.

Table C5: Industry comparison OLS regression innovation output (Patents)

	Dependent Variable Ln Patents t+2									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	Agriculture	Mining	Construction	Manufacturing	Transport & Utilities	Wholesale Trade	Retail Trade	Finance & Real Estate	Services	Public Admin
M&A_Last_3_Years	3.271	0.604***	0.0511	0.128***	-0.0849	0.0585	0.362**	0.150	-0.142*	4.314*
	(.)	(0.192)	(0.180)	(0.0425)	(0.0929)	(0.230)	(0.176)	(0.123)	(0.0830)	(1.743)
Ln_Total_Assets	-3.371	0.0310	0.00413	0.0544***	-0.00394	-0.0157	0.0254	-0.0282**	0.0327***	-0.492
	(.)	(0.0201)	(0.0454)	(0.00500)	(0.0128)	(0.0202)	(0.0183)	(0.0140)	(0.00946)	(0.235)
Leverage_Growth	0	0.236	0.558	-0.00789	0.0571	-0.188	0.0489	-0.294***	-0.0906	2.896**
	(.)	(0.221)	(0.308)	(0.0621)	(0.117)	(0.147)	(0.245)	(0.112)	(0.0970)	(0.839)
Ln_Sales_Growth	-1.130	-0.455**	-0.566	0.00565	0.00346	0.0559	-0.0629	0.333***	0.389***	-1.551*
	(.)	(0.210)	(0.332)	(0.0624)	(0.120)	(0.116)	(0.221)	(0.0969)	(0.0934)	(0.556)
EBIT_Margin	0	0.0132	-0.0156	0.000629	-0.000599	-0.00248	0.00411	0.00272	-0.00322	-0.0411
	(.)	(0.0134)	(0.0138)	(0.00140)	(0.00838)	(0.00786)	(0.00489)	(0.00807)	(0.00315)	(0.0926)
Current_Ratio	0	-0.00117	-0.00197	0.000212	-0.000279	-0.00275	-0.00396	0.000181	-0.00207**	0.0469**
	(.)	(0.00472)	(0.00313)	(0.000346)	(0.00194)	(0.00295)	(0.00258)	(0.00198)	(0.000955)	(0.0144)
Same_Nation	0	0.00125	-0.000726	0.0000263***	0.0000296	0.00938	0.00304	-0.00142	0.000116***	-0.00102*
	(.)	(0.00266)	(0.0114)	(0.00000937)	(0.0000652)	(0.00853)	(0.00257)	(0.00154)	(0.0000260)	(0.000398)
Same_Industry	0	0.0114	-0.0708	0.0000528	-0.0254***	0.0161	0.0621	-0.00331	0.00843	-0.155
	(.)	(0.0212)	(0.0448)	(0.00309)	(0.00894)	(0.0379)	(0.0585)	(0.00771)	(0.00948)	(0.150)
Constant	38.50	0.418	1.820	0.894***	1.334***	1.467***	0.438	1.809***	-0.0624	3.575
	(.)	(0.423)	(1.176)	(0.138)	(0.283)	(0.310)	(0.408)	(0.347)	(0.169)	(2.133)
Obs.	4	108	27	4,115	341	118	152	403	859	19
Firms	2	31	13	870	85	28	47	112	226	5
R^2	1.00	0.22	0.68	0.09	0.22	0.16	0.24	0.09	0.10	0.97
Adj. R^2	.	0.07	0.07	0.08	0.17	0.03	0.11	0.04	0.07	0.81
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS regression with *LnPatents_t+2* as dependent variable. See Table 8 for variable definitions. Comparison across industries, based on two-digit SIC-codes (*Agriculture*: 01-09; *Mining*: 10-14; *Construction*: 15-17; *Manufacturing*: 20-39; *Transport & Utilities*: 40-49; *Wholesale Trade*: 50-51; *Retail Trade*: 52-59; *Finance & Real Estate*: 60-67; *Services*: 70-89; *Public Admin*: 91-99). Standard errors are in parenthesis. Industry and year dummies are included, but not shown. *** p<0.01, ** p<0.05, * p<0.1.

Table C6: OLS regression with one-year M&A treatment variable

	Dependent Variable					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	ΔR&D intensity avg	ΔR&D intensity t+1	ΔR&D intensity t+2	ΔR&D intensity t+3	LnPatents t+1	LnPatents t+2
M&A_Current_Year	0.112	0.0666	0.0802	0.657	0.144***	0.101*
	(0.707)	(0.483)	(0.444)	(0.429)	(0.0551)	(0.0592)
Ln_Total_Assets	-0.977***	-0.406***	-0.365***	-0.295***	0.0444***	0.0446***
	(0.138)	(0.103)	(0.0994)	(0.0993)	(0.00356)	(0.00387)
Leverage_Growth	-0.0664	-0.0708**	-0.115***	-0.0963***	0.00292***	0.000673
	(0.0425)	(0.0335)	(0.0326)	(0.0329)	(0.00110)	(0.00120)
Ln_Sales_Growth	0.0192	-0.00281	0.00993	0.00736	0.000210	-0.0000402
	(0.0145)	(0.0113)	(0.0112)	(0.0117)	(0.000279)	(0.000311)
EBIT_Margin	0.00537***	0.0109***	0.0126***	0.0128***	0.000031***	0.000032***
	(0.00118)	(0.000997)	(0.000983)	(0.00101)	(0.000008)	(0.000009)
Current_Ratio	0.156*	0.328***	0.194***	0.0781	-0.00468**	-0.00210
	(0.0839)	(0.0725)	(0.0679)	(0.0653)	(0.00221)	(0.00266)
Same_Nation	0.434	0.214	-0.164	-0.482	-0.112**	-0.0652
	(0.580)	(0.372)	(0.332)	(0.328)	(0.0507)	(0.0542)
Same_Industry	-0.901	-0.137	0.363	0.102	0.0716	0.0601
	(0.580)	(0.385)	(0.356)	(0.331)	(0.0465)	(0.0503)
Constant	10.28***	0.492	3.298**	3.685**	0.979***	0.833***
	(2.047)	(2.120)	(1.614)	(1.616)	(0.216)	(0.226)
Obs.	31,036	34,361	30,593	27,133	7,082	6,146
Firms	3,422	3,817	3,521	3,170	1,546	1,419
R^2	0.02	0.06	0.09	0.11	0.11	0.10
Adj. R^2	0.02	0.06	0.09	0.11	0.10	0.09
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS regression with *M&A_Current_year* as M&A dummy and treatment variable. Innovation input- and output-based dependent variables See Table 8 for variable definitions.Standard errors are in parenthesis. Industry and year dummies are included, but not shown. *** p<0.01, ** p<0.05, * p<0.1.

Table C7: OLS regression with additionally winzorized sample (2nd and 98th percentile)

	Dependent Variable									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	ΔR&D intensity avg	ΔR&D intensity t+1	ΔR&D intensity t+2	ΔR&D intensity t+3	LnPatents t+1	LnPatents t+2	LnCitations t+1	LnCitations t+2	Innovation Productivity	% ch. of Pat/LnR&D
M&A_Last_3_Years	-0.146	0.0343	-0.0276	0.0293	0.0776***	0.0944***	0.108**	0.0986**	4.645***	27.58***
	(0.112)	(0.0780)	(0.0807)	(0.0817)	(0.0297)	(0.0322)	(0.0465)	(0.0494)	(1.682)	(5.851)
Ln_Total_Assets	-0.167***	-0.0274	-0.0366*	-0.0321	0.0419***	0.0409***	0.0363***	0.0310***	-0.163	1.961
	(0.0266)	(0.0187)	(0.0193)	(0.0198)	(0.00351)	(0.00381)	(0.00539)	(0.00570)	(0.328)	(1.342)
Leverage_Growth	-0.0339***	-0.0284***	-0.0320***	-0.0333***	0.00329**	0.000999	0.00554**	0.00548**	0.0163	0.00616
	(0.00854)	(0.00640)	(0.00655)	(0.00685)	(0.00142)	(0.00158)	(0.00230)	(0.00256)	(0.0945)	(0.270)
Ln_Sales_Growth	0.00646**	0.000914	0.00487**	0.00315	0.000257	-0.0000322	0.000903	0.000594	0.00153	-0.00240
	(0.00291)	(0.00208)	(0.00216)	(0.00229)	(0.000357)	(0.000391)	(0.000604)	(0.000648)	(0.00324)	(0.0141)
EBIT_Margin	0.00133***	0.00393***	0.00416***	0.00429***	0.000103***	0.000105***	0.0000955**	0.0000901**	0.634	0.506
	(0.000461)	(0.000324)	(0.000337)	(0.000354)	(0.0000233)	(0.0000259)	(0.0000408)	(0.0000441)	(0.641)	(2.254)
Current_Ratio	0.0479**	0.0895***	0.0583***	0.0425***	-0.00490*	-0.00203	0.00315	0.00600	9.464	-38.21
	(0.0201)	(0.0151)	(0.0157)	(0.0160)	(0.00262)	(0.00304)	(0.00457)	(0.00517)	(12.41)	(37.08)
Same_Nation	0.169	0.0593	-0.00224	-0.0255	-0.0640	-0.0435	-0.0572	0.000539	14.02	118.6***
	(0.111)	(0.0704)	(0.0724)	(0.0725)	(0.0390)	(0.0428)	(0.0588)	(0.0616)	(12.64)	(37.98)
Same_Industry	-0.0653	0.108	0.199***	0.169**	0.113***	0.0761*	0.0736	0.0696	-28.94	-499.1***
	(0.111)	(0.0698)	(0.0713)	(0.0717)	(0.0391)	(0.0425)	(0.0590)	(0.0614)	(24.45)	(119.3)
Constant	1.422**	-0.736	0.0746	0.260	1.008***	0.884***	1.661***	1.631***	4.645***	27.58***
	(0.579)	(0.554)	(0.534)	(0.586)	(0.212)	(0.214)	(0.358)	(0.392)	(1.682)	(5.851)
Obs.	31,036	34,361	30,593	27,133	7,082	6,146	7,082	6,146	3,810	2,450
Firms	3,422	3,817	3,521	3,170	15,46	1,419	1,546	1,419	806	578
R^2	0.02	0.05	0.05	0.06	0.11	0.10	0.25	0.24	0.03	0.04
Adj. R^2	0.01	0.04	0.05	0.06	0.10	0.09	0.24	0.23	0.01	0.02
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS regression on sample winzorized on all variables (except M&A dummy at the 2 and 98 percentile, instead of 1 and 99 percentile. See Table 8 for variable definitions. Standard errors are in parenthesis. Industry and year dummies are included, but not shown. *** p<0.01, ** p<0.05, * p<0.1.

Appendix D. Usage of AI in thesis

AI was mainly used as a tool to manage our Stata coding. We employed OpenAI's ChatGPT to support with this, where we used prompts, clearly stating what type of issues and error messages we faced in coding, ChatGPT then helped us identify the issue and helped us remedy them. This allowed us to become more time-efficient, as opposed to spending countless hours in Stata. Additionally, it has been used to provide nuance in respect to how we could clarify certain areas in the of our paper, with respect to the formality and softness of the language. Effectively using it as a tool to change the narrative, avoiding becoming too critical in challenging previous literature. We pasted sections of text to get suggestions on how to rephrase them, drawing inspiration from this advice reformulating the narrative of specific sections (Introduction / Literature Review) of our paper.

As the use of these generative AI tools entails a set of inherent risks, we mitigate this by avoiding overreliance on the tools, focusing on formulation and coding assistance rather than sourcing ideas and generating content. Thus mitigating the possibility of hallucination, we deemed the risk of hallucination to be limited and effectively only drew inspiration from the wording and the code.

Altogether, we argue that the use of these tools has helped us streamline the process in a sense, ticking boxes, opposed to directly improving the quality of our thesis. Using ChatGPT allowed us to devote more time to focus on quality-enhancing tasks, rather than getting stuck on mundane tasks such as error searching in Stata. Instead, we focused on tasks like assessing past literature, interpreting findings, and discussing our results by ourselves. In that way, one could argue that it has had an indirect positive effect on the overall quality of the thesis.