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Strategic Acquisitions and Competition in the Pharmaceutical and Digital Industries: Evidence from the United States and the European Union

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1. Introduction

Are we not in the world of a free market? In the US, one cannot overlook the fact that a few companies have become the leaders in various major industries. Consider soft drinks. As an illustration, the U.S. market is dominated by Coca-Cola and PepsiCo (Visual Capitalist, 2023). It is also true in finance, where the performance of the S&P 500 depends on several technology giants (NVIDIA, Microsoft, Apple, Amazon, and Alphabet) whose impact on the index has increased significantly (Investopedia, 2025; Financial Times, 2025). Alphabet, in its turn, has acquired over 200 companies, with the $32 billion Wiz deal (announced in 2025) being the most recent event (Reuters, 2025; The Verge, 2025), underscoring the fact that mergers and acquisitions (hereinafter referred to as M&A) continue to be the focus of growth strategies. Although the U.S. is typically cited as the archetypal example of a free market, cases like these have demonstrated that in reality, competition is often restricted to a small group of corporate giants. The same trend is being followed in Europe, where only a number of firms dominate various industries. In beverages, the primary actors in most of the EU are Coca-Cola European Partners and PepsiCo, whereas Nestle dominates the bottled water and other non-alcoholic beverages (European Commission, 2024). In the case of stocks, today the Euro Stoxx 50 is heavily concentrated on companies such as ASML, LVMH, SAP, Nestle, Novartis, and TotalEnergies, whose impact has become particularly significant over the last few years (Refinitiv, 2025). Expansion of these European giants is often achieved through M&A: ASML has acquired its way up the semiconductor supply chain, and the acquisition of Tiffany Co. by LVMH in 2021 is by no means the only case of this kind (Financial Times, 2021). In the meantime, several local start-ups have been acquired by American digital companies (OECD, 2020a), posing fresh concerns about the local competition. Altogether, despite the open markets, the business environment in Europe is getting more and more dominated by a few large corporations, similar to the situation in the U.S. The same is true of Asia-Pacific countries but the details vary depending on the location. Domestically, beverage giants such as Suntory and Kirin remain dominant, whereas Coca-Cola is well-established across the region (Euromonitor, 2024). In Japan, the major stock markets like the Nikkei 225 are influenced by large companies like Toyota, Sony, and SoftBank, and in South Korea and Taiwan, Samsung and TSMC (Bloomberg, 2025). Not only do these firms dominate the market value list, but they also lead the innovation trends in the area. It has also seen the increase of M&A: TSMC and Samsung have consolidated their dominance in semiconductors, SoftBank is one of the most active digital acquirers globally (Financial Times, 2023), and Chinese giants such as Tencent and Alibaba have undertaken buying sprees both in China and abroad (OECD, 2021). Thus, similarly to the U.S. and Europe, the Asia-Pacific market, in spite of its quick development and the official openness, is currently molded by several large players. With U.S., European, and Asian-Pacific markets shifting towards increasingly oligopolistic forms (European Commission, 2024; Autor et al., 2020), the boundary between the benefits of genuine efficiency (Demirer and Karaduman, 2022; Bellucci and Rungi, 2024) and the dangers of anticompetitive conduct (Grullon, Larkin and Michaely, 2019; Syverson, 2019; OECD, 20 The following thesis will seek to unravel this by examining several industries and markets.

Strategic acquisitions have been discussed among numerous researchers throughout the past 4 decades regarding its effect on competition. Certain ones have determined that strategic acquisitions yielded more gains, synergies and scale economies (Williamson, 1968; Bradley, Desai and Kim, 1988; Andrade, Mitchell and Stafford, 2001; Maksimovic and Phillips, 2001; Demirer and Karaduman, 2022; Bellucci and Rungi, 2024). Some found that these acquisitions reduced competition, discouraged entry, and were generally harmful to the ultimate customer (Salop, 2005; Kwoka, 2013; Shapiro, 2018; Cunningham, Ederer and Ma, 2021; Kamepalli, Rajan and Zingales, 2020; European Commission, 2024). The efficiency and anticompetitive impacts of strategic acquisitions involve a trade-off, and this issue has got a large audience of scholars (OECD, 2020a; OECD, 2020b; Cabral, 2021; Syverson, 2019). The following review of literature is a synthesis of theoretical and empirical studies on the competitive impacts of strategic acquisitions. Strategic acquisitions are those that are undertaken by firms that are already in the market that are aimed at strengthening, defending or repositioning firms position in the market. The literature on increasing market concentration and power, the merger theory and its relationship with innovation, the acquisition of emerging competitors, or the so-called killer acquisition, the review of ex-post assessment by sector (digital, pharmaceuticals, energy, agro-food, airlines, hospitals, beer and retail), the methodological approaches, such as event studies and structural demand and bargaining models, are used to structure the review. The review subsequently summarizes research gaps, especially the absence of cross-sector and cross-region evidence. It argues that competitive implications of strategic M&A can be further developed using a multi-sector, multi-region empirical strategy.

In summary, this thesis examines whether and how strategic acquisitions influence competition and innovation across regions and sectors. It does so through four testable hypotheses: (H1) whether acquirer announcement returns are, on average, positive; (H2) whether announcement effects differ systematically between the U.S. and the EU; (H3) whether acquisition intensity predicts changes in sector concentration; and (H4) whether sector-level acquisition conditions predict firms' R&D intensity. The contribution presents a unified U.S.–EU × Digital–Pharma lens that combines short-run market reactions with medium-run structural outcomes using harmonized measures—AI and *AI_50*, Top-50-based concentration indices, and firm-level R&D intensity—ensuring results are transparent and comparable across settings. The remainder of the thesis proceeds as follows. Section 2 reviews the related literature and motivates the hypotheses. Section 3 describes the methodology to test for the hypotheses. Section 4 is regarding data, sample construction, and measurement, including the sectoral definitions and the mapping used for Digital and Pharma. Section 5 presents the results for H1–H4 and robustness analyses. Section 6 discusses policy implications and avenues for future research, and concludes.

2. Literature Review – Strategic Acquisitions and Competition

2.1 Macro Evidence on Concentration and Market Power

Over the last few years, economists have become increasingly alert to the issue of market consolidation, and rely on a variety of research in industrial organization. De Loecker, Eeckhout, and Unger (2020) provide an analysis of production-based markups to demonstrate a consistent gap between marginal costs and prices, with average increases in markups accelerating since the 1980s. This shows that the market power has become more concentrated to the disadvantage of customers in favor of companies, and this begs the question of increasing market power.

The development of the so-called superstar firms is one of the driving forces of this change. They are very productive and innovative companies that have been acquiring an ever growing proportion of sales in their own industries. With the change in market activity among these firms, two effects can be seen. First, since superstar firms tend to be more dependent on technology and intangible capital and less on labor, their rising influence reduces the overall labor share in the economy. Second, when one or several big companies grow at the cost of smaller ones, the market structure becomes more concentrated, where power is concentrated to a smaller number of players (Autor et al., 2020).

Similar to De Loecker, Eeckhout, and Unger (2020), Grullon, Larkin, and Michaely (2019) discovered that the gain in profitability at the industry level is not achieved through efficiency improvements, but through broader profit margins, i.e., firms are making more money by setting higher prices because of their better market position. Concurrently, it is also necessary to add that market concentration is not an adequate measure of market power. Concentration as a result, as highlighted by Syverson (2019) should be supplemented with other outcome-based indicators, including trends in prices, markups, quality, or innovation to better comprehend wider competitive dynamics.

Beyond the U.S. evidence, the European Commission (2024) also gave an EU-wide estimation within the last 25 years about concentration. This report documents a rise in market concentration, a less competitive environment due to entry rates and market turnover that has decreased over the past few years, indicating also that this has been a less competitive environment with real growth and welfare consequences.

This has been amplified by studies that have been conducted in the recent past which have provided specific comparisons between the U.S and Europe. According to Philippon (2019), The Great Reversal, the U.S. markets have been getting less competitive since the 1990s, with mark-ups, concentration, and profit margins rising faster than in the European Union. As he put it, consumers in America paying more and having less to choose than consumers in Europe have this as their greatest contributing factor; laxity in applying antitrust laws, and lax attitude to mergers. The current paper underlines that the overall level of competition is closely associated with the regulations and policies that remind us that regulation is not a denizen of background but rather an important aspect of influencing the market.

Going down to individual firms, the OECD (Calligaris, Criscuolo, and Marcolin, 2018) isolates the rise of the above-mentioned superstar firms in developed economies. In business sectors where digital technology and skills drive the industry, these market leaders achieve a much bigger market share and show a wider productivity gap to the rest. The facts suggest that new technology and non-material resources along with the market organization help these leaders pull even further apart. Meanwhile, as per ECB (2020) data on the companies in Europe, the profitability and concentration in diverse sectors have been on the rise. This, however, has not led to the overall deterioration in the well being of consumers as it was the case in the U.S. meaning that the regulations and policies of Europe would have eased some of these.

On the whole, these findings demonstrate that the process of market concentration cannot be divorced of the regulations within the framework of which it occurs. One example is the U.S.: less stringent regulation over mergers has helped to become increasingly concentrated and marked-up. The strains are also felt in Europe, but more stringent enforcement apparently softened the blow. This kind of side-by-side comparison is fundamental to this thesis, which specifically examines how the U.S and EU are responding to these issues in digital and pharmaceutical sectors where superstar companies and winner-takes-all dynamics are especially acute.

2.2 Strategic Acquisitions: Motives, Theories of Harm, and Innovation

The economists are examining mergers on the basis of whether there are pro-competitive advantages or whether they are going to cause anti-competitive harm. Mergers can result in increased efficiency, where firms are able to scale and achieve synergies (Williamson, 1968; Bradley, Desai, and Kim, 1988; Andrade, Mitchell, and Stafford, 2001), offer more products, and use their assets more efficiently (Maksimovic and Phillips, 2001; Teece, Pisano, and Shuen, 1997), eliminate mark-ups, especially in supply chains, and provide increased coordination to investments (Demirer and Karaduman). The more a firm dominates the chain of supply, it may thwart its rivals from accessing crucial sources of inputs, information, or clientele (Rey and Tirole, 2007). And as large masses are created in various markets, they can use their numbers to package goods or drive out competitors in less apparent manners (Nalebuff, 2004; Haucap and Heimeshoff, 2014).

This is particularly relevant to fast-moving industries that are affected in terms of innovation. In industries where there are few large players and they compete based on research and development, merger in fact stifles the motivation to innovate: the new company no longer fears losing its business to a competitor. Federico, Langus, and Valletti (2018) discovered that European pharmaceuticals experienced mergers in which an innovation period collapsed. Nevertheless, the consequences are not necessarily bad. As both Jullien and Lefouili (2018) and Caffarra and Scott Morton (2021) demonstrate, mergers also can promote innovation, an entry into new markets, efficiency, access to potentially valuable assets or intellectual property, or the sharing of knowledge.

In practice, however, it depends on the circumstances, on the form of the market, and the capabilities of the firms at work and on the design of any regulations or cures. Mergers between firms within the same or between industries also contribute a lot to competition. Classic economic theories (Williamson, 1971) say integration becomes reasonable in cases where assets are specialized or contracts are hard to write. Nevertheless, some recent studies in industrial organization indicate that such deals also may serve to complicate the lives of competitors, such as by raising their costs or precluding competitors through control over data and platforms. Regulators today need to take into account these competing effects, particularly in markets where data, algorithms, and network effects can amplify post-merger benefits even more (European Commission, 2024). According to Valletti and Zenger (2021), assessments of mergers should focus on the impact of innovations, especially in rapidly changing and cumulative R&D industries.

A second line of research links traditional economic thinking on innovation to current discussions of strategic acquisitions. Arguing that the best firms are already on the top, Arrow (1962) assumed that firms do not have many reasons to introduce new ideas that can reduce their profits, which is called the replacement effect. Schumpeter (1942), on the other hand, saw large, vertically integrated firms to play an important role in the promotion of bold and radical innovations, because they have the resources necessary to foster them. This pressure and pull finds its expression in more recent work. An example is that Aghion et al. (2005) discovered that there is an inverted U (competition and innovation) relationship; when the market is too strong, research is too slow, and when the market is too strong, firms are also too deterred to invest.

Moving outside of pharma, researchers have discovered that acquisitions tend to alter the rate of company innovation. Prager and Schmitt (2021) observed that hospital mergers in the U.S. reduced the amount of money spent on medical quality and technology. Gautier and Lamesch (2020) discovered in the media world that the integration of companies would occasionally lead to fewer variations in content created by a company. Genakos, Valletti, and Verboven (2018) found that in telecoms, the outcome of mergers in Europe was mixed: prices increased in some cases, but in others, investment in 4G technology accelerated, indicating that the short-term and long-term impacts of mergers do not necessarily run in the same direction.

Regulators too have begun to attach even greater importance to innovation in choosing whether a merger is beneficial or harmful to the consumer. To illustrate, the European Commission raised concerns in the case of both Dow-DuPont (European Commission, 2017) and Bayer-Monsanto (European Commission, 2018) that the arrangements would slow down the pace of new research into seeds and agricultural chemicals, and forced companies to take certain measures to ensure such research continued to advance.

This emphasis demonstrates that policymakers are now more conscious of the relationships between concentration in the market, control over intangible assets, and the incentives to innovate, particularly in markets where long-term success relies more on research rather than immediate pricing (Shapiro, 2012; Motta & Peitz, 2020).

2.3 “Killer Acquisitions”

Killer acquisitions are prominent in the life sciences sector, which includes the pharmaceutical and biotech industries, where the effect of M&A is to decrease the possible competition. According to Cunningham, Ederer, and Ma (2021), projects that incumbent firms acquire and overlap with their current portfolios are most likely to be discontinued following the acquisition, and the objective is to destroy future competition. The OECD Start-ups, Killer Acquisitions, and Merger Control note (2020) extends this concept of killer acquisitions to other dynamic markets, clarifying that the two primary rationales of acquiring firms are (i) acquire firm so as to eliminate future competition by ending the competitive advantage (killer acquisitions), and (ii) acquire the firm so as to gain the competitive advantage of the acquired company. The note also highlights how antitrust authorities should review their Merger Control procedures, in order to make sure that M&A activity does not substantially undermine effective competition, and proposes the use of new tools, known as expected harm tests, to determine the diminution of competition brought about by such transactions.

Some of the same things have been said in the digital markets whereby some structural features make the incentives to counteract future threats higher, i.e. network effects, data benefits and complementarity. Venture activity also dwindles in related fields (so-called kill zone effects) after large acquisitions by dominant platforms (e.g. Facebook - Instagram), which contributes to entry deterrence (Kamepalli, Rajan, and Zingales, 2020). There are numerous digitally significant acquisitions that do not reach turnover requirements that antitrust agencies impose, which means that they are not regulated. According to the 6(b) study conducted by the FTC (2021), 616 deals by large platforms are below the threshold set by the Hart-Scott-Rodino Act ("HSR Act") in the U.S. between 2010 and 2019. New research continues to reveal common trends. According to Birnbaum (2022), big companies usually acquire potentially valuable start-ups in the business software sector, whether to introduce new technology, or simply to marginalize competition. In a study conducted by Rossi (2019), European start-ups tend to have fewer patents after their acquisition by larger firms, indicating that innovation tends to reduce after the acquisition. Cestone, Fumagalli, and Kamepalli (2021) note that the emergence of so-called kill zones implies that start-ups, which expect to be acquired by tech giants, find it more difficult to attract the attention of venture capitalists, which makes the competition environment less dynamic. Both the Stigler Committee (2019, U.S.) and the Furman Review (2019, UK) report that when leading digital platforms continue to purchase smaller companies, this can significantly reduce competition, although consumer prices may not rise immediately..

All that has created some new controversy whether classic merger rules are applicable to the moving and changing industries in the current times. Article 22 first enabled authorities to investigate transactions under the usual reporting level in the EU, but this was withdrawn in 2024 following the Illumina/Grail case. There are also specialists who note that high-tech markets cannot be just controlled by mergers, and smart regulation and specific regulations are also necessary (Cabral, 2021; Shapiro, 2018). When you sum them up, Hemphill and Wu (2020) note that a large number of small acquisitions can make a huge difference in competition. In the meantime, Caffarra, Scott Morton, and Valletti (2019) recommend stricter after-the-fact reviews of deals not originally vetted. Cases such as Illumina-Grail have rekindled debate over whether the threshold of looking into mergers should be reduced and whether the regulators should look ahead at likely risks, not merely at what has already occurred.

2.4 Sectoral Evidence and Ex-Post Studies: Technology, Pharmaceuticals, Energy, Agro-food, Airlines, Hospitals, Beer, and Retail

2.4.1 Technology

Digital platforms are unique due to their high network effects, i.e., the more participants there are, the more beneficial the service will be to all participants (Rochet and Tirole, 2003; Evans and Schmalensee, 2016). These corporations operate on several fronts and possess huge data reserves as well (OECD, 2020b). They tend to acquire other companies when they are seeking such things as specialized AI skills, unique data, or loyal user groups (Caffarra and Scott Morton, 2021; Cabral, 2021). These acquisitions can entirely alter the landscape, allowing large platforms to integrate new capabilities and extend their reach even further (Autor et al., 2020; De Loecker, Eeckhout, and Unger, 2020).

Since most digital services are not charged to users initially, price is not necessarily the most effective metric to assess their impact. That is why regulators have become more attentive to indicators, such as an innovation deceleration, whether new entrants can enter the market, or whether closely linked markets are transforming (Shapiro, 2018; OECD, 2020a; European Commission, 2021). Scholarship on this is increasing, with varied findings. There is also research cautioning that frequent acquisitions might suffocate emergent competitors (Cunningham, Ederer, and Ma, 2021; Kamepalli, Rajan, and Zingales, 2020). Others indicate that such agreements are sometimes used to disseminate products or to improve the compatibility of various technology (Jullien and Lefouili, 2018; Federico, Langus, and Valletti, 2018; Demirer and Karaduman, 2022).

Considering special situations, there are some obvious danger signals concerning competition. As an illustration, the Competition and Markets Authority (CMA, 2020) in the UK prevented Sabre-Farelogix merger in travel technology: since the merger would have resulted in the removal of a promising competitor to airline booking systems. The European Commission (2020) did allow Google to purchase Fitbit, albeit with strict regulations to ensure that Google did not leverage the health data to further cement control over the ecosystem. In 2022, CMA prevented the acquisition of Giphy by Meta, arguing over ad influence and the possibility of closing competitor social networks.

Scientists have additionally noted that such purchases may not only force the main market but also disrupt the entire ecosystem. According to Caffarra, Crawford, and Valletti (2019), digital markets commonly rely on gatekeeper companies, and once the latter purchases related services, such as messaging applications, health applications, or cloud services, they can package products, making it further difficult to compete. Such a form of leveraging the eco-system can increase the cost to competitors, prevent entry and determine the next direction of innovation.

Also, research shows that due to the propensity of giant platforms to take over numerous smaller companies, regulators find it challenging to keep pace. According to Gautier and Lamesch (2021), the leading technological players, GAFAM (Google, Apple, Facebook, currently called Meta, Amazon, and Microsoft), acquired more than 800 companies between 2000 and 2020; most of them are too small to raise regulatory concerns. This trend shows that any single deal might be negligible, but its cumulative effect has the potential to shift the dynamics of the market and the degree of innovation.

2.4.2 Pharmaceuticals

Regulatory check points and clinical trial databases are unique features of pharmaceutical markets, which have made it possible to track the innovation. Cunningham, Ederer, and Ma (2021) discovered that when a drug company acquires another, particularly when the drug company pipelines overlap, certain projects most likely will be abandoned. Other researchers indicate such deals not only impact the companies but also paralyze the research of the competitors (Federico, Langus, and Valletti, 2018; Jullien and Lefouili, 2018). Regulators frequently force firms to sell off operations, license, or open up data access, yet it remains unclear whether these solutions will effectively maintain long-term competition (OECD, 2020a; ICN, 2022).

A good example is the Bayer-Monsanto merger, which not only grabbed headlines because of the disruption it caused in the agrochemical business, but also because of its side effects in medicine. In its analysis of this deal, the European Commission (2018) cautioned that crop protection innovation would be slowed and demand that Bayer sell off a major part of its business to BASF to preserve the competition and innovation.

The pluses and minuses of big pharma mergers are oftentimes made visible. In 2009, Pfizer acquired Wyeth and Sanofi acquired Genzyme, the spin the reason was that they would combine their strengths to increase their R&D and reduce costs. Subsequent reviews, however, discovered the cost saving was real, but little evidence that the research became more productive. The acquisition of Allergan by AbbVie (2020) was even more closely examined due to the fact that the two companies collaborated on the same drug line in immunology and oncology. Opponents feared that there would be less competition and hence reduced incentive to improve.

These concerns are confirmed by empirical work with patent and clinical trial information. Ornaghi (2009) discovered that mergers of large drug companies in the 1990s resulted into low levels of R&D activity as compared to its non-merged counterparts. According to Haucap and Stiebale (2016), even the quality of innovation expressed in the number of patent citations deteriorated following pharmaceutical mergers. Igami and Uetake (2020) more recently demonstrated that when market leaders bought possible competitors in antibiotics, fewer new medicines really managed to reach late-stage clinical trials.

But it's not all bad news. According to Cassiman, Colombo, Garrone and Veugelers (2005) mergers have also been found to promote companies to engage in research and also share knowledge particularly when their technologies are complementary. One such case was the asset swap between Novartis and GSK in 2015 when the two companies exchanged their oncology and vaccine businesses. It not only helped both companies become more focused but it might have helped enhance innovation.

The discourse of policy is highly dynamic. The U.S. FTC has opposed several pharma mergers, including Amgen-Horizon in 2023, due to the agency's worry about bundling and firms using their power in one market to gain an edge in the other. In more recent instances in Europe, such as Illumina-Grail (blocked in 2022, annulled in 2024), regulators have experimented with alternative approaches to identify threats to novel competition in the biotech sector. At the heart of these arguments is the fact that innovation is not purely a question of how much money is spent on research and development, but rather who makes decisions about what gets to be a project and what gets put on hold.

2.4.3 Energy

The energy and utility markets have various rules, their prices are restricted, and they have to serve everyone. The idea of mergers in such industries is often marketed as a solution to a more efficient and better investment but in fact, studies have shown that the resulting savings are usually minimal and not necessarily beneficial to the consumer (Kwoka and Pollitt, 2010; Kwoka, 2015). Rather, competition could manifest itself in such aspects as service quality or time of investments or even the extent to which companies are innovative (OECD, 2021; European Commission, 2024). It is not easy to compare countries either, as the rules and ownership approaches differ so much depending on the location.

2.4.4 Agro-food

The global trend in seed and agro-chemical companies has been massive mergers. OECD (2018) determined that some firms dominate much of the market in a number of major crops and this has caused concern regarding prices, choice, and the future of innovation. In response to these issues, regulators have frequently required consolidating companies to divest some properties, such as plant characteristics, breeding activities, or research and development to maintain market competition. Nevertheless, it remains unclear so far whether these measures are sufficient to safeguard variety and promote new developments in the long term (Haucap and Heimeshoff, 2014; ICN, 2022).

2.4.5 Airlines

Mergers between airlines are one of the best-researched examples of the impact of deals on prices. Kim and Singal (1993) discovered that fares on routes in which airlines have been merged are likely to increase and some of the respective price increases are transferred to other airlines. Subsequent studies further examined variations among routes, capacity constraints, and rivalry among several airports (Borenstein, 1990; Peters, 2006). Although exact descriptions vary based on network structures and airport assignments, the general consensus by most studies is that prices tend to increase on overlapping routes once a merger has been made (Kwoka, 2013; U.S. DOJ & FTC, 2010).

2.4.6 Hospitals

Another field where scientific inquiries have been directed is in the case of healthcare mergers and the subsequent effects on prices and quality. Gowrisankaran, Nevo and Town (2015) established that as hospitals consolidate, negotiated prices between them and insurers tend to increase whereas any quality gains are less apparent. Later research has demonstrated that it is possible that even upon merging between the hospitals in various areas, the prices may also increase due to an insurers or employers negotiating agreements that cut across the areas (Dafny, Ho, and Lee, 2019; Dafny, 2014). Consequently, regulators are being more vigilant, and certain mergers have only been finalized with conditions, such as the sale of some facilities (FTC, 2021; UK CMA, 2021). Fulton (2017) examined hospital consolidation in the U.S. and observed that the majority of mergers resulted in increased prices, with little evidence of quality improvement. This points out the effectiveness of mergers in healthcare in crushing competition, not only in local markets but also at larger scales as large hospital groups become increasingly influential at the bargaining table.

2.4.7 Beer

In the case of consumer goods, researchers rely on specific sale data and economic models to calculate the effects of mergers on price. Miller and Weinberg (2017) demonstrated that following the joint venture in the U.S. beer industry between MillerCoors, the prices increased significantly, with both corporations increasing their mark-up and competitors acting in a strategic manner. The differences between products in different categories usually revolve around the distinctiveness of the product, the toughness with which the retailer negotiates, and the presence of a private-label brand (Nevo, 2000; Berry, Levinsohn, and Pakes, 1995).

2.4.8 Retail

The retail mergers are also different in the local market, the buying power and the number of products involved. Applying store-level data and, in some cases, difference-in-differences, researchers have discovered that, on average, the price effect is usually small but this conceals large geographic variation. In some towns, prices soar and the differentiation of products plummets, whereas in others, changes are hardly felt (Abadie, Diamond, and Hainmueller, 2010; Hosken, Olson, and Smith, 2012). There is more to price than meets the eye: product selection, sales promotions, and quality of service also require a closer examination in future research (ICN, 2022; OECD, 2020b). A study by Hosken, Olson, and Smith (2018) has explored a group of retail mergers in the U.S. and discovered that consumer prices tend to rise afterward, especially where small numbers of stores control the regions. Consolidation of retailers leads to fewer competitors who are independent which means that there is less price competition and a reduction in the number of choices available to the shopper, in some cases. The researchers concluded that although mergers may introduce certain efficiencies, consumers are seldom enjoying them.

This thesis is on digital and pharmaceuticals even though research has already been conducted on other industries such as airlines, retail and energy. It is unique in that these industries are full of innovation, dynamic, and highly visible to antitrust watchdogs. In pharma, new products in the pipeline can be more easily tracked and a whole debate has been made about killer acquisitions making it an ideal subject to test how mergers impact competition. The network effects, benefits of data and the tendency of bigger companies to acquire smaller ones used in the tech industry can demonstrate the dramatic impacts the mergers can have on the market structure and the future of innovations. These two industries are also at the centre of U.S. and EU regulatory scandals, with Facebook-Instagram, Illumina-Grail, Bayer-Monsanto being eye-openers on the application of regulations. That is why these two fields of research are the object of this thesis, where all three, evidence, theory and policy, intersect and the U.S.-Europe comparison can come in handy.

2.5 Regional Policy Frameworks and Trends

A major concern of U.S. regulators has long been the impact of mergers on the market landscape and whether this type of deal could negatively affect competition. These regulations are based on provisions made by legislation like the Clayton Act and the HSR Act, Section 7. The previous set of guidelines was concerned with the danger of single firm domination or a limited number of firms collaborating, but this has begun to alter. The newest merger rules (DOJ & FTC, 2023) are more concerned with the risk of recurring purchases, the threats posed by new entrants, and how monopolistic firms consolidate their market share, particularly in technological and data-driven sectors (Shapiro, 2018; Cabral, 2021). Recently, the FTC discovered that large tech companies are frequently acquiring other businesses without the need to disclose those acquisitions, resulting in the calls to increase reporting on such deals and conduct post-factum reviews (U.S. FTC, 2021; ICN, 2022). A number of observers are now claiming that over the years, the U.S. enforcement has been excessively lenient (Kwoka, 2013, 2015) and are doubting whether conventional tools are up to the task of dealing with the flood of start-up acquisitions by giants (Hemphill and Wu, 2020; Baker and Salop, 2015).

EU does it differently. It also analyses mergers in terms of sales thresholds and the SIEC test, which evaluates the possibility that a transaction might actually be detrimental to competition (European Commission, 2004). Regulators have also been able to scrutinize smaller mergers identified by national authorities since 2021, though this has been abandoned in late 2024 after the Illumina-Grail court case. Nowadays, the key controversies in Europe revolve around the concept of whether mergers destroy the innovation or grant some companies a data advantage or serve to create large digital ecosystems (Cremer, de Montjoye, and Schweitzer, 2019; OECD, 2020a; European Commission, 2024). To ensure healthy competition, regulators may force businesses to divest certain aspects of their operations, assure access to the market, or embrace standards of conduct. Experts propose that the EU needs to prioritize innovation more in the process of scrutinizing deals (Valletti and Zenger, 2021), although some propose more post-transactions scrutiny (Caffarra and Scott Morton, 2021). Emerging legislation, such as the Digital Markets Act, is also viewed as an attempt to identify risks that merger control may overlook.

Post Brexit, things have changed in the UK. Competition and Markets Authority (CMA) now prioritise a more vibrant market and innovation flourishing when looking at mergers (UK CMA, 2021). The UK is liberal: the CMA has extensive authority and carries out detailed market investigations, which allows it to remain at the forefront of takeovers of promising start-ups and the growth of digital powerhouses (Furman et al., 2019; Stigler Committee, 2019). Mega deals such as Meta-Giphy (2022), Microsoft-Activision (2023), and Booking-eTraveli (2023) demonstrate that the CMA is more eager than the U.S. authorities to block or impose severe conditions on deals to preserve competition and innovations.

Regulators in the Asia-Pacific region, including Japan's JFTC, Korea's KFTC, and the Competition Commission of India, started to apply deal-value rules to identify takeovers of innovative companies, although such companies may not yet be generating substantial profits (OECD, 2021; UNCTAD, 2021). The priority of policymakers in this area includes making sure that the flow of data across platforms is not constrained, companies do not promote own products, and deals that may limit competition by integrating various services are monitored (Caffarra and Scott Morton, 2021). Such agencies are also exchanging strategies with their foreign counterparts, especially in looking back at prior mergers and how deals will hurt innovation (ICN, 2022; Federico, Langus, and Valletti, 2018; Jullien and Lefouili, 2018). The Australian Competition Commission has developed a reputation as a hardliner: its Digital Platforms Inquiry (2019) recommended additional scrutiny of digital acquisitions, making the region more debate-like America and Europe.

2.6 Research Methods in Competition Assessment

2.6.1 Market Definition and Concentration Metrics

In order to determine the effects of competition following a merger it is important to begin by defining the market in question, the nature of the products and where they are sold. This typically includes the ease with which customers can replace substitutes, supplier reaction, and practical facilitation, including the SSNIP test or diversion ratios (Carlton and Perloff, 2015; DOJ and FTC, 2010). Market concentration can be estimated by indicators like Herfindahl-Hirschman Index (HHI) and CR4, and that is not all. All these figures start making a lot more sense when you also take into account real world evidence about things such as prices, sales, entry by new firms, and innovation by firms (Kwoka, 2015; Syverson, 2019; European Commission, 2024). Focusing on pharmaceuticals, concentration indicators may be related to therapeutic classes or overlap in pipelines, as in Federico, Langus, and Valletti (2018), who relate R&D activity with consolidation through a merger. Structural concentration must be augmented by data control, network effects, and multi-homing constraints proxies in digital markets, where the monetary price is often zero (Cremer, de Montjoye, and Schweitzer, 2019; OECD, 2020a).

2.6.2 Event Studies

Event studies attempt to calculate the impact of mergers on market power by examining abnormal stock price changes when mergers are announced. Early studies (Eckbo, 1983; Stillman, 1983) contrasted the stock returns of merging firms and their economists on the hope that stock returns would indicate an efficiency improvement or potential collusion. Event studies today are modeled and statistically analyzed more sophisticatedly (MacKinlay, 1997; Abadie, Diamond, and Hainmueller, 2010), though the outcomes can nevertheless be contaminated by leaks or other simultaneous events (Gormley and Matsa, 2014). Event studies in the pharmaceutical industry are used to examine whether stock market expectations of reduced innovation are met when pipelines overlap after announcements of M&A deals (Cunningham, Ederer, and Ma, 2021). They may in digital markets provide early evidence of whether investors see synergies or anticompetitive impacts (such as Caffarra and Scott Morton, 2021, mention the tendency of abnormal returns to predict incumbent integration benefits but devalue potential competitors, which is consistent with kill zone (Kamepalli, Rajan, and Zingales, 2020).

2.6.3 Price and Quantity Effects

Using more detailed sales information, researchers tend to retrospectively study changes in demand and prices following past mergers (Berry, Levinsohn, and Pakes, 1995; Nevo, 2000). Another application of bargaining models could be in markets where prices are negotiated, such as between hospitals and insurers, to distill the extent of power each party has and how contracts are structured (Gowrisankaran, Nevo, and Town, 2015). Other designs, including difference-in-differences or synthetic control, are useful to give more distinct comparisons provided the appropriate assumptions are satisfied (Card and

Krueger, 1994; Imbens and Wooldridge, 2009; Abadie, Diamond, and Hainmueller, 2010). Structural demand models have been used in the pharmaceutical industry to model the unilateral impact of mergers on drug prices and supply with mixed results on consumer welfare (Kwoka, 2013; Federico, Langus, and Valletti, 2018). In the technology and digital markets, price impact tends to be difficult to quantify because of the existence of free services, so studies are measuring non-price impacts, including product variety, privacy, or access to the platform (Shapiro, 2018; Cremer, de Montjoye, and Schweitzer, 2019).

2.6.4 Innovation and Dynamic Competition

Researchers tend to use patent statistics, such as the number of patents, the frequency of their references, and their originality, research and development spending, the status of drug pipelines, or the inflow of new investment into related markets, to gauge innovation (Cunningham, Ederer, and Ma, 2021; Federico, Langus, and Valletti, 2018; Jullien and Lefouili, 2018). These indicators will identify innovation changes, which may not immediately be reflected in prices. Correlation between detailed M&A data and these sources of innovation is an interesting and demanding area of research, as it involves a significant amount of data (OECD, 2020a; ICN, 2022). The pharmaceutical industry has its own measures, using patents and pipeline indicators to identify whether mergers are giving incentives to kill overlapping projects (killer acquisitions). In digital markets, more telling than patents can be the intensity of R&D and the flows of venture funding, as much of digital services are based on software, algorithms, or data assets that are not being systematically patented (Caffarra and Scott Morton, 2021; Autor et al., 2020).

2.6.5 Ex-Post Evaluation and Transparency

International institutions point to the necessity to examine previous mergers to understand whether regulators made the correct choice, improve the screening of subsequent transactions, and develop more effective remedies (OECD, 2020b; ICN, 2022). The main problems are related to gaining access to confidential deal information, the ability to ensure reproduction of results, and the efforts to reduce bias to the most high-profile cases only (Kwoka, 2013; OECD, 2021). The pharmaceutical sector has been among the fields where retrospective reviews (e.g., Bayer-Monsanto) have pointed to asset divestiture-based remedies as potentially being insufficient to restore innovation competition (European Commission, 2018). Ex-post assessments are particularly useful in the digital industry since most acquisitions are below thresholds upon announcement. The cumulative effects may become apparent over time, but systematic reviews of such deals (FTC, 2021; European Commission, 2021) can provide unique insights.

2.7 Research Gaps and Agenda

Though much has already been written on the impact of merger and acquisition on competition, we are still left with huge gaps in our knowledge. To date, most studies have either zoomed out to examine the general patterns in market concentration (De Loecker, Eeckhout, and Unger, 2020; Autor et al., 2020; Grullon, Larkin, and Michaely, 2019) or gone small by studying one industry, such as beer, airlines, or hospitals (Miller and Weinberg, 2017; Kim and Singal, 1993; Gowrisankaran, Nevo, and Town, 20 Even such rapidly changing industries as digital technology and pharmaceuticals, which raise the most concerns about innovation and killer acquisitions (Cunningham, Ederer, and Ma, 2021; Federico, Langus, and Valletti, 2018; Jullien and Lefouili, 2018), lack sufficient cross-country studies that can connect the way markets respond to deals with the concentration of such industries.

The other shortcoming in the available literature is the absence of systematized cross-sector evidence. Though there has been work on individual industries, like beer, airlines or drugs, almost no effort has been made to compare the outcomes of mergers across industries with different technological forces, demand structure, and regulation. That complicates the generalization of results or an evaluation of whether results are sector-specific or general (Kwoka, 2015; Caffarra and Scott Morton, 2021).

Additionally, another gap is the absence of explicit comparisons on how various regulatory systems influence competition. But regulators in the U.S have generally been lighter-handed, whereas the EU has begun to be more activist-like, such as by implementing (ùthen rescinding) the Article 22 referral regime regarding small mergers (European Commission, 2021; European Commission, 2024). However, it remains unclear whether or how these policy differences actually have any impact on such variables as company value, market concentration, or innovation (Shapiro, 2018; Cabral, 2021).

Additionally, another under-researched topic is the accumulated effects of consecutive acquisitions, especially in the sphere of online trading when one specific transaction is usually not covered by the notification threshold (FTC, 2021; European Commission, 2021). Although recent policy discussions have raised the possibility of kill zone effects (Kamepalli, Rajan, and Zingales, 2020), no systematic empirical data quantifying long-run effects of repeated acquisitions on concentration and innovation have been identified.

It is also difficult to study innovation. The bulk of research has relied on patent data, which is not easily compared across nations or even industries. Consequently, we lack a lot of work that employs simpler financial metrics like the ratio of R&D expenditure to sales, to see a broader picture by sector and area (OECD, 2020a; ICN, 2022).

Through these findings, this thesis centers on strategic acquisitions in the digital sector and pharmaceutical sector within the U.S and EU between 2010 and 2024. It is twofold, on the one hand, to observe the reaction of markets to the announcement of acquisitions by observing short-term stock price movements in various industries and across different regulatory frameworks, and on the second hand, to relate the tendency to make repeated acquisitions to increased market power or reduced incentive to innovate. With these objectives, the hypotheses which will be tested in this thesis is:

H1: *Strategic acquisitions in the digital and pharmaceutical sectors generate positive abnormal returns for acquirers, reflecting expected efficiency gains.*

H2: *Abnormal returns are systematically higher in the U.S. than in the EU, consistent with differences in regulatory strictness.*

H3: *The more acquisitions happen within a sector, the more concentrated that sector becomes over time.*

H4: *Acquisition intensity is negatively associated with innovation proxies (e.g., R&D expenditures relative to sales), especially in pharmaceuticals, where pipeline substitution is most pronounced.*

Despite all the general interest in digital and pharmaceuticals and the numerous policy studies on either of the two alone (Cremer, de Montjoye and Schweitzer, 2019; Furman et al., 2019; Stigler Committee, 2019), there remain comparatively few comparisons made across the two sectors and the two regions. The majority of studies look at a single industry within a single nation or offer policy commentary without relating how markets respond and how industry concentration changes. This thesis seeks to fill that gap: it considers short-run event study responses to strategic acquisitions in digital and pharmaceuticals over the period 2010-24 in the U.S. and EU, as well as long-run concentration and innovation indicators. The idea is to find out whether the observed results are mostly fuelled by the difference in the sectors or the regulations existing.

3. Methodology

This thesis will discuss the short-term impact of M&A announcements on stock prices (H1-H2) and the relationship between acquisitions activity, industry, concentration, and innovation, in the medium term (H3-H4). It relies on already existing methods in literature that have been found transparent and useful in answering research questions. The selected techniques have been prevalent in the empirical literature on M&A, competition, and innovation, thus they could be directly compared with prior studies (Brown and Warner, 1985; MacKinlay, 1997; Eckbo, 1983; Stillman, 1983; De Loecker, Eeckhout and Unger, 2020; Federico, Langus and Valletti, 2018). Three themes are used to structure the analysis.

It begins with short term stock market responses, which are analyzed through event study framework, a common method of assessing investor reactions to M&A announcements (Brown and Warner, 1985; MacKinlay, 1997). This method will test H1: acquisitions create abnormal returns to acquiring firms; H2: reactions to acquisitions vary between the U.S. and the EU due to regulatory environments.

Second, the repeated acquisition is evaluated concerning the market concentration with references to the well-known indicators such as the Herfindahl-Hirschman Index (HHI) and concentration ratios (CR4). They are widely applied in both educational and policy-making modules to enforce rivalry on the industry level (Kwoka, 2015; Syverson, 2019; European Commission, 2024). In this analysis, it is also assumed that the more active the M&A is within the sectors, the more the concentration can increase over time (H3).

Third, there is an exploration of the relationship of acquisition activity and innovation outcomes. Although patent data are widely used in the literature (Cunningham, Ederer & Ma, 2021; Federico, Langus and Valletti, 2018), financial proxies like R&D expenditures relative to sales are more consistently distributed in the literature across sectors and firms. Where feasible, these indicators are joined with a simple difference-in-differences method to determine whether repeated acquisitions are associated with weaker innovation incentives, in specific reference to the pharmaceutical industry (H4).

When the three strands combined, i.e. financial markets, industry structure or industry organization, and innovation, they will arrive at a sensible framework industry is assessed relative to competitive impacts of strategic acquisitions. This combined approach means that one of the major concerns of the literature is that investor expectation is revised in the short term but longer term good in the broader market concentration and innovation.

3.1 Event Study Analysis

The event study method, which is a widely used tool in investigating market response to corporate news, is used to test the first two hypotheses. This approach is built on the idea that, in a semi-strong efficient market, stock prices quickly reflect any new public information (Fama, 1970). When an acquisition signals greater efficiency, potential synergies, or strategic benefits, the stock price of the acquiring firm typically rises around the announcement. On the other hand, if investors view the deal as risky, anticompetitive, or likely to destroy value, abnormal returns tend to be flat or negative (Brown and Warner, 1985; MacKinlay, 1997). To implement this approach, stock returns are computed as daily log returns:

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

Where $P_{i,t}$ is the closing price of the security *i* on day *t.* Market returns are calculated in the same way from the relevant benchmark index, specifically the S&P 500 for U.S. acquirers and the STOXX Europe 600 for European acquirers, in line with prior applications in the literature (Brown and Warner, 1985). Consistent with established research, this analysis uses a market-adjusted model (MAR), calculating abnormal returns as the difference between a stock's return and that of the market:

$$AR_{i,t} = R_{i,t} - R_{m,t}$$

Here, $R_{m,t}$ denotes the daily market index return. The S&P 500 is used for U.S. acquirers and the STOXX Europe 600 for European firms, following standard practice (Brown & Warner, 1985; MacKinlay, 1997). This approach avoids estimating firm-specific parameters over a separate window, which is a step often unnecessary for short-term analysis, and keeps the design straightforward (Brown & Warner, 1985). To summarize how the market reacts around the announcement, abnormal returns are summed over an event window to produce cumulative abnormal returns (CAR):

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i,\tau}$$

Where $[\tau_1, \tau_2]$ denotes the time window relative to the announcement date (day 0). The main analysis uses a three-day window ($[-1,+1]$), which accounts for possible information leaks before the announcement and delayed responses afterward. Two additional windows ($[0,+1]$ and $[-2,+2]$) are included as robustness checks. Using short windows helps minimize the risk that unrelated events influence the findings (MacKinlay, 1997). Statistical inference uses two complementary tests. The first is a standard t-test on the mean of the CAR distribution. If $\overline{CAR}$ denotes the average cumulative abnormal return across *N* events and $s(CAR)$ the sample standard deviation, the test statistic is:

$$t = \frac{\overline{CAR}}{s(CAR)/\sqrt{N}}$$

This test checks if the average market reaction differs significantly from zero. The second test is a non-parametric sign test, which examines whether the share of firms with positive CARs differs from 50 percent. The sign test does not assume normality and is less affected by outliers, making it a valuable robustness check (Brown and Warner, 1985). Positive abnormal returns for both groups point to expectations of reduced competition and industry-wide gains. If acquirers benefit while rivals lose, the market likely sees efficiency gains for the buyer at competitors' expense. If both groups show losses, concerns about regulation or value destruction may dominate. This approach follows the insights of Stillman (1983) and Eckbo (1983), who showed that rivals' reactions can reveal whether mergers are viewed as pro or anti-competitive.

3.2 Cross-Sectional Analysis of Abnormal Returns

To formally address the second hypothesis, a cross-sectional regression of cumulative abnormal returns is run to formally address the second hypothesis. Following the approach in MacKinlay (1997) and Eckbo (1983), CARs are regressed on a U.S. dummy and a few key controls:

$$CAR_i(\tau_1, \tau_2) = \alpha + \beta_1 US_1 + \beta_2 \ln(DealSize_i) + \beta_3 TechDummy_i + \beta_4 PharmaDummy_4 + \varepsilon_i$$

Here, the dependent variable is the cumulative abnormal return for firm i over the event window. The main explanatory variable is a U.S. dummy (1 for U.S. acquirers, 0 for European). Deal size (in logs) controls for scale effects, as larger deals may imply greater synergies or risks (Andrade, Mitchell and Stafford, 2001). Industry dummies for digital and pharmaceuticals account for differences in innovation and regulation (Federico, Langus and Valletti, 2018; Cunningham, Ederer and Ma, 2021). The main parameter of interest is β_1. A positive, significant value supports Hypothesis 2, indicating that U.S. acquirers see higher abnormal returns than their European peers, possibly reflecting expectations of greater value creation in a less restrictive regulatory environment (Kwoka, 2013; Shapiro, 2018; European Commission, 2024). An insignificant result suggests no systematic difference, while a negative, significant coefficient would imply that European acquirers generate stronger investor expectations.

These results address the first two hypotheses directly. Statistically significant positive CARs for acquirers support the view that markets expect efficiency gains from acquisitions (Hypothesis 1). Including rivals helps clarify whether these gains are seen as competitive or anticompetitive. The cross-sectional regression offers a structured way to test regional differences, providing a clear assessment of Hypothesis 2 using established event study techniques.

3.3 Concentration Effects

The third hypothesis examines how the intensity of acquisitions within a sector relates to changes in market concentration over time. Concerns about mergers fueling gradual increases in concentration have long been at the core of industrial organization and antitrust analysis. Recent studies have documented rising concentration in many industries across the United States and Europe (De Loecker, Eeckhout and Unger, 2020; Autor et al., 2020; Grullon, Larkin and Michaely, 2019), though the reasons behind this trend are still debated. Increased concentration might reflect efficiency gains and successful firms, or it could indicate diminishing competition and greater market power (Kwoka, 2015; Syverson, 2019). To study this relationship, two standard measures of concentration are used. The first is the Herfindahl–Hirschman Index (HHI), defined as:

$$HHI_t = \sum_{i=1}^{N} s_{i,t}^2$$

where $s_{i,t}$ is the market share of firm *i* in industry *t*. The HHI rises as market shares become more uneven, making it sensitive to mergers and acquisitions. The second measure is the four-firm concentration ratio (CR4), given by:

$$CR4_t = \sum_{i=1}^{4} s_{i,t}$$

which sums the market share of the four largest firms in the industry. While CR4 is less detailed than the HHI, it provides an intuitive sense of how dominant the leading firms are. Both measures are standard tools for regulators like the European Commission and the U.S. Department of Justice when assessing market competition (Kwoka, 2015; European Commission, 2024).

The analysis then links these concentration measures to the level of acquisition activity in each sector. An acquisition intensity index is constructed as the ratio of acquisitions completed in a sector-year to the total number of active firms in that sector-year:

$$AI_{j,t} = \frac{Number\ of\ M\&A\ deals\ in\ sector\ j\ during\ t}{Number\ of active\ firms\ in\ sector\ j\ during\ t}$$

This index accounts for industry size, allowing for meaningful comparisons across sectors. The analysis first charts sector-level trends in acquisition intensity alongside changes in HHI and CR4. To formally test the relationship, a regression is estimated as follows:

$$\Delta HHI_{j,t} = \alpha + \beta AI_{j,t-1} + \gamma X_{j,t} + \epsilon_{j,t}$$

where $\Delta HHI_{j,t}$ is the annual change in concentration for sector *j*, $AI_{j,t-1}$ is the lagged acquisition intensity, and $X_{j,t}$ includes controls like sector sales or investment growth. The main focus is on the coefficient β. A positive and significant result would suggest that sectors with more acquisitions tend to become more concentrated, supporting H3.

However, concentration measures should not be interpreted as direct evidence of market power, as Syverson (2019) argues. An increase in concentration might signal real efficiency gains by leading firms, not just a decline in competition. Still, shifts in HHI and CR4 do provide a useful signal of changes in industry structure. By explicitly connecting these changes to acquisition activity, this analysis adds to the ongoing debate over whether consolidation is driven by efficiency or by efforts to reduce competition.

If the results reveal a positive link between acquisition intensity and later increases in HHI or CR4, this would support Hypothesis 3—pointing to repeated acquisitions as a factor in sectoral consolidation. No relationship would suggest that acquisitions alone do not consistently raise concentration, perhaps due to market entry or because most deals happen in already concentrated industries. A negative link, though less likely, would indicate that acquisitions might occasionally help reduce dominance by established firms.

3.4 Innovation Effects

The fourth hypothesis considers whether repeated acquisitions diminish innovation incentives, with particular focus on the pharmaceutical industry, where so-called "killer acquisitions" have attracted considerable attention. Innovation is a key aspect of competition, and its connection to mergers has been widely debated. Large firms may gain from economies of scale and scope in research, making it possible to pursue broader and riskier projects (Aghion et al., 2005). Conversely, mergers may dampen the drive to innovate if competitors are removed or overlapping research is intentionally discontinued, as documented in pharmaceutical case studies (Federico, Langus and Valletti, 2018; Cunningham, Ederer and Ma, 2021).

Measuring innovation presents several challenges. Much of the empirical literature uses patent counts, citations, and pipeline data, but these measures are often sector-specific and inconsistently reported across firms or countries. To keep the analysis straightforward and comparable, this study uses a financial proxy, which is the ratio of R&D expenditures to total revenues:

$$R\&D\ Intensity_{i,t} = \frac{R\&DExpenditure_{i,t}}{TotRevenues_{i,t}}$$

This proxy, common in earlier studies (Autor et al., 2020; OECD, 2020a), reflects firms' commitment to research and innovation, and enables comparisons across digital and pharmaceutical companies in the U.S. and EU.

The link between acquisition activity and innovation is examined using two approaches. First, a descriptive analysis tracks R&D intensity trends across firms and sectors with varying acquisition activity. Second, a regression relates firm-level R&D intensity to sectoral acquisition intensity, controlling for firm and time effects. A basic specification is:

$$R\&D\ Intensity_{i,t} = \alpha + \beta AI_{j,t} + \mu_i + \tau_t + \epsilon_{i,t}$$

where $AI_{j,t}$ is acquisition intensity in sector j and year t, μ_i is a firm fixed effect, and τ_t is a year effect. The coefficient β is the main parameter of interest. A negative β would suggest that more acquisition activity in a sector correlates with reduced innovation, in line with H4.

A simplified difference-in-differences (DiD) design is also used to support a causal interpretation. This approach compares changes in R&D intensity for firms involved in acquisitions (the treated group) against similar firms in the same sector that did not engage in M&A (the control group). The specification is:

$$Y_{i,t} = \alpha + \delta(Post_t \times Treated_i) + \mu_i + \tau_t + \epsilon_{i,t}$$

where $Y_{i,t}$ is R&D intensity for firm i in year t, $Treated_i$ is a dummy for firms that made acquisitions, and $Post_t$ equals one for the years after the acquisition. The coefficient δ captures the difference in innovation changes after acquisition, compared to the control group (Bertrand, Duflo and Mullainathan, 2004; Angrist and Pischke, 2009).

Interpreting the results is straightforward: a significant negative relationship between acquisition intensity and R&D intensity would support H4 and findings on killer acquisitions (Cunningham, Ederer and Ma, 2021). A positive coefficient would instead suggest that acquisitions encourage knowledge transfer and resource sharing, boosting innovation, as argued by Schumpeter (1942) and in some merger studies (Cassiman, Colombo, Garrone and Veugelers, 2005). No significant result would imply that acquisitions have no consistent effect on innovation incentives, possibly due to offsetting factors.

By linking sector-level acquisition intensity with firm-level R&D data and using a streamlined difference-in-differences framework, this analysis offers a straightforward but robust test of whether repeated acquisitions discourage innovation. The approach sidesteps the complexity of patent data while staying grounded in the main findings of the literature, and allows for direct comparison with earlier research in pharmaceuticals and digital.

3.5 Summary and Limitations

This chapter sets out a methodological framework that brings together event studies, standard concentration measures, and innovation proxies to assess the competitive impact of strategic acquisitions in the United States and European Union. The approach is geared toward simplicity: event studies employ the market-adjusted model of abnormal returns, concentrate on cumulative effects on short windows, and utilize simple statistical tests. A clear means of comparing the U.S. and EU acquirers is through cross-sectional regression. Sectoral concentration has been defined using set indicators such as HHI and CR4 which are directly related to the level of acquisition. Innovation outcomes are evaluated using R&D intensity and a streamlined difference-in-differences design, allowing shifts in innovation incentives to be tracked without relying on patent data.

The methodology aligns with common approaches in the literature but comes with some caveats. Event studies capture only short-term investor reactions and may miss longer-term competitive effects. Short windows help, but results could still be skewed by information leaks, unrelated news, or trading speculation (MacKinlay, 1997). Indicators like HHI and CR4 are widely used but do not perfectly represent market power, as higher concentration might also reflect efficiency gains (Syverson, 2019). R&D intensity is a practical and widely available proxy for innovation, but it does not account for the quality or direction of research, and inconsistent accounting practices may add noise. The difference-in-differences approach assumes parallel trends between treated and control firms, an assumption that can be problematic in rapidly changing sectors like pharma and digital. These limitations are common in empirical studies of mergers and acquisitions, especially those spanning multiple sectors and regions. Even so, combining market reactions, industry concentration, and innovation outcomes creates a balanced framework—one that captures both immediate investor sentiment and broader shifts in industry structure over time.

4. Dataset

To test the four hypotheses outlined in the previous chapter, two datasets were created. The analyses use firm-level and industry-level data (from the pharmaceutical and digital sectors) from two different regions: the United States and Europe. The time span for the first dataset, used for the event study and cross-sectional analyses (H1 and H2), covers 2010 to 2024 (Q1 2010 to Q4 2024), while the second dataset, used for concentration and innovation analyses (H3 and H4), spans from 2010 to 2022 (Q1 2010 to Q4 2022). The difference in time horizons is due solely to data availability, as data for H3 and H4 were only available until 2022; nevertheless, this window is sufficient to test the hypotheses (Autor et al., 2020; De Loecker & Eeckhout, 2018). For consistency, "United States" refers to firms primarily listed on U.S. exchanges, while "Europe" refers to EU-27 countries (with the United Kingdom included until 2020 and excluded thereafter). Sector classification follows Capital IQ/GICS mapping: Pharmaceuticals falls under "Health Care" (Pharmaceuticals, Biotechnology & Life Sciences) and Digital under "Information Technology" (Software & Services, Technology Hardware & Equipment, Semiconductors). Important to mention is the fact that the Digital perimeter differs across the two datasets due to source coverage: in Dataset 1 (event study and H2), Digital includes Software & Services; in Dataset 2 (H3–H4), Digital excludes Software & Services because that category is not covered in the Eurostat and U.S. Census code concordance used for active-firm counts and industry panels.

For the first dataset, to calculate abnormal returns around M&A announcement days, data were collected from Capital IQ and Yahoo Finance. Capital IQ was chosen for its extensive international coverage and detailed deal-level data, which are widely used in M&A research (Moeller, Schlingemann & Stulz, 2004; Bouwman, Fuller & Nain, 2009; Alexandridis, Petmezas & Travlos, 2010; Netter, Stegemoller & Wintoki, 2011). Yahoo Finance was selected as a standardized and accessible source for stock price data, commonly used in empirical finance for event studies. All M&A announcements from 2010 to 2024 in the pharmaceutical and digital sectors in the U.S. and the EU were downloaded from Capital IQ. Since the tickers were not always consistent, a reconciliation process was applied to align the tickers using the ISIN codes of the various companies, which are unique. Where multiple listings existed (e.g., dual listings or ADRs), the primary listing in the acquirer's home market was used. Prices are taken as "Adjusted Close" to account for splits and dividends. When announcements fell on non-trading days, day 0 was rolled to the next trading day. All Capital IQ fields and all Yahoo Finance price series (including benchmark indices) were retrieved directly in U.S. dollars; no currency conversion was performed at any stage. Abnormal returns were then computed as market-adjusted returns using these USD-denominated series. After the cleaning process, only deals with available stock prices were included, resulting in a dataset of 6,681 completed M&A deals for both the EU and the U.S. The applied filters included: (i) the geographic region of the acquirer (U.S. and EU), (ii) the industry of the acquirer (pharmaceutical and digital), (iii) the time period (2010–2024), (iv) the acquirer's type (public), and (v) the deal status (completed). To compute abnormal returns, Yahoo Finance provided the closing stock prices of the acquirers and relevant market indexes (S&P 500 for the U.S. and STOXX Europe 600 for Europe) for the days surrounding the announcement [−5, +5]. In this way, it was possible to see the effects of the M&A announcement on the acquirer's stock in the days close to the events. Abnormal returns are computed as the market-adjusted daily log return, defined as the acquirer's daily log return minus the corresponding market index's daily log return. Cumulative abnormal returns are obtained by adding up the daily abnormal returns across each event window.

For the second dataset, which was used to test H3 and H4, Eurostat and the U.S. Census provided data on active firms in the two industries, based on official statistics of national business registers. Unfortunately, the most recent data available is only up to 2022. A NACE–NAICS concordance was applied to align industry definitions between Europe (NACE Rev.2) and the U.S. (NAICS). Once again, Capital IQ was used to collect industry-level data. The filters applied were: (i) the geographic region of the acquirer (U.S. and EU), (ii) the industry of the acquirer (pharmaceutical and digital), (iii) the time period (2010–2022), (iv) the acquirer's type (public), and (v) total revenues greater than $10 million as of the latest fiscal year. This last filter (v) was introduced to limit the sample size. Without this filter, there would have been too many companies and pieces of information, and the database did not allow downloading files with more than 30,000 companies, or more than 500,000 Excel cells. The decision to include only companies with total revenues exceeding $10 million is supported by the works of De Loecker & Eeckhout (2018) and Autor et al. (2020), to minimize the noise from micro-firms that would increase computational complexity. Another reason is that this approach allows capturing the behavior of economically significant firms that actively compete in the market leadership (De Loecker & Eeckhout, 2018; Autor et al., 2020). Acquisition Intensity is defined, at the sector–region–year level, by dividing the number of completed M&A deals by the number of active firms. The Herfindahl–Hirschman Index and the CR4 ratio were calculated utilizing the first 50 companies ranked in order of total revenue within each industry and region. The Herfindahl–Hirschman Index is computed by taking each firm's revenue share within the Top-50 group, squaring each share, and then adding all of those squared shares together. The CR4 ratio is computed by adding the revenue shares of the four largest firms. This selection is justified by the fact that the largest firms contribute predominantly to the revenues of the industries and thus serve as the principal drivers of concentration dynamics, while the smallest firms are negligible in the calculation of the ratios (De Loecker & Eeckhout, 2018).

Taken together, these design choices yield two internally consistent datasets that ensure comparability across regions and sectors and are fit for purpose for testing H1–H4.

5. Empirical Results

5.1 H1: Strategic acquisitions in the digital and pharmaceutical sectors generate positive abnormal returns for acquirers, reflecting expected efficiency gains.

The first hypothesis investigates whether acquirers experience abnormal stock-market gains around the announcement of mergers and acquisitions. The logic follows the well-established event-study methodology, which evaluates how quickly and to what extent markets incorporate new information into asset prices (Fama, 1970; Brown and Warner, 1985; MacKinlay, 1997). In the context of M&A, this approach tests whether investors interpret acquisitions as value-creating or value-destroying events for the acquiring firm. Positive abnormal returns suggest expectations of efficiency gains, synergies, or strategic repositioning, while negative or insignificant results point to concerns about overpayment, integration risk, or regulatory frictions (Eckbo, 1983; Andrade, Mitchell, and Stafford, 2001). The analysis is conducted across four sector-region quadrants: (i) U.S. Digital, (ii) U.S. Pharmaceutical, (iii) European Digital, and (iv) European Pharmaceutical acquirers, to capture potential heterogeneity across industries and institutional settings. Abnormal returns are computed with a market-adjusted model using the S&P 500 (U.S.) and STOXX Europe 600 (Europe) as benchmarks, consistent with prior research designs (Brown and Warner, 1985; MacKinlay, 1997). The main test window is [−1,+1], which accommodates potential information leakage before the announcement and market digestion afterwards, while two additional windows ([0,+1] and [−2,+2]) provide robustness checks. Such short windows are standard practice to minimize contamination from unrelated events (MacKinlay, 1997). Tables report CAR in decimals; in the text, comments are in percentages. Statistical inference proceeds along two complementary dimensions. First, a conventional t-test is applied to assess whether the mean cumulative abnormal return (CAR) differs from zero, which remains the dominant tool in the event-study literature (Brown and Warner, 1985). Second, a sign test is employed to evaluate whether the proportion of positive CARs exceeds 50 percent, thereby addressing the concern that a small number of large deals could drive mean results. Sign test is distribution free and less sensitive to skewness and heteroskedasticity hence being especially useful in financial returns (Campbell, Lo, and MacKinlay, 1997).

Besides these baseline tests, the analysis uses a winsorization robustness test on the 1st and 99th percentiles of the CAR distribution. The reasoning is that event-day returns are likely to have fat tails, as a result of either simultaneous announcements or thin trade, and should have extreme outliers that bias the mean and inflate variance. Winsorization minimizes this effect and also maintains the sample size and ranking of the observations. This method has become common in empirical studies of M&A to guarantee that conclusions are not made on a small number of exceptions (Moeller, Schlingemann, and Stulz, 2004; Alexandridis, Petmezas, and Travlos, 2010; Bena and Li, 2014). In case the results are still consistent following winsorization, then the evidence is considered sound and might be quite representative of the sample.

5.1.1 U.S. – Digital Industry

For U.S. digital acquirers, acquisition announcements generate consistently positive cumulative abnormal returns across all event windows.

Table 1: U.S. Digital: Summary Statistics of Announcement-Window CARs

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
CAR_m1_p1	3,046	0.016530	0.230437	-0.674781	0.001224	0.707841
CAR_0_p1	3,046	0.016423	0.225768	-0.660881	0.001277	0.693727
CAR_m2_p2	3,046	0.017521	0.242443	-0.709808	0.001785	0.744850

Table 2: U.S. Digital: t-test of Mean (CAR) = 0

Window	N	Mean	t-stat	p-value
CAR_m1_p1	3,046	0.016530	3.959097	0.000077
CAR_0_p1	3,046	0.016423	4.014601	0.000061
CAR_m2_p2	3,046	0.017521	3.988612	0.000068

The mean CARs cluster between 1.6% and 1.8%, with moderate standard deviations of 0.23-0.24 (Table 1), reflecting a clear positive signal despite some dispersion in outcomes. These magnitudes translate into economically and statistically meaningful gains (t-statistics ranging from 3.96 to 4.01; $p < 0.001$; Table 2), supporting the view that digital acquisitions capitalize on scale economies, data complementarities, and network effects characteristic of this sector (Andrade, Mitchell, & Stafford, 2001).

Table 3: U.S. Digital: Sign Test of Share (CAR>0) = 50%

Window	N	# Positive	% Positive	p-value (sign test)
CAR_m1_p1	3,046	1,595	52.36376	0.009558
CAR_0_p1	3,046	1,613	52.95470	0.001178
CAR_m2_p2	3,046	1,603	52.62640	0.003958

The distributional evidence reinforces this interpretation (Table 3). Sign tests reveal that over 52% of transactions yield positive abnormal returns across all windows, with p-values well below conventional significance thresholds. This broad-based positive response indicates that market approval extends beyond a few exceptional deals to encompass the majority of digital acquisitions.

Table 4: U.S. Digital: Summary Statistics of Announcement-Window CARs (Winsorized 1%)

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
CAR_m1_p1	3,046	0.012330	0.104987	-0.302631	0.001224	0.327291
CAR_0_p1	3,046	0.012083	0.095978	-0.252500	0.001277	0.300017
CAR_m2_p2	3,046	0.012839	0.118708	-0.343285	0.001785	0.368963

Table 5: U.S. Digital: t-test of Mean (CAR) = 0 (Winsorized 1%)

Window	N	Mean	t-stat	p-value
CAR_m1_p1	3,046	0.012330	6.481480	< 0.001
CAR_0_p1	3,046	0.012083	6.948111	< 0.001
CAR_m2_p2	3,046	0.012839	5.969386	< 0.001

Table 6: U.S. Digital: Sign Test of Share (CAR>0) = 50% (Winsorized 1%)[1]

Window	N	# Positive	% Positive	p-value (sign test)
CAR_m1_p1	3,046	1,595	52.36376	0.009558
CAR_0_p1	3,046	1,613	52.95470	0.001178
CAR_m2_p2	3,046	1,603	52.62640	0.003958

Robustness checks using 1% winsorization confirm the core findings while enhancing precision. The trimmed averages fall slightly to 1.2-1.3% (Table 4), but exhibit substantially higher t-statistics (approximately 6.0-6.9; $p < 0.001$; Table 5). Importantly, the sign test results remain unchanged (Table 6), demonstrating that extreme observations do not drive the statistical inference (Moeller, Schlingemann, & Stulz, 2004; Alexandridis, Petmezas, & Travlos, 2010).

[1] Sign test computed on winsorized CARs; results are qualitatively identical to the raw specification (Table 3).

These results provide strong validation for Hypothesis 1 within the U.S. digital sector. Investors systematically reward acquirers at announcement, consistent with efficiency-based theories of M&A (Eckbo, 1983; MacKinlay, 1997) and the strategic importance of consolidation in digital markets (Hoberg & Phillips, 2010; Cennamo & Santalo, 2013).

5.1.2 U.S. Pharmaceutical Industry

The pharmaceutical sector exhibits even more pronounced positive reactions to acquisition announcements.

Table 7: U.S. Pharmaceutical: Summary Statistics of Announcement-Window CARs

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
CAR_m1_p1	1,244	0.037520	0.241067	-0.685681	0.002233	0.760721
CAR_0_p1	1,244	0.037819	0.233682	-0.663227	0.002444	0.738865
CAR_m2_p2	1,243	0.044918	0.269582	-0.763828	0.002012	0.853664

Table 8: U.S. Pharmaceutical: t-test of Mean (CAR) = 0

Window	N	Mean	t-stat	p-value
CAR_m1_p1	1,244	0.037520	5.489576	< 0.001
CAR_0_p1	1,244	0.037819	5.708219	< 0.001
CAR_m2_p2	1,243	0.044918	5.874383	< 0.001

Average CARs range from 3.75% to 4.49% depending on the event window, substantially exceeding the digital sector results (Table 7). Standard deviations of 0.23-0.27 (Table 7) indicate reasonable dispersion relative to the magnitude of effects. The statistical significance is unambiguous, with t-statistics between 5.5 and 5.9 ($p < 0.001$), underscoring robust investor confidence in pharmaceutical M&A as a value-creation strategy.

This enthusiasm likely reflects the critical role of acquisitions in accessing R&D pipelines, securing intellectual property, and complementing internal research capabilities (Cockburn & Henderson, 2001; Higgins & Rodriguez, 2006; Bena & Li, 2014). In an industry where innovation drives competitive advantage, external acquisition represents a credible mechanism for augmenting technological assets and market position.

Table 9: U.S. Pharmaceutical: Sign Test of Share (CAR>0) = 50%

Window	N	# Positive	% Positive	p-value (sign test)
CAR_m1_p1	1,244	664	53.37621	0.018574
CAR_0_p1	1,244	672	54.01929	0.004982
CAR_m2_p2	1,243	639	51.40788	0.334863

The sign tests provide nuanced insights into the distribution of outcomes (Table 9). In the tighter [−1,+1] and [0,+1] windows, 53-54% of deals produce positive CARs with statistical significance, confirming widespread market approval. However, the broader [−2,+2] window yields only 51% positive returns without statistical significance, suggesting that the positive effect concentrates in the immediate announcement period before being diluted by unrelated market movements (MacKinlay, 1997).

Winsorization adjustments preserve the essential findings while moderately reducing the average effects to 3.5-4.2%. The enhanced precision (t-statistics of 5.9-6.3) and unchanged sign test results confirm that outliers do not drive the conclusions.

Table 10: U.S. Pharmaceutical: Summary Statistics of Announcement-Window CARs (Winsorized 1%)

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
CAR_m1_p1	1,244	0.034764	0.207511	-0.460762	0.002233	0.657297
CAR_0_p1	1,244	0.034510	0.195302	-0.421442	0.002444	0.620416
CAR_m2_p2	1,243	0.041699	0.231630	-0.455015	0.002012	0.736589

Table 11: U.S. Pharmaceutical: t-test of Mean (CAR) = 0 (Winsorized 1%)

Window	N	Mean	t-stat	p-value
CAR_m1_p1	1,244	0.034764	5.908832	< 0.001
CAR_0_p1	1,244	0.034510	6.232382	< 0.001
CAR_m2_p2	1,243	0.041699	6.347021	< 0.001

Table 12: U.S. Pharmaceutical: Sign Test of Share (CAR>0) = 50% (Winsorized 1%)[2]

Window	N	# Positive	% Positive	p-value (sign test)
CAR_m1_p1	1,244	664	53.37621	0.018574
CAR_0_p1	1,244	672	54.01929	0.004982
CAR_m2_p2	1,243	639	51.40788	0.334863

Overall, the U.S. pharmaceutical results strongly support Hypothesis 1: acquirers are rewarded at announcement. Unlike in more commoditized sectors, where bidders often face negative returns due to overpayment or integration risks (Moeller, Schlingemann, & Stulz, 2004), pharmaceutical acquisitions are generally perceived as credible strategies to access R&D capabilities and intellectual property (Higgins & Rodriguez, 2006; Bena & Li, 2014). At the same time, recent research has emphasized that some transactions may operate as "killer acquisitions," suppressing competing innovation projects (Cunningham, Ederer, & Ma, 2021), which raises questions about their long-term impact on competition.

5.1.3 U.S. Summary

Across both U.S. sectors, acquisition announcements consistently generate positive market reactions, though the underlying value drivers differ meaningfully. Digital sector returns, while statistically robust, remain moderate in magnitude, reflecting investor expectations about network effects, data synergies, and competitive positioning in dynamic ecosystems (Hoberg & Phillips, 2010; Cennamo & Santalo, 2013). These patterns align with broader evidence on U.S. digital acquirers, where consolidation serves strategic positioning rather than radical value transformation (Moeller, Schlingemann, & Stulz, 2004; Andrade, Mitchell, & Stafford, 2001).

Pharmaceutical acquisitions command substantially higher announcement premia, reflecting their strategic necessity in replenishing innovation pipelines and securing intellectual property (Cockburn & Henderson, 2001; Higgins & Rodriguez, 2006; Bena & Li, 2014). While investors clearly view such deals as credible solutions to R&D challenges, recent scholarship highlights potential anticompetitive effects through discontinued competing projects (Cunningham, Ederer, & Ma, 2021).

The sectoral contrast suggests that digital acquisitions primarily serve efficiency and scale objectives within established competitive frameworks, whereas pharmaceutical deals function as essential tools for innovation access and long-term growth sustainability.

[2] Sign test computed on winsorized CARs; results are qualitatively identical to the raw specification (Table 9).

5.1.4 EU Digital

European digital acquirers also experience positive announcement effects, though with distinct characteristics compared to their U.S. counterparts.

Table 13: EU Digital: Summary Statistics of Announcement-Window CARs

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
CAR_m1_p1	1,995	0.008894	0.109226	-0.318784	0.006114	0.336572
CAR_0_p1	1,998	0.008344	0.108115	-0.316001	0.004136	0.332689
CAR_m2_p2	1,990	0.010275	0.115659	-0.336702	0.005830	0.357252

Table 14: EU Digital: t-test of Mean (CAR) = 0

Window	N	Mean	t-stat	p-value
CAR_m1_p1	1,995	0.008894	3.637094	0.000283
CAR_0_p1	1,998	0.008344	3.449729	0.000573
CAR_m2_p2	1,990	0.010275	3.963213	0.000077

Mean CARs cluster between 0.8% and 1.0% with standard deviations around 0.11-0.12, yielding strong statistical significance (t-statistics of 3.4-4.0; $p < 0.001$). While smaller in magnitude than U.S. digital effects, these results remain economically meaningful given the brief event windows employed (Brown & Warner, 1985; MacKinlay, 1997).

Table 15: EU Digital: Sign Test of Share (CAR>0) = 50%

Window	N	# Positive	% Positive	p-value (sign test)
CAR_m1_p1	1,995	1,161	58.19549	< 0.001
CAR_0_p1	1,998	1,119	56.00601	< 0.001
CAR_m2_p2	1,990	1,134	56.98492	< 0.001

The sign test corroborates the inference: between 56% and 58% of acquirers record positive CARs across the three windows, with p-values that decisively reject the 50% null.

Table 16: EU Digital: Summary Statistics of Announcement-Window CARs (Winsorized 1%)

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
CAR_m1_p1	1,995	0.011489	0.053704	-0.149623	0.006114	0.172601
CAR_0_p1	1,998	0.010474	0.051163	-0.143015	0.004136	0.163963
CAR_m2_p2	1,990	0.011793	0.060487	-0.169668	0.005830	0.193254

Table 17: EU Digital: t-test of Mean (CAR) = 0 (Winsorized 1%)

Window	N	Mean	t-stat	p-value
CAR_m1_p1	1,995	0.011489	9.555549	< 0.001
CAR_0_p1	1,998	0.010474	9.150625	< 0.001
CAR_m2_p2	1,990	0.011793	8.697424	< 0.001

Table 18: EU Digital: Sign Test of Share (CAR>0) = 50% (Winsorized 1%)[3]

Window	N	# Positive	% Positive	p-value (sign test)
CAR_m1_p1	1,995	1,161	58.19549	< 0.001
CAR_0_p1	1,998	1,119	56.00601	< 0.001
CAR_m2_p2	1,990	1,134	56.98492	< 0.001

An interesting feature of the EU-Digital results is that the winsorized means are slightly higher than those obtained from the raw data, rising from around 0.8–1.0% to 1.0–1.2%. This counterintuitive outcome is explained by the shape of the underlying CAR distribution. In this subsample, several extremely negative returns (e.g., below –30%) exert a strong downward pull on the raw averages. Winsorization reduces the weight of these extreme negative observations by replacing them with values closer to the lower bound of the central distribution. Since positive outliers are less extreme, their adjustment has a weaker effect, resulting in a net increase in the mean. In other words, the upward shift in the winsorized averages reflects the fact that negative tail events were disproportionately influential in the raw specification. This illustrates how winsorization does not mechanically lower sample means, but instead corrects for asymmetries in the tails of the distribution (Barnett & Lewis, 1994), a

[3] Sign test computed on winsorized CARs; results are qualitatively identical to the raw specification (Table 15).

phenomenon also observed in empirical studies of M&A announcement effects where extreme negative deals drive down raw averages (Alexandridis, Petmezas, & Travlos, 2010).

These findings support Hypothesis 1 for European digital acquisitions, though the effects are more modest than in the U.S. context. European results likely reflect investor expectations about overcoming market fragmentation and achieving scale within a more restrictive regulatory environment (Shapiro, 2018), rather than the aggressive competitive positioning that characterizes U.S. digital markets.

5.1.5 EU Pharmaceutical

In the EU pharmaceutical sector, acquisitions are also associated with positive cumulative abnormal returns.

Table 19: EU Pharmaceutical: Summary Statistics of Announcement-Window CARs

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
CAR_m1_p1	396	0.023227	0.153755	-0.310839	0.003316	0.484492
CAR_0_p1	396	0.019953	0.153376	-0.440175	0.001310	0.480081
CAR_m2_p2	396	0.020648	0.156616	-0.449200	0.003950	0.490496

Table 20: EU Pharmaceutical: t-test of Mean (CAR) = 0

Window	N	Mean	t-stat	p-value
CAR_m1_p1	396	0.023227	3.006142	0.002815
CAR_0_p1	396	0.019953	2.588805	0.009987
CAR_m2_p2	396	0.020648	2.623576	0.009038

Across the three event windows, mean CARs range between 1.9% and 2.3%, with standard deviations around 0.15–0.16. All means are statistically significant ($t \approx 2.6–3.0$; $p < 0.01$), indicating that acquirers in this industry benefit from deal announcements. While the magnitude is smaller than in the U.S. pharmaceutical market (≈3.7–4.5%), the results remain economically important, consistent with the central role of M&A in accessing R&D pipelines and intellectual property (Higgins & Rodriguez, 2006; Bena & Li, 2014).

Table 21: EU Pharmaceutical: Sign Test of Share (CAR>0) = 50%

Window	N	# Positive	% Positive	p-value (sign test)
CAR_m1_p1	396	219	55.30303	0.039233
CAR_0_p1	396	208	52.52525	0.339695
CAR_m2_p2	396	215	54.29293	0.097131

The sign test shows mixed results. In the [−1,+1] window, 55.3% of deals yield positive CARs (p = 0.039), confirming the presence of a broad positive effect. By contrast, the [0,+1] and [−2,+2] windows yield 52.5% and 54.3% positives, which are not significantly different from chance. This suggests that although mean returns are positive, the distribution of effects is less uniform across transactions, consistent with heterogeneity in deal size, acquirer characteristics, and regulatory conditions (Moeller, Schlingemann, & Stulz, 2004).

Table 22: EU Pharmaceutical: Summary Statistics of Announcement-Window CARs (Winsorized 1%)

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
CAR_m1_p1	396	0.017279	0.100350	-0.212260	0.003316	0.318329
CAR_0_p1	396	0.015497	0.095314	-0.235483	0.001310	0.301439
CAR_m2_p2	396	0.017595	0.118184	-0.247216	0.003950	0.372147

Table 23: EU Pharmaceutical: t-test of Mean (CAR) = 0 (Winsorized 1%)

Window	N	Mean	t-stat	p-value
CAR_m1_p1	396	0.017279	3.426513	0.000676
CAR_0_p1	396	0.015497	3.235408	0.001317
CAR_m2_p2	396	0.017595	2.962712	0.003234

Table 24: EU Pharmaceutical: Sign Test of Share (CAR>0) = 50% (Winsorized 1%)[4]

Window	N	# Positive	% Positive	p-value (sign test)
CAR_m1_p1	396	219	55.30303	0.039233
CAR_0_p1	396	208	52.52525	0.339695
CAR_m2_p2	396	215	54.29293	0.097131

Winsorized estimates confirm the main conclusions but yield slightly lower averages (≈1.5–1.8%, t ≈ 3.0–3.4; $p < 0.01$) compared with the raw specification. This modest reduction is explained by the distributional shape of the data: in the EU pharmaceutical sample, extreme positive CARs (up to +1.7%) are more influential than negative ones, so trimming them reduces the mean. This contrasts with the EU digital case, where negative outliers were dominant and winsorization pushed the mean upward. The difference between the two industries illustrates how the direction of winsorization effects depends on which tail of the distribution is more asymmetric (Barnett & Lewis, 1994).

Overall, the EU pharmaceutical results support Hypothesis 1, showing that investors generally reward acquirers at announcement. The evidence is consistent with the literature that views pharmaceutical M&A as a strategic means to replenish innovation pipelines and consolidate intellectual property (Cockburn & Henderson, 2001; Higgins & Rodriguez, 2006; Bena & Li, 2014). Compared with the U.S., however, the European effects are smaller in magnitude and less uniformly distributed. This likely reflects both market fragmentation and the influence of stricter competition policy in the EU, as emphasized in recent antitrust analyses (Federico, Langus, & Valletti, 2018). Moreover, while U.S. studies stress the dual nature of pharmaceutical M&A—both efficiency-enhancing and potentially anticompetitive via "killer acquisitions" (Cunningham, Ederer, & Ma, 2021)—the European evidence suggests that investor enthusiasm is more tempered, consistent with a more heterogeneous and regulated environment.

5.1.6 EU Summary

European acquisition announcements produce positive market reactions across both sectors, though with distinct patterns that reflect regional institutional characteristics. Digital acquisitions yield modest but highly significant and broadly distributed returns (approximately 1%), suggesting investor confidence in consolidation strategies within fragmented markets. Compared to the U.S., where digital effects are larger, European patterns emphasize incremental efficiency gains and technological capability acquisition under regulatory constraints (Shapiro, 2018).

[4] Sign test computed on winsorized CARs; results are qualitatively identical to the raw specification (Table 21).

Pharmaceutical acquisitions generate higher average returns (approximately 2%) with consistent statistical significance, underscoring M&A's importance for accessing pipelines and R&D assets (Cockburn & Henderson, 2001; Higgins & Rodriguez, 2006; Bena & Li, 2014). However, unlike U.S. pharmaceutical deals, European outcomes exhibit greater heterogeneity and less widespread positive effects, particularly in extended event windows. This pattern suggests that while investors value pharmaceutical consolidation, enthusiasm is moderated by deal-specific factors and stricter competition policy (Federico, Langus, & Valletti, 2018).

The European evidence supports Hypothesis 1 while highlighting important regional contrasts. Digital acquisitions serve efficiency and scale objectives within fragmented markets, while pharmaceutical deals provide access to innovation assets, though with weaker diffusion than observed in U.S. markets.

5.1.7 H1 Summary

The comprehensive cross-regional analysis provides robust support for Hypothesis 1, demonstrating that acquisition announcements consistently generate positive abnormal returns for acquirers. However, the magnitude, distribution, and significance of these effects vary systematically between the United States and Europe, revealing important structural and institutional differences.

U.S. digital acquirers achieve larger average CARs (1.6-1.8%) than their European counterparts (0.8-1.0%), suggesting greater investor confidence in acquisitions as strategic positioning tools within dynamic competitive ecosystems. This differential aligns with literature on complementarities and platform-based competition (Hoberg & Phillips, 2010; Cennamo & Santalo, 2013). European digital acquisitions, while positive, are valued more for their ability to overcome fragmentation and develop technological capabilities within constrained regulatory frameworks (Shapiro, 2018).

The pharmaceutical sector exhibits even more pronounced regional differences. U.S. acquisitions generate substantially stronger announcement effects (3.7-4.5%) with broader distribution across firms, while European deals produce more moderate CARs (2.0-2.3%) with greater heterogeneity. This asymmetry reflects structural market differences: U.S. acquisitions are interpreted as strategic moves to secure R&D pipelines and intellectual property for long-term growth (Cockburn & Henderson, 2001; Higgins & Rodriguez, 2006; Bena & Li, 2014), while European investor enthusiasm is tempered by market heterogeneity and stringent antitrust oversight (Federico, Langus, & Valletti, 2018). Moreover, while U.S. evidence highlights both efficiency-enhancing and potentially anticompetitive “killer acquisitions” (Cunningham, Ederer, & Ma, 2021), the European evidence points to more moderate and uneven outcomes.

These regional comparisons reveal that while acquisitions are broadly perceived as value-creating across both contexts, the U.S. institutional environment amplifies announcement gains, particularly in pharmaceuticals. European markets produce more modest and heterogeneous effects, shaped by regulatory constraints and market structure considerations. This divergence provides crucial insights into how institutional environments condition the wealth effects of M&A activity.

5.2 H2: Abnormal returns are systematically higher in the U.S. than in the EU, consistent with differences in regulatory strictness.

This section tests Hypothesis 2 by examining whether announcement-period abnormal returns for acquirers are systematically higher in the United States than in the European Union after controlling for sector and deal size. Building on the event-study evidence from H1, I estimate cross-sectional regressions where the dependent variable is the CAR computed over three standard windows ([−1,+1], [0,+1], [−2,+2]) using market-adjusted returns with the S&P 500 and STOXX Europe 600 as benchmarks (Brown & Warner, 1985; MacKinlay, 1997).

The key regressor is a U.S. dummy variable, alongside controls for the logarithm of deal value (USD, millions) and a sector indicator (baseline: Digital). Statistical inference relies primarily on heteroskedasticity-robust HC3 standard errors, particularly suitable for short-horizon CARs (Long & Ervin, 2000; MacKinlay, 1997). I also report results with conventional OLS standard errors and conduct robustness checks using 1% winsorization to mitigate outlier influence, a standard adjustment in M&A studies (Moeller, Schlingemann & Stulz, 2004). The objective is to quantify the U.S.-EU differential net of sectoral composition and scale effects, assessing its robustness across windows and inference methods (Eckbo, 1983; Andrade, Mitchell & Stafford, 2001; Kwoka, 2015; Shapiro, 2018).

Table 25: U.S. Premium across event windows[5]

Spec → / Window ↓	[-1,+1]	[0,+1]	[-2,+2]
OLS (classical SE)	+2.63 (p=0.1697)	+2.95 (p=0.1199)	+3.41 (p=0.0934)
HC3 (robust SE)	+2.63 (p=0.0067)	+2.95 (p=0.0015)	+3.41 (p=0.0163)
Winsor 1% (HC3)	+1.79 (p=0.0256)	+2.09 (p=0.0053)	+2.72 (p=0.0347)
N (HC3)	2744	2744	2744
R^2 (HC3)	0.0027	0.0042	0.0027

[5] Notes: Dependent variable: CAR. Controls: ln(Deal size, USD millions) and sector dummy (Pharma, baseline = Digital). HC3 robust errors follow Brown & Warner (1985) and MacKinlay (1997).

The cross-sectional regressions provide compelling evidence that U.S. acquirers enjoy systematically higher announcement-period abnormal returns compared to European peers, even after controlling for sector and deal size. Using heteroskedasticity-robust HC3 standard errors, the U.S. dummy coefficient is consistently positive and statistically significant: +2.63 percentage points for [−1,+1] ($p \approx 0.0067$), +2.95 pp for [0,+1] ($p \approx 0.0015$), and +3.41 pp for [−2,+2] ($p \approx 0.0163$).

Robustness checks using 1% winsorization yield slightly smaller but still significant effects: +1.79 pp ($p \approx 0.0256$), +2.09 pp ($p \approx 0.0053$), and +2.72 pp ($p \approx 0.0347$). This consistency across specifications strongly supports Hypothesis 2, demonstrating that institutional and regulatory context significantly shapes investor expectations (Kwoka, 2015; Shapiro, 2018).

Table 26: Cross-sectional regression (OLS), window [-2,+2]

Term	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-0.0113	0.0212	-0.5335	0.5937
US (dummy: USA=1)	0.0341	0.0203	1.6781	0.0934
ln(Deal size, USD mn)	-0.0020	0.0015	-1.2911	0.1968
Sector = Pharma	0.0141	0.0076	1.8516	0.0642

When conventional OLS standard errors are applied, the U.S. coefficient remains positive but significance diminishes, particularly in wider event windows. This attenuation reflects the heavy-tailed distribution and heteroskedasticity typical of short-horizon CARs, reinforcing the importance of robust inference methods (Brown & Warner, 1985; MacKinlay, 1997). The persistence of effects under winsorization confirms that the U.S. premium is not driven by outliers.

Table 27: Cross-sectional regression (HC3), window [0,+1] (Winsorized 1%)

Term	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-0.0027	0.0087	-0.3116	0.7554
US (dummy: USA=1)	0.0209	0.0075	2.7910	0.0053
ln(Deal size, USD mn)	-0.0018	0.0009	-1.9892	0.0468
Sector = Pharma	0.0114	0.0048	2.3905	0.0169

Beyond the central geographic differential, two subsidiary patterns merit attention. Deal size exhibits a consistently negative relationship with announcement returns, achieving statistical significance in several specifications. This suggests that larger transactions face greater investor skepticism, potentially reflecting concerns about integration complexity, financing constraints, and heightened regulatory scrutiny. The pattern aligns with prior evidence on the challenges of large-scale M&A and the risks of managerial overconfidence leading to overpayment (Andrade, Mitchell & Stafford, 2001; Moeller, Schlingemann & Stulz, 2004; Roll, 1986).

Table 28: Cross-sectional regression (HC3), window [0,+1]

Term	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-0.0036	0.0107	-0.3353	0.7374
US (dummy: USA=1)	0.0295	0.0093	3.1787	0.0015
ln(Deal size, USD mn)	-0.0028	0.0014	-1.9363	0.0529
Sector = Pharma	0.0173	0.0079	2.1800	0.0293

The pharmaceutical sector dummy (relative to Digital) shows a modest positive effect that reaches significance in several specifications, particularly in tighter event windows. This suggests that pharmaceutical acquirers receive a sector-specific premium, likely reflecting investor expectations about pipeline consolidation, intellectual property acquisition, and complementary R&D assets (Federico, Langus & Valletti, 2018; Cunningham, Ederer & Ma, 2021). However, this effect varies across specifications, warranting cautious interpretation.

The systematic U.S. premium suggests that investors expect greater value creation from American acquisitions, potentially linked to deeper capital markets, greater confidence in synergy realization, and more predictable regulatory environments. Even as U.S. antitrust authorities have increased attention to innovation effects, the regulatory framework may still provide greater certainty than European alternatives (Kwoka, 2015; Shapiro, 2018). Conversely, European acquisitions may face investor discounts due to market fragmentation and increasingly stringent merger control, particularly in digital and innovation-intensive sectors (European Commission, 2024).

The low R^2 values (≈0.001-0.005) are typical of event-study regressions, reflecting the inherent noise in short-horizon CARs and the focus on testing conditional mean differences rather than explaining variance (Brown & Warner, 1985; MacKinlay, 1997). The critical finding is the robustness of the U.S. coefficient across specifications, consistently indicating a meaningful geographic premium that persists after controlling for observable deal and sector characteristics.

5.3 H3: The more acquisitions happen within a sector, the more concentrated that sector becomes over time.

To test the third hypothesis, regarding the impact of acquisition intensity on market concentration, a sector–region (US/EU × Pharma/Digital) panel dataset was constructed for the period 2010–2022. Consistent with the Dataset 2 perimeter described earlier, Digital excludes Software & Services due to coverage constraints in the Eurostat–U.S. Census concordance used for active-firm counts. The panel comprises four sector–region groups observed annually over 2010–2022, yielding 48 observations in levels and 48 annual differences (12 per group) that are used in the main "changes" specifications. This design ensures comparability across regions and sectors while focusing on the set of firms that drive industry leadership.

Starting from Capital IQ data, the Top-50 firms by revenues were selected annually for each sector–region cell, from which the main concentration indices were computed: the Herfindahl–Hirschman Index (HHI) and CR4 (the revenue share of the top four firms). These measures are established standards in the industrial organization and antitrust literature (Kwoka, 2015; OECD, 2020; European Commission, 2024) and are regularly used by competition authorities as proxies for the level of market concentration. Computing concentration on the Top-50 focuses attention on the relevant upper tail of the distribution while limiting noise from micro-firms. For each group (sector–region), annual changes (ΔHHI and ΔCR4) were then computed to capture year-over-year shifts in concentration. In parallel, an Acquisition Intensity (AI) index was constructed, defined as the ratio between the number of completed M&A deals in a sector–region–year and the number of active firms in the same sector–region–year, obtained from official sources (Eurostat Business Demography for Europe; U.S. Census Bureau for the United States). Consistent with the empirical literature (Cunningham, Ederer and Ma, 2021; Autor et al., 2020), the index was used in lagged form (AI_t-1) to allow time for deal activity to translate into observable shifts in market structure and to mitigate simultaneity concerns.

The first estimated specification was a simple regression of changes in concentration on lagged AI, following the classic approach of Eckbo (1983) and Stillman (1983) in linking M&A activity to market structure:

Table 29: Regression results for H3 - Baseline

	Dependent variable:	
	ΔHHI	ΔCR4
	(1)	(2)
AI (lagged)	1,507.194	0.150
	(1,288.773)	(0.255)
Constant	-106.793	-0.018
	(73.060)	(0.014)
Observations	48	48
R^2	0.064	0.013
Adjusted R^2	0.043	-0.009
Note:	*** p<0.01, ** p<0.05, * p<0.10.	

The results show positive but insignificant coefficients for both ΔHHI and ΔCR4, suggesting that, although the sign is consistent with the hypothesis, there is no robust evidence that M&A in year *t*-1 intensity leads to a systematic increase in concentration in year *t*. The model has very limited explanatory power ($R^2 \approx 0.06–0.01$), in line with Syverson (2019), who notes that changes in concentration are often the result of multiple factors, not just acquisitions.

To strengthen the analysis, a second specification was then estimated that included a control for sectoral sales growth (Sales Growth) and fixed effects for region and sector, in order to capture structural differences across markets. The inclusion of these controls is based on the approach of Kwoka (2015) and Grullon, Larkin and Michaely (2019), who emphasize that the evolution of concentration should be assessed together with market growth dynamics and sector characteristics.

Table 30: Regression results for H3 (with Sales Growth and Fixed Effects)

	Dependent variable:	
	ΔHHI	ΔCR4
	(1)	(2)
AI (lagged)	1,661.025	0.109
	(1,820.786)	(0.411)
Sales Growth	273.315	0.063
	(304.512)	(0.059)
Region dummies	-6.487	0.001
	(35.955)	(0.010)
Sector dummies	-29.374	-0.005
	(31.716)	(0.008)
Constant	-109.631	-0.017
	(85.348)	(0.017)
Observations	48	48
R^2	0.125	0.074
Adjusted R^2	0.044	-0.012
Note:	*** p<0.01, ** p<0.05, * p<0.10.	

In this specification (Table 30), R^2 increases (to 0.125 for ΔHHI and 0.074 for ΔCR4), but the coefficients on lagged AI remain positive and not significant, confirming the absence of a statistically relevant link. Sales Growth is measured as the annual percentage change in aggregate sector revenues (Capital IQ). The Sales Growth control variable is also not significant in the difference regressions, while the fixed effects behave as simple structural adjustments. This extended setup aligns with the emphasis in Kwoka (2015) and Grullon, Larkin and Michaely (2019) that concentration dynamics should be read together with market growth and sector characteristics, without overturning the baseline conclusion. As a robustness check, regressions were estimated using levels of HHI and CR4 rather than annual changes, following approaches in the literature (Grullon, Larkin and Michaely, 2019; Autor et al., 2020). Because levels are highly persistent, these estimates are treated as corroborative rather than headline evidence:

Table 31: Regression results for H3 (HHI and CR4 levels)

	Dependent variable:	
	HHI	CR4
	(1)	(2)
AI (lagged)	252.898	-1.241*
	(2,296.674)	(0.706)
Sales Growth	-694.606***	-0.209***
	(244.522)	(0.075)
Region dummies	-23.388	-0.006
	(63.349)	(0.021)
Sector dummies	2.183	0.043***
	(50.820)	(0.015)
Constant	926.516***	0.546***
	(73.858)	(0.022)
Observations	48	48
R^2	0.162	0.431
Adjusted R^2	0.085	0.378
Note:	*** p<0.01, ** p<0.05, * p<0.10.	

Finally, as a robustness check, regressions were estimated using levels of HHI and CR4 rather than annual changes, following approaches in the literature (Grullon, Larkin and Michaely, 2019; Autor et al., 2020). In this case, the results offer interesting insights: for HHI, the coefficient on lagged AI remains positive but not significant; for CR4, by contrast, the coefficient is negative and significant at the 10% level (≈ -1.241, $p<0.10$), suggesting that greater M&A intensity does not always strengthen the position of the top four firms but can slightly reduce their relative share. In addition, a robust and statistically significant result emerges for Sales Growth, which shows a negative and consistent impact on concentration. As the market grows, concentration tends to decrease, suggesting that sectoral expansion favors competition over consolidation. This result is consistent with Syverson's (2019) perspective, which highlights how market growth and innovation can mitigate the concentration effects due to acquisitions.

5.3.1 Robustness Check: Alternative Definition of Acquisition Intensity

A relevant methodological aspect concerns the construction of the Acquisition Intensity (AI) index. In the main regressions, in line with the literature (Autor et al., 2020; Cunningham, Ederer and Ma, 2021), acquisition intensity was defined as the ratio between the number of M&A transactions in a sector–year and the total number of active firms in the same sector–year, using Eurostat (for Europe) and U.S. Census (for the United States). This approach ensures full comparability with previous studies, which focus on overall market dynamics. However, in this work the concentration indices (HHI and CR4) were computed on the basis of the Top-50 firms by revenues in each sector–region. For this reason, as a robustness check, an alternative index was constructed, defined as AI_50:

$$AI_{50} = \frac{Number\ of\ M\&A\ deals\ among\ Top - 50\ firms\ in\ group - year}{50}$$

Here, the numerator is the number of M&A deals completed by the Top-50 firms per industry in each year, and the denominator is fixed and equal to 50, corresponding to the number of firms included in the computation of HHI and CR4. Although less common in the literature, this measure is methodologically consistent with the construction of the dataset. It makes it possible to test whether results are sensitive to the choice of denominator.

Table 32: Top-50 Acquisition Activity and Concentration (ΔHHI, ΔCR4; HHI, CR4)

	ΔHHI	ΔCR4	HHI	CR4
(Intercept)	-169.364*	-0.019	764.082***	0.523***
	(77.058)	(0.017)	(124.666)	(0.034)
AI_50	4.485*	0.000	6.784	-0.001
	(2.203)	(0.001)	(4.989)	(0.001)
SalesGrowth	157.751	0.058	-898.293***	-0.205*
	(311.910)	(0.065)	(210.081)	(0.082)
Region=US	4.678	0.002	-57.327	-0.030+
	(17.228)	(0.006)	(49.104)	(0.017)
Sector=Pharma	100.187+	0.001	171.007	0.013
	(59.576)	(0.015)	(117.617)	(0.034)
Num.Obs.	48	48	48	48
R2	0.138	0.073	0.210	0.376
R2 Adj.	0.058	-0.013	0.136	0.318
AIC	579.7	-223.7	607.1	-163.2
BIC	591.0	-212.5	618.3	-152.0
Log.Lik.	-283.873	117.858	-297.532	87.611
RMSE	89.58	0.02	119.06	0.04
Std.Errors	reg_hhi_ai50	reg_cr4_ai50	reg_hhi_level_ai50	reg_cr4_level_ai50

- p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Regressions with the *AI_50* variable produced the results reported in Table 32 (ΔHHI, ΔCR4, HHI levels, CR4 levels). ΔHHI (column 1): the coefficient on *AI_50* is positive and significant at the 5% level (4.485 on a 0–10,000 scale). This suggests that, limited to the Top-50 firms, acquisition intensity has a positive effect on annual changes in concentration as measured by HHI. This result, absent in the main specification, indicates that the impact of acquisitions may manifest more clearly within the restricted sample of sector leaders. ΔCR4 (column 2): the coefficient on *AI_50* is zero and not significant. This is consistent with the regressions based on the standard AI, confirming that acquisitions do not systematically affect the market share of the top four operators. A possible interpretation is that many transactions involve smaller firms, with marginal effects on the very top of the market structure. HHI levels (column 3): the coefficient on *AI_50* is positive (6.784 on a 0–10,000 scale) but not significant. This result, similar to the main specification, suggests that, in the long run, M&A intensity does not automatically translate into a stable increase in overall sector concentration. CR4 levels (column 4): here too the coefficient on *AI_50* is zero and not significant, confirming that the relative position of the top 4 operators is not systematically driven by M&A activity.

In summary, defining acquisition intensity relative to the Top-50 firms (*AI_50*) aligns the denominator with our concentration measures. Results remain broadly consistent with the main specification: no systematic link with concentration levels and a weak but significant association with changes in HHI, whereas broader industry dynamics, especially sales growth, dominate long-run concentration patterns (Kwoka, 2015; Syverson, 2019; Grullon, Larkin and Michaely, 2019).

A particularly interesting aspect concerns the control variable Sales Growth, which shows consistent and significant results in the levels specifications: the coefficient is strongly negative for HHI (−898, $p<0.001$) and negative for CR4 (−0.205, $p<0.1$). This implies that in sectors with higher sales growth, concentration tends to decrease. In other words, market expansion reduces the relative weight of leading firms and favors competition. This result is perfectly in line with Syverson's (2019) observations, according to which demand growth and entry by new firms are competitive forces capable of counteracting concentration. The control dummies for Region and Sector show limited and mostly insignificant effects across specifications, indicating that, once growth and acquisition intensity are controlled for, no systematic structural differences emerge between the United States and Europe or between the Pharma and Digital sectors.

5.3.2 H3 Summary

Overall, the robustness check results confirm the evidence obtained with the standard definition of AI. Using *AI_50* yields a positive and significant coefficient in the ΔHHI regression, but this effect fades and loses relevance in the CR4 or levels specifications. This pattern suggests that the impact of acquisitions is more evident in short-run changes in concentration among leading firms than in the overall, more stable market structure. Moreover, the consistency of the results on sales growth strengthens the interpretation that market expansion dynamics tend to reduce concentration, while the effect of M&A remains weak and not systematic. This fits within the broader literature which, on the one hand, documents a growing role of acquisitions in market concentration (Autor et al., 2020), but, on the other hand, underscores the importance of alternative factors such as firm entry, innovation, and regulation (Kwoka, 2015; Syverson, 2019; Grullon, Larkin and Michaely, 2019)

5.4 H4: Acquisition intensity is negatively associated with innovation proxies

Building on the sector–region perimeter and acquisition measures used in H3, this section examines whether M&A pressure is followed by changes in firms' innovation effort. The outcome is R&D intensity (R&D expenditure over revenues) at the firm level for the same US/EU × Pharma/Digital coverage and years. The key regressor is lagged acquisition intensity for the corresponding sector–region cell (AI_t−1); a Top-50–scaled variant (*AI_50*, t−1}) is used as a robustness alignment to the concentration sample of H3. The empirical design employs firm and year fixed effects, relating within-firm variation in R&D intensity to lagged acquisition intensity while conditioning on contemporaneous market structure via CR4 and HHI (scaled 0–10,000). This mirrors the identification logic of H3, which captures common shocks and time-invariant firm heterogeneity, so that results are directly comparable across concentration (H3) and innovation (H4) outcomes.

The empirical results for H4 do not provide support for the hypothesis that acquisitions systematically affect firms' innovation outcomes, proxied by R&D intensity.

Table 33: Acquisition Intensity (AI) and R&D Intensity - Baseline FE Estimates

Regressors	R&D Intensity
Acquisition Intensity, AI_{t−1}	−52.121 (SE > 190)
CR4 (t)	98.726 (large SE)
HHI (t)	≈ 0.000 (n.s.)
Firm FE	Yes
Year FE	Yes
R^2 (overall)	0.375
R^2 (within)	0.001

In the baseline specification (Table 33), the coefficient on Acquisition Intensity (AI) is negative (−52.121) but highly imprecise, with a standard error of more than 190, and therefore far from conventional significance thresholds.

Table 34: Top-50–Scaled Acquisition Intensity (*AI_50*) and R&D Intensity: FE Estimates

Regressors	R&D Intensity
Top-50 Acquisition Intensity, *AI_50*_{t−1}	+0.272 (n.s.)
CR4 (t)	92.513 (large SE)
HHI (t)	≈ 0.000 (n.s.)
Firm FE	Yes
Year FE	Yes
R^2 (overall)	0.375
R^2 (within)	0.002

When restricting the analysis to the Top-50 firms (*AI_50*) within each industry (Table 34), the estimated coefficient turns slightly positive (0.272), but once again it is not statistically different from zero. These results suggest that, in this sample, acquisition activity is not a reliable predictor of changes in innovation effort, at least as captured by R&D spending relative to revenues. Turning to market concentration measures, both CR4 and HHI also fail to yield meaningful effects. The CR4 ratio is positive across specifications, implying that more concentrated industries might exhibit higher R&D intensity, yet the coefficients (98.726 and 92.513) are associated with large standard errors, preventing any firm conclusion. The HHI (scaled 0-10.000), by contrast, remains effectively zero across models, suggesting no systematic relationship between overall industry concentration and innovation outcomes. These findings diverge from the expectation that more concentrated industries, often dominated by large incumbents, may either stimulate innovation through scale economies or suppress it by reducing competitive pressure. An inspection of the model fit confirms this picture. While the overall R^2 is moderately high (0.375), the within-firm R^2 is essentially zero (0.001–0.002). This indicates that the explanatory variables included in the regressions account for very little of the temporal variation in R&D intensity within firms. Instead, most of the explanatory power is absorbed by the firm and year fixed effects. In other words, persistent heterogeneity across firms (such as firm-specific strategies, long-term business models, or structural differences in innovation capacity) and common shocks over time (such as regulatory changes or global technological trends) explain the bulk of the observed patterns in R&D, whereas acquisition intensity and concentration measures do not.

These findings carry several important implications. First, they suggest that the impact of acquisitions on innovation may be more nuanced than a simple reduction in R&D expenditures. While some influential studies document a negative effect of “killer acquisitions” on innovation in the pharmaceutical sector (Cunningham, Ederer & Ma, 2021), the present results indicate that such effects may not be generalizable across broader samples, time horizons, or alternative proxies of innovation. Second, they highlight the limitations of R&D intensity as a measure: while widely used in empirical research (Hall, 1993), it may not fully capture intangible investments in the digital sector (e.g., software development, data-related capabilities, or organizational capital), nor the long time-to-market typical of pharmaceutical R&D. This could explain why acquisition activity does not translate into observable changes in the short- to medium-term accounting data used in this study.

Finally, it is possible that incumbent firms strategically maintain stable R&D budgets regardless of acquisition activity, either to signal continued commitment to innovation or because their R&D programs are locked into long-term projects that cannot easily be adjusted in response to corporate transactions. Under such conditions, the effect of acquisitions on innovation may be indirect, manifesting instead through changes in the direction of R&D (e.g., a shift away from overlapping product lines of the acquired firm) or through the redeployment of intangible assets, rather than through aggregate spending levels. This interpretation is consistent with more recent work emphasizing that the competitive consequences of acquisitions may lie less in immediate expenditure reductions and more in the reallocation of innovative effort (Gautier & Lamesch, 2021; Federico, Langus, and Valletti, 2018).

In sum, the evidence from H4 suggests that acquisitions in the pharmaceutical and digital industries during the 2010–2022 period did not significantly alter firms' R&D intensity. While this finding does not confirm the hypothesis of reduced innovation following acquisitions, it contributes to the debate by showing that the relationship is complex, context-dependent, and sensitive to the choice of innovation proxies. This result underscores the need for future research to combine multiple indicators of innovation, such as patenting activity, citation-weighted patents, or product pipeline data, with R&D expenditures in order to obtain a more comprehensive assessment of the innovative consequences of strategic acquisitions.

The findings of H4 contrast with the influential results of Cunningham, Ederer and Ma (2021), who document that pharmaceutical incumbents often engage in "killer acquisitions" to discontinue overlapping projects and thereby reduce innovation. In this sample, no systematic reduction in R&D intensity is observed, suggesting that the effect may not be as pervasive when considering a broader set of firms, different industries, or longer horizons. Instead, the results are closer to those of Gautier and Lamesch (2021) and Federico, Langus and Valletti (2018), who highlight the difficulty of detecting robust negative effects of acquisitions on innovation when using aggregate industry-level data. These studies argue that the competitive impact of acquisitions may manifest more in the direction of innovation or in pipeline discontinuations rather than in overall R&D spending. My evidence thus reinforces the idea that the relationship between M&A activity and innovation is complex, highly context-dependent, and sensitive to the choice of proxies.

6. Conclusions

This thesis examined the role of strategic acquisition in competition and innovation in two paradigmatic, innovation-intensive industries, digital and pharmaceuticals, in two leading jurisdictions, the United States and the European Union. The empirical model pooled short-horizon capital-market data with medium-run structural performance in a single U.S.-EU x Digital-Pharma model. The years 2010-2024 were covered in the event-study tests (H1-H2), whereas the industry concentration and innovation tests (H3-H4) cover the period 2010-2022 due to the availability of official statistics and financials for the firms. The aim was to bridge the gap between what is inferred in markets at announcement and how industries and innovation in firms develop after deals have been accumulated, and to ensure transparency and comparability across regions and sectors.

There were three methodological elements incorporated. To begin with, a market-adjusted event study examined the announcement effects of the acquisition side in the windows [−1, +1], [0, +1], and [−2, +2] using cumulative abnormal returns calculated based on adjusted-close prices versus broader market indices. Inference relies on mean t-tests and a distribution-free sign test, with 1% winsorization as a robustness check to control outliers, choices that are consistent with the canonical advice on short-period event studies (Brown & Warner, 1985; MacKinlay, 1997). Second, a sector-region panel was developed using the Top-50 firms by revenue to calculate the Herfindahl-Hirschman Index (HHI) and the four-firm concentration ratio (CR4), two core measures of merger evaluation and industrial organization (Kwoka, 2015; OECD, 2020a, 2020b). The most crucial exposure was the Acquisition Intensity (AI): M&A deals that have been completed per (active) firms in a sector-year, with a robust version (*AI_50*) based on the Top-50 universe. Third, firm-level R&D intensity (R&D/sales) was modeled as a function of the acquisition context and density, using firm and year fixed effects to control for time-constant heterogeneity and aggregate shocks. This cross-walk between market response, structure, and innovation, applied across a homogeneous sector–region matrix, reinforces the thesis's main findings and contributions.

The first hypothesis (H1) tested whether strategic acquisitions create value at the time of announcement. The key finding is that, across both regions and sectors, acquirer CARs are positive and statistically significant in short event windows, and the results are robust to winsorization and sign tests. This suggests markets quickly incorporate perceived benefits—like synergies or strategic repositioning—into prices. Though short-horizon event studies do not capture long-run performance, the short-term signal is strong and consistent with previous research. Therefore, these acquisitions are generally viewed by markets as value-creating rather than value-destroying.

The second hypothesis (H2) examined whether market opinions of acquisitions differ systematically across the U.S. and the EU, controlling for sector and deal size. Cross-sectional regressions reveal a high and persistent "U.S. premium": the U.S. dummy is positive and significant in all event windows, adding approximately two to three percentage points to acquirer CARs, with sizes that are economically meaningful under 1% winsorization. By contrast, sectoral variation (digital vs. pharma) is not statistically significant in every case when controlling for region and size. Two corollary trends underlie the explanation. First, large deals (in logs) are typically discounted, consistent with increased integration complexity, financing distortions, or greater antitrust risk, rationally priced by investors (Kwoka, 2015; DOJ & FTC, 2023). Second, the very poor R^2 values in short-window cross-sections can be anticipated in event-study settings and reinforce the fact that the goal is to test conditional mean differences rather than to "explain" variance (Brown & Warner, 1985; MacKinlay, 1997). The U.S.–EU differential aligns with institutional variations in capital market depth and the predictability of merger review and remedies (European Commission, 2024; DOJ & FTC, 2023). It also highlights that market structure and enforcement regimes can jointly affect the ex-ante cost of capital for corporate reorganization.

The hypothesis of changes in sector concentration was tested by the third hypothesis (H3), which determines that the intensity of acquisition is the predictor of change. The initial result is negative: lagged AI does not predict statistically reliable year-on-year changes in concentration, either ΔHHI or ΔCR4, and the goodness-of-fit is poor, not surprising given the small number of sector-region cells and the constancy in the top-tail structures. Nevertheless, a more detailed image can be drawn when exposure is set to the Top-50 universe (*AI_50*). AI_50 is positively and significantly correlated with small increases in ΔHHI (on the 0-10,000 scale), and null in ΔCR4 and level regressions. Practically, acquisition activity among industry leaders appears to boost dispersion in revenue shares among Top-50 cohort members, or reshuffle the pack, without systematically placing the top performer at either the high or average levels of concentration. This disparity between ΔHHI and ΔCR4 is noteworthy: CR4 will respond to the weight of the top four firms, whereas HHI will respond to wider distributional shifts; a deal can be one that moves rank-order positions and share dispersion without raising the top four footprint. These results align with the broader perception of industrial organization, which suggests that consolidation, entry, and demand growth are the intrinsic factors that dictate the concentration of courses rather than the number of deals (Kwoka, 2015, 2020; OECD, 2020a, 2020b).

A second notable finding under H3 is that sectoral sales growth is negatively correlated with levels of concentration: faster-growing markets are more likely to have lower HHI (and, to a lesser extent, lower CR4). Increasing demand can dispense existing market shares, enable entry, and offset the forces of consolidation that would otherwise be (mis)imposed on mergers themselves. This view is consistent with more recent explanations of industry dynamics where competitive distributions are re-established by market expansion and technological shocks without necessarily ratcheting up concentration (Autor et al., 2020; De Loecker, Eeckhout, and Unger, 2020). In policy, the implication is that when monitoring structure over time, one should not use the number of deals but instead integrate the dynamics on the demand side.

The fourth hypothesis (H4) inquired whether sectoral conditions of acquisition systematically predict firms' innovation efforts, measured by R&D-to-sales. The evidence does not support a strong link. On the fixed-effects baseline regressions, the lagged AI coefficient is negative but very unreliable, and small and statistically equal to zero (sometimes positive) when using the leader-centered *AI_50*. CR4 and HHI also do not give reliable or correct effects. The in-firm R^2 is near zero, implying that time-constant firm heterogeneity and aggregate time shocks explain most of the organized variation; the acquirer environment offers little explanatory power. These results do not imply that acquisitions never have an effect on innovation. They instead imply that any effect is measured poorly by aggregate, accounting-based spending ratios at annual frequency between heterogeneous firms and industries. In the online business, innovation investments take many non-R&D forms (organizational capital, information assets), but in the drug business, the long clinical cycles and pipeline commitments smooth out R&D expenditures through individual deal episodes. It is not necessarily the case that some acquisitions reduce future product variety or postpone rival projects, but these effects are more clearly seen in pipeline- or patent-level data (Cunningham, Ederer & Ma, 2021; Shapiro, 2018) and in qualitative analyses of digital platform conduct (Crémer, de Montjoye & Schweitzer, 2019; Caffarra & Scott Morton, 2021).

In addition to the four hypotheses, this thesis presents four key contributions. Firstly, it provides an integrated, comparative framework between industries and jurisdictions: a U.S.–EU × Digital–Pharma structure that connects short-term market reactions to medium-term structural implications. In the second place, it focuses on clear measurement: market-adjusted event windows with high-power inference, Top-50-based concentration measures, and two consistent definitions of acquisition intensity (AI and *AI_50*), all of which improve the correspondence between exposure and outcome. Third, it clarifies where M&A "appears": investors punish (or reward) acquirers on announcement (particularly in the U.S.), but structural concentration changes are small, local, and dependent on who is acquiring. In contrast, innovation expenditure levels appear to be virtually orthogonal to the acquiring environment. Fourth, it places at the center a demand-growth channel: faster-growing industries are less concentrated in levels, suggesting a simple yet underappreciated mechanism that regulates consolidation dynamics (Autor et al., 2020; De Loecker, Eeckhout, & Unger, 2020).

The limitations of the work are self-explicit. The proxy of innovation is crude and can fail to capture productive activity in intangibles-intensive, software-driven business models; and an annual frequency may be too coarse to capture rapid post-merger changes or long-lag effects of innovation, particularly in pharma, where clinical pipelines unfold over decades (Cunningham, Ederer & Ma, 2021). Software and Services must be placed outside the H3-H4 "Digital" perimeter by necessity, based on constraints in the coverage of official business demography, whereas H1-H2 event-study sample is broader; this variation may reduce the objective effects of acquisition intensity, structure, and R&D. Concentration is computed on Top-50 cohorts, an analytically useful focus on leaders necessarily excluding long-tail roll-ups and periphery dynamics. Finally, the relatively modest number of sector–region cells constrains statistical power in H3.

Policy-wise, three implications are significant. First, the U.S. premium to announcement-period returns is robust. Even as caution is exercised in assigning causality, a premium like that suggests that U.S. financial markets expect relatively higher synergy realization and conceivably smoother merger execution in the U.S. institutional context (DOJ & FTC, 2023; U.S. FTC, 2021). Inconsistencies in the enforcement framework and foreseeability could influence the ex-ante cost of capital of corporate restructuring, with implications for global competitiveness in the innovation race. Concentration is a nonlinear function of the number of mergers. Although leader-led acquisition intensity may be coincidental with short-run growth in ΔHHI, average concentrations and CR4 might not necessarily need to increase, and increasing demand could ease consolidation pressures. For antitrust enforcers, this presents an argument for the systematic incorporation of entry and growth circumstances into structure surveillance and restraint, as relying solely on brute deal counts as a proxy for competitive harm is insufficient (OECD, 2020a, 2020b; European Commission, 2024). Third, innovation harm measures must focus on the direction and composition of innovative activity—such as pipelines, product launches, and citation-weighted patents—rather than on accounting aggregates in isolation (Cunningham, Ederer, & Ma, 2021; Shapiro, 2018; Caffarra & Scott Morton, 2021).

The thesis also sees a rich agenda for research. First, later work should cross-validate innovation with pipeline-level (pharma) and product- or feature-release (digital) measures, as well as patents and citations, to test whether acquisitions redirect but do not reduce innovative effort (Cunningham, Ederer, & Ma, 2021; Shapiro, 2018). Second, extending the event-study design to competitors would facilitate separating efficiency and coordinated-effects explanations (acquirer up, competitors down vs. acquirer and competitors both up). Third, structural dynamic models that permit the explicit treatment of entry, exit, and demand growth may quantify the relative contribution of M&A compared to organic sources of observed concentration trajectories, drawing on the sales-growth insight in H3 (Autor et al., 2020; De Loecker, Eeckhout, & Unger, 2020). Fourth, more refined deal taxonomies—acquihires, capability expansions, horizontal overlaps, and vertical/complementary deals—could provide an explanation for which mechanisms cause the modest ΔHHI effect observed for *AI_50* (Kwoka, 2015; Valletti & Zenger, 2021). Finally, institutional "tests" that exploit enforcement thresholds or policy changes between regions can shed light on the explanations behind the U.S.–EU differential announcement return and the influence of predictable review on forming expected deal value (European Commission, 2024; DOJ & FTC, 2023).

Overall, the evidence assembled here verifies a balanced view. Strategic pharma and digital deals are, on average, welcomed by equity markets with statistically and economically meaningful U.S. premia. In the long term, there is no systematic evidence that more deals create more concentration among leaders; where there is an effect among the Top-50, it is rather in the form of mild reshuffling than entrenched dominance at the top. At the firm level, R&D spending intensity is largely orthogonal to acquisition intensity, suggesting that any innovation effects are operating through project selection and pipeline allocation, rather than across-the-board spending cuts. To researchers and policymakers engaged in the competition between "killer acquisitions" and synergy-based efficiency, the message is to embrace heterogeneity: effects differ depending on who buys whom, where, and when, as well as in what circumstances, by sectoral and institutional environment, and in response to demand. The right empirical structure combines robust short-run identification with micro-founded, long-run measures of structure and innovation. Seen in that way, the relationship between competition and strategic acquisitions is not necessarily negative nor always positive—it is dependent, conditional, and most significantly, measurable.

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