MASTER THESIS

Exploring the Impact of Mergers on Innovation: An Empirical Analysis

MSc Economics: Competition & Regulation Track

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Submission date: 20. 06. 2023

Word count: 13 046

Abstract

Recent merger cases have initiated a debate about the relationship between mergers and innovation. The theoretical literature shows contradicting results on the topic. Therefore, this paper aims at investigating the effect of mergers on innovation, using data from the European Commission database. The study employs three econometric models, including Two-Way Fixed Effects, Difference-in-Differences in a multivariate setting, and Staggered Difference-in-Differences. This enhances the robustness of the findings and addresses the potential limitations of individual methods. The three models show a consistent positive effect of mergers on R&D intensity and on R&D expenditures, suggesting the existence of positive synergies, outweighing the negative innovation externalities. The findings contribute to the work of the antitrust authorities and shed light on potential policy implications.

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1. Introduction and Motivation

Mergers have been increasingly capturing the attention of researchers and control organs. This is due to the fact that mergers could be a potential barrier to healthy competition. Recently, the European Commission established new jurisdictional and procedural developments related to market definition and merger control. Namely, the Digital Market Act was adopted and article 21 and 22 of the EU Merger Regulation (EUMR) were recently applied in some controversial cases (Fountoukakos et al., 2022). Furthermore, in recent speeches officials both from the EU and US competition authorities have talked about a potential negative effect of mergers on research and development (Haucap, Rasch and Stiebale, 2019). The culmination of these statements was realized in the case Dow/DuPont. The European commission concluded that the merger of the two firms will affect innovation in the sector negatively. The Commission wrote:

> Today's decision follows an in-depth review of the merger. The Commission had concerns that the merger as notified would have *reduced competition on price and choice* in a number of markets for existing pesticides. Furthermore, the merger would have *reduced innovation*. Innovation, both to improve existing products and to develop new active ingredients, is a key element of competition between companies in the pest control industry, where only five players are globally active throughout the entire research & development (R&D) process (*Press Release*, 2017).

The merger was only conditionally cleared, and the firms will have to fully commit to the concerns of the Commission. Haucap et al. (2019) summarized another merger that triggered a discussion about the effect of mergers on innovation. It was the merger between Pfizer and Hospira. The merger was cleared only after Pfizer agreed to sell its European rights on a drug that they were developing. The Commission suspected that after the merger Pfizer would had stopped working on the drug since Hospira already had a competing drug on the market.

These have been one of the first cases in which the commission emphasized the importance of the effect of mergers on R&D. Up until this moment, only the direct effect on competition had been taken into account. This might be a logical consequence of the increasing amount of scientific literature on the topic. Many publications have questioned the effect of mergers on innovation and there have been a lot of theoretical proofs that mergers have a negative impact on research and development (Mota & Tarantino, 2021; Federico, Langus & Valletti, 2018). Therefore, it is essential to continue analyzing the effects of mergers to prevent undesirable reduction in innovation incentives.

In addition, both the EU and US jurisdictions allow for the so-called “efficiency defence” of otherwise anticompetitive mergers (Haucap et. al., 2019). This implies that if firms are able to prove that a potential merger might lead to substantial efficiencies, even anticompetitive mergers could be cleared by the authorities. Usually, the efficiency gains are reached through cost-savings. However, very often firms also claim R&D efficiencies (Matsushima Sato & Yamamoto, 2013). One reason why firms mention innovation as a main motive for merging is due to the possibility of R&D budget increase of the merged entity. The larger budget may allow for the realization of larger R&D projects and for the achieving of larger economies of scale (Matsushima et. al., 2013). Therefore, it is crucial for the competition and regulation authorities to understand the consequences of such statements of efficiency gains.

As shown with the examples above, it is essential for policy makers to gain a better understanding of the effect of mergers on innovation. Otherwise, there is a substantial risk of some anticompetitive mergers happening that might not only distort the prices and consumer welfare, but also research and development. It is important to emphasize that our society has achieved a lot through innovation, especially in the last decades. Innovation is one of the main drivers of consumer welfare and economic growth (Federico et. al., 2018). Therefore, the process of innovation should be supported and everything that might jeopardize it should be cautiously investigated.

Federico et. al. (2018) analyze the impact of horizontal mergers on product innovation through two channels – price coordination and innovation externality. They conclude that the reduction in price competition through price coordination favors competition. However, in their model the negative innovation externality prevails and the overall effect of mergers on innovation is negative. Mota and Tarantino (2021) reached similar findings. They concluded that mergers always reduce innovation and consumer welfare, assuming lack of efficiency gains.

On the other hand, Denicolò and Michele (2019), as well as Jullien and Lefouili (2018), show a different point of view and argue that mergers might affect innovation positively or negatively depending on the circumstances of the merging parties. According to Denicolò and Michele (2019), the theoretical mode of Federico et. al. (2018) lies on the very restrictive assumption that the returns to R&D decrease by a large enough amount with the level of R&D expenditures. However, if the returns decrease by small enough amount, the additional coordination and efficiency gains from the merger might actually lead to higher rate of innovation activities. Therefore, more empirical work is needed to investigate the effect of mergers on innovation in practice.

Due to the lack of consensus among the researchers on the matter, this paper is going to present an empirical analysis on how mergers affect innovation in the merged firms and whether the effects differ across industry. It is also going to show whether the effect is more negative for horizontal mergers than for other types of mergers, such as vertical and conglomerate mergers. The research is done using a panel dataset for 9 years, from 2011 till 2019, for 1057 individual firms.

A few methods capture the causal relationship between the mergers and innovation and guarantee for the robustness of the results. The first one is Two-Way Fixed Effects (TWFE), which captures the difference in the outcome for the treated group of firms and the untreated group, while controlling for time and firm-specific fixed effects. The second model that I use to capture the effect for the different industries, is the difference-in-differences in a multivariate setting, using a control for time and industry fixed effects. The last method I implement is staggered difference-in-differences, which computes the group-time average treatment effect. I include it into the analysis due to the weakness of the fixed-effects models to precisely estimate the treatment effect when units become treated at different points in time.

The analysis is based on two measures of the dependent variable – R&D expenditures and R&D intensity. Both measures are R&D inputs, which show the willingness of firms to innovate instead of their success in doing so.

The results suggest a positive relationship between mergers and innovation. They also show that horizontal mergers are likely to be more detrimental to innovation than vertical mergers. However, these findings should be interpreted with caution due to an endogeneity problem and huge scale disparities between the treatment and control group. The weaknesses of the control group and how they affect the results are going to be further discussed in the following chapters.

The findings presented in this paper will make significant contributions both in terms of theoretical advancements and managerial implications. First of all, even though the subject has been heavily researched in recent years, the contradictory findings on the topic call for more empirical work. Since, there are so many factors that contribute to a firm's decision to merge and to innovate, it is hard to capture the right ones. Therefore, this paper is going to concentrate on the differences across industries and see if the effect changes depending on the sector in which the company operates. This in turn could help future researchers find the right factors of interest by looking at industry specific effects.

In addition, the findings are going to benefit managers and competition authorities by showing the heterogeneous effects of mergers across different sectors. This will support decision making in antitrust law and individual company decision making, which is important for the growth of R&D and the development of our society.

The paper is organized as follows: I discuss the relevant literature and hypotheses in the next chapter. After that, there is a discussion of the data collection process and methodology. The next two chapters include the results from the empirical work and the discussion. Finally, there is a conclusion, where I mention the main findings, limitations and recommendations for future research.

2. Literature Review

This section gives some theoretical background on the problem and provides additional insides on the main concepts in the analysis of the effect of mergers on innovation. Furthermore, I present the hypotheses that follow from the literature review.

As mentioned in the introduction, Federico et. al. (2018) presents a theoretical model that shows the effect of horizontal mergers on product innovation. Their model does not consider cost reducing process innovation. They assume that the improved product entirely replaces the new one since they consider it to be unprofitable for a firm to sell both high- and low-quality versions of the same product. As previously mentioned, Federico et. al. (2018) assume that horizontal mergers affect product innovation through two channels – price coordination and innovation externality. Price coordination implies the elimination of price competition between the merging firms. In the model of Federico et. al. (2018) the reduction of price competition between the merging firms has a positive effect on innovation due to the increase in profits following the increase in prices. The second channel included in the analysis, namely, innovation externality, is defined as the reduction in profits of the merging partner, due to the diversion of profitable post-innovation sales or cannibalizing of pre-innovation sales of the merging partner. This channel is of significant interest, since in the simulation it overcomes the positive effect of price coordination and leads to a strong negative effect on innovation. In addition, Federico et. al. (2018) found that the negative effect is stronger for firms that are close competitors and that overall, the merger is welfare reducing for consumers, since it leads to lower levels of innovation and higher prices. It is important to note that their model considers innovation-related efficiencies such as reduction in R&D cost due to merger-specific enhancements.

Mota and Tarantino (2021) conduct a similar analysis on mergers and innovation. However, their main model considers process innovation instead. They show that price and cost-reducing investments in a merger ultimately lead to lower innovation incentives due to the internalization of the externality of the innovation. This is evident when the price decreases due to a process innovation, reducing the demand for other products in the merged entity. Mota and Tarantino (2021) then extend their results to quality-improving innovation and support the findings of Federico et. al. (2018) that a merger reduces competition in innovation and therefore leads to lower innovation incentives.

It is worth noting that the models in the above-mentioned articles consider mostly negative innovation externality. This means that the profits of the merging partner are negatively affected by the innovating party. This could happen in several ways. Federico et. al. (2018) differentiates between two cases of negative innovation externality by the innovating merging firm – one in which the merging partner has innovated and one in which it has not. In the first case the innovation of one of the merging firms negatively affects the post-innovation sales of the other merging firm. In the second case, where the merging partner is not innovating, the innovating firm reduces its partner's pre-innovation sales by cannibalizing them.

Moreover, Mota and Tarantino (2021) also consider partly the internalization of negative innovation externality. They suggest that a process innovation will decrease the post-innovation prices of the innovating firm, while at the same time reducing the demand for the products of the merging partner. This will lead to upward pressure on the prices of the merged entity and lower quantities sold, which at the end will cause lower revenues due to the previous investment, leading to a decrease in future investments. However, Mota and Tarantino (2021) also consider the effect on outside firms. Their model assumes that outsiders' prices will increase less than the ones of the insiders and therefore their demand will increase, leading to increase in future investments. At the end their models show that the effect on outside firms' R&D could be both positive or negative.

Jullien and Lefouili (2018) also investigate innovation externality or as they call it innovation diversion effect. However, in contrast to the assumptions of Federico et. al. (2018), they show that its impact can be either negative or positive and depends on the nature of the innovation. According to Jullien and Lefouili (2018) the paper by Federico et. al. (2018) provides an incomplete picture of the effect of mergers on innovation. In addition, Jullien and Lefouili (2018) completely disagrees with the statement of Federico et al. (2018) that the innovation externality effect is the most impactful in a merger. Therefore, they include additional merger effects that in the end lead to a different result. Another difference in the approaches of these two papers is connected to the literature on the effect of competition on innovation. An example of such an article is the paper by Aghion et al. (2005), which obtains an inverted U-shape relationship between competition and innovation. Federico et. al. (2018) and Mota and Tarantino (2021) have pointed out that papers on this topic have little to no implications for merger cases. Their reasoning suggests that mergers allow firms to coordinate their decisions and internalize the competition externalities. However, according to Jullien and Lefouili (2018) the findings of Aghion et al. (2005), are relevant for merger cases as well. They conclude that policy makers should be neutral in their assessment of the effect of mergers on innovation.

Another study that supports the hypothesis of a mixed effect of mergers on R&D is the paper by Bourreau et al. (2021). In contrast to Federico et al. (2018) who found that innovation diversion effect is stronger and dominates the price coordination effect, Bourreau et al. (2021) created a model showing that the interaction between the two effects is the main factor determining the impact of mergers on incentives to innovate. In particular, they found that the effect of mergers can be both positive or negative, depending on which effect is greater. Moreover, their results suggest a trade-off between the impact on incentives to innovate and the effect on prices. In particular, increase in incentives to innovate by the merger might lead to increase in prices and therefore ambiguous impact for consumer surplus. However, the authors left this result and its implications for future research. Still, this is a strong contradiction to the definite results of Federico et. al. (2018) and Mota and Tarantino (2021) who concluded that mergers are welfare reducing.

This opposing theoretical findings and the newly sparked debate by the European Commission called for an empirical study investigating the above-mentioned effects of mergers on innovation. However, the empirical literature on the topic is not that extensive. For example, Chemmanur et al. (2020) investigate the effect of mergers on innovation and find a positive relationship, but their research concentrates on positive innovation externalities. Most theoretical papers that we discussed so far have assumed negative innovation externalities. Régibeau and Rockett (2019) summarize the reasons for that. According to them, positive innovation externalities can occur in certain cases and in certain industries. However, policy makers are mostly concerned with negative externalities as they present a greater threat for R&D. In addition, the existence of positive externalities and their positive effect on innovation does not lead to a positive effect for consumer welfare, since the price effects also need to be taken into account. The analysis then could become quite complicated. Therefore, positive externalities should not be considered during a merger review.

Haucap et al. (2019) conducted an empirical analysis not only for the effect of mergers on innovation of the merging firms but also the effect on outside firms in the pharmaceutical industry. They found that for research intensive industries, such as pharmaceutical markets, the effect of mergers is negative both for insiders and outsiders of the merger. Only in industries with a low level of innovation activity, the merger can have a positive effect on the merged entity and on outside competitors. Haucap et al. (2019), however, only consider one industry – the pharmaceutical industry. The reason for that lies in the specifics and characteristics of this industry. According to Régibeau and Rockett (2019), industries such as chemicals, pharmaceuticals and information and communication technology are likely to have strongly negative innovation externalities and therefore the effect of mergers on innovations is more likely to be negative. In addition, the higher degree of substitutability in these industries leads to more intense competition. Therefore, a merger in these competition intensive industries is going to have a strong competition-softening effect and this will lead to negative effects on innovation incentives (Haucap et al., 2019). On the other hand, industries such as automotive and beverage have strong differentiation potential, meaning that innovation is likely to be more competition-softening and therefore mergers might not lead to lower innovation incentives (Régibeau and Rockett, 2019).

In his book, Tyagi (2019), calls for the consideration of industry-specific factors when enforcing merger control, in order to effectively take into account merger efficiencies and competition disruption.

According to Comanor and Scherer (2013) the recent mergers in the pharmaceutical industry have put at risk R&D productivity. Due to the high uncertainty in the technological progress of the innovation in this industry, it is usually highly uncertain whether the innovation is going to be successful. Therefore, the most certain way to ensure innovation is to provide widespread dispersion of R&D efforts. This condition, however, is broken once a merger is performed.

Walsh and Lodorfos (2002) emphasize that pharmaceutical and chemical companies usually give technologically related reasons for mergers, such as the gaining of new patents, skills and technologies. However, Comanor and Scherer (2013) argue that these exact gains cannot offset the high uncertainty in these industries and might lead to slower rate of innovation due to the reduction in parallel technological paths taken.

On the other hand, in her book, Rama (2008) discusses some mixed findings for the food and beverage industry. Due to the large differentiation potential in this industry, non-price competition is of great importance. Therefore, large companies are the ones that are more likely to afford better marketing and R&D efforts on product differentiation. However, she concluded that there is not enough evidence that concentrated markets support innovation in the food and beverage industry since competition is still the most important factor. Still, due to the different nature of this industry, it is worth seeing whether the results would differ in comparison to the ones mentioned above.

Another industry of interest is the automotive industry. According to Zapata and Nieuwenhuis, (2010) the pressure from the governments and the public has led to the so-called “regulatory innovation”. The constant need for safety and ecological improvements is an important driver for the industry’s innovation development. Therefore, we might be able to see different effects of mergers on innovation.

The nature of the ICT sector is one of the most interesting in the case of how mergers may affect innovation. This industry has both a high degree of technological intensity and product differentiation (Tyagi, 2019). This means that each firm has market power and at the same time some firms compete more closely than others for the same consumers. According to

Tyagi (2019), the disruptive nature of the ICT industry may call for a different approach in merger investigation.

In this paper, I would like to study the effect in different industries and show how the effect of mergers on innovation varies across sectors. The different types of industry structures with respect to competition can lead to different outcomes for the intensity of innovation (Aghion et al., 2005). Therefore, it would be essential to see whether the same applies in the case of a merger. This will allow for more precise merger reviews by antitrust authorities. The paper will show that it is crucial for the regulators to take into account industry specifics while investigating merger cases. This discussion of the literature leads us to the hypotheses mentioned below.

2.1. Hypotheses

The first two hypotheses follow from the papers of Federico et. al. (2018) and Motta and Tarantino (2021). Both theoretical articles conclude that mergers cause negative innovation externalities and reduce innovation. Jullien and Lefouili (2018) and Bourreau et al. (2021) claim that there might be a positive effect of mergers on innovation. However, their results were mixed. Therefore, my first hypothesis is

1. Mergers have a negative effect on innovation.

The second hypothesis takes into account the guidelines of both EU and USA competition authorities, which allow for the so-called efficiency defense for otherwise anticompetitive horizontal mergers (Haucap et. al., 2019). These claims are often related to R&D efficiencies (OECD, 2012). If companies are able to prove that a merger results in a substantial increase in R&D efficiencies, then the merger is more likely to be cleared by the antitrust authorities. Therefore, it is important to investigate the credibility of these claims and based on the findings of Federico et. al. (2018) that the negative effect is stronger for firms that are close competitors I propose the second hypothesis

2. Horizontal mergers have more negative impact on innovation than other types of mergers.

The third hypothesis follows from the discussion of the literature, which highlighted some industry related factors that affect innovation. It is also based on the research by Haucap et.

al. (2019), who suggested that mergers have different impact on innovation across industries. Thus, my third hypothesis is

3. Mergers have heterogeneous impact on innovation activities across industries.

3. Method and Research design

3.1 Data

I construct a panel dataset on publicly traded firms from 2011 to 2019 including data from 5 different datasets. First of all, I download all merger cases from the EU commission database. Typically, the Commission investigates larger mergers of EU dimension that pass certain turnover thresholds. The merging firms are not only based in Europe, but all over the world. The only thing that matters is whether they participate in the European market. The commission then reviews each case either by the simplified procedure or carries out a full investigation, depending on whether the merger passes a market share threshold or not. I filtered all merger cases by industry and year. The final dataset includes 368 merger cases for the period 2014 – 2016. I restrict the merger period to these years so that I could estimate the effect, accounting for a period of three years before and after the mergers, without capturing the potential negative effects from the COVID crisis and the 2008 crisis. Based on the literature review in the previous section, I include mergers from 6 industries, namely, Pharmaceutical, Chemical, ICT, Electronics, Automotive and Food and Beverages.

After that I download two datasets with financial data for all publicly traded companies from the Compustat database. Compustat has two separate databases – one for companies with headquarters in the USA and Canada and another for non-US and non-Canadian companies. As already mentioned above, the merging firms are positioned all over the world. Therefore, I download the financial data both from the USA and non-USA database. Both contain data for more than 60 000 companies with financial information available for the period 2011 – 2019. The datasets include information on the firms' R&D expenditures, number of employees, sales and other balance sheet data. There is also an identification code for every company and a four digit SIC code, which represents the unique industry the company operates in. Furthermore, I download a similar dataset from Amadeus database which includes information for more than 24 000 companies. I do that so I could fill in the missing values from the Compustat dataset. I use one additional dataset specifically to fill in gaps in the

R&D expenditures column. This dataset was a merge of the European Scoreboard datasets for the years from 2011 until 2019. It includes data for every year's top 2500 most innovative companies globally.

After I have downloaded all datasets with all the data that is needed, I hand-match the companies from the EU commission merger dataset to their financial information from the other datasets. Many of the companies in the EU commission merger dataset are either private or lack R&D expenditures data. According to Koh and Reeb (2015), 10.5% of firms with missing R&D expenditures, in reality still, receive patents. The received patents are 14 times lower for firms that have indicated that they spend zero on R&D. This implies that many companies are not revealing their true R&D expenditures on purpose, by leaving the field blank. Therefore, it is not appropriate to handle the missing values by transforming them into zeros as this will most certainly produce biased results. For this reason, I drop all companies that have missing values for their R&D expenditures. This drastically lowers the units in my treatment group.

I construct the treatment group by hand-matching each firm from the EU commission merger dataset to their financial information from the other datasets. While matching, I left out all mergers with missing values in the R&D section. Therefore, my initial dataset for companies that participated in a merger contains 131 firms. Additionally, to make sure that each unit is observed over equal time periods, I removed all firms with less than 9 yearly observations. At the end, I have a treatment group that contains data on 107 individual merged firms. Table 1 shows the steps leading to the final sample of the treatment group. According to Tyagi (2019, Chapter 4), the competition authorities make no distinction between merger, acquisition or takeover and they are collectively called mergers. This is due to the fact that competition law deals only with firms' market power and this broader definition serves its objective. I, therefore, include firms from different kinds of mergers. However, I add an additional dummy variable for firms that participated in horizontal mergers. To precisely determine the type of the merger, I go over the documentation for each individual merger in the European Commission database. In addition, for the sake of completeness, I added a variable, capturing the role of the firm in the merger – an acquirer, a target or a joint venture.

Table 1 Steps for filtering the treatment group sample

Step	Filtering action taken	Number of firms left in treatment group
1	The initial number of merger cases	368 merger cases (around 1104 individual firms)
2	Constructing the treatment group by leaving out firm with missing values for R&D expenditures	131 firms left with no missing values for R&D
3	Excluding all firms that contain data for less than the 9 years from 2011 till 2019	107 firms left in the treatment group

Once the data for the treatment group is collected, I continue with selecting the control group. Table 2 presents a summary of the process. I search for companies from the same industries as my treatment group, who did not participate in M&A activities in the period 2011-2019. To construct this group, I download two datasets – one with firms' financial data and one with firms who participate in a merger during the period of interest. After having the two datasets, I exclude all firms from the first dataset who are present in the second.

Firstly, I download financial data from Compustat. I export firms participating only in the industries of interest - Pharmaceutical, Chemical, ICT, Electronics, Automotive and Food and Beverages. I use the four-digit Standard Industrial Classification (SIC) codes, which I already have in the treatment group dataset, to select the companies based on their industries. I download panel data, similar to the treatment group, again for the period 2011-2019. The file contains data for 13 154 individual firms. Afterwards, I download another dataset from the Bureau van Dijk on companies who participated in M&As in the period 2011-2019. The file contains 148 992 companies that have participated in a merger in the period of interest. In addition, I check which firms from the Compustat dataset are present in the M&A dataset and exclude them with the intention to have data left only for companies that did not participate in

M&A in the years 2011-2019. For that reason, I need to make sure that both datasets contain identical identification number variables, which can be used to perform the check. I use the International Securities Identification Numbers (ISIN), since it is present both in the Compustat database and the database of the Bureau van Dijk. However, this variable was not available for the USA and Canada database in Compustat. Therefore, I used only the Global database to form the control group. I perform an anti-join of the two datasets by excluding all firms from the financial dataset that are present in the M&A dataset. This leads to a new dataset containing 6 544

Table 2 Steps for filtering the control group sample

Step	Filtering action taken	Number of firms left in control group
1	Initial number of firms in both datasets	Compustat - 13 154 Bureau van Dijk - 148 992
2	Excluding firms from Compustat that are present in the Bureau van Dijk dataset	New control group contains 6544 firms
3	Removing all observations with missing R&D expenditures	New control group contains 3547 firms
4	Removing all firms who are left with less than 9 observations	Final control group contains 970 firms

firms that have not participated in M&A deals. Furthermore, I remove all companies who have missing values for their R&D expenditures, and the remaining number of firms is 3 547.

Lastly, I remove all companies, which do not have observations for the full 9-year period. At the end the control group contains a panel dataset for 9 years for 970 firms.

I export both treatment and control datasets to Excel and I merge them manually into one dataset. The merged file contains data for 1077 companies. At the end I removed a few outliers using the z scores method, calculated based on the R&D expenditures. The final dataset contains 1057 companies, out of which 107 are treated and 950 are a control group.

Thus, only the smallest companies from the control group are excluded from the data, which is expected to enhance the accuracy and reliability of the results.

As mentioned earlier, each company has been assigned a unique four digit SIC code representing a single sub-industry. Since I had filtered the industries in the European commission dataset before matching them to the data from Compustat database, I know that all of the SIC codes belong to one of the 6 main industries. There are only two SIC codes that did not belong to any of my desired industries, and they concern two firms from the treatment group. I exclude them from the research.

I use the EU commission dataset for main reference, while matching the codes to their industry. I also cross reference them with data from the internet. After that I replace all codes in the data with the names of the main industries to make it easier to analyze later.

Furthermore, I need to check for the currency the data is in. The Compustat Global database provides the data for each company in its home currency. The final dataset contains data from 53 different countries in 36 different currencies. To make different companies comparable and prevent biased results I convert all currencies to Euro, using the most recent exchange rates. To do that, I transfer the dataset to Google Sheets and use the GOOGLEFINANCE() function, which automatically calculates the most recent exchange rate by a given currency code. I already had the currency codes present in my dataset. Therefore, I just had to order the dataset by currency, and multiply each set of values from a given currency by the exchange rate supplied by the function mentioned above. The complete set of exchange rates is available in Appendix A. Table 3 below shows the main descriptive statistics of my dataset with respect to the treatment and the control group.

From the table, it is evident that the treatment group includes larger firms. They have on average 82 000 employees and average R&D expenditures of 5 990 million euro. In comparison the firms from the control group have on average 3000 employees and their R&D expenditures are on average 26 million euro. This is due to the fact that my treatment group consists of firms participating in mergers, which were reviewed by the EU commission. As previously mentioned, the Commission only reviews mergers that cross a certain threshold in market share. Therefore, it is logical that the companies in the treatment group are going to be some of the largest firms on the market. For that reason, finding a proper control group is extremely hard due to the lack of direct competitors to large corporations, which did not participate in mergers. As a result, my control group includes many smaller firms and only a few larger ones. This is not ideal research setting and the results should be carefully interpreted. I further explain the possibility of bias due to the suboptimal control group in the discussion section.

The graph also shows the minimum and the maximum of years included. As can be seen, the minimum starts from 2010. This is due to the fact that some firms in Japan have different ways of presenting their fiscal years so the data for them starts from 2010 and it is until 2018.

In addition, the table displays the percentage of firms in different industries. It can be seen that the control and the treatment group, have similar weights in each industry, with the Chemical and Electronics industries being small exception.

Table 3. Descriptive statistics of treatment and control group

Variable*	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Group	Control group						Treatment group					
Date - Year	2015		2010	2012	2017	2019	2015		2010	2012	2017	2019
Role												
❖ None	100%						0%					
❖ Acquirer	0%						72%					
❖ JV	0%						14%					
❖ Target	0%						14%					
Horizontal merger	0%						52%					
Employees**	3	28	0.002	0.18	1.4	671	82	92	1.4	20	112	803
R&D Expenditures	26	385	0.000088	0.45	4.8	13199	5990	46103	0.3	122	1667	757011
Total Sales	778	8564	0.0057	18	166	252632	82751	658184	66	6802	41774	7567394
Capital Expenditures	48	630	0	0.26	5.7	21133	2495	14707	0	261	1884	315514
Industry												
❖ Automotive	15%						16%					
❖ Chemical	14%						26%					
❖ Electronics	27%						13%					
❖ Food & Beverage	6%						12%					
❖ ICT	26%						20%					
❖ Pharmaceutical	12%						13%					

*Numbers are in millions (Euros)
**In thousands

3.2 Variables description

There are a few ways to measure innovation. The most popular methods used in the literature are R&D expenditures and the count of patents and citations. Both of these measures have advantages and disadvantages. The drawback of the R&D expenditures measure is that firm-level data is not always available especially for smaller companies. In addition, not all firms report their R&D expenditures and that is the reason why there are many missing values in the fields for R&D expenditures in the databases. Moreover, the presence of large conglomerates in most industries makes it difficult to find firm-level data as the financial statements only show the total R&D investments (Doan and Mariuzzo, 2022). On the other hand, the problem with patents as a measure of innovation is that not all patents lead to meaningful innovation with commercial value. It is also more time consuming and due to the time restrictions imposed by my deadline I chose to use the logarithm of *R&D expenditures* of firms as proxy for innovation (Entezarkheir and Moshiri, 2018). I use the logarithm of the variable to account for the skewness of the data and to restore the assumption of normality. A histogram of the standardized residuals before and after the use of the logarithm is available in Appendix B.1.1 and B.1.2. In addition, I use one more variable to measure the innovation in a firm. The *R&D intensity* is used to measure the dependent variable, in order to provide more clarity of the innovation inputs of a firm. It is defined as the *R&D expenditures* divided by *sales* and is used to control for the size effects in the sample (Szücs, 2014). In addition, the R&D intensity is a ratio, which is a number between zero and one. One drawback of using R&D intensity as a proxy for innovation is that the effects might be based on the increase or decrease in sales. Therefore, for this measure I include an additional control variable in the model, the natural logarithm of sales, to isolate the effect of sales on the ratio. However, this might lead to an endogeneity problem. Thus, the results of the study will require careful interpretation. Another solution to the problem, concerning the firm size differences between the treatment and the control group, would be to divide R&D expenditures by the full-time equivalent (FTE), instead. However, I could not find sufficient data for this variable.

In the model, innovation is the dependent variable, measured by the logarithm of *R&D expenditures* and the *R&D intensity*. The key test variables are two dummy variables. The first dummy, *dummy merger,* is equal to one if a merger has taken place at time t and zero otherwise. The second dummy, *horizontal merger,* equals one if a merger is of a type horizontal and zero otherwise.

In addition, there are a few control variables. The *country code* is the variable showing the country of the merging firm. The *industry* is the variable that is used to control for the industry of the firms. Moreover, as in the paper by Chemmanur et. al (2020), I also include control variables that may affect innovation. I control for the return on assets, defined as the *operating income divided by total assets,* and the *capital expenditures divided by total assets*. I also control for the leverage of the company, expressed as the total debt divided by total assets. *Table 4* provides summary of the variables of interest.

Table 4. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Control group						
R&D intensity	0.3	2.5	0.0000004	0.0086	0.083	0.98
Return on assets	0.015	0.32	-18	0.0032	0.09	12
Capex	0.028	0.027	0	0.0073	0.042	0.12
Leverage	0.18	0.38	0	0.007	0.27	15
ln R&D expenditures	0.31	2.1	-9.3	-0.81	1.6	9.5
Treatment group						
R&D intensity	0.65	5.5	0.0000041	0.012	0.061	0.994
Return on assets	0.08	0.051	-0.12	0.049	0.1	0.31
Capex	0.039	0.023	0	0.02	0.055	0.12
Leverage	0.26	0.13	0	0.18	0.33	0.97
ln R&D expenditures	6	2.1	-1.2	4.8	7.4	14

3.3 Empirical strategy

This section describes the three methods I implement to investigate the problem about how mergers affect innovation. I start with the implementation of two different strategies, in order to capture the effect of the treatment on the treatment group. The first strategy involves employing a linear panel model at the firm-year level to investigate how mergers affect innovation using Two-Way Fixed Effects.

In the expanded multivariate model, I include a control for country and industry fixed effects as well as for a time trend. However, I leave out the firm-fixed effects due to the occurrence of multicollinearity between the firm and industry fixed effects.

At the end, I take a rather new approach to account for the downsides of the fixed effects methods of capturing the true effect of the treatment when it takes place at different points in time. I implement the model by Callaway and Sant'Anna (2021), which is specifically designed to estimate the group-time average treatment effect for treatment occurring at different times. The group is defined as the particular time period at which the treatment occurred. The results are going to show whether the estimates from the first two models are robust.

I apply three different methods in my research to strengthen the robustness and address the limitations associated with each individual method.

TWFE is employed to account for unobserved heterogeneity, by including fixed effects at both the unit and time levels. Multivariate Difference-in-Differences is applied to extend the analysis beyond a single treatment variable. By incorporating multiple covariates, this method allows for an in-depth evaluation of the treatment effects. Finally, Staggered Difference-in-Differences can handle treatments occurring at different time periods across units and allows for a more precise estimation of the causal effects.

Achieving consistent results across these different approaches strengthens the validity and credibility of the research findings and provides more reliable evidence to support the research hypotheses. Each method is discussed in detail in the following sections.

3.3.1 Two-Way Fixed Effects

I start the analysis by performing a simple TWFE regression of the following kind:

$$\text{Innovation}_{it} = \beta 0 + \beta 1 \cdot Dummy\ merger_{it} + \beta 2\ Horizontal\ merger_{it} + \beta 3 Dummy\ merger_{it} \times Horizontal\ merger_{it} + \psi i + \delta t + \varepsilon i,t\ ,$$

where the $innovation_{it}$ is the dependent variable and is measured once as the natural *logarithm of R&D expenditures* and once as the *R&D intensity*. $Dummy\ merger_{it}$ is a dummy variable that is equal to one if there was a merger in year t and zero otherwise. The coefficients $\beta 1$ is the coefficient of interest. $Horizontal\ merger_{it}$ is the second dummy variable that is equal to one if a merger is horizontal and zero otherwise. There is also an interaction term between the two dummy variables. Its coefficient shows whether the horizontal type of a merger has a significantly different effect of the innovation activity of the company than other types of mergers. The model also includes firm-specific fixed effects to control for time-invariant differences among firms and time-fixed effects to control for unobservable common trends among all firms. This regression helps to estimate the causal effect of the treatment.

3.3.2 Difference-in-differences in a multivariate setting

After I conduct the simple TWFE model, I extend it to perform a difference-in-differences regression analysis in a multivariate setting based on the papers by Chemmanur et. al (2020). This model tries to estimate the effect of mergers on R&D intensity using a treatment and control group. Specifically, I use the following regression:

$$\text{Innovation } n_{it} = \beta 0 + \beta 1 \cdot Dummy\ merger_{it} + \beta 2\ Horizontal\ merger_{it} + \beta 3 Dummy\ merger_{it} \times Horizontal\ merger_{it} + \beta 14 \cdot Dummy\ merger_{it} * {}_{j=1}\sum_{m} \cdot Dummy\ Industry_{j} + {}_{j=1}\sum_{m} \beta 5_{j} \cdot Dummy\ Industry_{j} + {}_{i=1}\sum_{n} \beta 6_{i} \cdot Dummy\ Country_{i} + \cdot {}_{l=1}\sum_{p} \beta 7\ Controls_{it} + \delta t + \epsilon_{it},$$

where the dependent and the main independent variables stay the same as in the linear panel model presented above. However, this regression also incorporates a set of dummy variables to control for time-invariant country and industry-fixed effects. Therefore, this regression estimates the effect of treatment on firm's innovation effort across different industries.

As already mentioned, the method does not include firm-fixed effects due to the problem of multicollinearity. However, one of the measures of the dependent variable, R&D intensity, helps to control for scale disparities across firms and individual fixed effects (Entezarkheir and Moshiri, 2018). This is due to the fact that this variable is a ratio ranging from 0 to 1. As a result, it does not capture the absolute difference between firms, but rather the percentage change within each firm. This is where the drawback of the other measure, logarithm of R&D expenditures, becomes visible. Even though, it helps for the support of the normality assumption, the absolute differences in the scale between firms are too large and the results are heavily biased as we will see in the results section. The difference between the two is going to be more obvious when I present the results and show the estimates of both measures.

I include three additional control variables that have been commonly used in the literature (Chemmanur et. al, 2020). The first one is the return on assets (ROA), defined as the operating income divided by the total assets. It controls for firm's profitability. The second control variable is the total debt to assets ratio, defined as the total debt divided by the total assets. It is a measure of the leverage of the company. The third dummy variable is the capital expenditures divided by total assets. Moreover, the model includes an argument, which controls for the time fixed effects.

Lastly, the error term ϵ_{it}, captures the unobserved variation in the model.

The main drawback of this approach is that it does not include a control for the endogeneity problem. The main reason for endogeneity is that the firms' decision to merge is often provoked by internal forces that might influence the outcome after the merger. If a firm experiences a poorer performance before the merger, then the merger dummy variables cannot account for the true effect of the merger (Ornaghi, 2009). The best way to deal with endogeneity is to use an instrumental variable (Haucap et. al., 2019), however due to the insufficiencies of my data, I cannot construct a valid instrument. The second problem this approach faces is the self-selection problem. Firms are more likely to initiate a merger if their R&D performance is deteriorating or a patent is expected to expire (Scherer, 2004). This is due to the fact that many companies see merging as a way to acquire new patents and expertise from competitors. The model does not contain a control for the selection problem as well.

3.3.3 Difference-in-Differences with multiple time periods

I implement staggered difference-in-differences to account for the possibility of biased results that may occur, while using fixed effects regressions for a treatment happening in multiple time periods. The results can be especially misleading in the case of treatment effect heterogeneity Goodman-Bacon (2021). Therefore, combining the two methods, staggered difference-in-differences and difference-in-differences in a multivariate setting, provides more robustness to the research.

The DID method for multiple time periods has first been implemented by Callaway and Sant'Anna (2021). They proposed a setup in which they test the group-time average treatment effect (ATT(g,t)). It is defined as the average treatment effect in period t for a group, first treated in period g. I perform this analysis in R studio, using the *did* package that has been specially developed for the theory presented by Callaway and Sant'Anna (2021). What is more, once the main effect has been calculated for g and t, the results can be presented for different dimensions of interest. For example, the results can be analyzed in the form of an event study that shows the length of exposure to treatment. In addition, they can be presented as a single treatment coefficient or as an average effect by group. I am going to illustrate this with the different function of the *aggregate* argument.

The general model of group-time average treatment effect is as follows:

$ATT(g,t)=E[Y_t(g)-Y_t(0)|G=g]$,

where Yit(0) represents the untreated potential outcome for unit *i*. It indicates the outcome they would experience in period t if they do not participate in the treatment. Yit(g) shows unit i's potential outcome in time period t, if they receive treatment in period g. G_i is the time period when unit I becomes treated (*groups* are defined by the time period of treatment).
There are two possible methods to test for ATT. One is by using a never treated group and the other is by using a not yet treated group. The second one is not recommended by the authors and therefore I perform the analysis using a never treated comparison group as in the following model

$ATT(g,t)=E[Y_t-Y_{g-1}|G=g]-E[Y_t-Y_{g-1}|C=1]$,

where, the notation is the same as the general model presented above. In addition, C stands for the never treated group.

In the *did* package in R, the estimation method includes a dependent variable, which is firm's innovation. Again, I include both measures of innovation as dependent variables. The dependent variable is explained by an independent variable, which captures the exact year of treatment for each company – 2014, 2015 or 2016. The variable is zero for all companies that are part of the never treated group. Moreover, there is an indicator for a single unit, which controls for firm fixed effects. In my case this is the individual identification number for each company. There is also a variable that indicates the time, which in my case is the variable including the years of observation from 2011 till 2019 for every company, and controls for time fixed effects.

The model of Callaway and Sant'Anna (2021) provides various alternatives for analysis - outcome regression, inverse probability weighting and doubly-robust estimates. As recommended from the authors, I have used the doubly-robust estimates, which according to them, demand less rigorous assumptions to ensure the reliability of the model.

It is worth noting that the drawback of this package is that it does not allow to control for the type of merger or the industry. Therefore, it is not sufficient to apply it alone, without the multivariate difference-in-differences method.

The package also includes a p-value for a Wald test for an evaluation of the pre-treatment parallel trends assumption. The results are visible in the following chapter.

4. Results

This section shows the main results from the empirical tests discussed above. First, I discuss the parallel trends assumption. Furthermore, I discuss the results from the TWFE difference-in-differences regression and the results from the expanded multivariate model, using the two measures for innovation. At the end, I summarize the results from the staggered difference-in-differences and present the relevant graphs for the analysis.

4.1 Assumptions

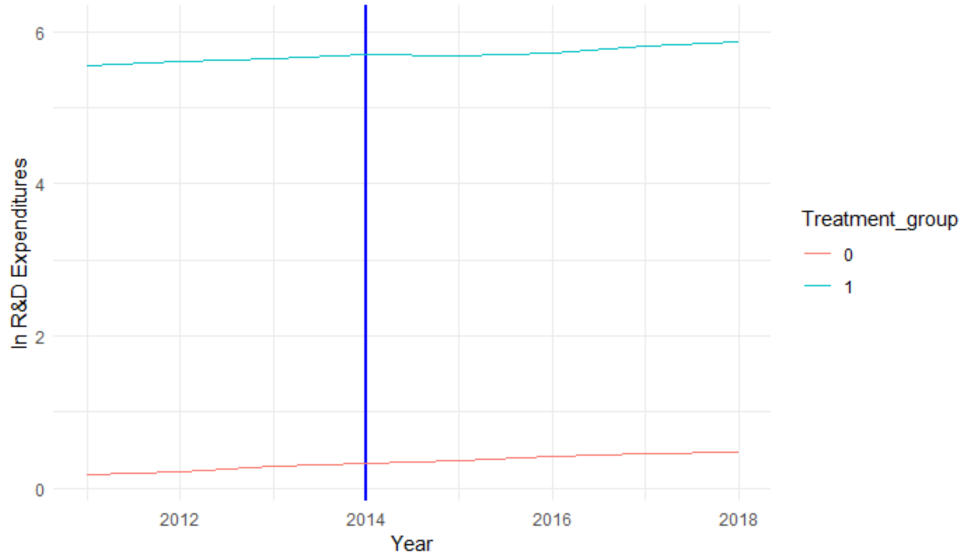
Before presenting the results, it is essential to first establish a set of assumptions that serve as a foundation for the chosen statistical methods. Discussing these assumptions provides a better understanding of the limitations and biases, related to the performed empirical tests. Moreover, it supports the credibility of the findings.

4.1.1. Parallel trends assumption

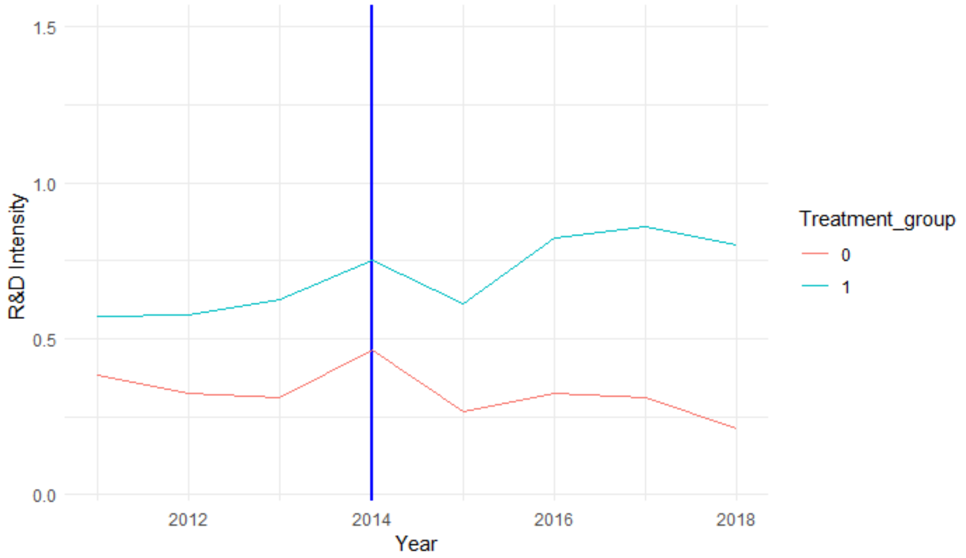
The parallel trends assumption is crucial for the implementation of any difference-in-differences model. It assumes that in the absence of treatment, both the treatment and the control group would have followed similar trends on average over time. In other words, it assumes that the control group would have been similar to the counterfactual of the treatment group.

Even though the parallel trends assumption is practically unobservable, the book by Huntington-Klein, N. (2022, Chapter 18) underlined a few requirements that might lead us to believe that the assumption is fulfilled. First of all, there should be no particular reason for the trend of the untreated group to change around the time of treatment. In the case of this study, no such reason was observed. Secondly, the treatment and control group should be generally similar. I cannot confirm that this is the case. As mentioned above, the difference in scale between the two groups of companies cannot be omitted. The violation of this requirement might lead to biased results, and we should keep this in mind while interpreting the results of the research in the following sections. Third, the treatment and the control group should have similar trends for the dependent variable right before the treatment. Thus, I construct a few graphs to gain some understanding of the trajectories for the dependent variable before treatment. Graphs 1 and 2 show the trends of the treatment and the control groups for both measures of innovation. I am interested in the trends before the year of 2014, since this is the year when the first treatment took place. At first glance both graphs show a mostly similar trend before treatment.

Graph 1. Parallel trend assumption of treatment and control group(lnR&D Expence)

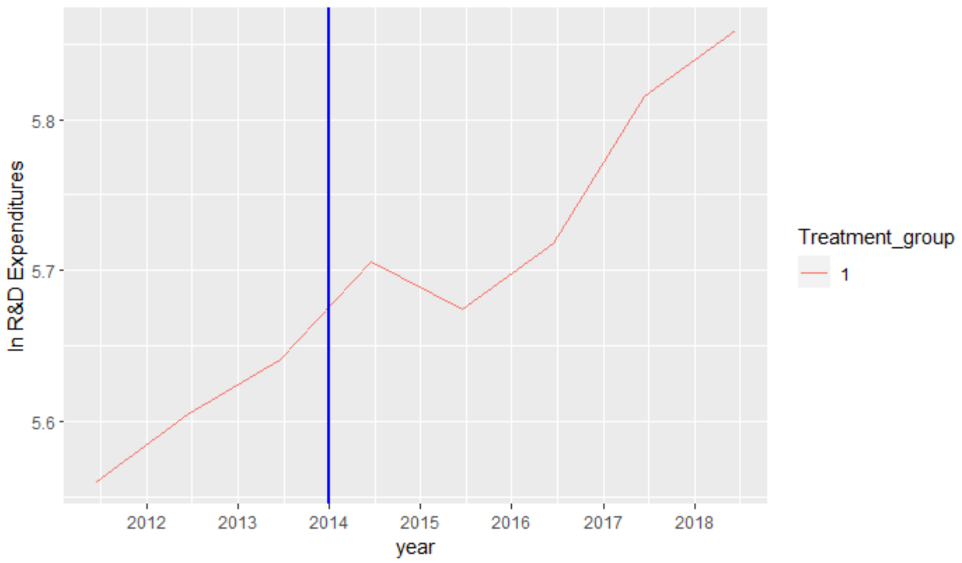


Graph 2. Parallel trend assumption of treatment and control group (R&D Intensity)

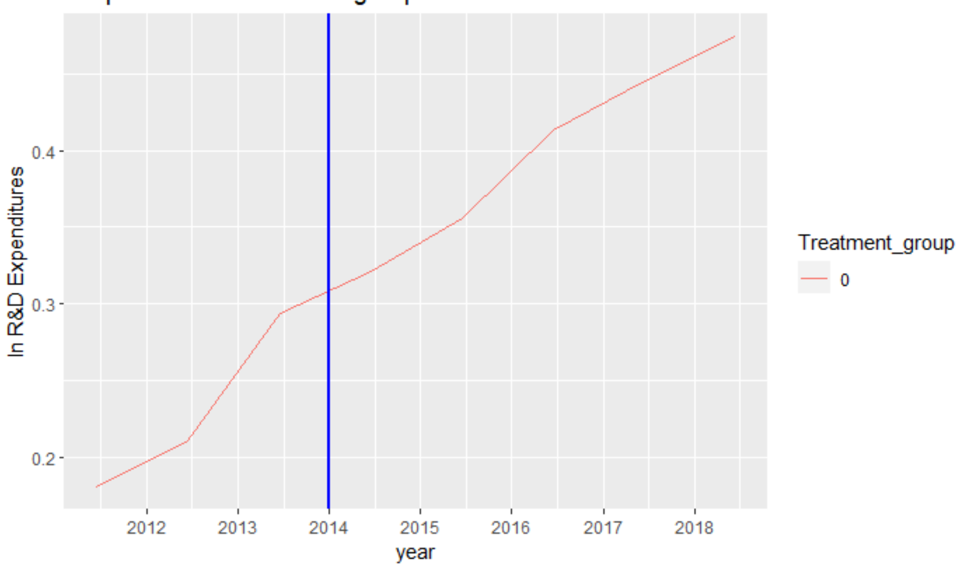


However, due to the large difference in the groups in *graph 1,* which employs the logarithm of R&D expenditures as a measure for innovation, we cannot get an idea whether the trends are truly similar, since the scale can be misleading. Therefore, I construct two additional graphs that show the trend for each group separately. As a result, the trends are more easily compared than they are in *graph 1*. *Graph 3* shows the trend of the treatment group and

Graph 3. Trend of treatment group



Graph 4. Trend of control group



graph 4 shows the trend of the control group. Both graphs use the logarithm of R&D expenditures as a measure.

Here, we observe the real trends of the two groups by avoiding the deception of the scale. The trends before 2014 are quite similar but they are definitely not perfect. We observe that the trend of the control group before treatment is steeper. Then in the treatment period, between 2014 and 2016, the treatment group is experiencing some shocks and finally after

2016 the trend stabilizes again and looks steeper than the trend of the control group. The results from the statistical analyses will give more insights of the actual effect of the treatment.

Graph 2 shows the trend of the groups for R&D intensity and in that way the difference in the scale between the two groups is decreased. Therefore, new graphs are not needed. However, we also observe small difference in the pre-treatment trends of the second graph. We also witness a significantly different trend after the years of treatment.

4.1.2 General regression assumptions

In order to improve the validity and reliability of the research, there are a few additional assumptions that need to be fulfilled before I perform the estimations. These include the normality of residuals, multicollinearity, homoscedasticity and autocorrelation.

The first assumption of *normality* implies that residuals should follow a normal distribution. Appendix B.1.2 and Appendix B.2. display the histograms for the standardized residuals for both measures of innovation. We observe that both histograms follow normal distribution. In addition, Appendix B.3. and Appendix B.4. present scatter plots for both measures. The requirement for the Q-Q residuals plot is for the residuals to approximately follow the line of normal distribution. This is the case for both measures. To conclude, we can observe normality for both measures. However, both in the histograms and in the scatter plots we observe better performance of the log R&D expenditures measure with respect to the normality assumption.

The second assumption that needs to hold is the absence of *multicollinearity*. Multicollinearity is present when two or more independent variables are highly correlated. The absence of this assumption might lead to unprecise estimates. Multicollinearity can be captured by obtaining the Variance Inflation Factor (VIF) for each independent variable (Franke, 2010). Appendix B.5. shows the complete set of VIF scores. The requirement for the VIF values is for all of them to be below 10. If one of the variables has a value higher than 10 then there is multicollinearity in the model. As seen in Appendix B.5., all values are below 10 so there is no harmful multicollinearity in the models.

The next assumption concerns the independence of residuals and is called *autocorrelation.* It implies that the residuals of any two variables should not be correlated (Bartels and Goodhew, 1981). To test for this assumption, I perform a Durbin – Watson test. The results from the test for the two measures of the model can be seen in Appendix B.6. and B.7. The aim of the test is not to reject the null hypothesis that assumes no autocorrelation. However, the p-values for both models is very small, indicating that I can reject the null hypothesis and conclude that there is autocorrelation in the models with both measures for innovation.

The last assumption is related to the equality of variance. It is known as the assumption of *homoscedasticity*, which implies that the variance of residuals should be similar (Breusch and Pagan, 1979). This assumption can be tested by plotting the residuals against the predicted values. No particular pattern should be observed, otherwise the assumption does not hold. Appendix B.8. and B.9. show the scatter plots for both measures of innovation. The homoscedasticity assumption is fulfilled for the model, including the measure logarithm of R&D expenditures. However, we can see that the assumption does not hold for the other model, including the measure R&D intensity.

Therefore, to prevent biased estimates, I include heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimation (Andrews, 1991). I implement the Newey-West method, which adjusts for both heteroscedasticity and autocorrelation (Newey and West, 1987).

4.2 Results from the linear panel models

4.2.1. Hausman test

Before I continue with the estimation of the models, I conduct a Hausman test to determine whether a fixed-effects (FE) or a random-effects (RE) model is more appropriate for my panel data analysis (Baltagi, 2014). For this purpose, I estimate the multivariate model with fixed effects and then with random effects. Following this, I perform the Hausman test to evaluate which of the statistical methods corresponds to the data. If the test statistics is statistically significant, it means that the FE method is to be chosen. Otherwise, the test suggests that RE method is more suitable.

The results from the test are included in Appendix B.10. As we can see, the p-value is equal to 0.04637, which implies that the test statistic is significant at 5% level and the fixed-effects method is more appropriate for the panel data analysis. The results are equivalent for the models with both measures of innovation and can be observed in Appendix B.10.1 and B.10.2.

4.2.2. Results from simple TWFE

First, I present the results from the two-way fixed effects (TWFE) models using the two measures of innovation. The results from these simple regressions can be seen in Table 5. The first and the third column show a simple model TWFE regressions that do not include any control variables. The regressions only control for firm-specific and time-fixed effects. We do not observe statistical significance for any of the two models. However, the results for both measures show a positive trend. The treatment effect for R&D intensity is 0.0004 and the effect for log of R&D expenditures is 0.037. However, the adjusted R^2 is negative for both models showing a bad fit of the models and lack of meaningful relationship between the predictors and the dependent variable. The F-statistics are also low and none of them is statistically significant. In the context of regression analysis, the F-statistic is used to test the null hypothesis that all regression coefficients are equal to zero. A high F-statistic indicates that the regression model is statistically significant and that at least one of the independent variables has a significant impact on the dependent variable. Therefore, due to the insignificant F-statistics in models 1 and 3, I cannot reject the null hypothesis. In addition, we observe insignificant results for the effect of horizontal merger types on innovation.

Columns 2 and 4 of the table include the results of the same models, but this time they contain control variables for profitability, leverage, and capital expenditures. Again, none of the coefficients of the variables of interest are significant. However, we observe that profitability and leverage are negatively correlated with innovation measures.

Table 5. Regression results from simple TWFE models

	R&D intensity			**R&D intensity**			**ln R&D Expenditures**			**ln R&D Expenditures**		
Predictors	*Estimates*	*std. Error*	*CI*	*Estimates*	*std. Error*	*CI*	*Estimates*	*std. Error*	*CI*	*Estimates*	*std. Error*	*CI*
Dummy merger	0.0004	0.01	-0.01 – 0.01	-0.003	0.01	-0.01 – 0.01	0.04	0.07	-0.10 – 0.18	0.05	0.07	-0.09 – 0.19
Dummy merger :: Horizontal merger	0.00	0.01	-0.01 – 0.02	0.01	0.01	-0.01 – 0.02	0.03	0.08	-0.13 – 0.19	0.02	0.08	-0.14 – 0.19
Log Sales				-0.04 ***	0.00	-0.04 – -0.04						
Capex				0.00	0.00	-0.00 – 0.00				0.00 **	0.00	0.00 – 0.00
Profitability				-0.05 ***	0.00	-0.06 – -0.04				-0.10 ***	0.03	-0.15 – -0.05
Leverage				-0.01 ***	0.00	-0.01 – -0.00				-0.14 ***	0.03	-0.21 – -0.08
Observations	9148			9109			9339			9310		
R^2 / R^2 adjusted	0.0 / -0.130			0.117 / 0.002			0.000 / -0.128			0.005 / -0.123		
F Statistic	0.077 (df = 2; 8098)			177.984*** (df = 6; 8055)			1.113 (df = 2; 8275)			8.286*** (df = 5; 8246)		
*Note: * p<0.1 ** p<0.05 *** p<0.01*												

As mentioned earlier, R&D intensity is the ratio of R&D expenditures to total sales. It contains not only the effect of change in R&D expenditures but also the effect of sales. Therefore, the model measuring the effect on R&D intensity includes an additional control variable, the natural logarithm of sales, to control for the effect of sales. As expected, the results suggest that this coefficient has highly significant negative effect on the dependent variable, since the increase of sales leads to lower R&D intensity ratio. After the sales effect has been isolated, we observe a decrease in the main coefficient of interest. However, the coefficient of interest is still not significant in any of the TWFE models.

It is important to keep in mind that these models do not include any control for endogeneity, which might cause biased or inconsistent estimates. Therefore, in the following sections I perform additional estimations, using two different methods, to increase the robustness of my results.

4.2.3. Results from main fixed effects regression

This subsection presents the results from the extended fixed effects model. Table 6 shows the results from the model with R&D intensity measure including the control variables and the country and industry fixed effects. However, this model does not include firm fixed effects, due to the arising multicollinearity between the firm fixed effects and the industry fixed effects. Here I include the results for the main coefficients of interests, while the full table with all country estimates can be seen in Appendix C.

As can be seen, the results now are a lot more conclusive than when we did not include country and industry-fixed effects. However, this is where we see the advantage of using R&D intensity, as a measure, over the natural logarithm of R&D expenditures. Due to the big difference in the scale of treated and untreated firms, the lack of firm-specific fixed effects inflates the coefficients of the model with R&D expenditures. However, we do not see such effects in the other model. R&D intensity is a ratio that varies from 0 to 1. Therefore, in a way, it already controls for firm-specific effects, and more concretely it controls for the size disparities between treatment and control firms. This is not the case for the measure including logarithm. Therefore, the results from the model including the logarithm of R&D expenditures measure are heavily biased and I am not going to discuss them. The results from it can be seen in Appendix C.

Table 6. Multivariate regression results

	R&D intensity		
*Predictors***	*Estimates*	*std. Error*	*CI*
Dummy merger	0.06 ***	0.02	0.03 – 0.09
Horizontal merger	0.05 ***	0.01	0.03 – 0.06
Pharmaceutical	0.06 ***	0.01	0.05 – 0.07
Automotive	0.02 ***	0.00	0.01 – 0.02
Electronics	0.04 ***	0.00	0.03 – 0.05
Chemical	0.01 **	0.00	0.00 – 0.02
ICT	0.05 ***	0.00	0.04 – 0.06
Profitability	-0.11 ***	0.01	-0.12 – -0.10
Leverage	-0.01 *	0.00	-0.01 – 0.00
Capex	0.00	0.00	-0.00 – 0.00
Log Sales	-0.02 ***	0.00	-0.02 – -0.02
Dummy merger :: Horizontal merger	-0.05 ***	0.01	-0.08 – -0.03
Dummy merger :: Pharmaceutical	-0.00	0.02	-0.04 – 0.03
Dummy merger :: Automotive	-0.00	0.02	-0.03 – 0.03
Dummy merger :: Electronics	0.02	0.02	-0.01 – 0.06
Dummy merger :: Chemical	-0.01	0.02	-0.04 – 0.02
Dummy merger :: ICT	-0.00	0.02	-0.03 – 0.03
Observations	9109		
R^2 / R^2 adjusted	0.312 / 0.307		
F statistic	60.352*** (df = 68; 9031)		

*Note: * p<0.1 ** p<0.05 *** p<0.01*

*Coefficients for industry are calculated with respect to the Food and Beverage industry***

With respect to the results for the model estimating R&D intensity, we observe that the effect of mergers on R&D intensity is positive and significant on 1% level. The coefficient of 0.06 implies that companies, which participate in a merger, are associated with 0.06 units increase in their R&D intensity. In addition, the interaction term between the treatment dummy and the horizontal merger dummy has a significantly negative effect on R&D expenditures, suggesting that horizontal mergers affect innovation in a more negative way, as mentioned by the theoretical literature. In particular, companies participating in horizontal mergers are associated with 0.05 degrease in their R&D intensity.

We can also see that all control variables, except for capital expenditures have significant negative correlation with the dependent variable - R&D intensity. The interaction terms of the treatment dummy and the industry dummies show different impacts across industries. However, they are not significant even at 10% level and I do not have enough evidence to conclude that the coefficients are different from zero.

The table also shows the R squared and the F-statistics of the model. In contrast to the previous models, we observe better fit of the model. The R squared is equal to 0.307 indicating that approximately 30.7% of the variability in the dependent variable can be explained by the independent variables, included in the regression model. The F-statistic is equal to 60.352 and is significant at 1%, showing that there is evidence for significant relationship between at least one of the independent variables and the dependent variable. The results without the control variable for sales are shown in Appendix C and this model shows no significant findings.

4.3 Results from staggered difference-in-differences

The final set of results are based on the difference-in-differences method for multiple time periods discussed by Callaway and Sant'Anna (2021). First, I present the results for the R&D intensity measure. For this model I once again include the natural logarithm of sales as a control variable. *Table 7* bellow shows the results from the estimation using simple aggregation. *Table 8* shows the result for the same model without controlling for the logarithm of sales. These two graphs return a weighted average of all group-time average treatment effects with weights proportional to the group size.

Table 7. Results for simple coefficient of staggered difference-in-differences (R&D intensity measure) with sales control variable

ATT	Std. Error	[90%	Conf. Int.]	P-value for Wald pre-test of parallel trends
0.0057**	0.0029	9e-04	0.0106	0.5862
Note: * p<0.1 ** p<0.05 *** p<0.01				

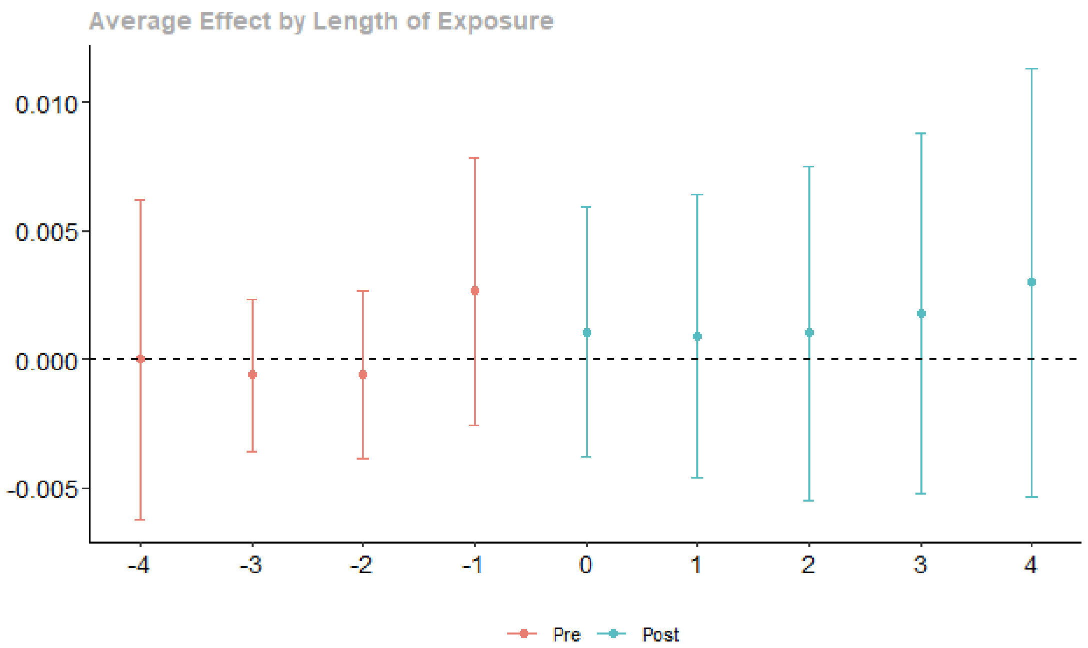
Table 8. Results for simple coefficient of staggered difference-in-differences (R&D intensity measure) without sales control variable

ATT	Std. Error	[90%	Conf. Int.]	P-value for Wald pre-test of parallel trends
0.0013	0.002	-0.0026	0.0052	0.51426
Note: * p<0.1 ** p<0.05 *** p<0.01				

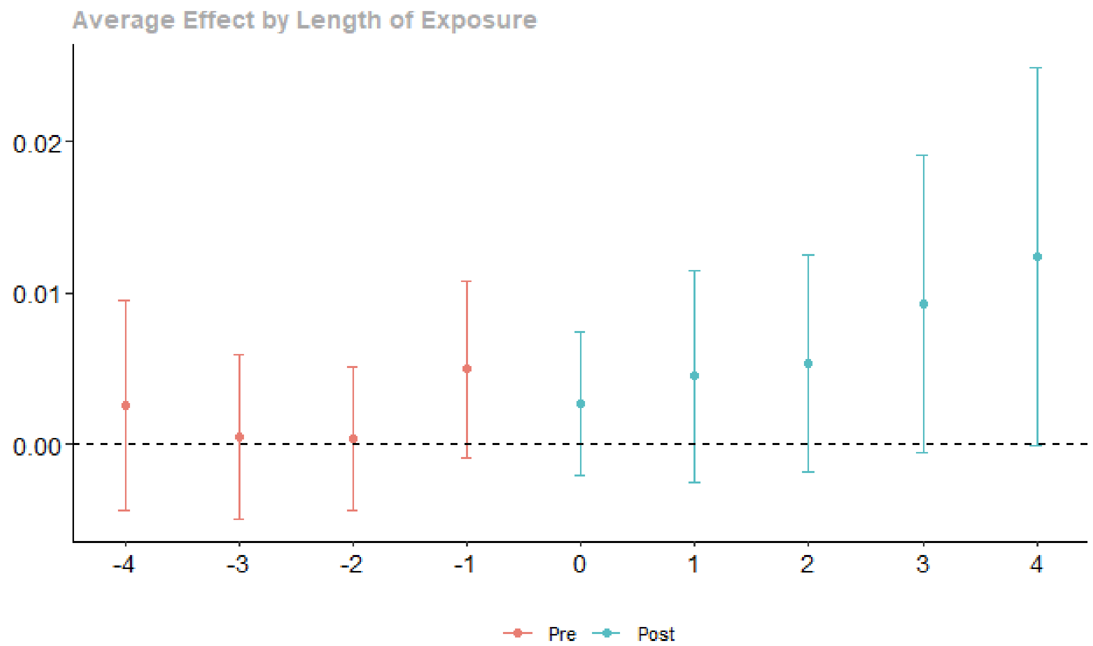
As can be seen, only the model that controls for sales presents significant results at 5% level. In addition, it precisely matches the results from the multivariate difference-in-differences presented above. The coefficient of 0.0057 implies that companies, participating in a merger, are associated with approximately 0.0057 increase in their R&D intensity. Therefore, we obtain a confirmation that mergers have a positive effect on R&D intensity. In addition, the *did* package provides a p-value for the Wald pre-test of parallel trend assumption. The null hypothesis states that there are no significant differences between trends of the treatment and control groups before the treatment. Therefore, a higher p-value will not let us reject the null hypothesis and will support the existence of parallel trends before treatment. The results for the p-value in both models do not let us reject the null hypothesis and therefore we have empirical evidence for the presence of parallel trends before treatment in both models.

Graph 4 and *graph 3* show the average effect by length of exposure with and without the control for sales respectively. The tables showing the coefficients from both models can be found in Appendix D.1.1. and D.1.2.

Graph 3 (Does not include a control for sales)



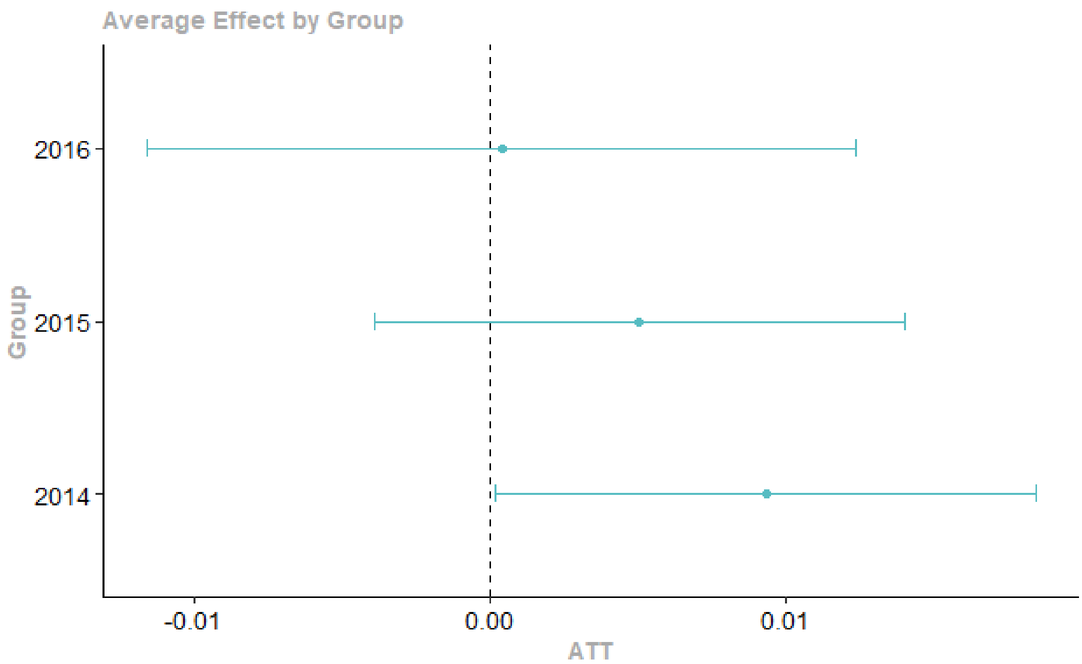
Graph 4 (Includes a control for sales)



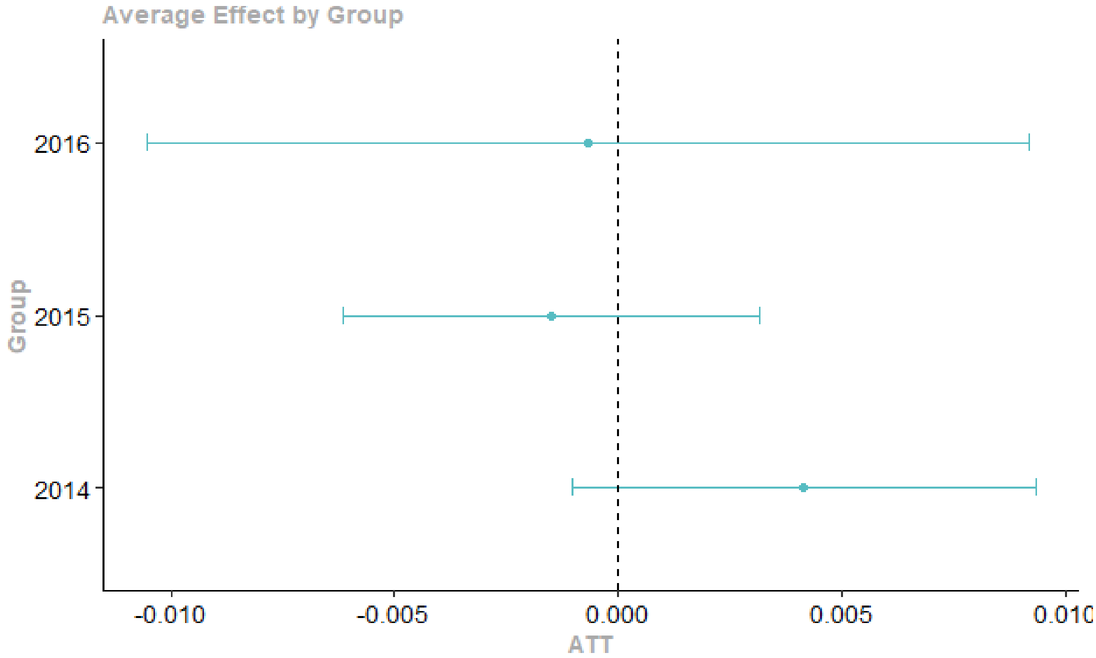
These graphs take the form of an event study plot and show the ATT at different lengths of exposure to the treatment. We see a strong positive trend after treatment in the second graph, where we control for the increase in sales.

The last two graphs 5 and 6 show the average effect by treatment group with and without a control for sales. The coefficients for both models can be found in Appendix D.2.1 and D.2.2 Here we observe large disparities between the model with the control variable and the one without. When controlling for the increase in sales, we observe higher R&D intensity after a merger. We also observe large standard errors for the year 2016. The results are the most conclusive for the year 2014, where we see a significant positive effect of mergers on innovation.

Graph 5 (Including control for sales)



Graph 6 (Without control for sales)



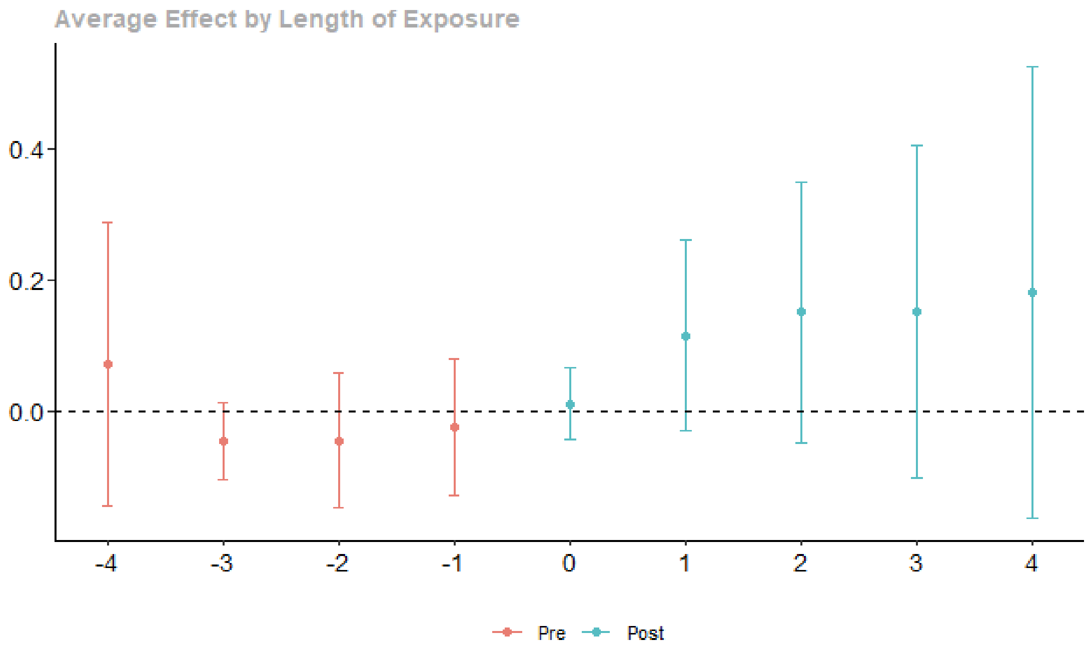
The second set of tests are performed for the other measure of innovation – the natural logarithm of R&D expenditures. First, in *table 9*, I present the simple ATT estimate. As opposed to the results from the multivariate panel regression, the results here are not biased due to the fact that this model accounts for firm and time fixed effects. Therefore, the disparities in scale between the treatment and control group do not inflate the results The ATT coefficient is also significant at 5% level and shows a positive effect of mergers on innovation. The coefficient of 0.1098 implies that companies, participating in a merger, are associated with approximately 11% increase in their R&D expenditures This is in line with all of the previous findings.

Table 9. Results for simple coefficient of staggered difference-in-differences (ln R&D Expenditures measure)

ATT	**Std. Error**	**[90%**	**Conf. Int.]**	**P-value for Wald pre-test of parallel trends**
0.1098**	0.0513	0.0092	0.2104	0.14748
Note: * p<0.1 ** p<0.05 *** p<0.01				

Bellow I present graphs 7 and 8, for the average effect by the length of exposure and the average effect by group, respectively.

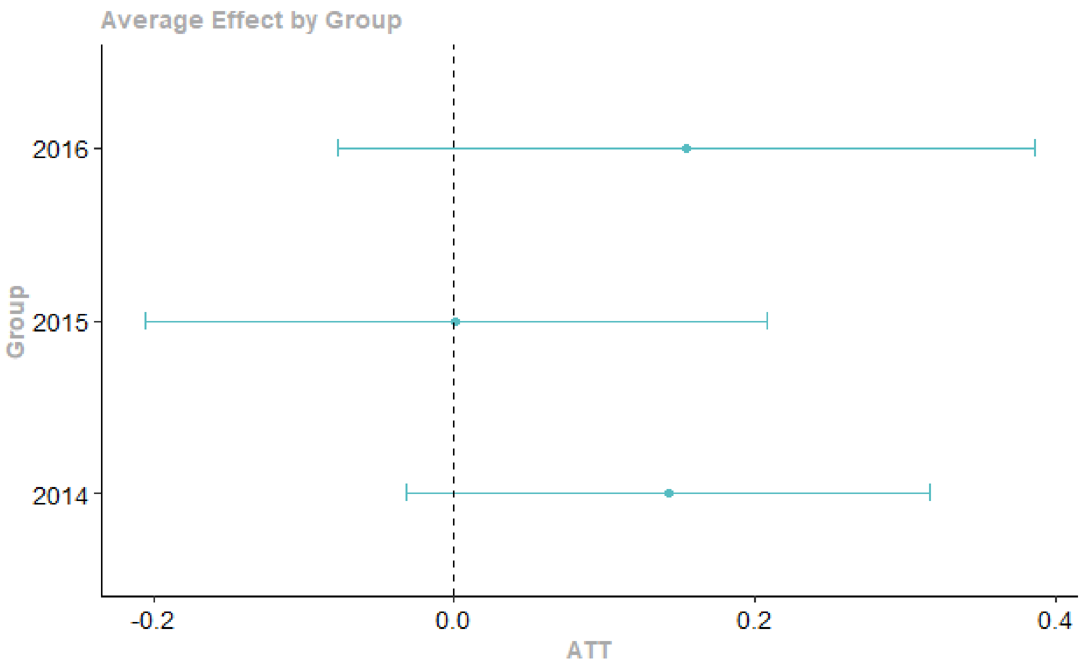
Graph 7



Again, we observe good performance of the parallel trends assumption. This is supported by the p-value of the Wald test for pre-treatment of parallel trends, which is equal to 0.14748. Therefore, we cannot reject the null hypothesis of different trends even at 10% significance level and the pre-treatment parallel trends assumption is supported. We also see the strong positive effect of the merger on innovation starting from period 1.

Graph 8 shows the effect by group – treated in 2014, 2015 or 2016. The estimates for the average effect by length of exposure and the average effect by group can be found in Appendix D.3. and D.4.

Graph 8



5. Discussion

I have taken three different empirical approaches to investigate the impact of mergers on innovation. All of them have advantages and disadvantages. I also included two different measures of the dependent variable. In the end, the results from all models point in the same direction and show positive impact of mergers on innovation. This convergence of results enhances the robustness of my findings.

The results presented above have suggested an overall positive effect of mergers on innovation. These findings are in line with the theoretical evidence presented by Bourreau et al. (2019) and Jullien and Lefouili (2018). Based on the significant results I got from the two of the empirical methods (difference-in-differences in a multivariate setting and staggered difference-in-differences) and the two measures for innovation, I cannot reject the first null hypothesis that mergers have a positive impact on innovation. There are a few reasons why that may be the case.

Most theoretical papers discussed in the literature review section, such as Federico et. al. (2018) and Motta and Tarantino (2021), assume negative innovation externality. They consider this effect to be stronger than the positive effect of the reduction of price competition. In contrast, Chemmanur et. at. (2020) found evidence for positive innovation externality. This could also be the case in my study. These findings highlight the importance of exploring different channels, through which mergers can stimulate innovation. Future studies could explore additional control variables, such as industry-specific factors or the level of technological capabilities, to gain a deeper understanding of the observed effects.

However, it is worth considering alternative explanations for these findings. One alternative factor could be related to the composition of the sample data. First of all, as mentioned in the data collection section, there are some major differences between the treatment and control group. Even though, I include firm specific fixed effects in the regressions, it is possible that there are unobserved variables linked to the size of the treatment group that could impact the results. For instance, the treatment group primarily consists of major corporations, which dominate their respective markets, since these are the mergers of interest to the European Commission. However, it is not feasible to construct an identical control group due to the absence of corporations comparable to Meta, for example, and the other large companies within the treatment group. Therefore, it is impossible to capture the true counterfactual as the dynamics and innovation patterns of large conglomerates cannot be compared to the smaller scale firms. These considerations highlight the need for further research with the implementation of alternative research designs. The use of instrumental variables or propensity score matching could address potential endogeneity concerns. It can also provide further insights into the causal relationship between mergers and innovation.

The findings related to my second hypothesis show that horizontal mergers indeed, have more negative effect on innovation, than other types of mergers. Therefore, we can reject the second null hypothesis. This result supports Federico et. al. (2018) and suggests that different types of mergers should be treated differently as they have a heterogeneous impact on innovation. In addition, it corresponds to the "escape-competition effect" (Aghion et. al., 2005), which implies that innovation is lower when competition is lower. However, we should keep in mind that only one of the estimated models showed a significantly negative effect of horizontal mergers on innovation.

There are no significant results that could lead us to reject the third null hypothesis related to the homogenous effect of mergers on innovation across industries. Even though, we observe different estimates across industries, which corresponds to the findings of Entezarkheir and Moshiri (2018), none of the coefficients are significant even at 10% level. Therefore, I do not reject the third null hypothesis.

The implications of this study are both theoretical and practical. I have shown that there might be positive synergies related to mergers that outweigh the negative innovation externalities, leading to overall positive outcomes. However, I also underlined the importance of selecting a comparable control group that could represent realistic counterfactual scenario. This generates a potential methodological challenge for future research that could improve the validity and reliability of the findings.

In practice there are policy implications that should be discussed. First of all, I have highlighted that antitrust authorities should be cautious when dealing with horizontal mergers as they have shown to affect innovation more negatively. In addition, the results hinted at the different impact of mergers across industries, even though, none of the investigated relationships was statistically significant. However, more research is needed to come up with industry-specific policy interventions.

6. Conclusion

This paper aimed at investigating the impact of mergers on innovation and to observe whether this effect was different across industries and across merger types. The results did not provide any proof of a negative effect of mergers on a firm's innovation activities. There were also no significant results that prove a heterogeneous impact of mergers across industries. However, they provided some evidence that horizontal mergers are more detrimental to innovation than other types of mergers.

The paper contains several limitations related to the empirical strategies and the sample data. First of all, the models I used to estimate the effect do not control for endogeneity and self-selection problem. In addition, the measures I use for the dependent variable, show only innovation input and do not indicate whether the innovation was successful or not. Incorporating additional indicators of innovation output can provide further insides of the effect of mergers on innovation. The results also provide insights only for large companies and might not be applicable to medium and small firms. In addition, the methods I implement do not provide any control for the spillover effect of the merging firms on their competitors. I have selected firms that do not participate in mergers during the period of interest, but that does not mean that they have not been affected by spillover effects.

More research on the topic is needed to further examine the robustness of the results, by selecting a better control group that is similar in scale to the treatment group. In addition, further research could apply instrumental variables or propensity score matching to address endogeneity and self-selection issues. It is important for future researchers to focus on further exploring the effects of mergers across industries and within medium and small enterprises. This will allow for more precise decision-making by the competition authorities. Moreover, it will help in the discovery of the risk factors that lead to bad innovation outcomes. If we manage to identify which industry characteristics and disparities in size and market share lead to bad outcomes for innovation in the presence of a merger, we will have a better chance of preventing them.

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Appendix

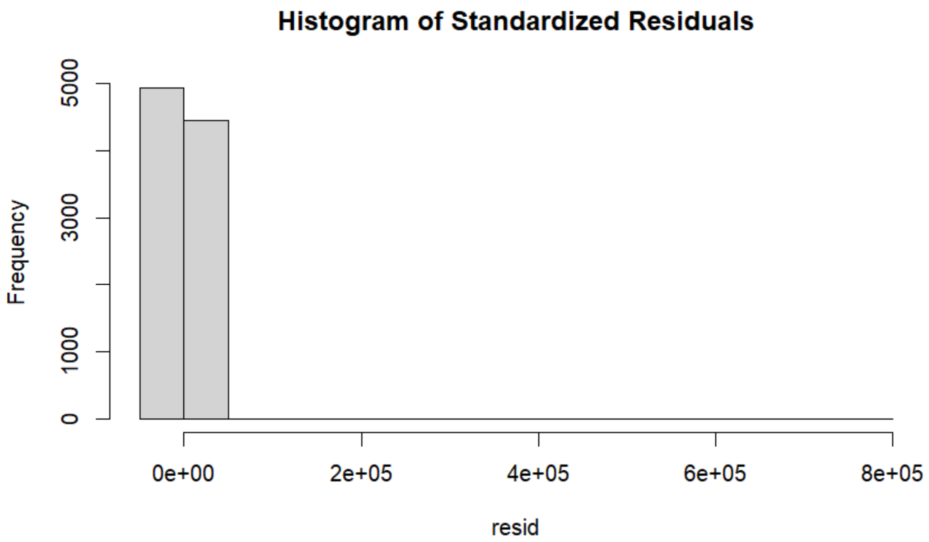
A. Table with the exchange rates used for conversion to EUR

Exchange rate to EUR	Currency
0,248400	AED
0,003677	ARS
0,629122	AUD
0,008446	BDT
0,189534	BRL
1,023109	CHF
0,134242	CNY
0,042032	CZK
0,134032	DKK
0,116661	GBP
0,116617	HKD
0,000061	IDR
0,257238	ILS
0,011138	INR
1,286102	JOD
0,006431	JPY
0,000714	KRW
1,422880	LVL
0,053421	MXN
0,198183	MYR
0,086620	NOK
0,568894	NZD
0,016375	PHP
0,003184	PKR
0,224060	PLN
0,010930	RUB
0,243248	SAR
0,086012	SEK
0,682054	SGD
0,026334	THB

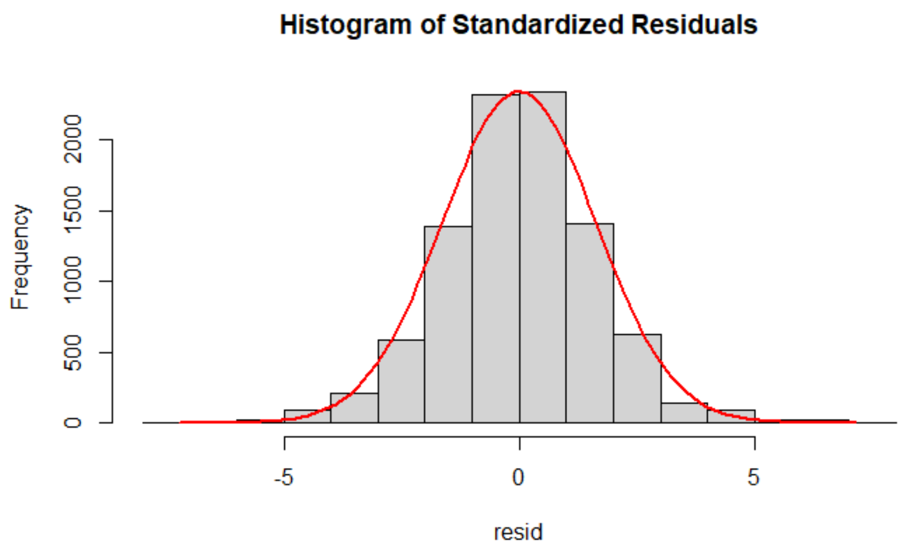
0,296362	TND
0,038675	TRY
0,029755	TWD
0,912350	USD
0,050168	ZAR

B. Assumptions

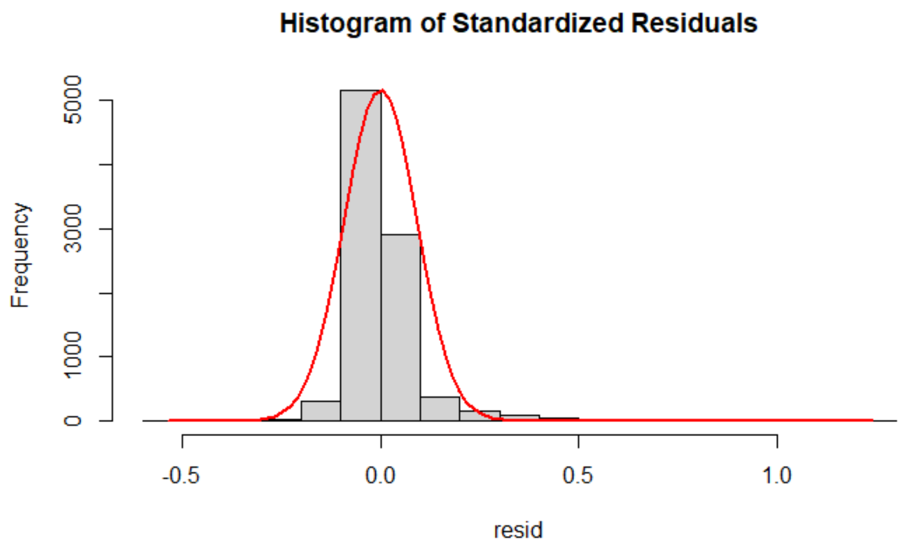
B.1.1 Histogram of standardized residuals before logarithmic transformation of the R&D expenditures:



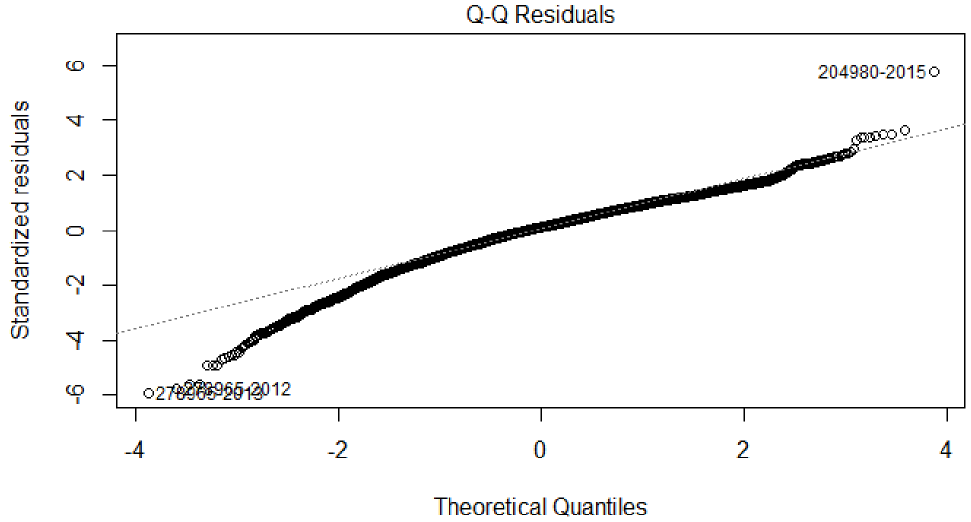
B.1.2. Histogram of standardized residuals after logarithmic transformation of the R&D expenditures:



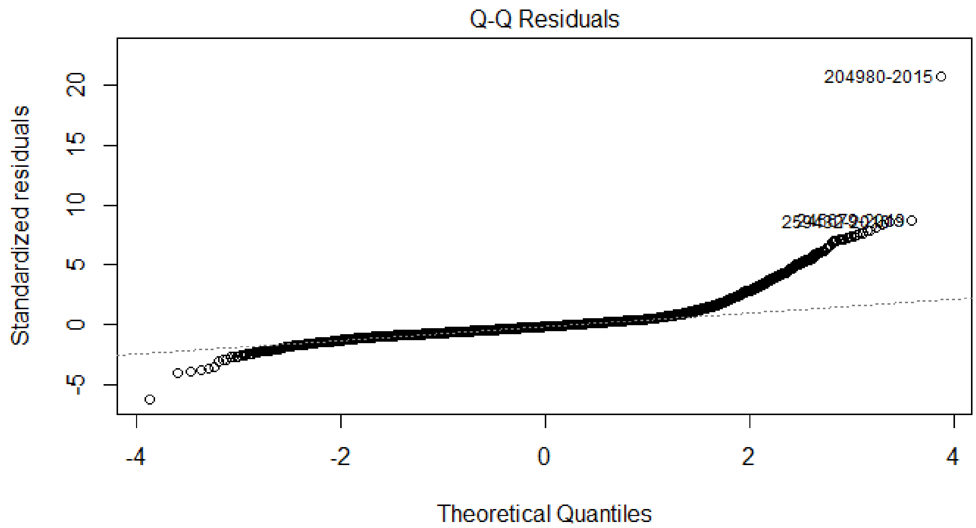
B.2. Histogram of standardized residuals of R&D intensity measure



B.3. The distribution of the residuals compared to a theoretical normal distribution for R&D expenditures



B.4. The distribution of the residuals compared to a theoretical normal distribution for R&D intensity



B.5. VIF scores for multicollinearity assumption

Variable	GVIF <dbl>
Dummy_during_merger	8.787316e+00
Horizontal_merger	1.864028e+01
SIC4f	1.288431e+01
Capex_div_Assets	1.052142e+00
OpIncome_div_Assets	1.150759e+00
Debt_div_Assets	1.208870e+00
ISO_Country_Code	3.185064e+06
logSales	2.822740e+00

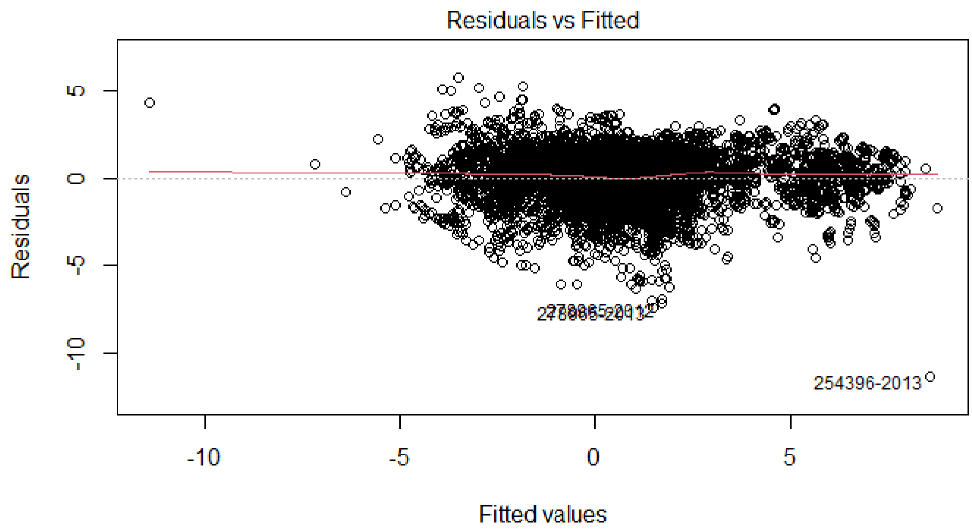
B.6. Autocorrelation assumption for the log of R&D expenditures measure

lag	Autocorrelation	D-W Statistic	p-value
1	0.80396	0.3919709	2.2e-16
Alternative hypothesis: rho != 0			

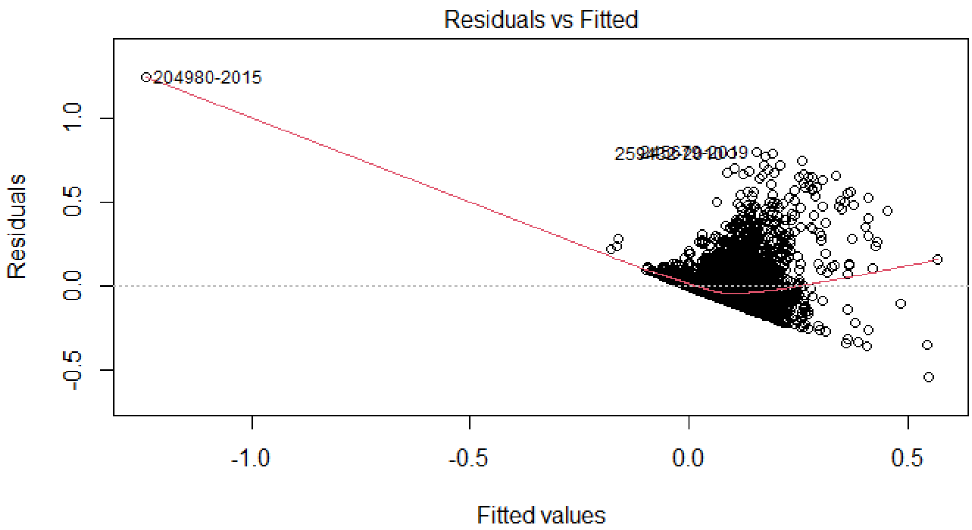
B.7. Autocorrelation assumption for the R&D intensity measure

lag	Autocorrelation	D-W Statistic	p-value
1	0.6855389	0.6289106	2.2e-16
Alternative hypothesis: rho != 0			

B.8.Homoscedasticity assumption for the log of R&D expenditures measure



B.9. Homoscedasticity assumption for the R&D intensity



B.10.1. Hausman test (log R&D expenditures)

Chisq	Df	P-value
371.91	67	2.2e-16
alternative hypothesis: one model is inconsistent		

B.10.2. Hausman test (R&D intensity)

Chisq	Df	p-value
88.754	68,	0.04637
alternative hypothesis: one model is inconsistent		

C. Complete results for multivariate panel model including the two measures of innovation.

(First column includes control for log of sales and the second does not)

	RD_div_Sales		**RD_div_Sales**		**logRD_Expense**	
Predictors	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*
Dummy merger	0.0574 ***	0.0153	-0.0046	0.0157	4.0562 ***	0.2715
Horizontal merger	0.0452 ***	0.0072	-0.0221 ***	0.0070	4.1041 ***	0.1206
Pharmaceutical	0.0567 ***	0.0054	0.0816 ***	0.0055	0.8357 ***	0.0929
Automotive	0.0151 ***	0.0049	0.0181 ***	0.0051	0.8444 ***	0.0881
Electronics	0.0355 ***	0.0049	0.0526 ***	0.0051	0.9907 ***	0.0871

Chemical	0.0116 **	0.0049	0.0221 ***	0.0051	0.5944 ***	0.0881
ICT	0.0462 ***	0.0049	0.0759 ***	0.0049	0.5426 ***	0.0852
Profitability	-0.1073 ***	0.0060	-0.1389 ***	0.0061	0.1699 ***	0.0603
Leverage	-0.0053 *	0.0029	-0.0055 *	0.0030	-0.1766 ***	0.0541
Capex	0.0000	0.0000	0.0000	0.0000	0.0002 **	0.0001
ISO Country Code [ARG]	-0.1222 ***	0.0443	-0.0546	0.0458	-6.1575 ***	1.3392
ISO Country Code [AUS]	0.0989 ***	0.0318	0.1407 ***	0.0330	-1.0762 *	0.5606
ISO Country Code [AUT]	0.0131	0.0436	-0.0011	0.0452	1.8373 **	0.7758
ISO Country Code [BEL]	-0.0158	0.0379	-0.0045	0.0393	-0.6888	0.6750
ISO Country Code [BGD]	-0.1027 ***	0.0357	-0.0748 **	0.0370	-3.0283 ***	0.6350
ISO Country Code [BMU]	0.0098	0.0332	0.0182	0.0344	0.0146	0.5919
ISO Country Code [BRA]	-0.0487	0.0436	-0.0011	0.0452	-1.7645 **	0.7757
ISO Country Code [BRL]	0.0133	0.0440	0.0055	0.0456	-0.6561	0.7835
ISO Country Code [CHE]	0.1015 ***	0.0336	0.0797 **	0.0348	2.3075 ***	0.6044
ISO Country Code [CHN]	0.0254	0.0316	-0.0097	0.0328	2.3321 ***	0.5631
ISO Country Code [CYM]	0.0140	0.0314	0.0008	0.0326	1.1957 **	0.5593
ISO Country Code [CZE]	-0.0145	0.0436	-0.0101	0.0452	-0.3527	0.7760
ISO Country Code [DEU]	0.0316	0.0315	0.0194	0.0326	1.1533 **	0.5605
ISO Country Code [DNK]	0.0164	0.0328	0.0194	0.0340	0.4943	0.5835

ISO Country Code [ESP]	0.0614 *	0.0346	0.0659 *	0.0359	0.4306	0.6156
ISO Country Code [EUR]	0.0488	0.0361	0.0135	0.0374	2.2523 ***	0.6418
ISO Country Code [FIN]	0.0751 **	0.0345	0.0782 **	0.0358	1.5633 **	0.6152
ISO Country Code [FRA]	0.0270	0.0313	0.0225	0.0325	1.3163 **	0.5575
ISO Country Code [GBR]	0.0481	0.0313	0.0792 **	0.0324	-0.3195	0.5564
ISO Country Code [GRC]	-0.0063	0.0323	0.0201	0.0335	-0.4131	0.5753
ISO Country Code [HKG]	0.0511	0.0358	-0.0177	0.0370	4.5397 ***	0.6359
ISO Country Code [IDN]	-0.0900 ***	0.0346	-0.0670 *	0.0358	-3.5643 ***	0.6154
ISO Country Code [IND]	-0.0513 *	0.0311	-0.0171	0.0322	-2.7105 ***	0.5526
ISO Country Code [IRL]	0.1250 ***	0.0435	0.1351 ***	0.0452	1.2242	0.7754
ISO Country Code [ISR]	0.0643 **	0.0327	0.0976 ***	0.0339	-0.1772	0.5768
ISO Country Code [ITA]	0.0366	0.0379	0.0010	0.0393	2.0691 ***	0.6754
ISO Country Code [JEY]	0.1191 ***	0.0454	0.1182 **	0.0471	1.8197 **	0.8096
ISO Country Code [JOR]	-0.0855 **	0.0376	-0.0342	0.0390	-2.4676 ***	0.6691
ISO Country Code [JPN]	-0.0136	0.0309	-0.0119	0.0321	0.1480	0.5511
ISO Country Code [KOR]	-0.0263	0.0313	-0.0192	0.0325	-0.2392	0.5578
ISO Country Code [LVA]	-0.0241	0.0436	0.0051	0.0452	-0.4389	0.7754
ISO Country Code [MEX]	0.0138	0.0441	0.0294	0.0457	0.4237	0.7854
ISO Country Code [MYS]	-0.0397	0.0318	-0.0077	0.0330	-2.0877 ***	0.5660
ISO Country Code [NLD]	0.0228	0.0358	0.0224	0.0371	1.3348 **	0.6317

ISO Country Code [NOR]	0.0252	0.0347	0.0437	0.0360	-0.6737	0.6186
ISO Country Code [NZL]	0.2216 ***	0.0403	0.2861 ***	0.0417	-1.3910 **	0.6798
ISO Country Code [PAK]	-0.0471	0.0328	-0.0019	0.0340	-4.6134 ***	0.5899
ISO Country Code [PHL]	-0.0470	0.0354	-0.0311	0.0367	-2.2434 ***	0.6301
ISO Country Code [POL]	-0.0890 **	0.0378	-0.0488	0.0392	-4.0878 ***	0.6724
ISO Country Code [PSE]	-0.0894 **	0.0436	-0.0635	0.0452	-1.5565 **	0.7763
ISO Country Code [RUS]	-0.0031	0.0382	-0.0027	0.0396	-3.7063 ***	0.6804
ISO Country Code [SAU]	0.0289	0.0378	-0.0009	0.0392	2.3578 ***	0.6733
ISO Country Code [SGP]	-0.0128	0.0338	-0.0059	0.0350	0.0094	0.6006
ISO Country Code [SVN]	0.1218 ***	0.0436	0.1660 ***	0.0452	-0.2231	0.7754
ISO Country Code [SWE]	0.0285	0.0326	0.0444	0.0338	-0.1561	0.5732
ISO Country Code [THA]	-0.0655	0.0435	-0.0701	0.0452	-2.7875 ***	0.7754
ISO Country Code [TUN]	-0.1414 ***	0.0436	-0.1081 **	0.0452	-4.7605 ***	0.7763
ISO Country Code [TUR]	-0.0357	0.0316	0.0018	0.0327	-2.0639 ***	0.5621
ISO Country Code [TWN]	0.0044	0.0310	0.0235	0.0321	-0.2705	0.5515
ISO Country Code [USD]	0.0549 *	0.0317	0.0415	0.0329	1.3955 **	0.5653
ISO Country Code [ZAF]	-0.0250	0.0344	-0.0008	0.0357	-1.2272 **	0.6122
logSales	-0.0176 ***	0.0007				

Dummy merger × Horizontal merger	-0.0549 ***	0.0113	0.0169	0.0114	-3.8234 ***	0.2022
Dummy merger × Pharmaceutical	-0.0020	0.0184	-0.0232	0.0191	0.1978	0.3417
Dummy merger × Automotive	-0.0005	0.0173	0.0008	0.0179	-0.2653	0.3083
Dummy merger × Electronics	0.0235	0.0181	-0.0031	0.0188	0.7697 **	0.3287
Dummy merger × Chemical	-0.0083	0.0160	-0.0118	0.0166	-0.6374 **	0.2843
Dummy merger × ICT	-0.0009	0.0165	-0.0280	0.0171	-0.1365	0.3015
Observations	9109		9109		9292	
R^2 / R^2 adjusted	0.312 / 0.307		0.260 / 0.254		0.582 / 0.578	
** p<0.1 ** p<0.05 *** p<0.01*						

D. Staggered difference-in-differences

D.1.1. Event study estimates (including control for sales)

Event time	Estimate	Std. Error	[90% Simult.	Conf. Band]
-4	0.0026	0.0031	-0.0045	0.0097
-3	0.0005	0.0024	-0.0051	0.0061
-2	0.0004	0.0020	-0.0042	0.0050
-1	0.0050	0.0028	-0.0013	0.0113
0	0.0027	0.0024	-0.0027	0.0081
1	0.0045	0.0032	-0.0029	0.0119
2	0.0054	0.0030	-0.0015	0.0122
3	0.0093	0.0042	-0.0004	0.0190
4	0.0124	0.0056	-0.0005	0.0253

D.1.2. Event study estimates (excluding control for sales)

Event time	Estimate	Std. Error	[90% Simult.	Conf. Band]
-4	0.0000	0.0025	-0.0058	0.0058

-3	-0.0006	0.0012	-0.0035	0.0022
-2	-0.0006	0.0013	-0.0036	0.0024
-1	0.0026	0.0021	-0.0022	0.0075
0	0.0011	0.0018	-0.0030	0.0051
1	0.0009	0.0023	-0.0043	0.0061
2	0.0010	0.0026	-0.0050	0.0070
3	0.0018	0.0030	-0.0050	0.0086
4	0.0030	0.0036	-0.0052	0.0112

D.2.1 Group-Specific Effects (without control for sales)

Group	Estimate	Std. Error	[90% Simult.	Conf. Band]
2014	0.0041	0.0029	-0.0011	0.0094
2015	-0.0015	0.0025	-0.0060	0.0030
2016	-0.0007	0.0055	-0.0106	0.0092

D.2.2. Group-Specific Effects (with control for sales)

Group	Estimate	Std. Error	[90% Simult.	Conf. Band]
2014	0.0093*	0.0044	0.0012	0.0174
2015	0.0050	0.0046	-0.0034	0.0135
2016	0.0004	0.0055	-0.0099	0.0106

D.3. Estimates for average effect by length of exposure (ln R&D Expenditures)

Event time	Estimate	Std. Error	[90% Simult.	Conf. Band]
-4	0.0734	0.0855	-0.1154	0.2621
-3	-0.0407	0.0230	-0.0914	0.0100
-2	-0.0438	0.0402	-0.1326	0.0450
-1	-0.0235	0.0444	-0.1216	0.0747
0	0.0105	0.0225	-0.0391	0.0602
1	0.1130	0.0608	-0.0212	0.2473
2	0.1487	0.0812	-0.0305	0.3279
3	0.1508	0.1109	-0.0940	0.3955

4	0.1826	0.1306	-0.1057	0.4709

D.4. Estimates for average effect by group (ln R&D Expenditures)

Group	Estimate	Std. Error	[90% Simult.	Conf. Band]
2014	0.1429	0.0891	-0.0192	0.3049
2015	-0.0040	0.1106	-0.2052	0.1972
2016	0.1555	0.1148	-0.0533	0.3643