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Acquiring R&D within the healthcare industry

Graduate School of Finance

Master's Thesis

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Abstract

This paper examines the effect of M&A on R&D intensity within the healthcare industry. The healthcare industry as defined in this paper consists of two industry segments; the pharmaceutical industry and the medical device industry that are both examined separately but with the same methodology using inverse propensity score weighting and weighted least squares. There is some trouble with the covariate balancing meaning that one should be cautious with over interpreting the results. I find that the effect on R&D intensity from acquisitions is insignificant but that cross border acquisitions appear to have a more positive impact on R&D than domestic acquisitions. I also find that there is some evidence of medical device manufacturers opting to acquire technology rather than developing in-house. No evidence that multi-acquirers behave differently from other acquirers is found.

Keywords: R&D Intensity, R&D Outsourcing, Healthcare M&A

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Contents

1 Introduction

The purpose of this study is to examine how companies within the healthcare innovation industry use Mergers and Acquisitions (M&A) in relation to their Research and Development (R&D). This is done by examining the change in R&D intensity during the first four years post acquisition. To reduce any problems with self selection bias I use a propensity score technique with inverse probability weighting developed by Hirano et al (2003). In this essay, the word healthcare innovation industry refers to the producing segments of the healthcare industry that either produce pharmaceutical products and/or medical devices and conduct R&D. The healthcare innovation industry is and has obviously been essential to the improvement of human quality of life as it is in this very industry where the drugs and treatments of the future are developed. It is therefore important to understand the specific characteristics of the industry and how these affect innovation.

The healthcare innovation industry can be largely broken down into two main segments consisting of the pharmaceutical industry and the medical device industry. The two sub industries being part of a larger shared industry are subject to many of the same macro conditions as they to large extent can be expected to see similar shifts in demand while still being different in a few other key aspects. This makes them interesting to study in relation to each other. While almost all aspects of the pharmaceutical industry are heavily researched the medical device industry appears to be comparatively understudied. To my knowledge no other study specifically examines the M&A to R&D relationship in the medical device industry and no other study examines the pharmaceutical industry in relation to the medical device industry.

From both a societal and academic point of view it is important to understand the actions of these companies and how their organizational structures operate. This is especially important in recent years where large pharmaceutical companies have seen decreasing R&D results despite ever increasing R&D funding (Denzon et al, 2007; Paul et al 2010; Burns et al, 2012).

The two studies that most resemble the study at hand are Hall (1999) and Vyas and Narayanan (2012). Hall (1999) used a very large sample but her focus was not specifically on the healthcare innovation industry. She found that companies with a high propensity to acquire saw increased R&D intensity while companies with low propensity to acquire did not see this effect. Vyas and Narayanan's (2012) study focused on the pharmaceutical industry but limited to Indian companies. This leaves a gap in the knowledge of more recent R&D-M&A behaviour among more established global healthcare innovators in the OECD economies. This study hopes to aid in filling this gap. A study using more recent data is especially motivated given the recent financial crisis combined with underperforming R&D in the pharmaceutical industry that could have changed the industry dynamics and company behaviour.

The industries under examination are the pharmaceutical industry (including the he pharma-

ceutical, biotechnology, genomics and proteomics sectors) and the medical device industry. The information technology sector that is associated with the healthcare industry is not studied in this paper. Further, the study examines the effect of M&A on R&D-intensity between 2007 and 2015. The effect is measured in from acquisition year to three years post acquisition. More long term effects are not examined empirically.

It should also be noted that R&D intensity is not the same as research efficiency but is only a matter of resource allocation. This study makes no claim to research the R&D efficiency around mergers but only the intensity. Understanding of the R&D intensity and company decisions will however likely aid in the understanding of R&D efficiency.

2 The healthcare industry

2.1 Research performance

Ageing populations in combination with increasing life expectancy has led to a large increase in health expenditures as percent of GDP in OECD economies, although this trend was somewhat dampened in the aftermath of the 07-08 financial crisis and the following fiscal crises experienced in many OECD economies (OECD Health Statistics, 2016). Given the demographic situation in many developed countries this trend is likely to continue for some time. Further, the problem is not limited to western countries; some developing nations such as China will also face the challenge of an ageing population over the coming decades (Li, 2011). As more people in developing countries are brought from relative poverty they will require more healthcare that will add to this effect. The combined trend can already be seen in the growing global market size as seen in data collected by marketline in figure 1. Growth in pharmaceutical sales has been slightly larger than sales growth in the medical device industry.

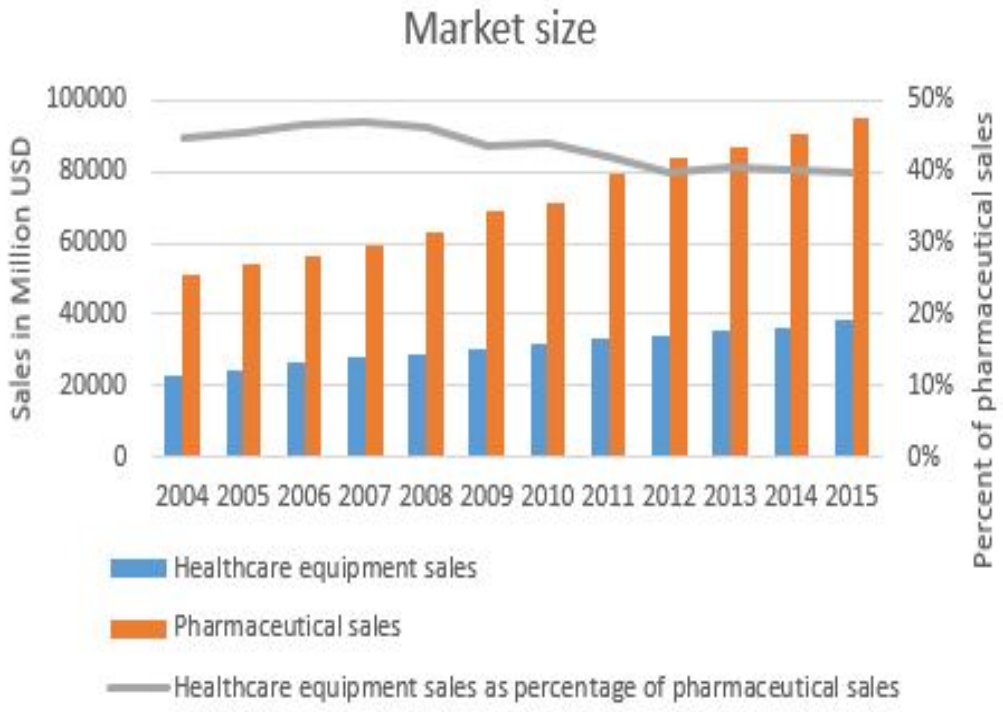

Figure 1: The sales in pharmaceutical and medical device industries. Medical device sales howers around 40-45% of pharmaceutical sales. Source: MarketLine

Burns (2012) divides the healthcare industry into five producing sectors where much of the innovation takes place.

- The pharmaceutical sector
- The biotechnology sector
- The genomics and proteomics sector
- The medical device sector
- The information technology sector

The line between the different segments is often blurred and there are many pharmaceutical companies that are involved in biotechnology or genomics. In many industry specifications, such as SIC codes it can be difficult to effectively distinguish between pharmaceutical, biotech

and the genomics and proteomics companies as they all fall under the same core category. The distinction between the pharmaceutical industry and the medical device sector is easier to make as there is a clearer difference in technology. Pharmaceutical companies are more focused on chemical / biochemical compounds while the medical device industry produce, using the definition used by the FDA, US Trade and WHO, medical devices that comes into contact with the patients. This encompasses a wide variety of technologies from diagnostics equipment and surgical equipments to implants.

Kruger and Kruger (2012) write that the medical device industry saw large growth in 90's and early 2000's of around 8% per annum but recently there has been a drastic slowdown in growth to around 3% a year. They attribute this fact to the industry not being able to innovate new business segments at the same rate as before and that the growth of the industry has attracted the focus of private and public clients that now are more cost aware as medical devices have become a larger part of their operation (and total costs).

According to MarketLine, a business information agency, the medical device industry is dominated by the american market that make up close to 40% of the total global market. Together with Europe this constitute slightly more than 70% of the global market with the majority of the remaining business originating in the Asia Pacific region. In 2015 the pharmaceutical industry saw 40.3% of its market in the United States, 29.1% in Asia Pacific and 21.6% in Europe. Between 2005 and 2015 the medical device industry grew with about 55% while the pharmaceutical industry grew with 75% measured in total US dollar revenues.

Denzon et al (2007), Paul et al (2010), Burns et al (2012) and others write that research productivity in the pharma industry has been declining since the 90s in combination with substantially increased research spendings. The reasons for this phenomenon are not completely clear but developed on later on in this text. According to data collected from Orbis, average industry R&D intensity among R&D companies within the OECD appears to have been slightly decreasing. As revenues have grown rapidly this does not conflict with what is found by Denzon et al (2007), Paul et al (2010) and Burns et al (2012). Only recently have pharmaceutical patents started to rise despite the observed increase in research investments.This research efficiency problem does not appear to exist in the medical device industry where the number of patents have increased rapidly and consistently in recent years as shown by data published by the European Patent Office (EPO). Today the medical device industry is granted more patents than the pharmaceutical and biotechnology industries combined. Infact, between 2007 and 2016 the industry had the highest number of patents awarded by the EPO amongst all fields of technology. Patents are of course a metric of limited usefulness when research efficiency is concerned so one has to be careful drawing conclusions from this alone.

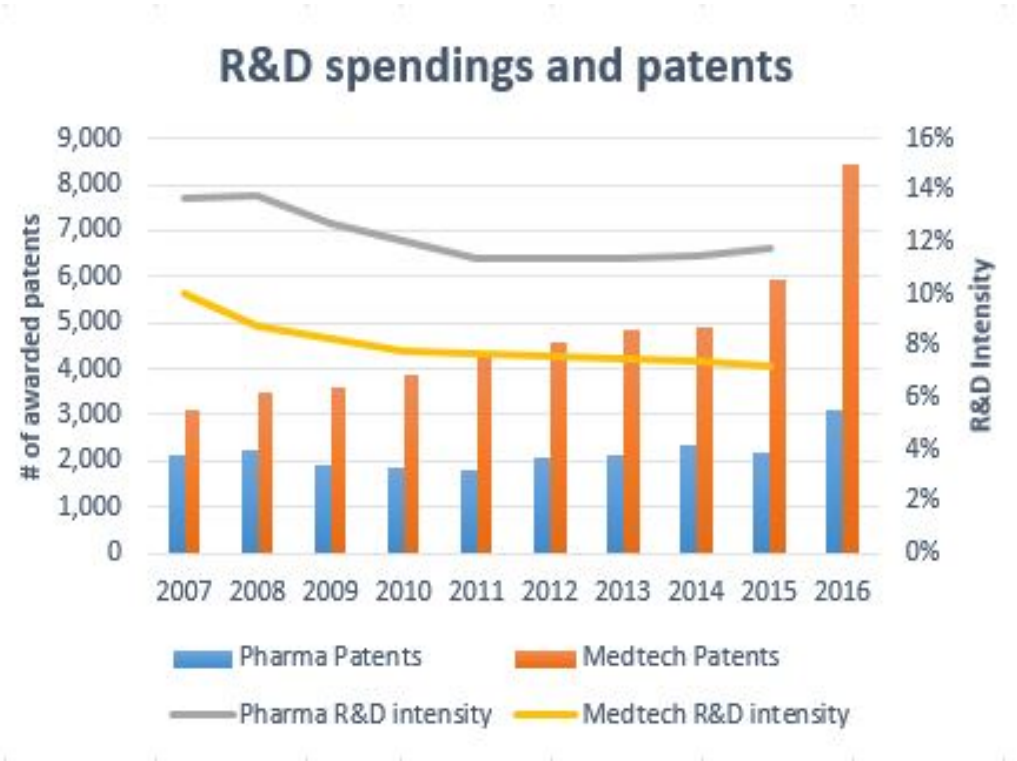

Figure 2: The medical device industry has seen a much faster growth in patents than pharmacuticals. Source: European Patent Office and Orbis

Kruger and Kruger (2012) describe the medical device market as a market with monopolistic competition where market participants are able to raise prices by adding new functions to their apparatus and a market where the brand name and track record is very important. This may partly explain the large number of patents granted in this industry.

2.2 M&A and the relation to R&D

According to M&A data published by the Institute for Mergers, Acquisitions and Alliances the number of deals within the biotechnology and pharmaceutical industry has been increasing consistently from about 400 deals world wide in the mid 90s to more than 1300 deals in the 2016; the exception being a few years following the financial crisis of 2007-08 where mergers temporarily went down slightly. This story appears to be fairly similar to other industries except that the average deal value of an acquisition within the pharma industry is larger. In the medical device industry the acquisitions are characterized by smaller deals than the pharma industry. The number of deals in the medical device industry was not published. Denzon et al (2007), Schweizer and zu Knyphausen-Aufsess (2008) and others have noted the increasing firm consolidation taking place from the 1980s into the 2000s. Denzon

et al (2007) note that the market share of the 10 largest firms in 1985 was 20% compared to 48% in 2002.

The sample used by Vyas and Narayananan (2012) show that far from all companies are engaged in M&A activity and that the companies that participate usually are involved in several deals over a short time. It also appears that larger companies are more prone to be the acquirers. Burns et al (2012) attributes this to the reducing returns to research which has forced large companies to acquire technology through acquisition to supplement the poor results of their own R&D efforts. Burns et al (2012) further write that the poor R&D performance within the pharmaceutical industry in part can be explained by the simple fact that the easy projects have already been completed and that only the difficult ones remain. While this might be true it is likely only part of the explanation given that the biotechnology industry has been relatively more successful in innovating. There are likely some other factors why the pharmaceutical industry has not been able to effectively conduct R&D within their own organizations.

Schweizer and zu Knyphausen-Aufsess (2008) do an overview of the biotechnology sector and describe that innovation in the biotech industry takes place at "university, research institutes or small biotechnology companies" but that these organizations lack the financial means and expertise to effectively bring a product to market. They describe the biotechnology sector as being the innovative engine of the pharma industry. This highlights the high integration between pharmaceuticals and biotechnology. Denzon et al (2007) point out that biotechnology companies have become more established since the mid 90's over the whole product cycle making them more similar to pharmaceutical companies.

Large companies potentially have a disadvantage in conducting research that could be attributed to the organization being slow to adapt to changes in the market and other bureaucracy. Schweizer and zu Knyphausen-Aufsess (2008) bring up the important point that the smaller biotechnology companies generally have smaller and more nimble organizations that appear to be more successful in innovation. According to Burns et al (2012) however there appear to be little evidence in the literature that company size would affect the R&D efficiency. Schuhmacher el al (2016) suggest that pharmaceutical companies could improve their R&D process by becoming more like biotechnology companies, that is smaller and more flexible. This appears to be something also noticed by the industry and many pharmaceutical companies are conducting joint research programs with academia and biotechnology companies (Knyphausen-Aufsess, 2008; Schuhmacher et al, 2016; and others).

There are many different theories and reasons for M&A stated in the literature. Hagendorff (2011) provides an excellent overview of the M&A literature and the main schools of thought that have developed up to this point. The most basic and often questioned motive is of course the motive to enhance shareholder value. Some researchers suggests that this is the fundamental driver of M&A but that factors such as information asymmetry generates poor outcomes. Others suggest that M&A is driven by an overvalued stock market (not necessarily in conflict with shareholder value creation), while others argue it is driven by behavioural explanations or agency problems within the organizational structures. While many of these

theories are realistic and plausible and sometimes even proven empirically under the right circumstances it is likely that M&A activity is driven by different motives at different times and that there is no one theory to explain all M&A activity.

The problem with agency costs is explained by the theory of the firm, originally developed by Jensen and Meckling (1976) of which Stein (2001) provides a thorough overview. When research is concerned two primary agents come mind. One is management that might be preoccupied with internal politicking, empire building (Denzon et al 2006) or distracted by other projects and therefore not direct research funds properly. Management could also be risk-avoiding trying to divert research to less risky projects to safeguard their own positions. The other agent that comes to mind are the researchers conducting and directing the research within the company. Both the researcher and the managers will generally have a less skewed payoff structure than the entrepreneur that make them opt for less risky projects. A researcher at a major company will only be able to pocket a fraction of the value of a possible breakthrough while the entrepreneur will pocket the full upside. This could lead researchers in large firms to avoid taking risk and focus on research that will generate a return with lower variance. This suggests that there is at least a possible theoretical advantage in R&D for small entrepreneurial organizations in high risk areas. Larger companies could possibly do less risky projects in-house and let venture capital and entrepreneurs develop riskier projects that they then can acquire through M&A.This view is strengthened by the Burns et al (2012) argument of the easy project already having been completed.

The counter argument to this is that by applying basic portfolio theory it could also be argued that large companies should be able to diversify their risk better allowing them to undertake riskier projects. On top of this there is also potential economies of scope to be gained when conducting several research projects as described by Henderson and Cockburn (2006).

Danzon et al (2007) bring up the importance of acquisition specific aspects and give the example of pharmaceutical companies acquiring technologies as it might be a cheaper and quicker alternative to in-house R&D. This is a plausible explanation for what has happened in the pharmaceutical industry. They write that pharmaceutical companies have two major production activities. The first one is R&D and second is production, marketing and sales. Any acquisition is likely intended to strengthen either of these production activities. They judge arguments of economies of scope in the pharmaceutical industry as unlikely given the relatively higher valuation of smaller biotechnology companies.

Much of the revenue streams used to cover the R&D expenditures in the innovative health care industry can be sourced back to patent protection. Danzon et al (2007) write that a few "blockbuster drugs" often account for 50% or more of a firm's revenues and that patent expiration quickly can destroy revenue streams and profitability. The patent race literature explained by Tirole (1988) and others offer a plausible explanation for the the R&D and M&A behaviour of firms within the healthcare innovation industry. As Gilbert and Newberry (1982) describe, there is incentive for the monopolist (patent holder) to buy out equivalent technology that does not constitute an improvement of their own technology

but only serve the purpose of reducing competition and protecting monopolistic profits.

Building on this literature Philips and Zdanov (2013) create a model that shows that larger companies have an incentive to let smaller firms develop high risk technologies and then acquire the successful firms as opposed to directly researching it in-house. They write that it might be optimal for acquiring companies to have lower R&D given that they are intending to acquire R&D instead of conducting it in-house.

The increased R&D expenditures in combination with increased M&A activity could simply be managers trying to protect their companies from new entrants, similar to the persistence of monopoly theories within the patent race literature. Once the company has spent money on R&D it is a sunk cost and the decision of acquiring in the next period should not depend on the sunk cost but only on the benefits of acquiring.

Since patents often are awarded around the time of discovery and the incumbent pharmaceutical producer already have their production and distributions network in place they also have a great advantage over the smaller entering firm in the later part of product development. The difference in time it takes for the smaller inexperienced firm until the product can reach the market compared with a more experienced firm makes it very attractive to obtain some type of deal with a more experienced pharmaceutical company. It is therefore a natural time to either enter some sort of joint venture or simply sell the asset to the incumbent firm. This in combination with the research advantage held by smaller firms could explain the large number of acquisitions by large firms in recent years.

2.3 Theoretical short-term effect of M&A on R&D.

Since there appears to be a tendency for larger firms to acquire younger firms in earlier stages of product development it is likely that these companies have high-R&D to small or no revenues. The short term effect of this would be that the larger acquiring company would see a temporary increase in R&D spendings as the targets R&D is added to its own R&D. Data on acquired firms is very hard to find as many of the acquired companies are smaller private firms with no disclosed financial information.

Bertrand et al (2006) and Danzon et al (2007) write that mergers have the possibility to reduce duplicative R&D which would act to reduce to total R&D post merger.

The resource based approach suggested by Hall (1999) and Vyas and Narayananan (2012) suggests that R&D will be reduced short term post acquisition as financing for the M&A has competed with R&D for limited resources.

Hitt, Hoskisson and Ireland (1990) suggest that managers might be preoccupied with integrating the acquired firm and establishing themselves in the firm's new competitive market

putting innovation on the organizational back burner.

It is possible that some companies effectively outsource their R&D through an active R&D to M&A substitution strategy while other companies that are more opportunistic acquirers experience a smaller effect on their in-house R&D long term.

In addition to above effects, company wide effects of possible scope or scale advantages and reduced competition resulting from a merger could have the potential to reduce R&D investments. If scale or scope advantages exist this does not necessarily equal reduced research output.

2.4 Hypothesis

I state two primary hypotheses based on the assumption that large acquirers primarily acquire smaller companies that are relatively more research intensive than themselves.

Hypothesis

1. In the acquisition period t+0 an initial increase in R&D intensity is expected assuming that companies are acquiring more research intensive companies and integration takes time. The targets R&D is subsequently added to the acquirers R&D causing the R&D intensity to rise. The initial jump in period t+0 can be seen in figure 3.

2. If M&A is complementary to R&D intensity it is expected to stay unchanged in period t+1 through t+3. If R&D intensity decrease in this period it would indicate that R&D is being substituted. The difference between a substitute and compliment between t+0 and t+3 can be seen in figure 3.

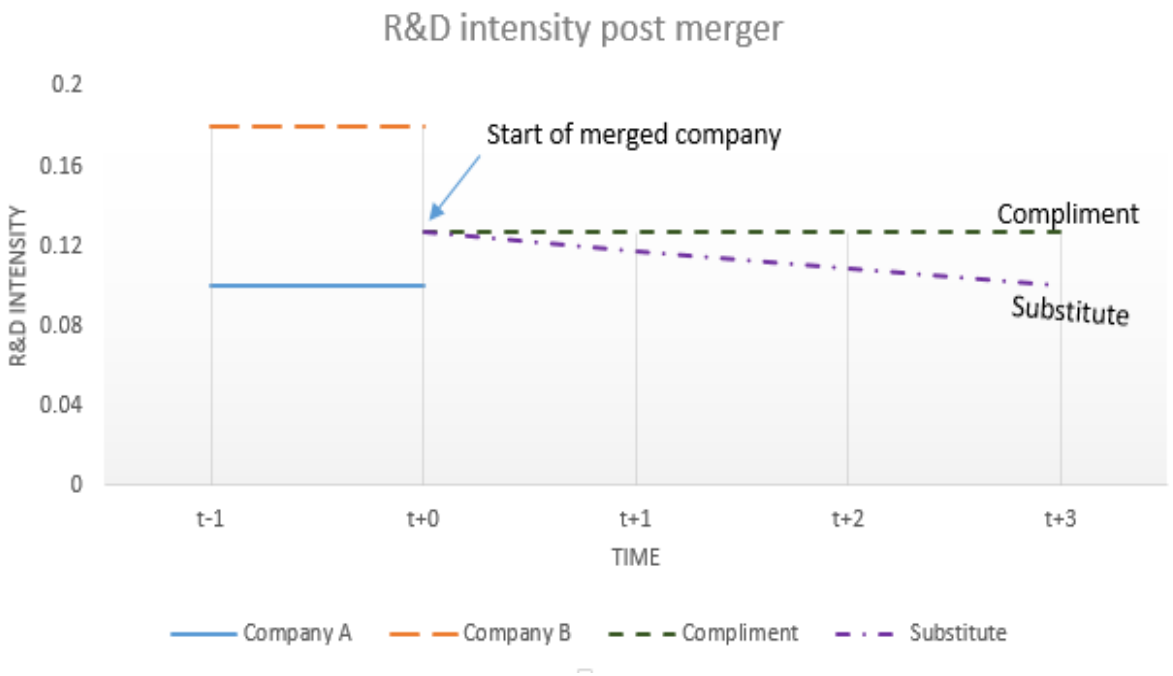

Figure 3: Plotted above is an example of the effect on R&D intensity post merger when the acquirer is larger and has lower R&D intensity. In this example Company A has 1000 revenue and 100 R&D while Company B has 500 revenue and 90 R&D. The merged company consequently has 1500 revenue with 190 R&D. If the R&D-intensity post merger goes down this would indicate that R&D is being substituted, illustrated by the pruple line. On the other hand if R&D is being used as a compliment we would expect no significant change in R&D intensity post merger, illustrated by the dark green line.

2.5 The observed effects of M&A on innovation

Henderson and Cockburn (1994), John, Weiss and Dutta (1999) and other have found that technology transfers between different fields are difficult. Prabu, Chandy and Ellis (2005) highlight that innovation is path dependent on existing knowledge and technology transfers are therefore difficult between differing companies. They further found that companies with "high breadth of knowledge", meaning that their knowledge stretched across several fields, saw a higher positive returns to innovation from acquisitions. They suggest that this could be because broad knowledge allow firms to select good acquisition targets and that the innovative outcome of a merger depends on the internal knowledge of the acquirer and its ability to incorporate acquired technology.

In a similar vein Higgins and Rodriguez (2005) found that pre-merger alliances reduces the

information asymmetry between companies and that acquisitions that took place after an alliance saw positive returns.

Hitt et al (1991) found that M&A activity reduced R&D intensity post acquisition. Hitt et al (1996) found that companies that were active acquirers relied less on internal R&D.

Kazutaka (2007) found that Japanese companies acquiring domestic company had on average lower R&D while companies acquiring foreign US companies had higher R&D. Vyas and Narayanan (2012) found that cross border mergers have more R&D intensity post acquisition.

Hall (1990) found that companies (not within the healthcare industry specifically) that made acquisitions saw reduced R&D spending in the three years following the acquisition when compared to companies that did not make acquisitions. Contrary to her hypothesis that scale or scope advantages would reduce R&D costs, she found that companies that acquired firms in the same sector saw increased R&D spendings in the period following the acquisition when compared to firms that made more diversifying acquisitions.

Using propensity scoring Hall (1999) found that companies with high propensity to acquire saw increased R&D spending growth post merger but that the sample on average did not see increased R&D from M&A activity.

Vyas and Narayanan (2012), inspired by the Hall (1999) study, examined the R&D intensity 3 years post acquisition for Indian pharmaceutical companies. They found that companies involved in acquisitions saw reduced R&D activity post acquisition. They also found that technological relatedness and cross border acquisitions improved R&D intensity post acquisition and that financial factors such as leverage played a role in R&D intensity post acquisition. They proposed that this could be the result of R&D funding being used to fund M&A activity.

Bertrand and Zuniga (2006) found that M&A activity only had a small effect on aggregate domestic R&D investment and that the effect differed depending on the technological level of the examined sector in their sample from OECD countries in the 90s.

Cassiman et al (2005) looked in-depth at 31 cases of M&A deals and found that companies with complementary activities that were involved in M&A activity saw increased research efficiency while companies with similar technologies saw reduced R&D efficiency after the deal. These findings suggests that an advantage to scope exists. On the other hand Oghani (2009) found that merged companies on average had worse R&D performance when looking at pharma companies between 1988 and 2004. He also found that technological relatedness did not have a positive impact on R&D.

3 Methodology

The aim of the thesis is to examine how companies use M&A in relation to R&D. To achieve this I will examine the change in R&D intensity post acquisition where R&D intensity is defined as:

$$\text{R\&D Intensity} = \frac{R\&D}{Revenue} \tag{1}$$

3.1 Propensity scoring

The data collected in this study is naturally occurring real world data. This pose a problem in the sense that the treatment might not be randomly assigned causing the covariates to be imbalanced between the treated and control sample. This is caused by self selection bias among the acquiring firms and has previously been noted by Hall (1999), Dranove and Lindroth (2003), Danzon et al (2007), Vyas and Narayanan (2012) and others. The problem arise in non-experimental studies where the control group might be different from the group subject to treatment. Using the notation of Imbens (2004) the Average Treatment Effect (ATE) to be examined is defined as:

$$\tau = E[Y_i(1) - Y_i(0)] \tag{2}$$

Where τ is the ATE, $Y_i(1)$ is the outcome of the treated variable and $Y_i(0)$ is the outcome of the untreated variable.

As each observation is unique and we only are able to observe it once every time period the observation will either be treated ($Y_i(1)$) or it will be untreated ($Y_i(0)$). No counterfactual exists for that specific observation meaning that the average treatment effect no longer can be calculated. In a fully randomized experiment this is not a problem as the treatment is randomly assigned causing treated and control groups to be equivalent in all other aspects than the treatment. In naturally occurring experiment the treatment might be non-randomly assigned making ordinary regression biased as we no longer can single out the treatment effect from the selection bias.

The problem, explained in the terms of this study, lies in that if the future changes in R&D spending and the decision to make an acquisition are both correlated with the same confounders we are no longer able to directly compare the means without introducing bias. The four mentioned studies above solved this problem by applying a propensity score technique originally developed by Rosenbaum and Rubin (1983) and modified by many others. The propensity score is a balancing score defined as the probability of receiving treatment given the confounding factors of treatment assignment and outcome. As the real propensity score is unknown it has to be estimated.

Rosenbaum and Rubin (1983) suggests estimating the propensity score using a logit model and pre-treatment variables that are determinants of both outcome and treatment assignment. Little and Lee (2017) writes that probit models and discriminant analysis also can be used when calculating the score but this study move forward using a logit-based score.

Using the propensity score we can reduce the self selection problem by finding a value that can act as a proxy to the missing counterfactual such that we are able to mimic a fully randomized experiment as described by Rosenbaum and Rubin (1983), Austin (2011), Imai and Ratkovic (2013), Austin and Stuart(2015), Imbens and Rubin (2015) and many others. A propensity score can be used to make the treatment assignment independent of the outcome such that:

$$\{Y_1(1), Y_i(0)\} \perp T_i | p(X_i) \tag{3}$$

Using the same notation as earlier and where T is a binary treatment variable, and p(X_i) is the propensity score p that constitutes the probability of being treated given the vector of X_i covariates.

For the propensity score technique to work there can exist no perfect predictors of treatment and the following condition applies:

$$0 < Pr(T_i = 1 | X_i = x) < 1 \tag{4}$$

For the propensity score to be unbiased it is also important that all variables that covariate with the treatment and the independent variable are included when estimating the propensity score. This is called called the strongly ignorable treatment assignment assumption (Rosenbaum and Rubin, 1983; Austin 2011; Austin and Stuart 2015). There exists no test for this assumption and the case for each variable has to be made theoretically. Lee and Little (2017) writes that interaction and polynomial terms can be included in the probability score function but that one has to be careful not to overfit the model.

3.2 Using the propensity score

Once a propensity score has been estimated there are several ways to proceed. Austin and Stuart (2015) writes that the four methods commonly used are covariate adjustment using propensity score, stratification, matching and the inverse probability treatment weighting (IPTW). This type of pre-processing done correctly will reduce both the bias and the model dependence of the model as explained by Ho et al (2007).

Other balancing technique not using propensity scores such as mahalanobis matching or

coarsened exact matching developed by Iacus et al (2011) also exists but these methods suffer from the curse of dimensionality making it very difficult to balance the covariates to reduce the bias. This problem increases with higher dimensionality in the data as explained by Ho et al (2007).

Rosenbaum and Rubin (1983) stratify their dataset into subclasses matched upon their assigned propensity score to examine the treatment effect. They state that 5 quantile based subclasses can account for more than 90% of bias in many continuous distributions. Gu and Rosenbaum (1993) examined paired matchings and find that greedy and optimal matching deliver similar results. Rubin and Imbens (2015) does not state a specific number of stratas but suggests dividing it into a number of substratas that fits the data. Hansen (2004) suggests using full matching where an observation is paired up in a group with several counterfactuals to form a set.

In a current working paper King and Nielsen (2016) show that propensity score matching is non-optimal as it is less efficient than other matching methods. The argument is that propensity scoring removes dimensions of the data that we are not able to account for when we match the treatment against the controls. For example, in the most extreme case when several propensity scores are identical we would have to prune at random which would increase the imbalance of the matching causing bias and increasing model dependence. Further they show that the problem with propensity score matching is increased with higher dimensions of co-correlation. According to their paper these findings do not apply to stratification or inverse weighting and only matching,

Acquisitions within the pharmaceutical and medical device industries appear to be focused around a few select acquirers as will be shown in the data section and has been mentioned earlier in the literature section. The effect of this is that the number of control observations will be larger than the number of treated observations. A model that is able to make use of all the information is likely to produce the best results when it comes to estimation. Using a 1 to 1 matching technique is therefore likely not the most efficient model in this case but some stratification or weighting scheme could be used to advantage. The findings of King and Nielsen (2016) also argue against using a matching strategy. This appears to also have been the conclusion of previous researchers such as Hull (1999) that used a stratified approach where she divided her sample into 6-quantiles while Desyllas and Huges (2010) and Vyas and Narayanan (2012) used the inverse propensity score weighting approach developed by Hirano et al (2003).

Depending on the type of matching selected the examined outcome will change. Two commonly examined effects are average treatment effect on the treated (ATT) and average treatment effect on the entire sample (ATE). Austin and Stewart (2015) and Lee and Little (2017) writes that matching and weighting by the odds results in ATT while subclassification and weighting by the inverse results in ATE. In relation to this study the question becomes whether to investigate the effect on R&D intensity from M&A on the whole population or if we are interested in the effect on the companies that actually were involved in M&A. As mentioned above previous studies use different approaches but most have opted for ATE

(Hull, 1999; Desyllas and Huges, 2010 and Vyas and Narayanan, 2012).

In this study I will use ATE as it measures how acquisitions affect the R&D expenditures of companies at large across the whole population. This will also make any findings comparable to previous literature.

Instead of pre-determining which model to use I will use the advice given in Lee and Little (2017), citing several papers, to try several different propensity score matching techniques and use the one that is the most successful in balancing the covariates. This leaves me to try both stratifying and inverse weighting after excluding matching and probability weighting by the odds.

The inverse weights used to estimate ATE presented by Hirano et al (2003) can be written as:

$$w_i = \frac{T_i}{\hat{p}(X_i)} - \frac{1 - T_i}{1 - \hat{p}(X_i)} \tag{5}$$

Where w is the weight, T is the treatment dummy variable, p the propensity score and X the set of confounding covariates. These weights can then be used when estimating a model using Weighted Least Squares (WLS) as shown by Imbens (2004). Imens (2004) and Ho et al (2007) writes that the model will be consistent as long as either the regression model or the propensity score with weights is specified correctly. Hirano et al (2007) and Lee and Little (2017) suggest leaving in the covariates used to estimate the propensity score in the WLS model.

Balance diagnostics will be conducted using measures of standardized difference (also known as Cohen's d) to measure the balance of the univariate distributions as initially introduced by Rosenbaum and Rubin (1985). The standardized difference is a measure of the difference in mean between treatment and control group measured in pooled standard deviations as explained by Austin and Stuart (2015) and Imbens and Rubin (2015) p 310. Using their notation the standardized difference of an unweighted sample using continuous variables is defined as:

$$d = 100 * \frac{\bar{x}_{treatment} - \bar{x}_{control}}{\sqrt{\frac{(s^2_{treatment} + s^2_{control}}{2}}} \tag{6}$$

Where $\bar{x}$ is the mean and s is the sample variance.

Austin and Stuart (2015) also write that the standard deviation and mean of the weighted sample can be calculated as:

$$\bar{x}_{weight} = \frac{\sum w_i x_i}{\sum w_i} \tag{7}$$

and

$$s^2_{weight} = \frac{\sum w_i}{(\sum w_i)^2 - (\sum w_i^2)} \sum w_i (x_i - \bar{x}_{weight})^2 \tag{8}$$

They also show that the same measure can be used using dichotomous variables.

They further write that some researchers have suggested that 10% or more difference is a sign of imbalance in the covariates. They suggest using comparative box plots and plots of the cumulative distributions of the weighted and unweighted sample to ensure balance.

Austin and Stuart (2015) writes that interpretation and diagnostics of propensity score modeling is subjective and that the researcher has to think of the model as a whole when balancing the different covariates.

Caliendo and Kopeinig (2008) points out that ATT and ATE only are defined in the areas of common support and suggests several techniques to ensure common support depending on the data at hand.

One approach to improve the scoring and solve this problem as suggested by Caliendo and Kopeinig (2008), Rubin and Imbens (2015) chapter 16 and others is to trim the sample by the propensity score such that there is overlap across all propensity scores.

3.3 Control variables used in the propensity score

All the variables used to estimate the propensity score are lagged one period so that they are measured in the period before the M&A took place. This is to minimize any problem with interpreting causal direction.

Revenue As explained above previous research would suggest that larger companies acquire smaller companies as a way to complement or substitute their in-house R&D efforts. If there is a substitution effect it would suggest that revenue would possibly be a confounder of R&D change and M&A. This variable was eventually dropped from the study as it was found that the listed companies in the sample were large companies and not the small "biotech like" companies discussed in the literature. The rationale for dropping the variable is further elaborated upon in "The revenue problem" section in Appendix on page 41.

Cash He and Wintoki (2016) found that research intensive companies had larger cash reserves and that this could be attributed to companies increasing their cash reserves when

subject to increased competition. Arrow (1962) noted that high risk projects like R&D are difficult to finance with outside financing. The combination of these two findings is one of the main arguments for why R&D and Cash is positively correlated. Jensen (1986) pointed out that managers have an interest in keeping cash to avoid monitoring associated with outside financing. Harford (1999) found that cash-rich firms are more likely to attempt acquisitions. This suggests that Cash is a confounding factor of M&A and R&D intensity change. The amount of cash is normalized by dividing by revenue.

Tobin's Q Tobin's Q is a measure of the ratio between a company's market value and its book value. Tobin's Q has been used in previous studies such as Hall (1999) and Denzon et al (2007). Denzon et al (2007) write that it can be difficult in interpreting the variable as its effect is dependent on two competing factors; future expected performance and short term financial troubles. Tobin's Q is a measure of expected future earnings that are highly related with expected future earning ability. This suggests that Tobin's Q is a better measurement than patents for measuring the potential of a company's technologies as patent information does not contain any information about the actual value of the innovation. Ideally patent data would also be included but no patent data was available to this study and as such Tobin's Q will act as a proxy of innovative power.

R&D-intensity The R&D-intensity level (not the change) is included as it is possible some companies substitute their R&D with an active acquisition strategy as described earlier in the theory section. Companies that substitute their in-house R&D are likely to have lower R&D-intensity to start with while opportunistic acquirers likely have a higher R&D to start out with.

Divestments I include a dummy for companies that sold part of their business in period t-1. I use this dummy to see if companies use the proceeds from divestments to fund internal R&D.

Joint venture I include joint venture as a dummy variable as it is likely to affect both M&A and R&D. Danzon et al (2005) examines a sample of 900 pharmaceutical and biotechnology companies between 1988 and 2000 and find that products developed in an alliance have higher success. This suggests that joint ventures could be related with R&D. Danzon et al (2007) however found joint ventures to be insignificant in predicting pharma M&A. The variable is one if it the company entered a joint venture in the year prior to acquisition.

Time Dummy A boolean indicator variable is included for each year in all regressions. I do this because the propensity to merge and research spendings are likely to change as a function of time. This dummy will be able to capture the general movements in the

market and the surrounding time dependent factors affecting the companies. There is also a substantial literature on merger waves which further emphasise the need of a time dummy.

3.4 Post deal variables

The post deal variables are included after the propensity score as they are either perfect predictors of M&A or are not believed to be confounders of both M&A and R&D.

Change in Assets The change in total assets divided by the revenue in the year preceding the deal is included as a control variable. This acts as a proxy for relative deal size. I divide by the revenue from the same year as this measure not is intended to capture changes in revenue but changes in assets while still being comparable between companies and across time. The variable is included as an interaction term with M&A to capture the size of the total acquisitions since no acquisition values are available.

M&A Dummy M&A is the independent variable in this study. Both single and several acquisitions will be recorded as one while no acquisitions are recorded as zero. No additional indicator of companies that made several acquisitions in a single year is included as the study has no information on the specific deal values. The number of deals within a year does not say anything about the financial or economical commitment of the organization as a single mega deal might have a much larger impact than several smaller deals. Acquisitions here constitute both fully buying out another business or just buying segments of a business. No difference is made between the two as it says little about the size of the deal or what it constitutes.

Multi-acquirers A dummy variable is included for companies that make more than two acquisitions during the examined years as their behaviour might differ somewhat from other companies as explained above. The reason for not including it in the propensity scoring is that this information only is known after two acquisitions are concluded and cannot therefore be used as a predictor of the same acquisitions. This dummy will be used as an interaction term to the M&A dummy to capture the additional or reduced effect of multi-acquirers.

Cross border acquisition Similar to Vyas and Narayanan (2012) I add a dummy variable for cross country acquisitions. For purposes of this study there exists three countries: The EU, US and Japan.

Horizontal Acquisition Again I follow Vyas and Narayanan (2012) and include a dummy to distinguish deals between similar companies and companies that operate in different areas. To this purpose I use a dummy variable that is one if the SIC group number (283 - Drugs or 384 - Surgical, Medical, and Dental Instruments and Supplies) is identical to that of the own company. This also relates back to the difficulties of technological integration. (Henderson and Cockburn, 1994; John, Weiss and Dutta, 1999)

SIC 873 Dummy I also include a dummy for acquisitions where the target has the SIC Code 873 - Research, Development, and Testing Services as I suspect that some research oriented companies are classified into this group. This variable is dropped in the data section due to data limitations.

Mixed SIC dummy As mentioned above some companies are involved in several deals during the same year. In these cases it could happen that an acquirer buys several companies that are registered in both their own and other industries. To account for this I record these deals within a "mixed SIC dummy" to avoid them diluting the effect of the other SIC dummies. If several acquisitions are made and they all have the same SIC code they are recorded into the horizontal dummy per usual.

Mixed country dummy Similarly to the mixed SIC dummy there is a risk of companies acquiring several companies that are both cross border and domestic in a single year. To single out the effect of cross border and domestic I encode these cases in the mixed country dummy. If several acquisitions are made and they all have the same target country they are recorded into the country dummy per usual.

3.5 A note on statistical software

All calculations are done in R using standard functions and packages with the exception of the logit function "glm" that is included in the "stats" package. As control I have also checked my results using the "MatchIt" package developed by Ho et al (2007) and the "twang" package developed by Ridgeway et al (2016). All R outputs in the report are exported into Latex using the "xtable" package.

4 Data

The financial data is obtained from the Orbis database and the M&A data is obtained from Zephyr, both published by Bureau van Dijk. Bollaert and Delanghe (2015) evaluated several databases for M&A research and write that deals with a deal value larger than 1 million GBP or involve a deal stake of more than 2% are included in the Zephyr database. Assuming that all deals up to this size were correctly identified and included in the database this should more than suffice for this study as most deals of importance involve substantially larger values or stakes.

As explained earlier the pharmaceutical industry can be divided into pharmaceutical, biotechnology and genomics/protonics focused companies. This division between the sectors is however not always clear and the informational value gained by the division is likely of small value given the overlap of industries. For practical reasons I therefore make no difference between the types of pharmaceutical companies. The focus is instead on differences in the financial and other quantifiable data.

I begin by identifying companies using their Primary SIC code. The two relevant SIC code for purposes of this study are the group 283 - Drugs and 384 - Surgical, medical and dental instruments and supplies.

SIC Code	Description
2833	Medicinal chemicals and botanical products
2834	Pharmaceutical preparations
2835	In vitro and in vivo diagnostic substances
2836	Biological products, except diagnostic substances

Table 1: SIC283 subgroups

SIC Code	Description
3841	Surgical and medical instruments and apparatus
3842	Orthopedic, prosthetic and surgical appliances and supplies
3843	Dental equipment and supplies
3844	X-ray apparatus and tubes and related irradiation apparatus
3845	Electromedical and electrotherapeutic apparatus

Table 2: SIC384 subgroups

The industry identification is US SIC but the ORBIS database has these values mapped to the corresponding values in different markets which makes using these values as a search criteria viable even when searching other markets.

Next I filter the companies based on their independence. I only look to include companies that are independent, meaning that they are not direct subsidiaries of other companies. Companies that are located outside the EU28, US or Japan are filtered out. To avoid problems with different accounting practices I add a dummy variable for the US and Japan region.

The original dataset downloaded from Orbis contains 346 companies out of which 344 are publicly listed companies. Neither of the two private companies made an acquisition during the examined period and I exclude them as they likely both are different in the way they operate and the fact that they not are subject to the same disclosure requirements as public companies. In addition no stock data is available so Tobin's Q would not be calculable.

I remove companies that have not submitted R&D spendings for some or all dates, submitted 0 or did not exist during the whole examined period. In the literature these firms are what is called no-R&D firms and other studies such as Hull (1999) and Vyas and Narayanan (2012) have included these firms but controlled for them using a dummy variable. I chose not to do include them as they might not follow the same data generating process as R&D firms since their reasons for acquiring companies are likely to be different. In both the medical device and the pharmaceutical industry the no-R&D firms are likely to be characterized by lower-tech industry segments while the high R&D firms are more high-technology oriented. In the pharmaceutical industry no R&D companies could for example be characterized by generic drug producers while high R&D companies are drug developers. This analogy is also true for the medical device industry where the lower technology companies likely are medical supplies producers (bandages, vials and other low-technology goods) whereas the R&D spenders likely are more involved high-tech medical device manufacturers. As the number of controls still heavily outweigh the number of acquirers it makes little sense to include these companies in the sample as they risk biasing the result with limited benefit.

Using the BVD ID number for the companies collected in the ORBIS database I collect information on completed M&A deals in the Zephyr database. As the two databases are from the same publisher and use the same ID numbers the matching is easily done. I then remove any acquisitions of minority stakes, majority stakes smaller than 90% ownership or acquisitions where the starting share was larger 90%.

I use the 90% stake as the cut off level as this in many jurisdictions is where an acquirer is able to squeeze out remaining minority shareholders (Martynova and Renneboog, 2011). In some jurisdictions this differs (such as in Germany where the rate is 95%) but no deals end up between 90% and 95% and very few deal percentages end up in this area so the problem is judged to be minimal.

Two companies in the sample have acquired unknown majority stakes and I chose not to include them in the sample as the final percentage is unclear. Three companies acquire an unknown percentage of remaining shares. I decide to include them into the sample despite not knowing what their initial share was since it is clear the final share is 100%.

One identified problem is that some companies appear to acquire their targets in stages that might be part of a longer term strategy. This likely makes any effect on R&D spread out over several years and more difficult to identify. I use the 90% acquisition date as the event date for all acquisitions and don't include partial acquisitions as it is only when the company is fully owned that the owner can reap the full technological benefits of the acquisition. I also keep any information on joint ventures in the dataset. There is unfortunately no information on the type of joint venture available so all joint ventures are treated the same.

Pharmaceutical Sample	Total	EU	US	Japan
Total number of companeis	102	37	28	37
Company Years	918	333	252	333
Percentage of Total	100.00%	36.27%	27.45%	36.27%
Company Years with acquistions	168	79	65	24
Percentage of subsample	18.30%	23.72%	25.79%	7.21%
Joint Ventures	23	13	7	3
Percentage of subsample	2.51%	3.90%	2.78%	0.90%
Deacquistions	117	50	27	40
Percentage of subsample	12.75%	15.02%	10.71%	12.01%

Table 3: Discripitve data for the pharmacutical sample

The pharmaceutical data is evenly spread out across the three regions but with a heavy emphasis on US and Europe when it comes to the number of acquisitions.

Medical Device Sample	Total	EU	US	Japan
Total number of companeis	69	16	38	15
Company Years	621	144	342	135
Percentage of Total	100.00%	23.19%	55.07%	21.74%
Company Years with acquistions	82	10	63	9
Percentage of subsample	13.20%	6.94%	18.42%	6.67%
Joint Ventures	3	0	1	2
Percentage of subsample	0.48%	0.00%	0.29%	1.48%
Deacquistions	38	12	18	8
Percentage of subsample	6.12%	8.33%	5.26%	5.93%

Table 4: Discripitve data for the medical device sample

There appears to be disproportionately many US companies in the medical device sample, but this is expected by theory suggesting that the market is US dominated. What is surprising is the extreme amounts of acquisitions in the US market over the measured 9 year period.

On average every listed company made 1.65 acquisitions per company. Noticeable is also the relative absence of joint ventures in all three markets.

For comparison, in the Hull (1999) sample approximately 1.8% of the measured company years involved acquisitions. This is evidence of the active merger market within these two industries over the last decade.

Next I use log transformations on all variables except Tobin's Q in both samples. I tried various other transformation such as square root and inverse but log performed the best.

Figure 6 on page 46 and Figure 7 on page 47 (Appendix) includes correlation plots of the continous variables in the datasets post tranformation. The correlation plots are plotted using the "Rarity" package in R.

Table 18 and 19 contain more detailed descriptive statistics of the data used in the propensity scoring. Table 16 and 17 contain descriptive data on the deal specific variables.

5 Results

5.1 Estimating the propensity score

The propensity score is estimated with an ordinary logit model using the control variables outlined in the theory section minus revenue.

Starting with the pharmaceutical logit model it is estimated as:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.9797	0.4859	-4.07	0.0000
Tobin's Q t-1	0.3094	0.1597	1.94	0.0527
Cash t-1	0.0287	0.1417	0.20	0.8393
R&D Intensity t-1	0.0114	0.0099	1.16	0.2471
Joint Venture t-1	1.5151	0.6344	2.39	0.0169
Divestment t-1	2.0943	0.2572	8.14	0.0000
US Company	-0.1861	0.2775	-0.67	0.5026
Japanese Company	-1.4792	0.2982	-4.96	0.0000
Time Dummy	Yes	-	-	-

Table 5: The logit regression used to estimate the propensity score in the pharmaceutical sample

Tobin's Q, joint venture and divestments are all positive significant predictors of M&A in this sample. The dummy variable indicating Japanese companies is significantly negative as they are less likely to be an acquirer. This is expected given what was seen in the decripitive data.

Next I remove the observations with propensity score outside the area of common support. I do this by removing any control observation that has a propensity score smaller than the smallest treated observation and any treated observation that has a propensity score larger than the largest control observation. This leaves 763 observations.

I repeat the process for the medical device sample:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.4990	0.9184	-2.72	0.0065
Tobin's Q t-1	0.0787	0.0987	0.80	0.4253
Cash t-1	0.2054	0.1442	1.42	0.1544
R&D Intensity t-1	-0.5838	0.1721	-3.39	0.0007
Joint Venture t-1	2.8107	1.5173	1.85	0.0640
Divestment t-1	2.2586	0.4358	5.18	0.0000
US Company	1.8629	0.4568	4.08	0.0000
Japanese Company	-0.1495	0.6196	-0.24	0.8094
Time Dummy	Yes	-	-	-

Table 6: The logit regression used to estimate the propensity score in the medical device sample

Joint ventures and divestments are significantly positive while R&D intensity is significantly negative.

I remove the observations outside the area of common support using the maxima and minima approach described above. This leaves 446 observations in the sample.

After pruning there exists no domestic acquisitions in the medical device sample that was not complimented with a foreign acquisition in the same year. This means that the mixed country dummy has to be excluded because of perfect linearity problems and instead the baseline is mixed country acquisition. The same is true for acquisitions into other industries and the baseline becomes mixed acquisitions.

After pruning the sample for common support there were several acquisitions of companies in SIC873 left in both samples but unfortunately all these acquisitions were part of several acquisitions in the same year. The consequence of this is that the effect cannot be isolated. I therefore chose not to include the variable in the final regressions.

5.2 Stratifying

The stratifying does not improve the covariate balancing and is therefore dropped in favour of the inverse weight balancing. The procedure and results of the stratifying can be found in Appendix on page 44.

5.3 Inverse Weight Balancing

Next I use the propensity score to calculate the inverse balancing weights.

In the pharmaceutical sample the largest weight constitutes 0.87% of the whole sample and in the medical device sample the largest weight constitutes 1.24% of the total sample. This is evidence that the balancing does not overly rely on any single observation.

	Unweighted	Weighted
R&D Intensity	20.19	10.61
Cash	9.06	-2.48
Tobin's Q	15.61	-0.64
Joint Venture	26.46	-8.13
Divestment	66.61	-4.13
US Company	24.79	-2.61
Japanese Company	-51.98	5.91
Average	30.67	4.93

Table 7: Standardized differences in the weighted and unweighted pharmaceutical sample

The weighting outperforms the stratifying approach in all covariates across all quantiles except in cash in quantile six and Tobin's Q in quantile three. This difference is however extremely small and well below any threshold of imbalance. The average imbalance is substantially lower than all quantiles in the stratified approach. All covariate are well balanced except R.D intensity that is just above 10% imbalance. The average bias has been reduced from 30.7% to 4.9%.

Next below is the standardized difference of the unweighted and weighted full medical device sample:

	Unweighted	Weighted
R&D Intensity	7.69	11.93
Cash	5.94	15.77
Tobin's Q	12.23	2.34
Joint Venture	12.48	0.56
Divestment	33.14	5.55
US Company	34.95	17.78
Japanese Company	25.98	3.79
Average	18.91	8.25

Table 8: Standardized differences in the weighted and unweighted medical device sample

The medical device dataset balancing does not perform as well as the balancing of the pharmaceutical dataset. There is still some imbalance left in several of the covariate although it is a large improvement over both the original sample and the stratified propensity score quantiles. R&D intensity and cash has increased imbalance after the weighting and the US dummy variable still has substantial imbalance left. The average bias has been reduced from 18.9% to 8.25%.

It is clear that the inverse weighting scheme has performed substantially better than the stratified approach hence I continue the next part only using the weighted data.

5.4 Regression results and analysis

Using WLS and the balancing weights I regress the same variables as in the propensity score estimation with the deal specific variables and the M&A dummy added on the change in R&D expenditure.

In addition to what is presented below I test several interaction terms between the deal specific variables but this gives nothing significant and only serves to increase the number of parameters estimated in with scarce data. I therefore do not include these regressions in the final results presented below.

Presented below in table 9 is the result of the weighted regression using the pharmaceutical data. The result is presented as the effect on change in R&D intensity over each period t+0, t+1, t+2 and t+3. In table 14 located in Appendix on page 48 the full effect across period t+0 to t+3 in the pharmaceutical sample can be seen.

	t+0		t+1		t+2		t+3	
	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
(Intercept)	3.18	3.78	-0.18	-0.32	-1.02	-1.64	-0.67	-1.64
M&A	-3.84	-0.88	1.32	0.44	0.46	0.14	0.65	0.31
M&A Multi	-0.02	-0.04	0.32	0.97	0.51	1.44	0.04	0.18
Total Assets Change	4.70	13.50	-1.04	-4.39	-1.67	-6.54	0.20	1.20
Cash t-1	0.68	2.86	0.12	0.72	-0.28	-1.61	-0.12	-1.04
R&D Intensity t-1	-0.21	-11.15	-0.06	-4.83	-0.07	-5.26	-0.02	-2.05
Tobin's Q t-1	0.05	0.17	0.38	2.04	0.49	2.43	0.18	1.35
Joint Venture t-1	-1.92	-1.60	-0.50	-0.62	-0.59	-0.66	0.12	0.20
Divestment t-1	1.12	2.11	0.94	2.60	1.03	2.62	0.34	1.33
Horizontal	-0.12	-0.04	-1.16	-0.48	-0.40	-0.15	-0.34	-0.20
Mixed Industry	-0.27	-0.08	-1.24	-0.52	-0.43	-0.17	-0.49	-0.29
Cross Border	4.55	2.45	0.24	0.19	0.33	0.24	0.62	0.69
Mixed Border	3.94	2.35	0.25	0.22	-0.16	-0.13	-0.23	-0.29
US Company	0.15	0.30	0.03	0.08	-0.00	-0.01	-0.13	-0.52
Japanese Company	0.63	1.45	0.23	0.77	0.49	1.52	0.14	0.67
Time Dummies	Yes	-	Yes	-	Yes	-	Yes	-
M&A * M&A Multi	1.20	0.58	-0.79	-0.56	-0.27	-0.18	0.06	0.06
M&A * Total Asset Δ	-4.81	-7.41	1.73	3.92	1.73	3.61	-0.06	-0.19

Table 9: Regression output t+0, t+1, t+2 and t+3 for the pharmaceutical sample

The M&A dummy is not a significant predictor of change in R&D intensity in the pharmaceutical sample in any of the examined periods. The M&A dummy in the pharmaceutical sample represents domestic acquisitions into other industries. The change in total assets is significantly positive in t+0, significantly negative in t+1, t+2 and not significant in t+3. The interaction term between M&A and change in total assets is significantly negative in t+0, significantly positive in t+1 and t+2 and not significant in t+3. The interaction term is almost perfectly counteracting the effect from change in total assets by acting in the opposite direction. The effect of the total change in assets is not of interest to this study as it likely has nothing to do with M&A activity, rather it is only included so that the interaction effect can be captured. What is of interest is the net effect of the interaction term and the change in total assets. This effect is positive in period t+1, t+2 and t+3 and negative in period t+0, but not significant.

The mixed border variable (indicating several acquisitions that were both domestic and cross border in the same year) and the cross border variable are both significantly different in t+0 from domestic acquisitions. Surprisingly this effect is not different from zero but only significantly more positive than the effect of domestic acquisitions. The effect appears to be lasting over time.

The significant difference could suggest that pharmaceutical companies acquire foreign companies that are more research intensive than in domestic acquisitions. The total effect on R&D-intensity across t+0 thorough t+3 is positive but not significant. The fact that the effect decrease with time but continually stays positive suggests that acquisitions are being used as a complement to in-house R&D. A possible explanation for this could be that companies, as observed in the literature, are moving research outside of the company and moving abroad where costs are lower. This explanation is in line with the findings of Nieto and Rodriguez (2011) who writes that offshoring R&D can increase innovative performance - which is precisely what the pharmaceutical industry needs.

That M&A appears to be a compliment can either be explained by that companies are increasing their total R&D expenditure when investing abroad or that the transition period is long and that domestic research initiatives are kept until the full transition can be made making it too long term to effectively observe in this study.

As explained below, the effect cannot be examined in the medical device sample due to lack of relevant acquisitions in the data but there is nothing in the results that would indicate that the two samples differ from each other in this aspect. In fact the size of the cross border coefficient is similar in the two samples when accounting for the difference in baseline. This result is similar to Vyas and Narayanan (2012).

Horizontal and mixed industry acquisition dummies are not significant in any of the time periods.

None of the deal specific variables except the cross border acquisitions have any significant effect on the change in R&D intensity.

I chose not to interpret the Tobin's Q and Cash variables as they primarily are controls for the other variables and not directly under examination. The level of R&D Intensity prior to the acquisition is a significant negative predictor in all four periods suggesting that R&D intensity between companies is becoming more homogenous over time.

Presented below in table 10 is the result of the WLS using balancing weights for medical device data. The result is presented as the effect on change in R&D intensity over each period t+0, t+1, t+2 and t+3. In table 15 located in Appendix on 49 the full effect across period t+0 to t+3 in the medical device is listed.

	t+0		t+1		t+2		t+3	
	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
(Intercept)	0.22	0.31	0.83	1.24	0.48	0.73	0.17	0.35
M&A	0.55	0.33	0.23	0.15	-0.20	-0.13	-0.40	-0.35
M&A Multi	-0.12	-0.27	-0.25	-0.64	0.16	0.41	0.06	0.21
Total Assets Change	0.59	1.95	0.81	2.86	0.12	0.45	-0.20	-0.96
Cash t-1	0.18	1.55	-0.03	-0.27	-0.08	-0.79	-0.10	-1.27
R&D Intensity t-1	-0.62	-4.32	-0.34	-2.52	-0.22	-1.70	-0.37	-3.72
Tobin's Q t-1	0.09	1.04	0.10	1.14	0.06	0.73	0.13	2.08
Joint Venture t-1	-0.20	-0.11	0.22	0.13	-0.23	-0.14	0.13	0.10
Divestment t-1	1.50	3.27	1.05	2.46	-0.58	-1.41	-1.32	-4.14
Horizontal	0.39	0.68	-0.08	-0.15	-0.07	-0.14	-0.14	-0.35
Cross Border	0.11	0.19	-0.28	-0.53	0.06	0.12	0.22	0.57
US Company	0.66	1.97	0.41	1.34	-0.11	-0.36	-0.04	-0.16
Japanese Company	0.11	0.27	0.20	0.51	-0.13	-0.34	-0.14	-0.50
Time Dummies	Yes	-	Yes	-	Yes	-	Yes	-
M&A * M&A Multi	-0.48	-0.29	0.07	0.04	0.01	0.01	0.35	0.30
M&A * Total Asset Δ	-0.86	-1.25	-0.70	-1.10	-0.03	-0.05	0.33	0.69

Table 10: Regression output t+0, t+1, t+2 and t+3 for the medical device sample

The M&A variable on its own is not a significant predictor of change in R&D intensity in any period. The M&A variable on its own here indicate mixed country acquisitions into mixed industries.

Change in total assets is significantly positively correlated with change in R&D intensity when measured across all four periods. However again the effect on M&A companies (interaction term) offset this effect and it not significantly different from zero.

The horizontal acquisition variable and cross border variable are insignificant in all time periods. The reason for them being insignificant can possibly be attributed to the base level being mixed industry and mixed target country acquisitions meaning that the pure effect of domestic or vertical acquisitions were not possible to be identified due to imperfections in the data. The result is therefore equivalent to the pharmaceutical sample.

The M&A dummy indicating domestic acquisitions (although representing slightly different things in the two samples) is not a significant predictor of R&D intensity change in either sample. The fact that the sign is negative in t+0 in the pharmaceutical sample is in contrast with the hypothesis that it should first increase and then either stay fixed or be reduced depending on if it used as a compliment or not.

While the null hypothesis never can be accepted there are several possible explanations for this insignificance. It could be that indeed companies are acquiring and using their the R&D as a substitution right away which would be in line with Bertrand et al (2006) and Danzon et al (2007)s idea that companies possibly reduce duplicate R&D. It would however seem improbable that a company would be able to cut R&D funding so quickly given the difficulties of informational integration described by Prabu, Chandy and Ellis (2005). It could also be the case that the acquisitions are too small to significantly impact the R&D intensity post merger. Another possible explanation is that acquired companies are equally or even less research intensive than the acquirer.

It could also indicate that domestic acquisitions are driven by efforts to consolidate markets rather than acquiring new technology and that the target therefore typically are low R&D companies which would push R&D intensity down.

The results do not provide any evidence that multi-acquirers behave differently compared to other companies with regards to R&D. This is not in line with the initial expectation that multi-acquirers would be especially likely to be involved in high R&D intensity acquisitions as they acquire R&D as part of a long term substitution strategy to researching in-house. It might be that multi-acquirers make smaller acquisitions that do not become significant but including an interaction term with the change in total assets does not provide any evidence of this. More likely the expectation presented is incorrect and the multi-acquirers are driven by something else than substituting their in-house R&D with acquisitions. One possible explanation would be that their acquisitions are driven by efforts of market consolidation rather than R&D considerations. This would explain why multi-acquirers also are much more prone to make divestments as they are looking to optimize their product portfolio.

Divestments appear to initially increase R&D intensity in both the pharmaceutical and medical device sample. In the pharmaceutical sample divestments continue to increase R&D intensity for a long period while the effect is being reversed with time in the medical device sample. It is hard to say anything specific about this behaviour without having more deal specific data. One can theorize that it has to do with divestments reducing revenues which would lead to an increasing R&D intensity initially. Reversing the constrained resource argument made by Hall (1999) and Vyas and Narayanan (2012) it could be said that the proceeds from the sale would reduce the competition for funding within the company allocating more resources to R&D in period t+1. As the medical device industry is more research productive this gap is covered by new products which again increases revenues returning the R&D intensity to old levels while this does not happen in the pharmaceutical industry. This also agrees with Arrow (1962) and Jensen (1986) who argue that more cash will make it easier for management to allocate resources to high risk projects like R&D.

Horizontal and vertical acquisition are not significantly different in the pharmaceutical sample. Again the baseline of the two samples is somewhat different and the pure effect of vertical acquisitions cannot be identified in the medical device sample. There is also no significant difference between the mixed and horizontal dummy. In the pharmaceutical sample the reduction in R&D after a horizontal acquisition is quicker post acquisition (the sign is negative) which is what we would expect given the findings of technological integration done by Henderson and Cockburn (1994), John, Weiss and Dutta (1999) and Prabu, Chady and Ellis (2005). The finding is not significant.

Interestingly the relative acquisition size also appears to have no effect on R&D intensity when measured as the change in total assets. The naive expectation would be that any effects from acquisitions would increase with size of the acquisition as the effect is amplified by the size. This does however not account for the fact that the larger and smaller deals might be inherently different in their effect on research intensity. Larger deals involving established companies are likely to see a small changes in initial R&D intensity, independent of subsequent substitution or complementation, while an acquisition of a smaller research intensive company would have a larger impact relative to the deal value with the added difficulty that the added effect would be small in relation to revenue making it hard to detect. This explains why the total change in assets appear to converge around zero and was not successful as a predictor of change in R&D intensity.

Another interesting finding in the logit model that estimate participation (from the propensity scoring) in M&A was that the R&D intensity was highly negatively significant in the medical device sample but not significant in the pharmaceutical sample. This would support the idea that there exists some type of strategy where companies with low R&D intensity are looking to acquire technology or products through M&A within the medical device industry. The t+0 through t+3 effect of M&A in the medical device sample is close to zero and any short term effect is insignificant which would suggest that acquisitions are being used as a complement to in-house R&D. This finding is in line with Philips and Zdanov (2013)'s model that show that larger companies might have an incentive to let smaller firms develop technologies and then acquire them. It could well be that they acquire only to obtain patents and that the impact on R&D intensity therefore is minimal in the short run.

A problem encountered is that multi-acquirers create a lot of noise in the sample. Assuming that acquisitions can have an effect across several time periods there is a substantial risk of these effects overlapping when a company makes several acquisitions. Depending on how the effect is structured it could bias the result in any direction. The effect is likely systematic and therefore not only increasing noise but actually inducing bias. To account for this problem I included the M&A multi variable and tried different interaction terms with it but this did not change the result. Another alternative would be to remove multi-acquirers from the sample altogether to examine the effect separately but this would have removed to many observations.

6 Conclusion

Due to most variables being insignificant it is hard to draw any definitive conclusions but all in all the pharmaceutical and medical device industry samples appear to behave similarly and the effect of acquisitions on R&D intensity appears to be limited and dominated by other factors. In contrast to the initial hypothesis the immediate effect of an acquisition is an insignificant reduction in R&D. Cross border acquisitions saw positive but insignificant increase in R&D intensity in the first period. Compared to domestic acquisitions, cross border acquisitions in the pharmaceutical sample produce significantly higher R&D intensity post acquisition. Pharmaceutical companies divesting appear to see increased R&D intensity long term while the effect in the medical device industry is shorter lived. I attribute both of these findings to the poor research performance documented in the pharmaceutical industry. No evidence that technological relatedness affect the R&D intensity post-merger is found.

Another finding is that multi-acquirers do not appear to behave any different when compared to other acquirers.

There also appears to be a connection between low R&D intensity and M&A within the medical device sample. This could be evidence of some medical device manufacturers opting to acquire technology rather than developing it in-house.

Several problems were encountered with the data in this study which also impacted the results. The assumption that revenue is not a confounder might be incorrect which would bias any M&A effect. Interestingly other financial factors such as Tobin's Q, the amount of cash at hand or the R&D intensity in the preceding period appears to be much more important predictors of change in R&D intensity than acquisitions.

There were also some covariate imbalances left in the both samples, and especially in the medical device sample which possibly have biased the results. Other problems causing potential bias would be missing confounders and the noise induced by the multi-acquirers.

7 Future research

Several problems encountered in this study could likely be solved with more complete data on the acquired companies. Unfortunately even public companies are prone to keep acquisition values secret as part of their competitive strategy. Adding to this is that more specific company information is difficult to find and quantify from news sources and analyst publications. One way way to extend this study to account for the acquisition size would be through analysis of the cash flow statements.

While the focus of this study was the effect on R&D intensity induced by acquisitions another

interesting approach would be to examine if companies in the healthcare industry making acquisitions have reduced innovation from the outset and how this then impact their R&D outcomes or spending. I tried to control for this using a multi-acquisition variable to see if multi-acquirers were different but using a different research strategy might provide a better answer to this question.

At the outset of this study I compared the number of granted patents to gauge the research efficiency within industries. This is a very crude measure at best. Examining the type of patent and the quality of patents in the medical device industry in an effort to determine the real research efficiency would also be an interesting research topic.

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9 Appendix

9.1 The revenue problem

The data clearly shows that larger companies are involved in more acquisitions than smaller companies. It is hard to know if this is a quirk of Zephyrs data gathering process where an emphasis is put on the larger companies or if this is representative of the population. As I have found no reports indicating faulty data and given that all firms in the sample are publicly listed companies with information that should be readily available in the jurisdictions selected I work under the assumption that the data is correct. One possible explanation for this is given by Danzon et al (2007) who suggest it could be because larger companies have larger absolute amounts of cash at hand that they can spend on acquisitions.

Plotted below in figure 4 and 5 is the relationship between log of Revenue and R&D in the pharmaceutical and medical device industries. In this data revenue is lagged one period but in practice this matters little as revenue is fairly consistent across time. As can be seen in the graph acquiring companies in red have a much higher revenue than non-acquirers and the overlap between the two groups is small. This creates a problem when estimating the propensity score as it creates probabilities very close to one or zero with almost no areas of common support and make the covariates impossible to balance and force us to throw out the vast majority of data. In this case more than 80% of the data would have to be pruned.

The underlying assumption for including revenue in the propensity score is that it is a confounder of both M&A and R&D intensity change. As explained earlier there is no test of confounding and the researcher has to rely on theory and examine the data.

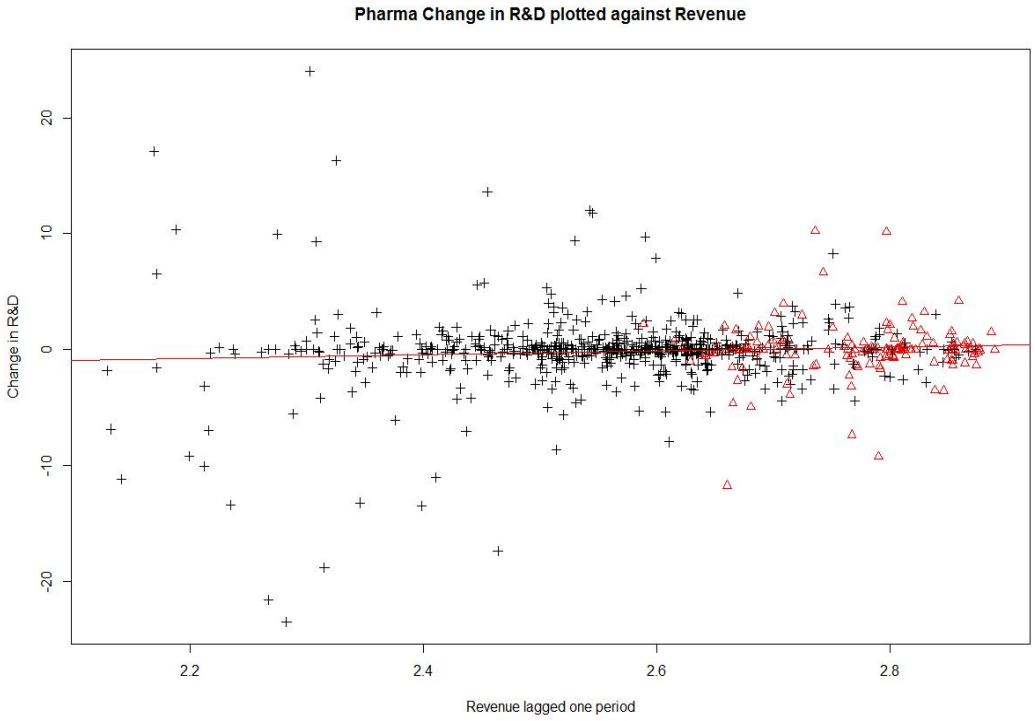

Figure 4: The relationship between log of revenue lagged one period and change in R&D-intensity in the pharmaceutical sample. The red dots are treated observations (including an M&A deal) and the black dots are untreated observations. The red line is a linear regression line estimated on the treated observations.

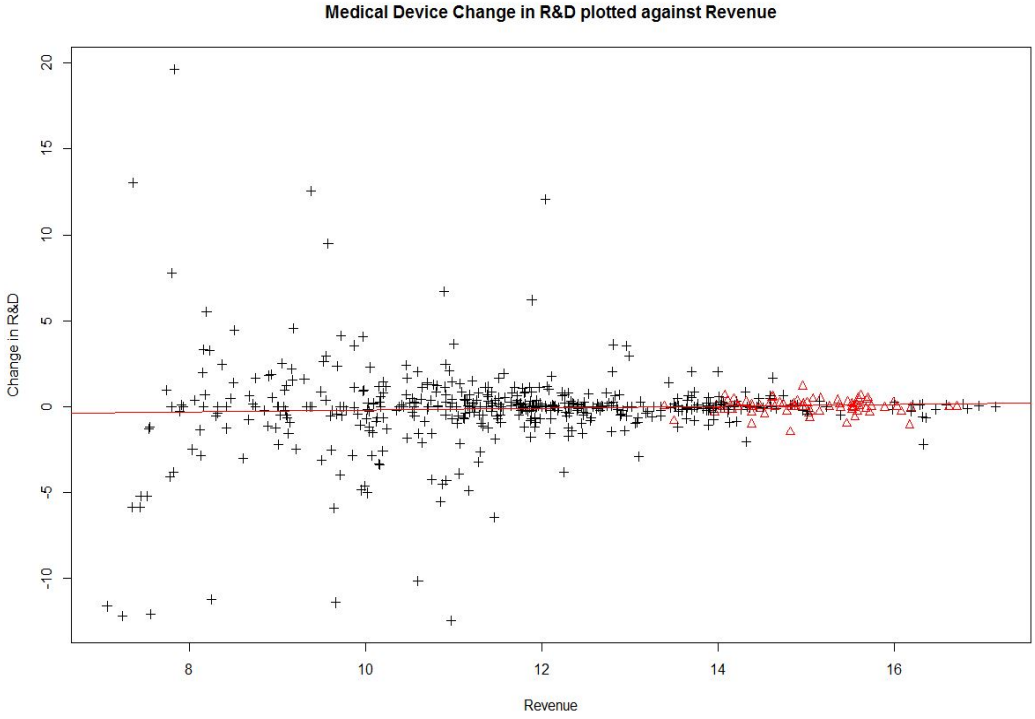

Figure 5: The relationship between log of revenue lagged one period and change in R&D-intensity in the medical device sample. The red dots are treated observations (including an M&A deal) and the black dots are untreated observations. The red line is a linear regression line estimated on the treated observations.

In this dataset the high revenue acquiring companies appear to follow the same data generating process as other companies which suggests that revenue is not correlated to R&D change in way that would affect the regression. I therefore decide not to include the revenue variable in the propensity score to achieve a better covariate balance. The disadvantage to this is of course that I risk introducing bias into the estimates if revenue is a confounder of M&A and change in R&D intensity.

The average revenue in the untreated pharmaceutical sample is 1 864 290 thousand Euros and 803 551 thousand Euros in the untreated medical device sample. These are by no means small research companies lacking the means to market their first product. This suggests that removing revenue as a control variable therefore not necessarily violate any assumptions assuming that revenue does not impact change in R&D intensity for companies of this size.

Including revenue in the IPTW in fact reduces the balance of the medical device revenue from an absolute standard difference of 44 to 122, in the case of pharmaceuticals it increases the absolute standard difference from 11 to 22 also worsening the problem. Checking the correlation between change in R&D spendings between period t and t+1 and revenue in

period t gives a correlation of 5.4% in the medical device sample and negative 6.6% in the pharmaceutical sample after log transformations to improve correlation.

When including the variable in the propensity score the covariates are balanced better in the pharmaceutical sample than in the medical device sample and running the final regression on R&D-change does not give any significance of revenue.

I therefore decide to drop the revenue variable from the study and proceed without it.

9.2 Stratifying

I stratify the data into six quantiles based on the propensity score. Treated companies have a higher propensity score on average as would be expected. Very few treated observations are in the first two quantiles making inference difficult.

	Pharmaceutical		Medical Device	
Quantile	Control	Treated	Control	Treated
1	122	6	71	4
2	119	8	69	5
3	108	19	68	6
4	100	27	64	11
5	102	25	53	21
6	63	64	50	24

Table 11: Distribution of treated and controls in the six stratas

I check the covariate balance within the six stratas using the standardized difference and compare against the full sample.

Below in table 12 are the standardized differences in the pharmaceutical sample:

	Full Sample	1	2	3	4	5	6
R&D Intensity	20.19	84.77	-34.71	99.27	14.29	34.57	-65.51
Cash	9.06	-5.44	-23.95	30.06	-16.25	0.92	-19.42
Tobin's Q	15.61	-8.43	8.41	0.31	13.30	-41.31	-17.20
Joint Venture	26.46	-	-	-13.61	-	-	21.00
Divestment	66.61	-	-	-	-20.10	9.16	34.47
US	24.79	-	-55.50	39.09	-6.02	-0.40	-14.01
Japan	-51.98	-	-6.12	-13.61	-20.10	9.16	-14.41
Average	30.67	32.88	25.74	36.47	15.01	15.92	26.57

Table 12: Standardized differences for the full sample and the six quantiles in the pharmaceutical sample

The balance was improved in all groups but quantile one and three. The individual balance of several covariates has been severely worsened in some groups which indicates that there might a problem with bias or model misspecification when using groups for estimation.

Below in table 13 are the standardized differences in the medical device sample:

	Full Sample	1	2	3	4	5	6
R&D Intensity	-7.69	-58.01	7.18	-48.33	13.02	-33.90	43.55
Cash	5.94	-89.23	9.24	20.37	5.44	3.51	-5.23
Tobin's Q	12.23	34.60	-9.66	55.89	-21.20	10.95	-37.88
Joint Venture	12.48	-	-	-	-	-	12.34
Divestment	33.14	-	-	-	-17.68	-3.98	24.49
US Company	34.95	-50.04	-22.91	-34.47	40.85	-4.80	-1.78
Japanese Company	-25.98	-37.34	-6.64	27.12	-31.12	-	30.70
Average	18.91	60.62	11.13	37.24	21.55	-	22.28

Table 13: Standardized differences for the full sample and the six quantiles in the medical device sample

The stratifying has improved the average balance in the second quantile but reduced the average balance across the other quantiles. A large part of the problem appears to be an increase in the imbalance of the R&D intensity and Tobin's Q covariates. All in all the groups suffer similar problems as in the pharmaceutical sample and across many covariates the problems have been exacerbated by the stratifying.

9.3 Graphs and Tables

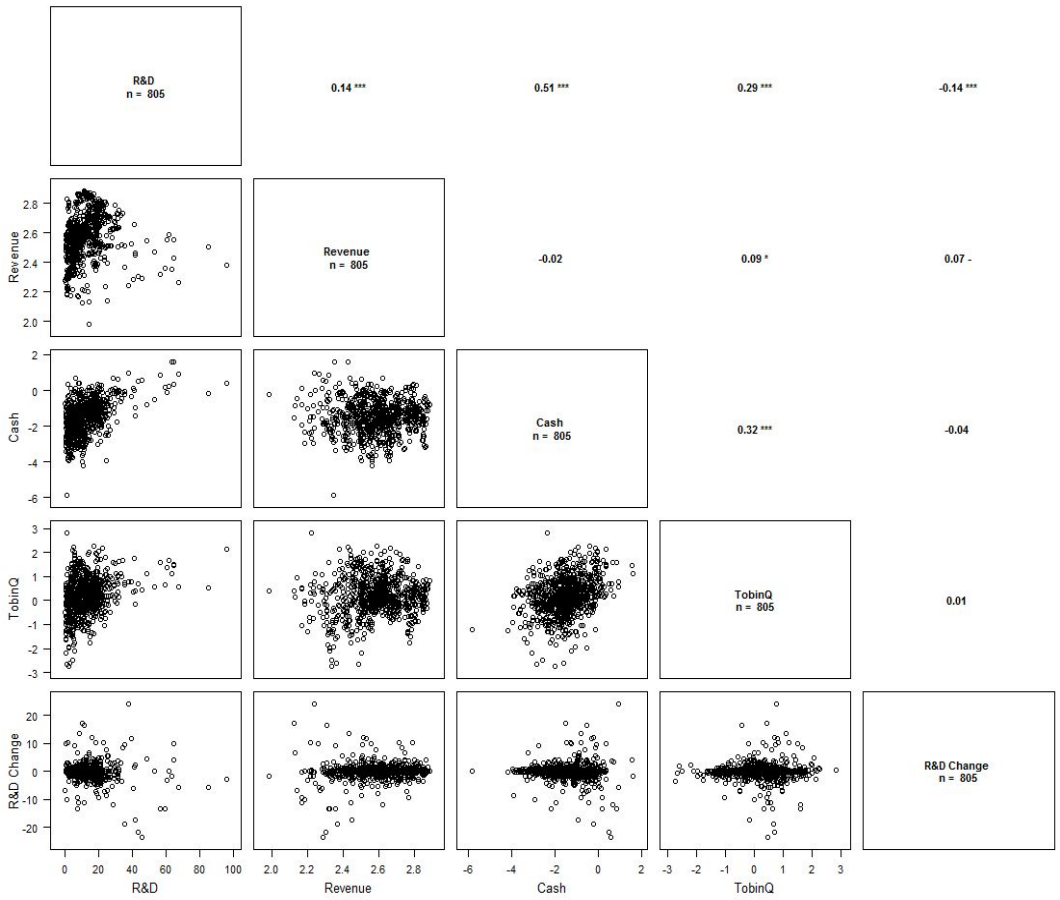

Figure 6: Correlation plot of the continous variables in the pharmaceutical subset

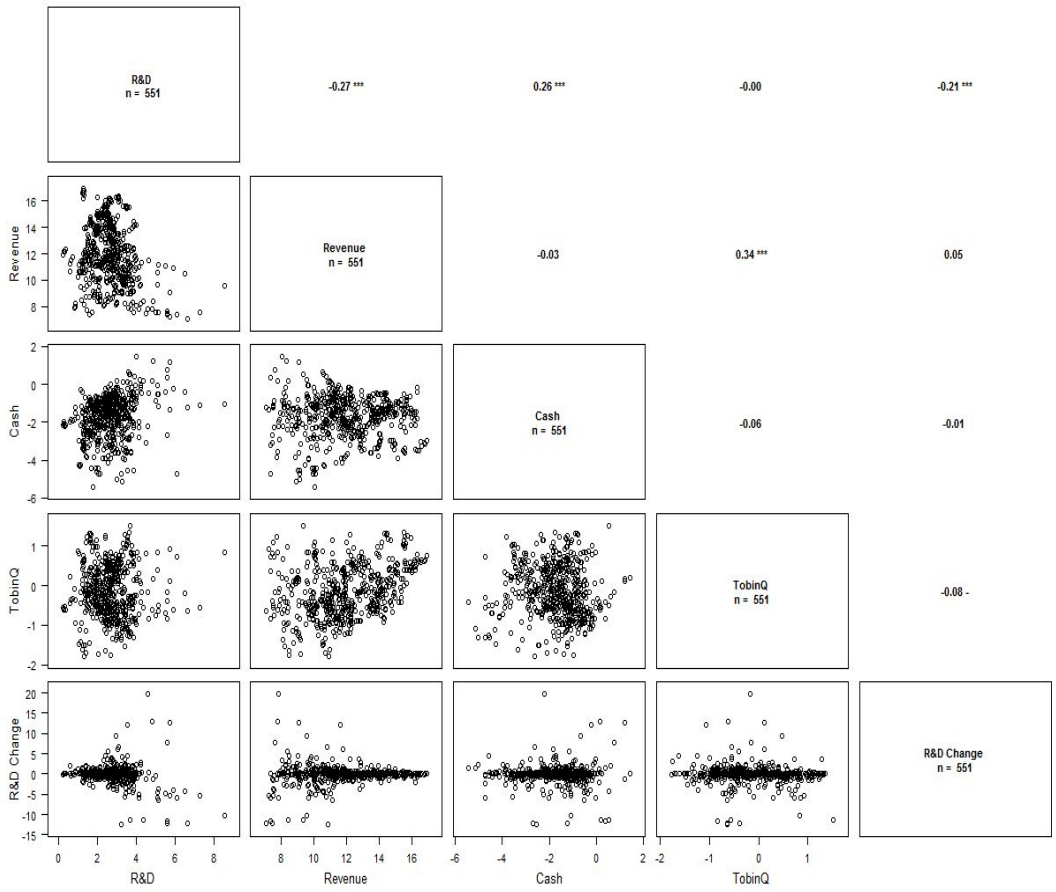

Figure 7: Correlation plot of the continous variables in the medical device subset

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.8797	1.0574	1.78	0.0759
M&A	-1.6999	5.4972	-0.31	0.7572
M&A Multi	0.6211	0.6061	1.02	0.3058
Total Assets Change	1.7774	0.4369	4.07	0.0001
Cash	0.4530	0.3007	1.51	0.1324
R&D Intensity	-0.3779	0.0231	-16.33	0.0000
Tobin's Q	0.8698	0.3441	2.53	0.0117
Joint Venture	-2.2244	1.5119	-1.47	0.1416
Divestment	2.7912	0.6686	4.17	0.0000
Horizontal	-1.5546	4.4338	-0.35	0.7260
Mixed Industry	-2.0828	4.3964	-0.47	0.6358
Cross Border	5.3341	2.3327	2.29	0.0225
Mixed Border	3.5317	2.1061	1.68	0.0940
US Company	0.1529	0.6373	0.24	0.8105
Japanese Company	1.6200	0.5474	2.96	0.0032
Time Dummies	Yes	-	-	-
M&A * M&A Multi	0.7410	2.5917	0.29	0.7750
M&A * Total Asset Δ	-1.7937	0.8151	-2.20	0.0281

Table 14: Pharmaceutical sample when the effect on R&D-intensity is measured between t+0 and t+3

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.7053	0.8681	1.96	0.0501
M&A	0.0252	2.0034	0.01	0.9900
M&A Multi	0.2529	0.5118	0.49	0.6215
Total Assets Change	0.7935	0.3662	2.17	0.0308
Cash t-1	-0.1185	0.1390	-0.85	0.3943
R&D Intensity	-1.3773	0.1728	-7.97	0.0000
Tobin's Q	0.2012	0.1080	1.86	0.0632
Joint Venture	-0.5731	2.2292	-0.26	0.7972
Divestment	0.2646	0.5545	0.48	0.6335
Horizontal	0.1301	0.7020	0.19	0.8531
Cross Border	0.0258	0.6848	0.04	0.9699
US Company	0.6217	0.4001	1.55	0.1210
Japanese Company	-0.1409	0.5019	-0.28	0.7791
Time Dummies	Yes	-	-	-
M&A * M&A Multi	-0.2445	2.0439	-0.12	0.9048
M&A * Total Asset Δ	-0.6254	0.8282	-0.76	0.4506

Table 15: Medical device sample when the effect on R&D-intensity is measured between t+0 and t+3

		Original Sample	Final Sample
Total	Total Number of Observations	808	763
	M&A	151	149
	Multi M&A Acquistions	304	301
	Horizontal	43	43
	Mixed Industry	105	103
	Cross Border	64	63
	Mixed Border	92	91
US	Total Number of Observations	224	221
	M&A	57	57
	Multi M&A Acquistions	88	88
	Horizontal	13	13
	Mixed Industry	42	42
	Cross Border	34	34
	Mixed Border	24	24
Japan	Total Number of Observations	288	248
	M&A	22	22
	Multi M&A Acquistions	80	79
	Horizontal	12	12
	Mixed IndJPtry	10	10
	Cross Border	8	8
	Mixed Border	16	16
EU	Total Number of Observations	296	294
	M&A	72	70
	Multi M&A Acquistions	136	134
	Horizontal	18	18
	Mixed Industry	53	51
	Cross Border	22	21
	Mixed Border	52	51

Table 16: Number of observations of the deal specific variables in the pharmaceutical sample

		Original Sample	Final Sample
Total	Total Number of Observations	552	446
	M&A	75	71
	Multi M&A Acquistions	136	120
	Horizontal	32	31
	Mixed Industry	43	40
	Cross Border	38	37
	Mixed Border	37	34
US	Total Number of Observations	304	293
	M&A	60	56
	Multi M&A Acquistions	88	84
	Horizontal	27	26
	Mixed Industry	33	30
	Cross Border	34	33
	Mixed Border	26	23
Japan	Total Number of Observations	120	78
	M&A	7	7
	Multi M&A Acquistions	16	12
	Horizontal	2	2
	Mixed IndJPtry	5	5
	Cross Border	2	2
	Mixed Border	5	5
EU	Total Number of Observations	128	75
	M&A	8	8
	Multi M&A Acquistions	32	24
	Horizontal	3	3
	Mixed Industry	5	5
	Cross Border	2	2
	Mixed Border	6	6

Table 17: Number of observations of the deal specific variables in the medical device sample

	Untransformed				Transformed				Weighted			
	Untreated		Treated		Untreated		Treated		Untreated		Treated	
	Mean	Var	Mean	Var	Mean	Var	Mean	Var	Mean	Var	Mean	Var
Cash	0.35	0.21	0.34	0.09	-1.51	0.92	-1.41	0.73	-1.50	1.34	-1.53	4.49
R&D	11.91	136.33	13.81	48.02	11.91	136.33	13.81	48.02	12.80	241.05	13.89	256.71
Tobin's Q	1.57	1.99	1.83	2.56	0.15	0.61	0.32	0.54	0.24	0.75	0.24	0.50
Joint Venture	0.01	0.01	0.07	0.06	0.01	0.01	0.07	0.06	0.03	0.15	0.02	0.01
Divestment	0.08	0.07	0.35	0.23	0.08	0.07	0.35	0.23	0.15	0.35	0.13	0.04
US dummy	0.25	0.19	0.38	0.24	0.25	0.19	0.38	0.24	0.30	0.32	0.28	0.19
Japan dummy	0.40	0.24	0.15	0.13	0.40	0.24	0.15	0.13	0.32	0.18	0.35	1.30

Table 18: Descriptive data for the non-deal specific variables in the pharmaceutical sample

	Untransformed				Transformed				Weighted			
	Untreated		Treated		Untreated		Treated		Untreated		Treated	
	Mean	Var	Mean	Var	Mean	Var	Mean	Var	Mean	Var	Mean	Var
Cash	0.30	0.15	0.27	0.03	-1.73	1.23	-1.62	0.80	-1.70	1.31	-2.03	9.76
R&D	8.37	59.91	6.63	9.47	2.68	1.19	2.51	0.33	2.55	1.21	2.65	5.95
Tobin's Q	1.57	2.34	1.83	1.08	1.57	2.34	1.83	1.08	1.68	2.89	1.85	4.04
Joint Venture	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00
Divestment	0.04	0.03	0.19	0.15	0.04	0.03	0.19	0.15	0.07	0.11	0.06	0.02
US dummy	0.51	0.25	0.80	0.16	0.51	0.25	0.80	0.16	0.67	0.28	0.62	0.29
Japan dummy	0.24	0.18	0.09	0.09	0.24	0.18	0.09	0.09	0.17	0.13	0.17	0.43

Table 19: Descriptive data for the non-deal specific variables in the medical device sample

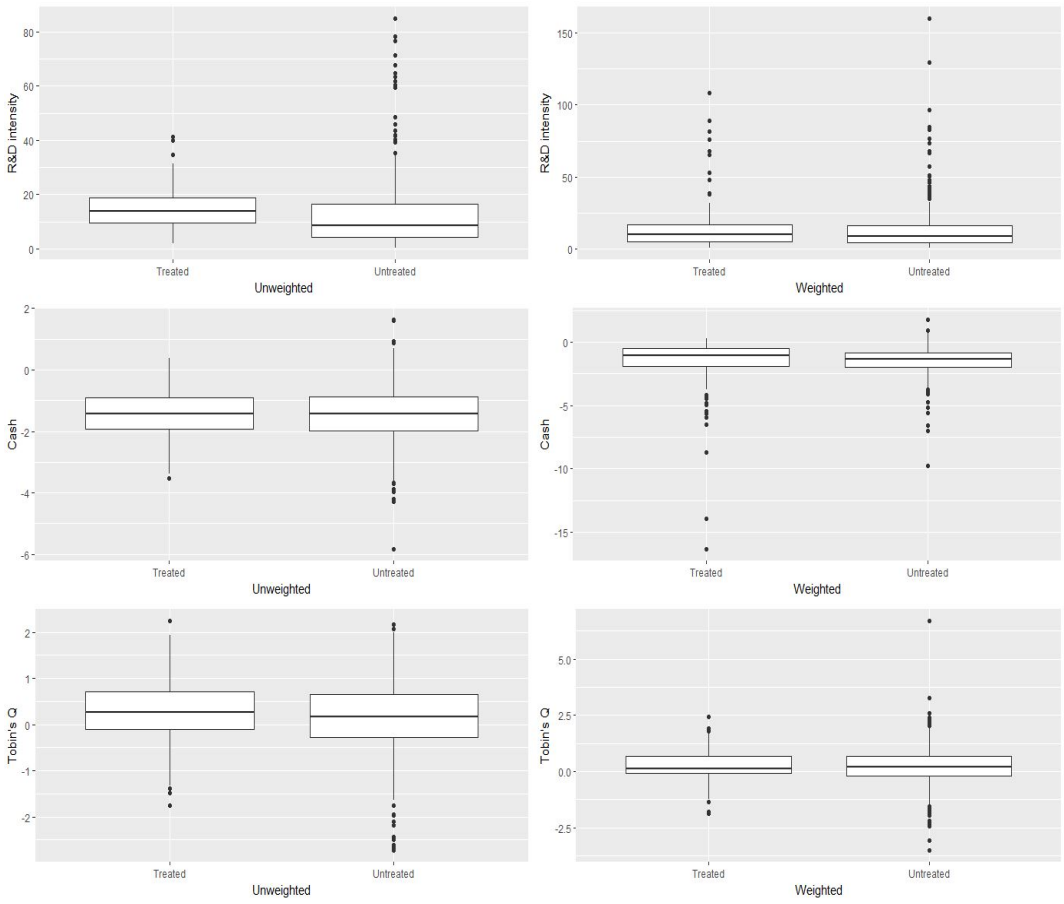

Figure 8: Boxplot of the continous variables in the pharmaceutical sample

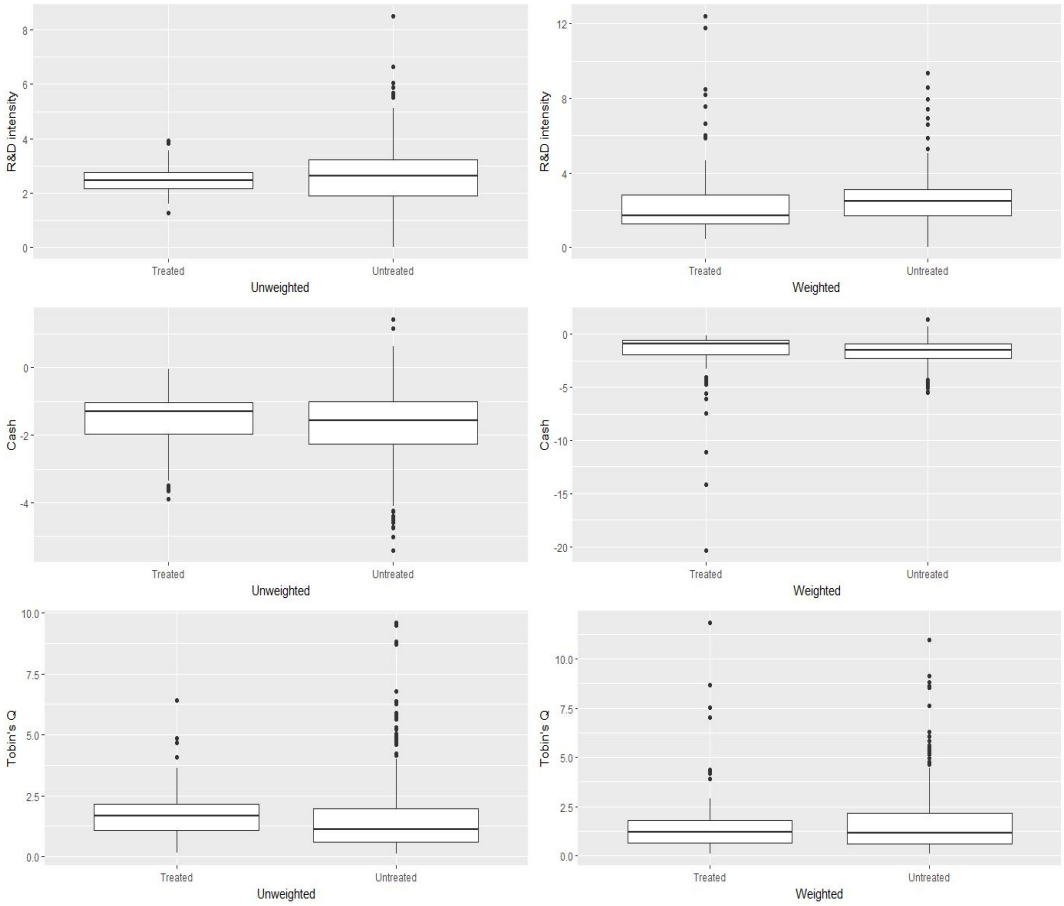

Figure 9: Boxplot of the continous variables in the medical device sample