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Discussion Papers

Deutsches Institut für Wirtschaftsforschung 2013

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IMPRESSUM

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http://www.diw.de

ISSN print edition 1433-0210
ISSN electronic edition 1619-4535

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M&A and R&D: Asymmetric Effects on Acquirers and Targets?

Florian Szücs*

October 2013

Abstract

We evaluate the impact of M&A activity on the growth of R&D spending and R&D intensity of 265 acquiring firms and 133 merger targets between 1990 and 2009. We use different matching techniques to construct separate control groups for acquirers and targets and use appropriate difference-in-difference estimation methods to single out the causal effect of mergers on R&D growth and intensity. We find that target firms substantially decrease their R&D efforts after a merger, while the R&D intensity of acquirers drops due to a sharp increase in sales.

Keywords: Mergers, R&D growth, R&D intensity, propensity-score matching, difference in difference estimation

JEL Classification: D22, G34, O3

1 Introduction

This article contributes to the growing empirical literature on the nexus between mergers and acquisitions (M&A) and the incentive of firms to allocate resources to research and development (R&D) and hopes to overcome some of the shortcomings of previous efforts on the same issue. An important improvement over the existing literature is the explicit differentiation of effects on acquiring and target firms. Previous studies either focus on only one group (Bertrand, 2009; Desyllas and Hughes, 2010) or include both acquiring firms and merger targets in a pooled estimation setting (Cassiman et al., 2005; Ornaghi, 2009), due to either small sample sizes or the inability to differentiate the correct roles. However, this means that either only half of the affected firms are examined or that it is assumed that acquirer and target are symmetrically affected in the aftermath of the merger. This, however, seems to be a strong and unjustified assumption: acquiring and target firms usually differ substantially with respect to their size

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I would like to thank Klaus Gugler as well as participants of the 4^{th} ZEW Conference on Innovation and Patenting in Mannheim for valuable comments. Supported by funds of the *Oesterreichische Nationalbank* (Anniversary Fund, project number: 14075).

and success (Gugler et al., 2003), but also with respect to their goals and bargaining power in managing post-merger business affairs. Thus, neglecting this distinction is likely to conceal an important source of heterogeneity in the impact of mergers on firm-level innovation activities.

Furthermore, earlier studies on the subject matter were usually either of limited geographical scope (Bertrand, 2009; Stiebale and Reize, 2011) or restricted to certain industries (Hagedoorn and Duysters, 2002; Ornaghi, 2009). The database utilized in this study contains firms from most major industrialized nations, active in numerous different industries. Thus we hope to overcome any industry or country-specific effects and provide a general overview of the phenomena in question.

Restructuring R&D activities is a protracted affair that can take a number of years to complete. Therefore the explanatory power of short-term studies on the topic is limited. To account for the relevant time horizon, we use balance sheet data from up to 6 periods after the acquisition year. Time windows of $[t+1, t+6]$ years after the acquisition year t allow us to check for drawn-out restructuring efforts after the combination. While we use pre-merger data (period $t-1$) in the estimation of the *ex-ante* probability to merge, data from the merger period t is excluded from the analysis to avoid the measurement of consolidation effects of the merger.

The goal of this article is to contribute to the empirical discussion on the relationship between mergers and the *incentive* to conduct innovative efforts. We therefore analyze the effect of mergers on two measures of R&D inputs: the growth of R&D expenditures and R&D intensity, defined as the ratio of R&D expenditures over sales. By making R&D inputs instead of R&D outputs (patents, new products) the focus of the analysis, we examine the firms' willingness to invest in innovation instead of their success in attaining it. Thus, questions about synergies and changes in the efficiency of research are not addressed by this article. However, Hagedoorn and Cloodt (2003) show that measures of R&D inputs and outputs are highly correlated and conclude that there is no major systemic disparity between them.

In terms of methodology, we follow the suggestion of Blundell and Costa Dias (2000) and combine matching techniques with difference-in-difference (DiD) estimation. In the baseline specification we first use propensity-score matching (PSM) to define a measure of similarity and then employ a nearest-neighbor (NN) matching algorithm to construct control groups. We corroborate the robustness of the matching procedure in both stages by creating alternative control groups using i) PSM but a caliper matching algorithm and ii) a measure of similarity based on vector-distances (instead of PSM) and NN matching. In each case, the heterogeneity of acquiring firms and targets is accounted for by constructing separate control groups from a very rich pool of potential control observations. The effects on R&D growth and intensity are then evaluated using DiD estimation in the three samples thus obtained.

Our findings are consistent with the interpretation that acquisition targets are chosen because they have an attractive technological portfolio, which the acquirers start to exploit in the post-merger period. The acquirers continue to pursue their own research agenda - their R&D growth is only slightly and mostly insignificantly lower than that of the control group - but experience a sizeable reduction in R&D intensity, caused by a vast increase in sales. For the targets, both

R&D growth and R&D intensity decline substantially in the post-acquisition period.

The article proceeds by reviewing the theoretical and empirical literature on the relationship of M&A and R&D in section 2. The data sources and the empirical strategy are discussed in section 3 and section 4 presents the findings. Section 5 concludes.

2 Theory & literature

The literature on the effects of mergers on innovation is a large and fast-growing field, since it receives attention from both economics and management scholars. Therefore this section does not aim to offer a comprehensive overview, but rather to first summarize the theory arguments on the relationship between M&A and R&D that have been brought forward and then present a selection of thematically and methodologically related empirical articles.

From a theory perspective, the relationship between mergers and innovation is quite ambivalent. Arguments from the literature of industrial organization tell us that mergers can entail economies of scale and scope, that they make possible the elimination the duplicate efforts in similar research projects or that they may increase the appropriability of inventions by reducing technological spillovers to competitors. Additionally, an increase in market power due to a merger could also feed back onto the innovation strategy of the merging firms. Thus while there exists a multitude of potential effects, their direction is not always clear. Economies of scale or scope could actually be diseconomies due to an increase in organizational requirements; elimination of duplicate efforts should reduce R&D inputs, but not outputs; if the appropriability of inventions is low due to technology spillovers, mergers could lead to increases in R&D, but if it is high the reverse would typically be the case. Finally, the relationship of competition and innovation is not conclusively settled from either a theoretical or an empirical point of view (Aghion et al., 2005).

Possible explanations from the corporate governance literature assert that mergers require an effort from the firms' managers and thereby reduce the attention they pay to R&D projects, that the financial expenditures caused by acquisitions will typically reduce the resources available for research in subsequent years, that managers become more risk averse after mergers or that increased debt will make it less attractive to conduct R&D for tax advantage reasons. All of these lines of reasoning would typically point to a decrease in R&D efforts after a merger.

Due to this multitude of explanatory approaches offered from theory (a more comprehensive overview is presented in Veugelers (2006)), many empirical studies assume an agnostic stance with respect to their expectations. Similar to the theoretical literature, there is a wide range of approaches and findings, some of which are discussed below.

An article closely related to this one is the study by Ornaghi (2009), which analyzes the effect of 27 mergers in the pharmaceutical industry on various measures of R&D inputs and outputs. A combination of PSM and DiD estimation and, alternatively, a measure of technological relatedness is used to address issues of endogeneity. When estimating the effects on acquirers and targets in a pooled setting, Ornaghi finds a decrease in innovative efforts after mergers. Stiebale and Reize (2011) report similar findings from a sample of 304 German merger targets and explicitly control for structural zeros in reported R&D values (see section 3.4 and Kleinknecht (1987)). The relationship between R&D intensity and acquisition activity in the electronic and electrical equipment industries is investigated in Blonigen and Taylor (2000). They find a strong negative correlation between the two and cautiously conclude that firms in their sample specialize in either 'making' or 'buying' technology. Hitt et al. (1991) report that acquisitive growth has a negative impact on firm innovation in terms of both inputs (R&D intensity) and outputs (patent intensity). They conclude that their findings are not compatible with research synergies, but could be caused by an increase in managers' risk aversion after mergers which lowers their commitment to innovation.

Studies that find increases in R&D activity after mergers include Bertrand (2009) and Stiebale (2013). Using a sample of 123 French acquisition targets in cross-border mergers and a combination of PSM and DiD methods, Bertrand (2009) finds that R&D budgets increased significantly three years after acquisition. Stiebale (2013) focuses on acquirers (324 firms) and finds that their R&D intensity significantly increases after mergers. Looking at firms in research alliances instead of mergers, Cefis et al. (2009) find that members of an alliance have higher aggregate R&D spending, but lower R&D efficiency than independently researching firms.

Ahuja and Katila (2001) distinguish technological acquisitions (i.e. acquisitions whose primary aim is technology transfer) from nontechnological acquisitions. Their sample consists of 72 large chemical companies, engaging in 534 acquisitions. Their analysis reveals that nontechnological acquisitions do not significantly influence innovative output. While technological acquisitions generally improve innovative output, the extent of the improvement depends on the technological relatedness of the two firms in a nonlinear fashion. Cloodt et al. (2006) extend this approach to four high-tech industries. While their findings with respect to technological acquisitions are largely compatible with those of Ahuja and Katila, they find that nontechnological acquisitions have a negative impact on innovative performance after the merger.

Desyllas and Hughes (2010) analyze a sample of 2624 acquirers in high-tech industries using a similar empirical strategy. They find that the R&D intensity of an acquiring firm decreases in the period after a merger ($t + 1$) but increases again in the $t + 3$-period. R&D productivity is not significantly affected. They also find evidence in favour of the view that mergers between technologically-related firms perform better than mergers between firms that differ greatly with respect to their knowledge bases. This argument is also advanced by Cassiman et al. (2005), who distinguish between technological and market-relatedness and use a detailed sample of 31 mergers. In contrast to Desyllas and Hughes (2010), they find that technologically complementary (substitutive) firms increase (decrease) their R&D level after the acquisition. Moreover, effects on R&D efficiency are more advantageous in complementary mergers.

Bertrand and Zuniga (2006) examine the influence of mergers on R&D spending in manufacturing on the industry level and differentiate between domestic and cross-border mergers. They find no significant relationship on an aggregate level, but show that domestic merger have a positive effect on R&D spending in low-tech industries. However, domestic mergers impact negatively on medium-tech industries, which are in turn positively affected by inward cross-border mergers. The co-evolution of sales, employment, profits and R&D is studied in Coad and Rao (2010). They show that profit growth has little effect on R&D expenditures in subsequent years. Growth of sales or employment, on the other hand, entail significant increases in R&D spending, leading the authors to conclude that the firms aim for a roughly constant ratio of R&D to sales and employment.

As illustrated by this brief overview, theory predicts and empirical studies find an either positive, negative or ambiguous relationship on the effect of mergers on R&D efforts and no clear-cut empirical conclusions have emerged so far. Still, most reviews (an excellent survey is provided by Veugelers (2006)) conclude in favour of a weak, negative relationship between M&A and R&D. The present study aims to advance the above literature in at least three ways. First, we account for potentially heterogeneous effects on acquirers and targets by separately measuring the effect of the merger on them. Second, the focus of analysis in this study is not confined to a specific industry or country. Finally, the use of PSM and DiD features prominently in the above studies. We follow the same approach here, but evaluate the robustness of our findings with respect to the choice of control group by using different matching techniques.

3 Data & empirical strategy

The dataset used in this study was created by joining datasets of mergers that were notified to either the European Commission (EC) or the US Federal Trade Commission (FTC) between 1990 and 2009.[1] These cases were reported to the respective regulatory authority by companies from 25 different nations[2] and many different product markets[3] and were either cleared or subjected to remedies by the authorities. The only common factor in all of these mergers is that they were significant enough to meet the notification thresholds of the EC or FTC.[4] Thus the sample does not include minor asset acquisitions, which entail no significant effect on companies, but major transactions resulting in significant corporate restructuring under the scrutiny of one of the two most important antitrust jurisdictions. Some of the firms in the sample merge more than once during the observation period; to ensure that the effects of multiple mergers do not confound the results, we drop firms with multiple acquisitions within four years from the sample.[5]

We combine this dataset of mergers with balance-sheet data containing the R&D expendi-

[1] See Morgan (2001) for a comparison of the EU and US competition authorities' approaches to innovation issues in merger control.

[2] Most of the firms involved have their headquarters in the US, followed by Germany, France and the UK.

[3] 38 different 2-digit SIC codes are represented in the sample. The biggest single sector is SIC 28 ('Chemicals and allied products'), which includes a quarter of all observations.

[4] A merger has to be notified to the FTC if the deal-value exceeds 70.9 million USD (as of 2013) and some additional conditions on total sales and assets are fulfilled. The EC uses a combined criterion of at least 5,000 million Euro worldwide turnover and at least 250 million Euro community-wide turnover, subject to further qualifications.

[5] While this cutoff is arbitrary, it affects only a small part of the sample and either increasing the number of years required between mergers or, alternatively, only retaining firms that merge only once in the sample period, does not materially affect the results.

tures of the merging parties and other relevant variables. After dropping all observations for which R&D expenditures data was not available in a time window of $[t-1, t+1]$ around the merger, we are left with 398 firms (265 acquirers and 133 merger targets) for which we have full R&D data.[6] When checking for the completeness of R&D data, all observations reporting missing R&D values were dropped, but companies reporting zero R&D expenditures were retained.

This sample of merging firms was then complemented with a very large sample of potential controls, from which the relevant control groups are constructed. Since the set of potential controls is more than 50 times larger than the set of merging firms, we are confident that a sufficiently close match can be found for each treated observation. For each of these firms we downloaded time series of balance sheet data on total assets, income, total sales, total debt, number of employees, firm age and R&D expenditures from the Thomson Reuters Worldscope database. After converting all values to USD and calculating the growth rate of R&D expenditures (defined as the percentage change in R&D expenditures between two consecutive periods) as well as R&D intensities (the ratio of R&D expenditures to total sales)[7] and profitability (the ratio of net income to total assets) for all firms in all periods, we take logs of the total assets, sales, employees and total debt variables.[8]

Table 1 provides summary statistics on the acquiring firms and the target firms in the periods prior to and after the mergers, while figure 1 illustrates the distribution of merger occurrences over the sample period.

A first look at the resulting dataset confirms that the mergers scrutinized by the FTC and the EC are indeed significant in terms of size: the average merging firm spends over 20 times more on R&D, has over 15 times more total assets and over 10 times more employees than the average firm in the dataset. Even when controlling for size effects by comparing R&D intensities, merging firms exhibit significantly higher values. It thus appears that the average firm involved in a merger, which is being scrutinized by an important competition authority, is quite different from the average firm listed on any stock market in the industrialized world. In consequence, when we want to infer the effect of merging activity on innovation efforts, we must take care in selecting an appropriate non-merging comparison group.

[6] Notice that acquirers are overweighed in the sample. This is due to the fact that post-merger data on targets is only available if the company continues to exist after the acquisition. Thus, the target firms in the sample display a high degree of organizational autonomy and fall in the preservation category of the acquisition integration matrix proposed by Haspeslagh and Jemison (1991) and the results of this study only apply to surviving targets, i.e. acquired firms, that do not become completely organizationally integrated with their buyer. See Puranam and Srikanth (2007) for a discussion of structural integration vs. structural separation of merger targets with a regard to innovation.

[7] In some cases, R&D intensities in excess of one were found, suggesting higher R&D expenditures than sales. Since these values are not implausible per se (most of them are found in high-tech sectors like pharmaceuticals or biotechnology) they were kept in the sample. To prevent any bias in the estimation coefficients due to outliers, R&D intensity values were capped at 0.5. All results are qualitatively robust to dropping these observations.

[8] We add one to all values of zero (e.g. the R&D expenditures of non-innovative firms) before taking the logarithm.

Table 1: Summary statistics for the pre- and post-merger periods

	Acquirers		Targets	
	Before	After	Before	After
R&D Intensity	0.07	0.06	0.08	0.07
R&D Growth	0.14	0.12	0.10	0.04
Profitability	0.06	0.04	−0.01	0.03
Total Assets	15.60	16.34	15.40	15.92
Net Sales	15.42	16.08	15.07	15.55
Employees	9.90	10.39	9.60	9.85
Total Debt	12.28	12.14	11.01	10.11
Age	37.02	39.22	38.33	40.69

Notes: Average values of firm-level variables for acquirers and targets in the pre- and post-merger periods.

3.1 Matching: missing data and self-selection

Studies estimating the causal effect of a treatment on a group of firms or persons receiving said treatment face the fundamental problem of not knowing what would have happened in absence of the treatment. This is often called the problem of the missing counterfactual. If we denote (following Rosenbaum and Rubin (1983)) the outcome of observation unit i receiving treatment by r_i^1 and the outcome in absence of treatment by r_i^0, the individual treatment effect is given by

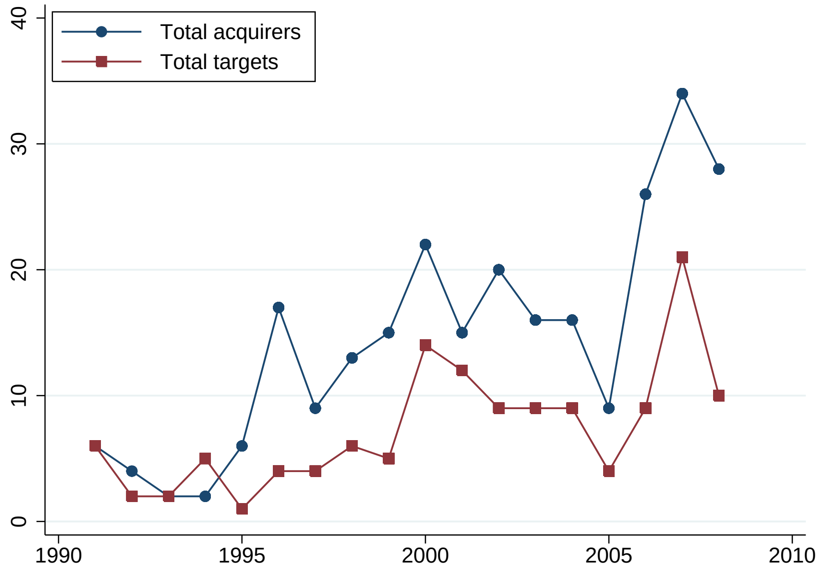
$$\Delta_i = r_i^1 - r_i^0. \tag{1}$$

Since in reality only one of the possible outcomes is observed, we are confronted with a missing data problem in estimating the individual treatment effect. Experimental studies overcome this hurdle by randomly assigning one group of observations to treatment - the treatment group - while another group of observations does not receive treatment, the control group. The difference in outcome between the two groups can then be attributed to the effect of the treatment and is called the average treatment effect (ATE):

$$\mathrm{ATE}_{\mathrm{exp}} = E(r_i^1 - r_i^0). \tag{2}$$

Non-experimental studies face the additional difficulty that an appropriate control group is often hard to come by. Since the decision to receive treatment is not randomly determined by an experimenter, but - in the case of mergers - decided by the management of the firms, the assignment to treated or control group cannot plausibly be assumed to be random. Therefore, in addition to the missing data problem, one also faces a problem of endogeneity or self-selection, suggesting that the decision to receive treatment is caused by certain firm-specific characteristics that, in turn, could also influence the effect of the treatment. Not recognizing this complication could cause a systematic bias in the estimated coefficients, since effects attributed to the treatment might actually be due to other factors.

Figure 1: Distribution of deals over time



For example, as mentioned above, merging firms in this sample are much larger than the average firm; not taking this fact into account might lead us to attribute certain effects to the merger, while they actually could be a consequence of the size of the merging firm. It is therefore necessary to construct a control group that has the same pre-treatment characteristics and thus the same *ex-ante* probability of receiving treatment (i.e. being involved in a merger as acquirer or target) as the group of merging firms. In non-experimental studies, the ATE needs to be calculated conditionally on the treated and control observations not being systematically different with respect to a vector of characteristics, c_i:

$$\text{ATE}_{\text{nonexp}} = E(r_i^1 - r_i^0 | c_i) = E(r_i^1 | c_i) - E(r_i^0 | c_i). \tag{3}$$

We thus need to artificially construct a sample in which the decision to engage in a merger is not driven by certain firm characteristics and hence, to the largest extent possible, random. If successful, this both yields an appropriate control group for the estimation of the average treatment effect and eliminates the problem of self-selection.

3.2 Matching: measures of similarity and selection algorithms

A common approach in the literature to account for the missing data and self -selection problems is to construct a control group using a matching procedure and DiD estimation.[9] The matching procedure consists of two separate steps: first a measure of similarity is calculated for both

[9]Other options would be to follow an instrumental variable approach or to formulate an equation describing selection into the treatment group and estimating it jointly with the average treatment effect.

treated and untreated firms, which then serves as the basis for a matching algorithm that selects the control group. Below we describe two different approaches to calculating similarity as well as two different matching algorithms, which are in turn used to create three different control groups for estimation. Thus, in addition to the baseline results, where the control group is created using PSM and NN matching, we present two additional sets of results: first, we employ caliper matching instead of NN matching to perform a check on the second stage of the matching procedure; in the second set of results the propensity-score is abandoned in favour of a vector norm based measure to perform a check on the first stage.

The propensity score (Rosenbaum and Rubin, 1983, 1985) predicts the probability of receiving treatment based on observable characteristics using maximum likelihood estimation. By matching treated observations to control observations based on their propensity scores, one obtains two groups that do not differ systematically with respect to the observable characteristics that the propensity score was calculated upon (see Rosenbaum and Rubin (1983) for the proof). PSM thus controls for the observable heterogeneity between treated and control observations. As an alternative to PSM, we employ a vector norm approach (proposed and described in detail in Abadie et al. (2004)), which treats the observable characteristics as a vector and calculates the distance to another observation as the norm of the difference between the two vectors. Both measures are calculated using pre-merger ($t-1$) data to ensure that the merger effect does not influence the matching.

We then use two different matching algorithms to construct control groups: nearest-neighbor matching and caliper matching. Each matching method faces a trade-off between variance of the estimates (depending on the size of the control group) and bias (depending on the similarity of the control group to the treated group, i.e. the quality of the matches).[10] Nearest-neighbor matching is probably the most intuitive matching algorithm and balances the trade-off between bias and variance: each merging firm is matched to exactly one non-merging firm from the same year. The match is thus the firm that is most similar to the merging firm based on the matching covariates in the year before the merger. Since every control is selected only once (matching without replacement), this yields a control group of the same size as the treated group. Caliper matching, on the other hand, matches each treated observation to multiple controls within a given radius and creates a control group that is larger than the treatment group, thus alleviating concerns about the variance of the estimates. Caliper matching is implemented by matching each treated observation to the three most similar control observations, given that none of them differ by more than 0.025 from the treated observation's propensity score.[11]

To summarize, we check the robustness of our findings with respect to the choice of control group by constructing three different control groups. In the baseline specification, we use propensity score and NN matching, which is a rather intuitive approach that has been frequently

[10]Caliendo and Kopeinig (2008) and Dehejia and Wahba (2002) discuss this trade-off and the merits of different matching approaches.

[11]The caliper was determined by following the suggestion of Rosenbaum and Rubin (1985) to choose a caliper size of $c = 0.25s$, where $s = \left[(s_1^2 + s_0^2)/2\right]^{\frac{1}{2}}$ and s_1^2 (s_0^2) refers to the estimated variance of the propensity score in the treated (control) group.

used. To construct the second control group, we again use PSM but employ a caliper algorithm to select the matches. For the third control group, we retain the NN matching but use a vector norm based approach in the calculation of similarity scores.

3.3 Matching: results

The covariates employed in the matching procedure are magnitudes that could potentially influence both the decision to merge and future R&D efforts, namely pre-merger R&D intensity and growth, as well as measures of pre-merger size and earnings (total assets, number of employees, profitability), debt and age of the firm. To account for possible nonlinearities in size and age we also include squared total assets and age terms. The dependent variable in both regressions is a dummy, indicating if a firm was an acquirer / a target in the following period.

Table 2 reports the estimated probit models and shows that acquiring firms are, on average, significantly more R&D-intensive, have more employees, a higher profitability and less debt than their non-merging peers. R&D growth is not a significant determinant for being an acquirer. While the coefficients of R&D intensity, total debt and employees of targets are comparable to those of acquirers in terms of sign and significance, R&D growth and profitability remain insignificant. The probability of being a target (an acquirer) appears to be convex (concave) in size as measured by total assets. The positive coefficient of the age of the firm along with the negative coefficient of the squared age term for both acquirers and targets suggest an inverse U-shaped relationship between age and the probability to merge: the average merging firm is neither very young nor very old.

Table 2: Propensity score estimation (probit model)

	Acquirers		Targets	
R&D Intensity	3.350^{***}	(0.328)	1.914^{***}	(0.377)
R&D Growth	-0.020	(0.059)	-0.087	(0.080)
Total Assets	0.636^{***}	(0.210)	-0.394^{***}	(0.137)
Total Assets^2	-0.014^{**}	(0.007)	0.021^{***}	(0.005)
Employees	0.187^{***}	(0.031)	0.144^{***}	(0.038)
Profitability	2.176^{***}	(0.268)	-0.232	(0.244)
Total Debt	-0.014^{**}	(0.006)	-0.031^{***}	(0.007)
Age	0.017^{***}	(0.005)	0.027^{***}	(0.006)
Age^2	-0.000^{***}	(0.000)	-0.000^{***}	(0.000)
Observations	66555		66423	
Pseudo-R^2	0.28		0.23	
Mergers	265		133	

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

After matching the respective control groups using the methods described above, we check whether a balanced sample was obtained by testing for systematic differences with respect to the covariates among treated and control observations in all six control groups. Table 3 reports the standardized biases before and after the respective matching procedures, as well as the reduction in bias achieved by matching. The standardized bias ($(\bar{X}_t - \bar{X}_c)/\sigma_t$, the difference in means of treatment and control group divided by the standard deviation in the treatment group) is the bias one incurs by comparing treated to non-treated firms. As can be seen from the first column of table 3, the initial biases between merging and non-merging firms are substantial.

All three approaches largely eliminate the biases between the treated and non-treated observations. Most standardized biases are reduced to below 10%, the percentage reduction in bias exceeds 90% for the majority of covariates and none of the remaining biases are statistically significant. Rubin (2001) and Stuart (2010) suggest that after matching, standardized biases should not exceed 25%. This criterion is generously met for all covariates by all matching approaches, allowing us to conclude that the matching algorithms succeed in purging the observable heterogeneity between treatment and control group: the two groups do not differ significantly with respect to the nine covariates employed in estimation of the propensity score.

Finally, we check the overlap of the three control groups (i.e. the amount of firms selected by more than one matching algorithm) to get an intuition of their dissimilarity. There is a moderate amount of control observations selected by both the PSM NN and the PSM caliper algorithm (the intersection of both sets of firms amounts to 25% of the union) and smaller overlaps for the PSM NN and vector norm NN samples (15%) and the PSM caliper and vector norm NN samples (16%). Thus while all approaches exhibit tendencies to select similar firms, there is enough variation among the samples to warrant separate analyses.

3.4 Structural zeros

Another possible bias arises due to the issue of structural zeros in accounting data on R&D spending (this is addressed in Stiebale and Reize (2011)). Many firms report zero R&D expenditures because they pursue very little or no innovative efforts and are therefore usually excluded from analysis. Yet, by excluding them one incurs a possible bias due to the selection into the group of innovative firms: it cannot be ruled out that the effect one analyzes works systematically different on innovative firms (R&D>0) than on non-innovative firms (R&D=0). To avoid any such bias, this sample includes both innovative and non-innovative firms: Almost 7% of merging firms in this sample report zero R&D expenditures in the merger period.[12]

3.5 Difference-in-difference strategy

After having created the relevant control groups, we proceed to estimate the effects of mergers on the variables of interest in a DiD setting. We construct time windows around the respective merger events and use observations of the merging firms and the relevant controls from $[t-3, t-1]$ and $[t+1, t+6]$, where t designates the period in which the combination took place. By using

[12]However, in an unreported robustness check we drop all firms reporting zero R&D expenditures and find that our results are only marginally affected.

Table 3: Standardized biases of covariates before and after matching

		PSM NN		PSM Caliper		Vector norm NN	
	Initial Bias (%)	Bias (%)	Reduction (%)	Bias (%)	Reduction (%)	Bias (%)	Reduction (%)
Acquirers							
R&D Intensity	16.25**	0.60	96.32	1.39	91.43	8.64	46.83
R&D Growth	14.80*	0.41	97.16	2.56	82.45	0.97	87.25
Total Assets	200.72***	1.15	99.43	8.69	95.68	10.26	94.85
Total Assets^2	203.97***	1.07	99.48	9.56	95.32	12.43	94.09
Employees	183.14***	0.41	99.78	6.59	96.41	9.54	94.79
Profitability	62.54***	1.47	97.67	1.31	97.92	6.26	90.76
Total Debt	89.05***	5.82	93.56	1.02	98.87	2.10	98.70
Age	65.62***	0.42	99.36	8.44	87.17	1.05	99.04
Age^2	59.00***	0.16	99.73	8.76	85.24	0.29	99.71
Targets							
R&D Intensity	6.05	1.70	71.90	1.89	66.92	3.86	46.10
R&D Growth	22.71*	1.12	95.08	6.26	72.53	0.17	98.85
Total Assets	163.29***	9.57	94.11	7.98	95.07	7.66	95.35
Total Assets^2	171.70***	10.76	93.70	8.83	94.83	10.10	94.32
Employees	146.17***	8.26	94.32	10.56	92.70	6.63	95.52
Profitability	19.72*	0.64	96.76	6.29	67.78	1.95	92.82
Total Debt	60.18***	20.72	66.62	1.59	97.40	2.72	97.85
Age	76.63***	5.66	92.56	2.32	96.92	5.91	95.17
Age^2	67.36***	9.37	85.95	4.15	93.71	4.76	95.65

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

a set of dummies indicating whether a firm was involved in a merger one year ago, two years ago and so on, we create a merger timeline, allowing us to track the effects on innovative efforts over the time window. In the R&D intensity regression, we include further dummies for all treated observations (separately for acquirers and targets, equal to one in all periods) to control for unobservable differences between the treated and control groups. We estimate the following model

$$\begin{aligned} \text{rdint}_{ij} &= \alpha + \sum_{t=1}^{6} \beta_t \text{acquirer}_{i,j-t} + \sum_{t=1}^{6} \gamma_t \text{target}_{i,j-t} + \delta \, \text{treat\_acq} \\ &+ \zeta \, \text{treat\_tar} + \eta \, \text{controls} + \varepsilon_{ij} \end{aligned} \tag{4}$$

The R&D intensity of firm i in year j is regressed on a set of merger dummies ranging from the year after the merger ($t = 1$) up to six years after the merger ($t = 6$) and indicating the role of the firm (acquirer or target), dummies for being an acquirer / a target and controls for industry, country and time effects. The β_t (γ_t) coefficients capture the deviation of acquirers' (targets') R&D intensity from that of their control group in period t, that is, they capture the treatment effect of the merger.

In the R&D growth regression, the dependent variable is a growth rate and thus purges individual fixed effects. We therefore exclude the acquirer/target dummies from the regression.

$$\text{rdgrowth}_{ij} = \alpha + \sum_{t=1}^{6} \beta_t \text{acquirer}_{i,j-t} + \sum_{t=1}^{6} \gamma_t \text{target}_{i,j-t} + \eta \, \text{controls} + \varepsilon_{ij} \tag{5}$$

Again, the merger's impact on acquirers (targets) is measured by the β_t (γ_t) coefficients. Period (t) is excluded from the regressions to avoid the measurement of consolidation effects.[13] For brevity, regression results in section 4 are reported in a pooled setting (targets and acquirers as well as their respective control groups), with the effects on the two groups being measured separately by the β_t's and γ_t's. Restricting estimation to the respective subsamples yields very similar results, which are available upon request.

4 Results

Figure 2 charts the mean growth of R&D spending by acquirers and targets around the merger. Prior to the merger both acquirers and targets exhibit strong R&D growth rates of between 9 and 14 percent. In the year of the merger, the R&D growth of acquirers jumps to almost 24% and then strongly declines in the periods after the acquisition, with a minimum of 2.5% growth 5 years after the merger. The spike in R&D growth at t can be attributed either to the consolidation of R&D efforts (i.e. R&D assets being moved from the targets' to the acquirers' books) or it could reflect one-shot investments by the acquirer to accomplish the absorptive

[13] Since R&D intensity is the ratio of two variables that are both similarly affected by consolidation effects, it might not be necessary to drop t in the R&D intensity regressions. While all results are robust to the inclusion of t, the set of results reported excludes the merger period in order to increase the comparability to the R&D growth regressions.

capacity required to successfully internalize the targets' R&D operations.[14] After this one-period spike, the incentive of acquirers to increase innovative assets seems to diminish.

The R&D growth of merger targets is high in the periods prior to the acquisition, but starts dropping immediately in the period of the merger. From $t-1$ to $t+2$, R&D growth declines from more than 10% to about 1%. After $t+2$, R&D growth starts to increase again, without reaching its former level in the observation period. It thus seems that the acquisition creates a slump in the target's R&D growth profile and that a substantial recovery period is needed to return to the former growth path. Using t-tests to compare pre- and post-merger periods, we find that that the R&D growth of acquirers (targets) is significantly lower at the 5% (1%) level after the merger.

Figure 2: R&D growth of acquirers and targets around the merger

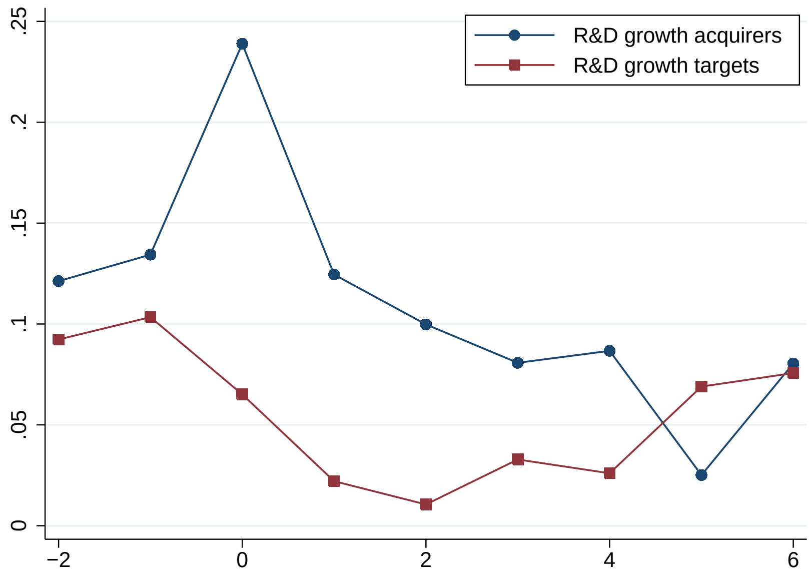
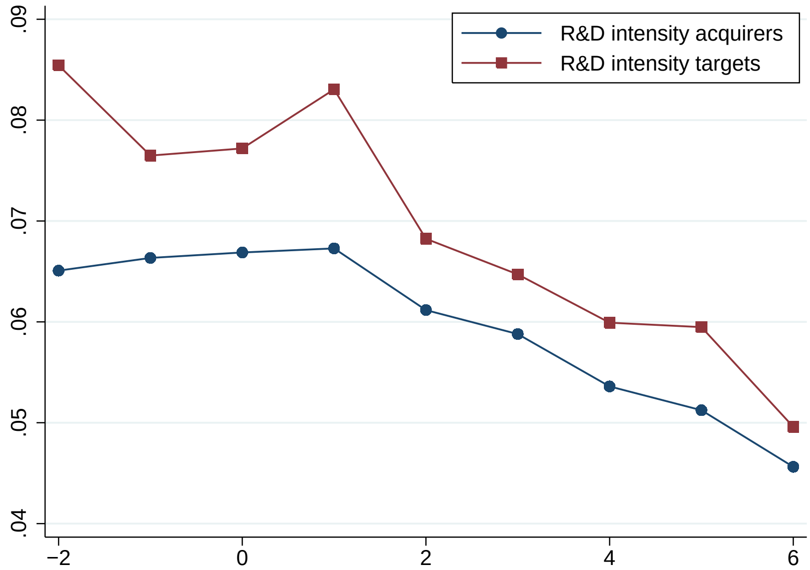


Figure 3 reports the R&D intensity of acquirers and targets from two years before until six years after the merger. Prior to the merger, the R&D intensity of acquirers is relatively constant around a high level of 6.5%. Acquirers are, therefore, on average quite R&D-intensive firms. This remains unchanged in the period of the merger and the one after it. From $t+1$ to $t+6$ we observe a monotonic decline in the R&D intensity of acquirers, which drops from 6.7% to 4.6%. Thus, R&D intensity is reduced by almost a third on average in the five years after an acquisition is made. A similar, but even stronger pattern can be observed in the R&D intensity of merger targets: while starting out at a very high level of about 8%, the graph monotonically decreases to 5% in the post-merger periods, suggesting a reduction in R&D intensity of more than a third. Both decreases are significant at the 5% level. Since for both groups R&D growth in the post-merger period - albeit lower than that of the control groups - remains positive, the

[14] Since, in the former case, the spike is an accounting phenomenon and not a causal effect of the merger, we exclude period t from all estimations. However, including t does not substantially change the results reported below.

decrease in R&D intensity points to an expansion of sales.

Figure 3: R&D intensity of acquirers and targets around the merger

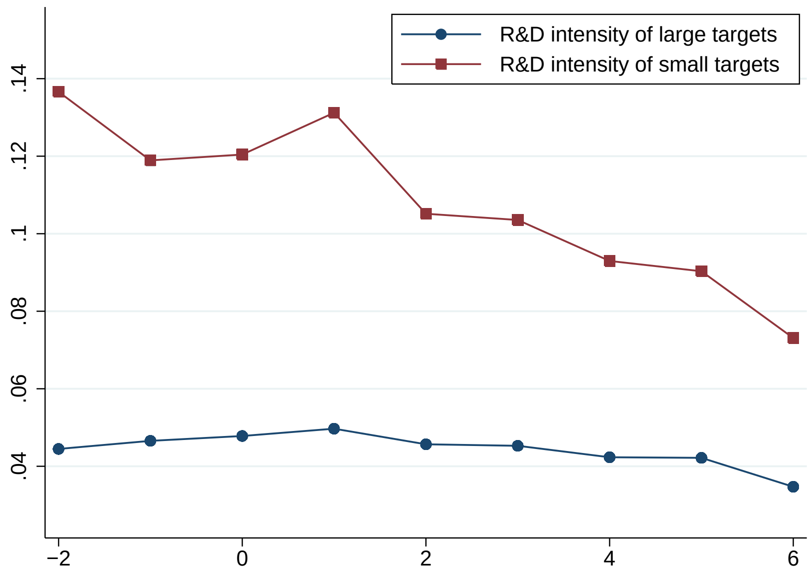


From figures 2 and 3 it appears that merger targets are chosen on the basis of being very innovative firms - they exhibit high R&D growth and intensity -, but that their innovative efforts decrease substantially after the acquisition. Similar, but less pronounced effects are observed for the buying firms.

To gain more insight into the post-merger dynamics we now differentiate between relatively large and small firms by splitting the sample at the mean level of sales. In doing this, we find that the effects on acquirers are rather homogenous in size and that the R&D growth of large and small targets does not strongly differ in the post-merger period. However, when contrasting the R&D intensity of large and small target firms after a merger in figure 4, we find that small targets initially display a much higher level of R&D intensity and subsequently experience a stronger decline than large target firms. Their average R&D intensity of 12% in the merger period decreases to 7.3% six years later, corresponding to a decline of 39%. Large target firms start out at a much lower level of 4.8% and experience a 28% decline down to 3.5% in the following years. Since the post-merger R&D growth of small and large targets is not significantly different, the larger reduction in the R&D intensity of small targets means that their acquirers use them mainly as sales outlets, while relatively neglecting their innovative activities.

While these figures suggest that certain changes in innovative behaviour occur around a merger, they contain only mean values and do not permit inferences of causality. To achieve this, we run regressions in a difference-in-difference setting (see section 3.5) within the relevant control group (see section 3.3). The dependent variables are R&D growth and intensity respectively.

Figure 4: R&D intensity of large and small targets around the merger



While all regressions are run pooled,[15] the effects on acquirers and targets are measured separately in the three different samples obtained by PSM NN, PSM caliper and vector-norm NN matching. All specifications include controls for industry, country and time effects (not reported). The results are reported in tables 4 and 5.

[15]As mentioned before, estimating in the subsamples does not qualitatively change the results.

Table 4: R&D growth of acquirers and targets from $t + 1$ to $t + 6$

	PS NN matching		PS Caliper matching		Vector-norm NN matching	
Acquirer t+1	0.009	(0.024)	0.016	(0.022)	0.015	(0.022)
Acquirer t+2	−0.016	(0.025)	−0.009	(0.023)	−0.012	(0.022)
Acquirer t+3	−0.031	(0.024)	−0.025	(0.026)	−0.028	(0.025)
Acquirer t+4	−0.024	(0.017)	−0.019	(0.019)	−0.023	(0.018)
Acquirer t+5	−0.082***	(0.021)	−0.078***	(0.019)	−0.084***	(0.020)
Acquirer t+6	−0.027	(0.056)	−0.024	(0.054)	−0.028	(0.052)
Target t+1	−0.082***	(0.016)	−0.081***	(0.014)	−0.086***	(0.013)
Target t+2	−0.095***	(0.016)	−0.091***	(0.022)	−0.100***	(0.021)
Target t+3	−0.071**	(0.028)	−0.067**	(0.024)	−0.079***	(0.025)
Target t+4	−0.078***	(0.024)	−0.072***	(0.024)	−0.082***	(0.021)
Target t+5	−0.034	(0.022)	−0.028	(0.025)	−0.039	(0.027)
Target t+6	−0.026	(0.058)	−0.024	(0.060)	−0.031	(0.062)
Observations	4714		7588		4543	
Acquirers	265		265		265	
Targets	133		132		133	
Σ Acquirer timeline †	0.032		0.054		0.008	
Σ Target timeline †	0.000		0.000		0.000	

Notes: All regressions include controls for industry, country and time effects. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors (in parentheses) are robust and allow for clustering on the year-level. † p-Values of the Wald-test with the null-hypothesis that the sum of timeline coefficients of acquirers (or targets) is not significantly different from zero.

Table 4 shows that the R&D growth of acquirers does not strongly differ from that of the control group in the post-merger period: even though most coefficients are negative, only the $t + 5$ coefficient assumes statistical significance. This finding is robust across all three samples. Thus, while there are some negative effects, the acquirer's incentive to continue to invest in its own research programmes is not greatly diminished.

The growth effects on targets are much more pronounced: in all periods from $t+1$ to $t+4$ and all three samples, merger targets experience significantly lower R&D growth than their peers. The size of the reduction of R&D growth - between 7 and 10% over a four year period - means that the effect is also economically significant: in $t + 4$ the R&D stock of the control group is almost 37% larger than that of the target firms.

The p-values reported at the bottom of the table test the null hypothesis that the sum of all acquirer (or target) timeline-dummy coefficients is not significantly different from zero. For the targets, all of these hypotheses can be rejected at the 1% level. While the overall reduction is significant for acquirers as well, the level of significance varies across samples.

Turning to the regression addressing R&D intensity, we find that the R&D intensity of acquirers is significantly affected by a merger: while the difference to the control group is insignificant in period $t + 1$ (and the periods prior to it), all coefficients are significantly negative and decline monotonically from periods $t + 2$ until $t + 6$ in all three samples. The coefficients indicate a cumulative reduction of R&D intensity amounting to 2.6 to 3.6 percentage points in comparison to the control groups in all three samples.

The effects on merger targets are also significantly negative from $t + 2$ and decrease monotonically until the end of the observation period in all three samples. The coefficients suggest an even larger effect, ranging from a reduction of R&D intensity of 3.5 to 4.7 percentage points six years after the merger. The acquirer/target dummies at the bottom of the regression table control for the generally lower level of R&D intensity among acquirers and their control group. Similarly to the R&D growth regressions, we report the p-values of the hypotheses that the sum of all period effects is not significantly different from zero. All null hypotheses are rejected at the 1% level suggesting that the R&D intensities of acquirers and targets are significantly reduced in the six periods after a merger.

Table 5: R&D intensity of acquirers and targets from $t + 1$ to $t + 6$

	PS NN matching		PS Caliper matching		Vector-norm NN matching	
Acquirer t+1	−0.006	(0.006)	−0.004	(0.008)	−0.009	(0.006)
Acquirer t+2	−0.012**	(0.005)	−0.011*	(0.005)	−0.016***	(0.005)
Acquirer t+3	−0.014**	(0.006)	−0.013**	(0.005)	−0.018***	(0.005)
Acquirer t+4	−0.020***	(0.006)	−0.017***	(0.006)	−0.025***	(0.005)
Acquirer t+5	−0.025***	(0.009)	−0.021**	(0.008)	−0.030***	(0.008)
Acquirer t+6	−0.030***	(0.010)	−0.026**	(0.010)	−0.036***	(0.009)
Target t+1	−0.007	(0.010)	−0.004	(0.011)	−0.009	(0.010)
Target t+2	−0.023***	(0.008)	−0.019**	(0.008)	−0.025***	(0.008)
Target t+3	−0.024**	(0.011)	−0.020*	(0.011)	−0.027**	(0.011)
Target t+4	−0.029***	(0.008)	−0.024***	(0.009)	−0.032***	(0.009)
Target t+5	−0.031***	(0.010)	−0.025**	(0.010)	−0.035***	(0.010)
Target t+6	−0.043***	(0.012)	−0.035***	(0.012)	−0.047***	(0.012)
Acquirer	−0.025***	(0.005)	−0.024***	(0.004)	0.006**	(0.002)
Target	0.004	(0.008)	0.004	(0.007)	0.032***	(0.006)
Observations	4939		7948		4762	
Acquirers	265		265		265	
Targets	133		132		133	
Σ Acquirer timeline †	0.001		0.006		0.000	
Σ Target timeline †	0.001		0.005		0.001	

Notes: All regressions include controls for industry, country and time effects. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors (in parentheses) are robust and allow for clustering on the year-level. † p-Values of the Wald-test with the null-hypothesis that the sum of timeline coefficients of acquirers (or targets) is not significantly different from zero.

5 Conclusion

In this article we estimate the effect of M&A activity on the growth of R&D spending as well as R&D intensity of the parties involved, using a sample of merger cases that went under the scrutiny of either the EC or the FTC. In doing so, we have explicitly recognized the roles of the firms involved as either buying firms or merger targets and have evaluated the impact on both groups separately, using appropriately constructed control groups.

In terms of merger mechanics the results suggest that merger targets are chosen on the basis of being highly innovative firms, as indicated by a pre-merger R&D intensity of over 8% on average and of almost 12% for small targets. This high ratio of R&D expenditures to sales supports the conjecture that these firms have not yet been able to reap the profits of their innovative efforts. Acquirers thus seem to cherry-pick firms with attractive technological portfolios that have not yet been fully commercially exploited. Acquirers themselves, on the other hand, are primarily characterized by being both large and profitable.

The mergers in this sample entail negative R&D growth effects, particularly on the target firms: their R&D spending grows 7-10% slower than that of their control group over a four year period, resulting in a 37% lower R&D stock. The effects on acquirers are modest in comparison, their lower R&D growth might be attributed to the diversion of managerial and financial resources from R&D after the acquisition (Hitt et al., 1991). This suggests that while acquirers still pursue their own research projects, they prefer to exploit rather than explore the targets' R&D stock (Wagner, 2011).

The effects on R&D intensity are more similar across both groups but, again, the impact on targets is more pronounced. The ratio of research expenditures to sales monotonically decreases for both types of firms, resulting in a reduction of roughly 3 (4) percentage points for acquirers (targets). Since the average R&D growth remains positive, this substantial decline is attributable to a large expansion of sales vis-à-vis the control groups. This seems to be particularly true for small targets, whose R&D intensity diminishes from a pre-merger level of 12 to a mere 7.3 percentage points.

While there may be competing explanations, the dynamics sketched above seem to suggest that acquirers pick highly innovative targets for acquisition and prefer not to push further R&D investments but instead start marketing the innovative accomplishments of the target, while continuing to pursue their own research agenda. On average, this strategy appears to be successful since both groups of merging firms substantially increase their sales in the post-merger period: on average the sales of acquirers have risen by 75% four years after the merger compared to pre-merger levels and they continue to grow strongly. Targets raise their sales by 30% in $t + 4$, which corresponds approximately to the reduction of their R&D intensity in absence of significant R&D growth. Their average profitability, which is negative prior to the merger, becomes positive and reaches a 4% return on assets after the merger.

The patterns found and described above are compatible with the notion of technology-driven acquisitions. Instead of conducting the necessary R&D in-house, the acquirers instead buy a firm (or the relevant division of a firm) that is developing or has already finished developing the desired technology or product. The post-merger period then reflects the process of exploiting that acquisition. The targets, which are initially highly innovative but unprofitable, reduce their research and become profitable enterprises. While this procedure appears to be lucrative for the firms, it also leads to the quasi-elimination of a highly innovative player in the market - a fact that should be taken into account by competition authorities in their assessment of notified combinations.

On a more methodological note, this article has followed the popular approach of combining matching and DiD estimation. However, we have corroborated the findings by running the regressions in three samples, obtained by three different approaches to matching. Even though the three resulting samples are rather dissimilar, the obtained estimates are remarkably coherent: the significance of the findings is virtually the same for all coefficients across the three samples and the estimated coefficients are reasonably close. Thus the results do not depend strongly on the choice of control group.

While we hope to make a contribution to the mounting empirical evidence on the topic in question, there are a number of avenues to extend and expand research on the innovation impact on acquirers and targets in mergers. For one, this article focusses on the effects of innovation inputs; it would be interesting to also analyze the evolution of acquirers and targets in terms of innovation output, measured by either patents or product innovations. Such an approach would allow to distinguish whether the reduction of inputs can be attributed to rationalization in research overlap areas or other motives. Another interesting extension would be to not only differentiate acquirers and targets, but to also take into account the degree to which they are technologically related. Finally, from a policy point of view, it would be desirable to evaluate the welfare impact of mergers with an innovation dimension. While many studies find a negative impact on various measures of innovation, the overall impact on welfare - factoring in cost savings, production efficiencies etc. - remains an elusive magnitude.

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