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How Mergers Affect Innovation: Theory and Evidence from the Pharmaceutical Industry

Justus Haucap Joel Stiebale [1]

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Abstract

This papers analyses how horizontal mergers affect innovation activities of the merged entity and its non-merging competitors. We develop an oligopoly model with heterogeneous firms to derive empirically testable implications. Our model predicts that a merger is more likely to be profitable in an innovation intensive industry. For a high degree of firm heterogeneity, a merger reduces innovation of both the merged entity and non-merging competitors in an industry with high R&D intensity. Using data on horizontal mergers among pharmaceutical firms in Europe, we find that our empirical results are consistent with many predictions of the theoretical model. Our main result is that after a merger, patenting and R&D of the merged entity and its non-merging rivals declines substantially. The effects are concentrated in markets with high innovation intensity and a high degree of firm heterogeneity. The results are robust towards alternative specifications, using an instrumental variable strategy, and applying a propensity score matching estimator.

JEL codes: *D22,L13,L4,G34,O31*
Keywords: *mergers & acquisitions, innovation, R&D incentives, merger policy.*

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1 Introduction

How to foster innovation has been at the heart of economic policy in many jurisdictions, as innovations are regarded as key factors to spur economic growth and productivity. At the same time, innovations are seen as one main factor for individual firms' success in competitive markets. Accordingly, an extensive body of research has been analyzing the factors that drive innovation at the firm level as well as at more aggregate (regional or national) levels (see, e.g., the contributions in Hall and Rosenberg, 2010).

Surprisingly little attention has been paid until recently to the question how mergers affect innovation incentives. While there is a large body of (mostly empirical) research on the relationship between market structure and innovation, the effects of single mergers are less well understood. Especially from a competition policy perspective this is unfortunate, as the analysis of merger cases mostly – with a few exceptions – focuses on price effects (and quantities), but often neglects effects on innovation incentives, a point of critique that has also been raised by Comanor and Scherer (2013) and Gilbert and Greene (2015) recently. Moreover, the analysis often has a strong focus on effects that are generated from within the merged entity (unilateral effects), for example, how the merged entity's prices and quantities change after the merger, while impacts on competitors are, if at all, only analysed in terms of coordinated effects. Put differently, in merger cases the main question regarding potential effects on rivals is whether (tacit) collusion is more likely to emerge. How rivals' incentives change more generally, apart from potential collusion, is rarely examined. While it is sometimes analysed how mergers directly affect the merged firm's innovation incentives, especially in high-tech industries, impacts on rivals' innovation incentives are only very rarely, if at all, analysed in competition cases.

To illustrate this observation note that section 6.4 of the US Horizontal Merger Guidelines, for example, specifies that "competition often spurs firms to innovate" and that US competition authorities "may consider whether a merger is likely to diminish innovation competition by encouraging the merged firm to curtail its innovative efforts below the level that would prevail in the absence of the merger." However, effects on competitors or the concerned industry's competition dynamics are not mentioned. In this context, it should also be noted that horizontal merger guidelines both in the US and the EU are explicitly allowing for a so-called efficiency defense for otherwise anticompetitive mergers. These efficiency claims often concern research and development (R&D) efficiencies (see OECD, 2012). If a firm can convincingly demonstrate that a merger results in a substantial and timely increase in efficiencies, an otherwise anticompetitive merger can be cleared. While efficiencies typically take the form of cost savings, innovation incentives can also be affected. A complete analysis of potential efficiencies from mergers should, however, not only analyse how the merged entity's prices, quantities and innovation incentives change (i.e., the direct effects of a merger), but also how these change for rival firms (indirect effects).

As there has been little analysis - be it theoretical or empirical - on the effects that a merger has on rivals' innovation incentives, we aim at closing this gap somewhat. Put differently, this paper does not only analyses the question how mergers affect the innovation incentives of the parties directly involved (see, e.g., Ornaghi, 2009a; Szücs, 2014), but also examines the largely neglected question how mergers affect outsiders' innovation incentives. For that purpose, we analyse a three-player Cournot oligopoly model in which firms can invest in product innovations. While there are two efficient firms, there is also one less efficient firm which faces higher costs of innovating. We analyse market outcomes in terms of prices, quantities and innovation levels (a) for the three-player pre-merger oligopoly and (b) for a post-merger duopoly in which one of the efficient firms has purchased the less efficient rival. The key results from the model are that a merger has (i) a negative effect on the merged entity's innovation efforts in an industry with a high research intensity and (ii) a negative effect on non-merging competitors in an industry with a high research intensity when the target firm is relatively inefficient compared to the other firms. Our model also predicts that a merger is more likely to take place (i.e., to be profitable) in markets with a high research intensity and in markets with high variation in firm efficiency. Hence, we expect to find negative effects of mergers on innovations for many cases.

The empirical part is based on a sample of pharmaceutical mergers under scrutiny by the European Commission between 1991 and 2007. The pharmaceutical industry is an interesting case study for the relationship between mergers and innovation for several reasons. First, according to the 2014 EU Industrial R&D scoreboard[1], it is the industry with the highest R&D to sales ratio (above 14%) and pharmaceutical firms account for more than 15% of total R&D spending among top 1400 firms in Europe. Further, the industry has experienced a series of large mergers that raised policy concerns about the effects on innovation in the industry (e.g. Morgan, 2001; Comanor and Scherer, 2013).

A unique feature of our data set is that we use merger reports that contain an expert market definition, which enables us to identify competitors for each merger case. Our empirical results are mainly based on the estimation of count data models with patent counts as a proxy for innovative activity as the dependent variable. We find that mergers are, on average, associated with a large decline in innovative activity of the merged entity and among non-merging competitors. This re-

[1] The R&D scoreboard is available at `http://iri.jrc.ec.europa.eu/scoreboard14.html`.

sult is consistent with the theoretical model's prediction for markets with a high research intensity – which arguably applies to most pharmaceutical markets. The results are robust towards using an instrumental variable strategy and applying a propensity score matching approach combined with a difference-in-differences estimator. Our empirical results are also consistent with other implications of the theoretical model. We find that the decline in innovation after mergers is most pronounced in markets with high pre-merger innovation intensity and high degree of firm heterogeneity. Further, we also find that the overall pre-merger innovation intensity is higher for firms that operate in markets in which mergers take place. Compared to the market average, firms that will be acquired in a merger have a relatively low research intensity.

The remainder of the paper is structured as follows: The next section provides an overview of related literature, before section 3 presents our theoretical model. Sections 4 and 5 describe the data and the empirical strategy, respectively. Results of the empirical analysis are presented in section 6 before section 7 concludes.

2 Related literature

The theoretical literature on the relationship between competition and innovation has advanced for more than 100 years now, arguably starting with Schumpeter (1912)'s treatise on the theory of economic development. The first formal model was proposed by Arrow (1962) who showed that innovation incentives can be stronger in competitive markets due to the so-called replacement (or profit) effect. This finding has been qualified later, e.g., by Gilbert (2006) for horizontally differentiated products and by Greenstein and Ramey (1998) for vertical product differentiation, and in particular by Gilbert and Newbery (1982) who pointed towards the competitive threat effect which may drive monopolists to innovate more. This result does not hold in general either though, as has been shown, e.g., by Boone (2001) or Vickers (1985). Vives (2008), Aghion et al. (2001) and Aghion et al. (2005) have used aspects of both approaches, employing an endogenous growth model with firms facing either "neck-to-neck competition" or one laggard being technologically behind the leader. As the authors show, if product substitutability is high and, therefore, competition intense, innovations are unattractive for laggards, but profitable for firms in neck-to-neck situations in order to escape competition. In contrast, if product substitutability is low and, therefore, competition soft, innovations are attractive for laggards, but less interesting for firms in neck-to-neck situations.

Schmutzler (2013) has recently presented a unified approach and identifies several channels by which competition affects investment. As Schmutzler concludes, "competition reduces margins, and increases the sensitivity of equilibrium output with respect to efficiency. Adding to these ambiguities, competition can have positive or negative effects on equilibrium output and on the sensitivity of prices with respect to marginal costs. Together, this explains why the effects of competition on investment are ambiguous."

It should be noted though that while all of the cited papers deal with the relationship between competition and innovation, they do not specifically address how single mergers change innovation incentives. This question has been addressed by Yi (1999), who explicitly analyses how an exogenous merger in a Cournot model affects innovation incentives. As he shows, the benefit of a small process innovation decreases with the number of firms, under reasonably weak conditions. Kleer (2012) uses a linear Cournot model and extends it to a number of related cases such as Stackelberg competition, showing that, departing from the well known merger paradox, mergers can be profitable even under Cournot competition, once one accounts for R&D competition, and that these mergers can also be welfare enhancing. A similarly spirited mode has been developed by Ishida, Matsumura, and Matsushima (2011). In their asymmetric Cournot model with one low-cost firm and several high-cost firms, an increase in the number of high-cost firms may increase the R&D effort by the low-cost firm. Our approach relates to these models, but differs as we allow firms to vary in their R&D cost function and only focus on profitable mergers, thereby endogenising the merger decision to some extent.

The majority of empirical studies report a negative effect of mergers on innovation in the merged entity, although the results seem to depend on both product and technology market characteristics (see Cassiman et al., 2005; Veugelers, 2006).[2] Most closely related to our paper are industry studies, such as Ornaghi (2009a), who finds a negative effect of mergers on patent counts and R&D expenditures within merged pharmaceutical firms. Szücs (2014) analyses a sample of mergers across different industries under scrutiny by the European Commission. He finds that mergers can reduce the R&D efforts of both acquiring and target firms but does not analyse effects on non-merging competitors. At the industry level, only small effects of M&As on R&D show up in Bertrand and Zuniga (2006). As they define markets by standard industry classifications, they cannot distinguish between merging firms, competitors, suppliers and firms which compete in different product or geographical markets. Clougherty and Duso (2009), Duso, Gugler, and Yurtoglu (2010) and Gugler and Szücs (2014) study the effects of mergers on profitability, sales, and firm value of competitors in well-defined product markets, but they do not analyse innovation outcomes. Empirical studies that investigate the role of innovation as a determinant of M&As often find that the level of innovative activity as well as

[2] The results of recent studies are discussed in Stiebale and Reize (2011). Another strand of related empirical literature studies the relationship between competition and innovation in general (see e.g. Aghion et al., 2005).

technological similarity between firms increases the likelihood of mergers (e.g. Ornaghi, 2009a,b; Frey and Hussinger, 2011). To the best of our knowledge, there is no existing empirical study that analyses the effects of mergers on innovation activities of rivals. This paper aims to fill this gap.

3 A model of mergers and product innovation

Consider a Cournot oligopoly with three firms i=1,2,3 which face a linear demand curve. Also assume that the firms can introduce product innovations, which increase consumers' willingness to pay for their products so that firm i's inverse demand function is given through a variant of the quadratic utility function (see, for instance, Vives, 2001, page 144ff).

$$p_i = 1 + \alpha_i - q_i - \sum q_j \text{ for } i, j = 1, 2, 3. \tag{1}$$

For reasons of simplicity we abstract from any fixed and variable cost, but assume that product innovation is costly. Moreover, we inject some heterogeneity into our model by assuming that firms 1 and 2 have an innovation cost of $I_i = \frac{k}{2}\alpha_i^2$ for $i = 1, 2$ while firm 3 is less efficient in its innovative efforts, facing an innovation cost of $I_3 = \frac{k+b}{2}\alpha_3^2$. Regarding the timing of the game we assume that firms decide on their innovative efforts before they subsequently compete in the product market.

Solving the game backwards, we obtain $q_i = \frac{1}{4}\left(1 + 3\alpha_i - \sum q_j\right)$ for $i, j = 1, 2, 3$ for the firms' equilibrium quantities as a function of their innovation efforts, which, in turn, brings us to the following best response functions in the innovation stage of the game:

$$\alpha_i = \frac{3 - 3\alpha_j - 3\alpha_3}{8k - 9} \text{ for } i, j = 1, 2 \text{ and } \alpha_3 = \frac{3 - 3\alpha_1 - 3\alpha_2}{8\,(k + b) - 9} \tag{2}$$

As can be easily seen, the firms' individual innovation levels are strategic substitutes. Whenever firm i increases its innovation efforts this induces firm j to reduce its innovation activities. Given our setting, the following equilibrium quantities and levels of product innovation finally result:

$$q_1 = q_2 = \frac{2k(2b + 2k - 3)}{9 + 16bk - 12b + 16k^2 - 30k};\; q_3 = \frac{(4k - 6)\;(b + k)}{9 + 16bk - 12b + 16k^2 - 30k} \tag{3}$$

$$\alpha_1 = \alpha_2 = \frac{6b + 6k - 9}{9 + 16bk - 12b + 16k^2 - 30k};\; \alpha_3 = \frac{6k - 9}{9 + 16bk - 12b + 16k^2 - 30k} \tag{4}$$

Given these equilibrium values we assume, in the following, that $k > 1.5$ (Assumption 1) in order to ensure that the profit maximization problem has interior solutions with $q_i > 0$ and $\alpha_i > 0$ for $i = 1, 2, 3$. Note that q_1 is increasing in b, while q_3 is decreasing in b. Also, α_3 and I_3 are decreasing in b while α_1 and I_1 are increasing in b. This is rather intuitive, as b is a measure for firm 3's inefficiency or competitive disadvantage. The larger b, the smaller is firm 3 in terms of its output. The comparative statics with respect to k are less straight forward though. Firstly, q_1 is decreasing in k, while q_3

is, ceteris paribus, increasing in k for all $k > 1.5$. The intuition is that an increase in k will lead to lower output of firms 1 and 2 which induces firm 3 to increase its output, following the Cournot logic, given that firm 3's competitive disadvantage (as measured through b) diminishes with increasing k.

Secondly, α_3 is increasing in k as long as $b > b^{'}$ with $b^{'} = \frac{4}{3}k^2 - 4k + 3$, and, thirdly, I_3 is also increasing in k as long as $b > b^{'}$. The intuition is here that for high levels of b, the distance between firm 3 and its two rivals in terms of efficiency is relatively high and, therefore, firm 3 is relatively small. An increase in k now has two effects: While it renders innovation more expensive, making it less attractive on the one hand, an increase in k also improves firm 3's relative position vis-a-vis its rivals, making innovation more attractive on the other hand. The latter effect dominates if firm 3's competitive disadvantage and, therefore, the asymmetry between the firms is relatively severe. Furthermore, both α_1 and I_1 are decreasing in k for all $b > 0$. Finally, the industry innovation level I is also decreasing in k. Hence, a low value for k characterizes R&D intensive industries, while high levels of k represent industries with low levels of R&D.

Now let us consider the case of a merger. Since firms 1 and 2 are both large firms in our setting, as they both enjoy a competitive advantage over firm 3, we rule out a merger between the two dominant players and concentrate on the effects of a merger between a large firm (say, firm 1) and the small firm (i.e., firm 3). This approach seems reasonable to us, as most competition authorities around the world would most likely not clear a merger between the two largest firms in a 3-player market. As we shall see later, this assumption also resembles the empirical merger pattern observed in the data. We will, however, analyse whether a merger between firm 1 and 3 would be profitable for the two firms involved.

In case of a merger, the market collapses into a Cournot duopoly and we also assume that the efficient innovation technology of firm 1 can be adopted by the new entity (complete technology transfer). Hence, a symmetric duopoly results. The firm's best response in the innovation stage of the game is now given by $\alpha_1 = 4\frac{1-\alpha_2}{9k-8}$, and the resulting equilibrium values for firms' quantities and innovation levels are given by $q_1 = q_2 = \frac{3k}{9k-4}$ and $\alpha_1 = \alpha_2 = \frac{4}{9k-4}$. Now let us first analyse whether a merger between firms 1 and 3 would be profitable by comparing the pre-merger equilibrium profit levels of firms 1 and 3 with the post-merger profit level of the merged firm 1. The results of this comparison are summarized in the following proposition.

Proposition 1: (i) For $1.5 < k < 3.9954$ a merger between a large firm and the small firm is always profitable. (ii) For $3.9954 < k < 5.2196$ there exists a critical value $b^*(k)$ so that for all $b > b^*$ the

merger is profitable while for all $b < b^*$ the merger is not profitable. (iii) For all $k > 5.2196$ the merger is unprofitable.
Proof: See Appendix.

What is the intuition behind proposition 1? For large values of k (case iii) the standard logic of mergers in Cournot markets as outlined by Salant, Switzer, and Reynolds (1983) prevails. Innovation costs are relatively high and, as a consequence, relatively little innovation activity is pursued. Hence, the three firms are relatively symmetric, and the standard Cournot merger logic applies. In contrast, if k is relatively small (case i) the industry is relatively R&D-intensive so that productive efficiencies can be generated by spreading R&D expenditures over a larger quantity of production. Hence, savings in R&D expenditures (the innovation cost efficiency gain) outweigh the negative market share effect which results from a merger in Cournot markets. For intermediate values of k (case ii) b has to be sufficiently high to render a merger profitable. The intuition is that high values of b imply that the third firm is relatively inefficient and, therefore, relatively small in equilibrium. Hence, the (negative) market share effect (i.e., that some market share of the target firm is lost to outside rivals) is also relatively small while the (positive) cost savings effect is relatively strong (due to the relative inefficiency of firm 3). Hence, in case (ii) a merger becomes more likely the less efficient firm 3 is relative to firm 1 or, put differently, the higher the asymmetry in the firms' innovation efficiency levels.

Now that we have established the range of cost parameters (k, b) for which mergers are profitable let us examine how a merger affects both the merged entity's as well as its rival's innovation incentives. For that purpose, note that both the innovation expenditures for firms 1 and 2 are identical due to the firms' symmetry, both before and after the merger, i.e. $I_1^{Pre} = I_2^{Pre}$ and $I_1^{Post} = I_2^{Post}$. For the comparison of pre- and post-merger innovation expenditures it is useful to note that $I_1^{Pre} + I_3^{Pre} > I_2^{Pre}$. Hence, $I_1^{Pre} + I_3^{Pre} > I_1^{Post}$ immediately follows from $I_2^{Pre} > I_2^{Post}$ in those cases where the latter inequality holds (but not vice versa). To simplify the analysis let us first concentrate on the change in the rival's innovation incentives, which are summarized in the following proposition.

Proposition 2: (i) For $3/2 < k < 12/5$ there exists a critical value $b^+(k)$ so that $I_2^{Post} < I_2^{Pre}$ for $b > b^+$. (ii) For $k > 12/5$ the outside firm always increases its innovation expenditures after the merger, i.e. $I_2^{Post} > I_2^{Pre}$.
Proof: See Appendix.

Before we present the intuition for the results of proposition 2, let us also analyse how the merger affects the innovation incentives of the merged entity.

Proposition 3: (i) For $3/2 < k < 12/5$ the merged entity always reduces its innovation expenditures compared to the two merged firms' pre-merger innovation expenditures, i.e. $I_1^{Post} < I_1^{Pre} + I_3^{Pre}$. (ii) For $k > 12/5$ there exists a critical value $b^{++}(k)$ so that $I_1^{Post} < I_1^{Pre} + I_3^{Pre}$ for $b < b^{++}$.
Proof: See Appendix.

To summarize these results, note that for relatively small values of k (i.e., relatively R&D intensive industries) the merged entity will always reduce its innovation efforts compared to the joint pre-merger innovation expenditures of firms 1 and 3. The outside firm 2 will also reduce its innovation level if b is relatively large, i.e. if firm 3 is relatively small and the firms are, therefore, relatively asymmetric. If the industry under consideration is less research intensive (i.e., k is relatively high), the outside firm 2 will always increase its innovation expenditures after the merger, while firm 1 may increase or reduce its innovation efforts, depending on b. How can these results be intuitively explained? First of all, note that two forces determine how firms' revenues are affected by product innovations. Firstly, an increase in α_i has an effect on equilibrium prices and, secondly, there is an effect on firm i's equilibrium quantity. The strength of these effects is also determined by the degree of competition in the market. Note that in a duopoly situation, an increase in α_i leads to an increase in price and quantity by a factor of 2/3 while in a three-player market the according factor is 3/4. More precisely, the effect of an increase in α_i on the firm's profit is given by $\frac{3}{4}q_i^T(\alpha_i) + \frac{3}{4}p_i^T(\alpha_i) - k\alpha_i$ in a three-player market and by $\frac{2}{3}q_i^D(\alpha_i) + \frac{2}{3}q_i^D(\alpha_i) - k\alpha_i$ under a duopoly. Intuitively, the so-called business stealing effect is weaker under a duopoly than in a three-player market. While both the firm's individual quantities and prices are higher under a duopoly than in a three-player market ($p_i^T(\alpha_i) < p_i^D(\alpha_i)$ and $q_i^T(\alpha_i) < q_i^D(\alpha_i)$), the joint pre-merger quantity of firms 1 and 3 is always larger than the post-merger quantity of the merged entity. Secondly, also note that innovation costs are convex so that the marginal cost of investment into innovation is increasing. Furthermore, when comparing innovation expenditures we also have to take into account that firm 3's expenditures are removed after the merger.

Taken together, the removal of firm 3's innovation expenditures, the reduced business stealing effect and the convexity of the innovation cost function dominate the increased innovation incentives resulting from the cost savings (induced by the superior innovation technology of firm 1) and increased equilibrium prices and firm 1's equilibrium quantities (when compared to only firm 1's pre-merger quantity) so that, overall, the merged entity's innovation expenditures are reduced. For the outside firm the case is less clear. If b is sufficiently large and, therefore, firm 3 relatively small, the additional quantity gained by firm 2 (the externality of the merger) is relatively small, the reduced business stealing effect (with a factor of 2/3 instead of 3/4) dominates the incentives so that firm 2 actually reduces its investment. In contrast, if b is relatively small and, therefore, firm 3 relatively large, the additional quantity gained by firm 2 suffices to increase its innovation incentive even though the business stealing effect is reduced.

For our empirical analysis it is also interesting to note that for small values of k the observed negative effect of mergers on innovation is increasing in b, i.e., the differences of $I_2^{Pre} - I_2^{Post}$ and $I_1^{Pre} + I_3^{Pre} - I_1^{Post}$ are larger the smaller the acquired firm is. As can be easily verified $I_2^{Pre} - I_2^{Post}$ is increasing in b for $3/2 < k < 12/5$, while $I_1^{Pre} + I_3^{Pre} - I_1^{Post}$ is increasing in b for $3/2 < k < 3/2 + (3/4)\sqrt{2} = 2.5607$.

What happens if k increases so that the industry becomes less research intensive? The merged entity will still reduce its innovation expenditures as long as b is sufficiently small. If b becomes sufficiently large, however, the merged entity will increase its innovation expenditures, as the cost saving effect becomes dominant so that the merged entity will invest more after the merger. Firm 2 will also invest more after a merger if the research intensity of the industry is relatively low, as the cost of innovation is relatively high. As an increase in k makes the innovation cost function relatively more convex, the additional quantity gained after a merger and the higher equilibrium price (due to softer competition) are sufficient to lead to an increase in innovation incentives (which are relatively low due to the relatively steep marginal cost function) even though the business stealing effect is weaker under duopoly. Given these theoretical findings, let us derive the following testable hypotheses:

H1: In research intensive industries (small k), a merger has negative effects on the merged firm's innovation expenditures.

H2: In research intensive industries (small k), a merger has negative effects on the outsider's innovation expenditures if the merger involves a relatively small firm (with large b).

H3: In research intensive industries (small k), the difference between pre- and post merger innovation activity is increasing with the competitive disadvantage of the target firm (increasing in b) for both outsider and the merged entity.

H4: In less research intensive industries (large k), a merger has negative effects on the merged firm's innovation expenditures unless the merger involves a relatively small firm (with large b).

H5: In less research intensive industries (large k), a merger has positive effects on the outsider's innovation expenditures.

From a competition policy perspective, the effects of mergers on innovation are most relevant in R&D intensive industries. Our empirical analysis is based on mergers in pharmaceutical markets, which are usually characterized by high innovation intensities. Hence, we mainly provide evidence related to hypotheses 1, 2 and 3. However, we also analyze heterogeneous effects with respect to pre-merger innovation intensity in the relevant product market and pre-merger differences between acquirer and target which are related to hypotheses 4 and 5.

4 Data

For the empirical analysis several data sources were combined. Data on mergers are collected from the website of the European Commission (`http://ec.europa.eu/competition`), which examines all mergers in which the annual turnover of the combined entity exceeds certain thresholds in terms of global and European sales. We downloaded all reports which referred to mergers that affected the pharmaceutical industry (defined by NACE Rev. 2, section 21) between 1991 and 2007. All reports include a market definition by officials of the European Commission and the names of all competitors active in the relevant product markets.[3] This results in a much more accurate definition of rival firms than a classification solely based on NACE or SIC codes.[4] According to official figures, there are several thousand European firms – and several hundred firms per country – active in the pharmaceutical industry (e.g. Eurostat, 2009). In contrast, the median number of firms affected by a merger in our sample is 10.

We collected the names of all acquirers, targets, and competitors from the reports and deleted a few firms that mainly operate in other sectors like financial companies, hospitals and non-profit organizations. Our treatment group consists of 65 merger cases, which affected a total of 381 firms. 52 firms acquired at least one of 67 target firms, 319 firms were affected by at least one rival firm's merger.[5] While the sample only contains mergers that affected European product markets, it includes more than 20% of firms with headquarters outside Europe, mostly US firms. Since limiting

[3]The same data source has been used in several recent empirical studies on the effects of mergers (see, for instance, Duso, Neven, and Röller, 2007; Duso, Gugler, and Yurtoglu, 2010; Clougherty and Duso, 2009).

[4]See, for instance, Werden (1988) for the inappropriateness of standard industry classifications for the definition of antitrust markets.

[5]A few firms were both competitors and part of a merged entity during our sample period.

our sample to listed firms would decrease our sample size substantially, we include both listed and non-listed firms. The number of mergers in our sample is still relatively small, but our data set has the advantage that it focuses on well defined product markets. The relatively small number of firms enables us to carefully account case by case for name changes and newly founded firms or subsidiaries after mergers, which is necessary to accurately match the data with other data bases. We believe that this construction and detailed examination of the dataset are essential to identify the effects of mergers in the relevant market.

We match the firms from the M&A sample with several other data sources. First, we collect accounting data such as sales, R&D, and profits from the R&D scoreboard, Compustat, and the Amadeus database.[6] We complement the data with information from company reports available on the internet for those firms whose names could not be matched to these data bases. The remaining pharmaceutical firms from Amadeus and the R&D scoreboard serve as our comparison group. We use Bureau van Dijk's Zephyr data base to exclude firms that engage in other M&As during our sample period. Further, we exclude firms that have linkages to our treatment firms via corporate groups. Finally, firms with a mean value of sales below 2 million Euros based on all available firm-years are excluded to ensure a minimum of comparability between treatment and comparison group in terms of firm size.[7] For a subsample, we were able to collect data from the Entrepreneurial Studies Source provided by EBSCO Publishing. This data base extracts data on the firms' main competitors from company accounts and industry reports. We use this information to define rival firms for a subsample of our comparison group which is necessary for the estimation of our instrumental variable (IV) strategy.

Data on patent applications comes from the PATSTAT database, which has been developed by the European Patent Office and the OECD. We collected patent applications for the years 1978-2008 for all companies in our sample. From the data base we extracted application date, patent citations, and technology class assigned to each patent. To ensure that different regulations across patent offices in different countries do not affect our results, we restrict our analysis to patents filed to the European Patent Office. We also focus our analysis on pharmaceutical technology fields. We therefore exclude most innovation activity that is unrelated to the geographical and product markets that have raised anti-competitive concerns.[8] Our main innovation indicator are the number of patents per year. We

[6] Amadeus is provided by Bureau van Dijk. The R&D scoreboard data is freely downloadable at: `http://webarchive.nationalarchives.gov.uk/20101208170217/http:/www.innovation.gov.uk/rd_scoreboard/`.

[7] All results are qualitatively robust to restricting the comparison group either to firms from the Amadeus database or the R&D scoreboard.

[8] The definition of pharmaceutical patents is based on Hall, Jaffe, and Trajtenberg (2001) (see also Ornaghi, 2009a).

only count patents that are ultimately granted but date them back to the application year. We also computed a count of citation-weighted patents. Our sample includes a few firms that do not engage in patenting at all, mainly producers of generic pharmaceuticals. We do not exclude them from the sample, because M&As might affect the decision to engage in innovation in the first place, although including these firms is not crucial for our results. Our sample includes up to 30,000 firm-year observations with information on patent applications for the years 1990-2008 for some 1,900 firms. Patent applications for the years 1978-1989 are used to construct a measure of pre-sample innovation activity. The subsample of firms for which we can identify competitors spans around 1,000 firms and 12,000 firm-year observations. Data on R&D could only be collected for about 10,000 firm-years as this variable is mainly available from the late 90ies and not for all firms.

It is useful to briefly discuss the innovation process in the pharmaceutical industry to understand what we measure by patent counts. The innovation process in pharmaceutical firms can be divided into a discovery and a development stage.[9] The discovery phase aims at detecting promising molecules, so called new chemical entities, which form the basis for further drug development and clinical trials. As soon as a molecule is discovered, a firm applies for a patent to secure the exclusive exploitation of the economic returns from drug development (Ornaghi, 2009a). Hence, our patent-based indicators primarily capture the effects of mergers on innovation in the discovery stage.

Using patent applications as an innovation indicator is advantageous in our application for several reasons. First, patent applications are available for a long time span which allows us to control for the entire relevant history of a firm's innovation activities. Patent applications are also available independent of a firm's listing status and are less affected by accounting manipulations and different reporting rules across countries than R&D expenditures. Further, as we discussed in the description of the innovation process, effects on patent applications can arise shortly after a merger, while a much longer time series dimension would be necessary to study innovation outcomes based on final products. As the number of patents is derived from administrative data, this indicator does not have to rely on self-reported measures of new products and processes, which are often used in innovation studies. Patenting is costly and a granted patent requires a certain degree of novelty which reduces the risk of counting innovations of little relevance. Finally, the number of patents is a well-established indicator

It includes a total of 14 patent classes from the USPTO: Drugs - patent classes 424 and 514; Surgery and Medical Instrument - 128, 600, 601, 602, 604, 606 and 607; Biotechnology- 435 and 800; Miscellaneous Drug and Medicals- 351, 433 and 623. We used the USPTO website to map these technology classes into the European patent system (cf. `http://www.uspto.gov/web/patents/classification/index.htm`). We also checked the robustness of the results towards using a narrower definition of pharmaceutical patents as employed by Harhoff and Reitzig (2004).

[9] See Malerba and Orsenigo (2002) for a detailed description of the innovation process in the pharmaceutical industry.

of innovation which has been used in several recent studies (Aghion et al., 2009, 2013; Bena and Li, 2014; Seru, 2014 to name a few), and patent applications seem to be highly correlated with other common indicators of innovative performance (e.g. Hagedoorn and Cloodt, 2003; Griliches, 1998).

The downside of using patents as an innovation indicator is that not every invention becomes patented, and depending on firms' innovation strategies, firms may make more or less use of formal intellectual property (IP) rights protection (see, e.g., Jaffe and Lerner, 2004; Hall and Ziedonis, 2001; Ziedonis, 2004). This can be problematic if M&As change the incentives to patent strategically. It can also be expected that there will be substantial variation in the value of patented innovations. To address this problem, we check the robustness of our results towards using a measure of citation-weighted patents which should be affected by IP strategies to a lesser extent (Blind, Cremers, and Mueller, 2009). If M&As induce an increase (decrease) in patenting for strategic reasons, we should see a decline (rise) in the average number of citations per patent (e.g. Bloom, Draca, and van Reenen, 2016). While the value of citation-weighted patents could be heterogeneous as well, previous research on stock market valuations indicates that citation-weighted patents are a reasonable measure of the importance of patents (Hall, Jaffe, and Trajtenberg, 2005) and can thus be interpreted as a quality-adjusted patent count. We also analyze effects of mergers on R&D expenditures for a subset of our data.

5 Empirical Strategy

The empirical model has to account for several problems. First, the outcome variable, the number of patent applications, is a non-negative integer variable with a large share of zeros.[10] Further, it is likely that unobserved firm attributes like managerial ability, corporate culture, technological or product characteristics are correlated with both the decision to engage in M&As and innovative activity. Finally, we want to include a measure of previous patent activity to account for state dependence in innovative performance. Due to the presence of lagged values of the dependent variable, strict exogeneity of the regressors – which rules out feedback from current values of the dependent variables to future values of the regressors – is violated by definition. It is also well possible that there is feedback from innovative activity to future decision about M&As, as our theoretical model predicts that a merger is more likely to be profitable when a market's innovation intensity is high.

To address these problems, we build our empirical model on a framework for analyzing innovative activity developed by Blundell, Griffith, and van Reenen (1995) and Blundell, Griffith, and Windmeijer

[10] Although most firms in our sample engage in innovation activity, many firms do not file patents every year.

(2002). To account for the fact that innovation is measured as a count variable, the first moment of the model is:

$$E\left[P_{it}\right] = \exp(x_{it}'\beta) \text{ where } x_{it}'\beta = \sum_{k=1}^{4} \phi_k MA_{i,t-k} + \sum_{k=1}^{4} \gamma_k CO_{i,t-k} + \theta G_{i,t-5} + Z_{it}^{'}\omega + c_i \qquad (5)$$

P_{it} denotes the number of (citation-weighted) patent applications by firm i in year t. If a firm was not affected by M&As as an acquirer or target during the sample period, P_{it} equals the number of patent applications of firm i. For merging firms, P_{it} equals the sum of patent applications of acquirer and acquisition target before the merger and the total number of patent applications in the merged entity after M&A.[11] An equivalent approach is used for control variables as well. This procedure is often employed in the M&A literature (e.g. Gugler and Siebert, 2007; Conyon et al., 2002a,b).

$MA_{i,t-k}$ denotes a dummy variable that takes the value of one if a firm has engaged in M&A activity in year $t-k$. The dummy variable $CO_{i,t-k}$ takes the value of 1 if a firm was affected by a merger of competitors in the respective year. G accounts for pre-merger innovation activity, measured as a lagged value of patent counts or patent stock. A firm's patent stock is defined as: $PS_{it} = (1-\delta)\, PS_{i,t-1} + P_{it}$ (see, e.g., Bloom and Van Reenen, 2002). δ denotes a knowledge discount factor which is set to 0.15 as it is common in the innovation literature. The patent stock in the year 1978, the first period we observe patent counts, is set to zero. This inaccuracy diminishes over time due to the depreciation of knowledge and thus becomes negligible in our main sample period (1990-2008). Accounting for previous patent activity ensures that we measure the effect of M&As on *changes* in innovative activity. Z denotes a vector of further firm-specific control variables such as time and region dummies or firm size. It also includes time-invariant dummy variables for M&A firms and their competitors to control for permanent differences in innovation activities between the different groups of firms. c_i accounts for unobserved time-invariant firm heterogeneity that might affect the growth path of innovation activity.

Introducing lagged dependent variables in a count data model is non-trivial. Simply including the number of previous patent applications in the exponential function can lead to a rapidly exploding series (e.g. Windmeijer, 2008). Further, this would imply that an increase in the number of previous patent counts by one unit induces a percentage change on the number of current patent applications.

[11] In cases where acquirer and target remain separate legal entities after a merger, we use the sum of acquirer and target patents after a merger. To avoid double counting of patents, we assign a patent to either the acquirer or the target in a few cases where both parties appear as applicants. Inventions that are filed as patents in different countries are only counted when filed for the first time.

Hence, we follow the suggestions by Crépon and Duguet (1997) and Windmeijer (2008) and define:

$$\theta G_{i,t-5} = \rho_1 ln\left(P_{i,t-5} + D\left(P_{i,t-5} = 0\right)\right) + \rho_2 D\left(P_{i,t-5} > 0\right) \tag{6}$$

where $D\left(P_{i,t-5} = 0\right)$ is a dummy variable that takes the value of one if $P_{i,t-5}$ equals zero. In this specification, $ln\left(P_{i,t-5}\right)$ enters the regression model for positive values of $P_{i,t-5}$, while zero values of lagged patent applications have a separate effect on current innovation output.

Following Blundell, Griffith, and van Reenen (1995) and Blundell, Griffith, and Windmeijer (2002), pre-sample information on firms' patent applications is used to control for unobserved firm heterogeneity. To be more specific, we use the log of the average number of patent applications per year (adjusted in the same way as G) and a dummy variable that takes the value of one if a firm filed at least one patent during the pre-sample period. Compared to other panel data techniques for count data models this specification has the advantage that it does not assume strict exogeneity of the regressors. In contrast to the estimation techniques proposed by Wooldridge (1997) and Chamberlain (1992), this procedure does not rely on the validity of lagged values of predetermined variables as instruments. It is particularly advantageous if the regressors are characterized by high persistence, since lagged values of the regressors can be weak instruments for quasi differenced equations in this case. Blundell, Griffith, and Windmeijer (2002) derive the formal conditions for consistency of count data models which use pre-sample information as a proxy for unobserved firm heterogeneity. Although the estimator is formally consistent for a large number of time periods only, Blundell, Griffith, and Windmeijer (2002) show that this estimator outperforms alternative estimation techniques even when there are only four pre-sample periods available.

Estimation can be undertaken by generalized method of moments (GMM) based on the moment condition $E\left[P_{it} - \exp(x_{it}^{'}\beta)|x_{it}\right] = 0$ or alternatively by quasi maximum likelihood estimation of a pooled Poisson model. Although the Poisson maximum likelihood function assumes equality of mean and variance, its consistency requires solely the first moment of the model to be specified correctly. Since we use robust standard errors, the exact distributional assumptions are relatively unimportant. We also cluster standard errors at the market level, to account for correlated errors between competing firms. In an alternative specification, we use simple fixed effect models which rely on strict exogeneity of the regressors and do not account for lagged dependent variables but have the advantage that no specific form of unobserved heterogeneity has to be specified.

Although the estimation techniques so far account for time-invariant unobserved heterogeneity and feedback from innovation to future decisions about M&As, it is still possible that the estimated coefficients do not reflect a causal effect of M&As on post-merger innovation. This is the case when unobserved time-varying factors such as technology shocks – if not sufficiently accounted for by control variables – affect the profitability of both M&As and innovation activities. To check whether these endogeneity problems affect our results, a non-linear instrumental variable (IV) approach estimated by GMM is used. Following Windmeijer and Santos Silva (1997), this GMM estimator is based on an additive error specification $P_{it} = \exp(x_{it}^{'}\beta) + u_{it}$, which yields the moment condition: $E\left[P_{it} - \exp(x_{it}^{'}\tilde{\beta})|w_{it}\right] = 0.$[12] w_{it} includes all exogenous variables in the vector x and at least one exclusion restriction that is assumed to affect the propensity to engage in M&As but has no direct effect on innovation output and is also uncorrelated with unobservables affecting innovation. To check the robustness of our results, we also implement a linear IV estimator in which we use the outcome variable $\ln(P_{it} + 1)$ to maintain an approximately exponential relationship between regressors and patents.[13]

To implement the IV estimators, merging firms are excluded from the estimation sample and the analysis is restricted to the responses of rivals and the comparison group as in several other empirical merger studies (see, for instance, Dafny, 2008; Eckbo, 2007; Hastings, 2004). The advantage of excluding merging firms is that IVs that affect the propensity of a merger are much more likely to be exogenous to competitors' innovation activities than to the outcomes of merging parties. An obvious drawback of this approach is that it only allows identifying the causal effect on non-merging competitors and not on the merged entity. However, in our theoretical model, a negative effect of mergers on rival firms is a sufficient condition for a negative effect on the merged entity. Hence, the sign of the effect on rivals' innovation outcomes can be informative about changes in innovation in the whole market. For the estimation of IV models, we use a dummy variable that takes the value of one if firm i was affected by a rival's merger between $t-4$ and $t-1$ instead of $\sum_{k=1}^{4} \gamma_k CO_{i,t-k}$. This avoids estimating a model with a large number of endogenous variables and excluded instruments.

Our first IV measures the average technological proximity between firms in a market – excluding firm i. Target firms with high technological proximity to a potential acquirer can be attractive for several reasons. For instance, knowledge spillovers might be higher within than across technological fields. Further, target firms with a similar technology portfolio might be easier to integrate into a new entity and duplicate R&D activities can be cut (Veugelers, 2006). Previous empirical research

[12] $\tilde{\beta}$ denotes a vector with a constant term that is different from those in β.

[13] This transformation of the dependent variable is rather arbitrary but is commonly used in empirical studies (e.g. Bloom, Draca, and van Reenen, 2016). Due to this transformation, the coefficients only have a qualitative interpretation since marginal effects on P_{it} cannot be derived from this specification.

has found that acquirers indeed prefer target firms with high technological proximity (e.g. Frey and Hussinger, 2011), particularly in the pharmaceutical industry (Ornaghi, 2009a,b). If technological proximity increases the probability of being a target, technological proximity between rivals of firm i should also affect the probability of a merger among firms i's rivals. The key identifying assumption is that technological distance between two firms is uncorrelated with the growth of patent applications of other firms. Note, that since our model is dynamic, it is only required that the excluded instrument is uncorrelated with the change and not with the level of innovation activity. To make this assumption more likely to hold, the average technological distance of firm i to its rival firms is controlled for.

To measure technological proximity between firms in a market, we follow Jaffe (1986) and describe a firm's technological activity by the vector $S_{it} = (S_{i1t}...S_{iMt})$ where S_{imt} denotes the fraction of firm i's patent stock in technology class m at time t. We define technology classes at the 3-digit IPC level.[14] Technological proximity between two firms i and j is defined as:

$$TP_{ijt} = \frac{S_{it}S_{jt}^{'}}{\sqrt{\left(S_{it}S_{it}^{'}\right)\left(S_{jt}S_{jt}^{'}\right)}} \tag{7}$$

This measure takes values between 0 and 1 and increases with the similarity of two firms' technological specialization.

As a robustness check, we use an additional IV, which measures geographical proximity between rival firms. The reasoning behind this variable is that costs of transmitting tacit knowledge are expected to increase with distance (Blanc and Sierra, 1999) as well as the costs of monitoring (Degryse and Ongena, 2005). Thus, geographical proximity should reduce the costs (in a broad sense) of undertaking a merger. Specifically, we calculate the share of firms within a market for which there is at least one other firm with a headquarter in the same country. We then define a dummy variable that takes the value of one if this share is above 0.5. Since the probability of geographical overlap may vary with the number of firms in a market, we additionally control for the pre-merger number of firms in IV regressions.[15]

As an alternative approach to handle potential endogeneity problems which does not require IVs, a propensity score matching approach combined with a difference-in-differences estimator is applied. We

[14]The 3-digit level divides patents into technology fields such as "medical or veterinary science" and "organic chemistry". It comprises 122 technology classes in our sample. As an alternative measure, we classified technologies at the 4-digit patent class level within pharmaceutical technology fields. This categorization refers to technology fields such as "Apparatus for enzymology or microbiology" or "micro-organisms or enzymes".

[15]Our identifying assumptions are similar to those used by Dafny (2008) who instruments mergers among a firm's competitors by a measure of their geographical location.

conduct a separate matching exercise for merging firms and non-merging competitors. To implement the matching procedure, a Probit model for the propensity score is estimated for firms affected by mergers and the comparison group. We exclude merging firms' competitors from the sample used to construct a control group for the merged entity, and vice versa, to ensure that the control group is unaffected by mergers. The matching procedure imposes common support and is performed without replacement. The change in $\ln(P_{it} + k)$ compared with the pre-merger period is used as outcome variable. As conditioning variables, we use pre-merger values of the number of patents, pre-sample patents, sales, profitability and the average number of citations per patent.[16]

6 Results

6.1 Descriptive statistics

Table 1 shows descriptive statistics for pre-merger values of several variables separately for merging firms, their competitors and the comparison group. The table shows considerable differences in innovation activities across the various groups of firms. Acquirers are characterized by the highest innovation intensity – indicated by the number of current patent applications as well as by the cumulative patent stock. The same is true if we look at citation-weighted patents or R&D expenditures. They are, however, only slightly more innovative than their non-merging competitors and these differences are insignificant at conventional levels of significance. All innovation indicators suggest that target firms are less innovative than their acquirers and rivals (statistically significant at the 1% level) but considerably more innovative than firms in markets without M&A activity (statistically significant at the 1% level). The pre-merger differences between acquirers, targets, and competitors are in line with our model setup which focuses on a merger between an efficient acquirer and a relatively less efficient target firm. The differences in innovation intensity compared to firms in markets without M&A activity are in line with proposition 1, which states a merger is more likely to be profitable – and hence more likely to take place – in markets with high innovation intensity. Acquirers are the largest firms within the sample measured by the amount of sales. On average, acquisition targets are relatively large but less profitable than firms in other markets and have similar values of sales compared to non-merging competitors. However, these figures include sales and profits which are generated in non-pharmaceutical product markets as well.

[16]Exclusion restrictions used in IV models are not used as conditioning variables in the matching approach, as recent research suggests that matching on variables which satisfy IV assumptions increases the amount of inconsistency of matching estimators (Wooldridge, 2009).

Table 2 shows patent-based measures of consolidated companies in the pre-merger year and four years after a deal. The table indicates an average decline in innovation output in the merged entity four years after a merger compared to the pre-merger period of more than 20%, while competitors experience a reduction of about 16%. These changes are also visible for citation-weighted patents. The amount of reduction is quite remarkable since there is a positive time trend for all innovation indicators in the data set. For instance, the average growth rate of yearly patent applications over a 5-year interval is about 17%, and M&A activity seems to be associated with changes in innovation activities that substantially outweigh this overall time trend.

Patent stocks after a merger are higher than in the pre-merger period, but accumulated knowledge is almost always increasing over time (unless the depreciation rate exceeds the rate of new patents). More meaningful measures are based on a comparison with non-merging firms. For this purpose, we calculated the expected change of a merged entity's patent stock in the absence of a merger from the growth rates of other firms in the same region that were not affected by a merger.[17] For a merged entity, the predicted patent stock is calculated as $\hat{P}_{t+k} = P_{ac,t-1}\frac{P_{Cac,t+k}}{P_{Cac,t-1}} + P_{ta,t-1}\frac{P_{Cta,t+k}}{P_{Cta,t-1}}$. $P_{ac,t-1}$ ($P_{ta,t-1}$) refers to the patent stock of the acquirer (target) one year before the merger. $P_{Cac,t+k}$ ($P_{Cta,t+k}$) is the patent stock of firms in the acquirer's (target's) region within the comparison group measured k periods after the merger. This measure assumes that in the absence of a merger, acquirers' and targets' patent stocks had grown at the same rate as the patent stocks of firms in the same region that are not affected by a merger. We divide firms into five different regions – UK and Ireland; Other Western and Northern European Countries; South, Central and Eastern Europe; USA; and the rest of the World. This classification ensures that we have a reasonably large number of comparison firms in each region. Merging firms' rivals are excluded from the comparison group to ensure that this group is unaffected by mergers. An analogue measure is calculated for the expected growth rates of competitors from a comparison group which excludes merging firms. We also calculated expected values of the patent stock in the years before the merger, based on previous realization of the patent stock and growth rates of the comparison group. The difference between the actual and predicted value of a firm's patent stock is a first descriptive indicator for pre- and post-merger innovation activity.

Figure 1 depicts this development for the pre- and post-merger periods for merged entities and rivals. The graph indicates that while deviations from predicted patent stocks are quite small in the pre-merger period they are negative and increasing over time in the post-merger periods. In relative terms, the numbers suggest that in the absence of a merger, the cumulative patent stock of merged

[17]The methodology builds on Gugler et al. (2003).

entities would be 30% higher and those of competitors would be about 5% higher in time period $t+4$. These observations are in line with our model's predictions for a research intensive industry and a high degree of firm heterogeneity. Nonetheless, these correlations might be due to observed and unobserved firm heterogeneity, group or market specific trends and dynamics in the innovation process. These issues will be tackled in the econometric analysis.

6.2 Post merger innovation outcomes

Table 3 shows results from Poisson and linear fixed effects estimators which include time dummies and two dummy variables which take a value of one for the merged entity and rivals in all post-merger periods. Again, merging parties are treated as one firm both before and after a merger. The results for patent counts confirm that within-firm (and within-market) variation in M&A activity is associated with considerable decline in innovation activity on average. In post-merger periods, innovation output by the merged entity and its competitors decreases on average by more than 30% and 7% compared to other firms, respectively. Similarly, the table shows that M&A activity is correlated with declines in R&D spending. Profitability increases in the post-merger period for both acquirers and competitors (possibly due to a reduction of R&D spending and other investments), which may indicate that mergers in our sample are profitable on average. The correlation between M&As and sales are in line with our theoretical model. Non-merging rivals increase their sales after a merger, while the merged entity decreases its scale of operation compared to the combined activities of acquirer and target before the merger.[18]

As discussed in the previous section, a caveat of fixed effects estimators is the assumption of strict exogeneity, which rules out feedback from innovation to future decision about M&A. The descriptive statistics as well as theoretical reasoning indicate that this assumption is unlikely to hold in the present application. Therefore, Table 4 shows variants of the dynamic count data estimators discussed in the previous section. The results indicate significantly negative changes in the growth of patent applications in all post-merger periods. This is the case for the unweighted patent count variable in column (1) and (2) as well as for citation-weighted patents in columns (3) and (4). Unobserved firm heterogeneity plays a significant role as indicated by the positive coefficients for pre-sample patent applications. The coefficients for lagged innovation output in Table 6 show that there is considerable persistence in patent activity. As columns (2) and (4) show, the results seem to be insensitive to

[18] Regressions for accounting variables are displayed for the sub-sample of firm-years for which sales, profits and R&D are available. The different numbers of observations between the two patent regressions are due to the fact that the likelihood function of the Poisson fixed effects estimator cannot be calculated for firms with zero (citation-weighted) patents in all time periods.

controlling for pre-merger patent stocks instead of lagged patent counts.

A drawback of the analysis up to this point is that the results do not allow for a correlation of M&A activity with contemporaneous unobserved factors. To address these endogeneity concerns, a combination of rival effects and IV techniques is used as discussed in the previous section. Tables 5 and 6 show (pseudo) first stage and second stage estimates of the IV approach.[19] Column (1) in Table 5 shows a significantly positive association between technological proximity in the market and the incidence of a merger. The Kleinbergen-Paap statistic, which can be regarded as an approximation of the distribution of the common weak-instrument test with non-iid errors, yields a value which is a multiple of the critical value for a maximum IV bias of 10% of the weak identification test proposed by Stock and Yogo (2005). The overall F statistic of the first stage is highly significant as well.

The validity of the IV cannot formally be tested. However, results of reduced form regressions displayed in Table 5 can give an indication about the validity of the identifying assumption that technological distance between competitors of firm i only affects its innovation activities via mergers among its competitors. Column (2) shows that not controlling for M&As, the instrumental variable is negatively correlated with innovation activity during the sample period of interest, presumably because it positively affects the likelihood of an M&A, and M&As in turn have a negative effect on innovation activity. For comparison, the reduced form is estimated for the pre-sample period 1982-1989 in which no M&As take place among the firms in our main estimation sample. Results in column (3) show that the estimated coefficient becomes statistically insignificant. Further, it is smaller in terms of its absolute value and even changes its sign. This indicates that technological distance only affects innovation activities through its effect on the likelihood of mergers.[20] In an alternative specification, we additionally use a dummy variable for a high share of co-located rivals as an excluded instrument as discussed in the previous section. The (pseudo) first stage regression in column (4) of table 5 shows that this variable is positively correlated with the likelihood of an M&A as expected. The regressions control for the pre-merger number of firms (both in first and second stage) to ensure that this IV does not capture the size of a market.

Table 6 shows results from non-linear GMM-IV estimation in columns (1) and (2). The results

[19]The label pseudo first stage is used, because the GMM approach does not use predicted values from this regression in a second stage as a linear IV estimator. The following discussion focuses on overall patents counts, although all results hold for citation-weighted patents which are highly correlated with overall patent counts.

[20]In this regression, there are only 4 periods to calculate the average number of pre-sample patents, the proxy for unobserved firm heterogeneity. However, this result holds with and without controlling for unobserved firm heterogeneity.

show even higher effects for competitors than the previous estimates that control for time-invariant unobserved heterogeneity only. The coefficient in column (1) indicates a decrease in the growth of patent applications of about 0.62 log points or 46% ($\approx exp(-0.62) - 1$). Since our specification is dynamic, the results have to be interpreted with respect to the growth, not the level, of innovation output. If anything, not accounting for endogeneity of M&As seems to lead to an underestimation of the effects of mergers. It seems intuitive that ignoring endogeneity of mergers leads to an upward bias of estimated coefficients since both empirical results and our theoretical model indicate that higher pre-merger innovation intensity is associated with a higher likelihood of mergers.

The results of the innovation outcome equation applying GMM and using both excluded IVs, depicted in column (2) of Table 6, confirms the negative effect of M&As on innovation outcomes. The estimated coefficient is in absolute terms even larger than in column (1). It indicates a reduction of the growth of patent applications within four years of about 0.8 log point or 56%. The use of two different exclusion restrictions allows the application of over-identification tests. Results of the Hansen test statistics, depicted in Table 6, show that the null hypothesis of orthogonality between the residuals and the IVs cannot be rejected at conventional levels of significance in both linear and non-linear IV models. Hence, once we accept co-location as a valid instrument, the test indicates exogeneity of technological proximity of rivals and vice versa.

While consistency of the GMM estimates does not hinge on distributional assumptions about the error term, it relies on a correct specification of the conditional expectation and an additive residual. As a robustness check, we estimated linear IV models corresponding to the first stage equations in table 5. As dependent variable, the transformation $\ln(P_{it} + 1)$ is used to deal with zeros and to retain the exponential relationship between dependent variable and regressors. The results are depicted in columns (3) and (4) of table 6. They confirm the negative effect of mergers on rivals' innovation outcomes.[21] The results do not necessarily have a quantitative interpretation, as it is not possible to derive marginal effects on the number of patents from this specification. However, they qualitatively confirms the results from previous specifications. There is a large and significantly negative effect of M&As on innovation activities of competitors.

It is possible that mergers induced by technological proximity have a particularly large impact on innovation outcomes, because an overlap of research activities might be associated with higher potential for elimination of duplicate research efforts or a larger reduction of competition in technol-

[21] This is not surprising since, in the case of one excluded instrument, the second stage coefficient for the endogenous variable equals the ratio of the reduced form and the first stage coefficient ($-0.1315/0.4955 \approx -.2655$).

ogy markets. A similar reasoning can be applied to instruments that measure geographical proximity (Dafny, 2008). If this is the case, the IV estimates capture a local average treatment effect that might be different from the average effect of a merger in the pharmaceutical industry. Nonetheless, these variables capture important motives for mergers and the results indicate that endogeneity of mergers is unlikely to be the only explanation for the negative association between M&As and post-merger innovation outcomes.

As an alternative approach that does not rely on the validity of exclusion restrictions, we implement a propensity score matching procedure that comprises a comparison between the actual outcome for firms affected by the merger and the situation had the merger not occurred. The matching procedure is combined with a difference-in-differences approach to account for a potential correlation of time-invariant unobserved firm heterogeneity and patents. As outcome variables, $\ln(P_{i,t+k}+1) - \ln(P_{i,t-1}+1)$ is calculated for up to 4 post-merger years. The matching procedure was performed without replacement and we imposed common support. All time-varying covariates were measured in the year before the merger took place. The propensity score matching was undertaken separately for merged entities and non-merging rivals in comparison to firms never affected by a merger to ensure independence of treatment and control observations.[22] Table 7 contains the results for the estimation of the propensity scores. As Table 8 and Table 9 show, the balancing property seems to hold as t-tests cannot reject the equality of means for any variable.

The results of the estimation of average treatment effects on the treated (ATT), based on a regression of the outcome on a " treatment dummy" for merger incidence on the matched sample, are depicted in Panel A and Panel B of Table 10. The coefficients are less precisely estimated than the regression coefficients from previous specifications, but they confirm the negative effects of mergers on innovation for both merged entities and non-merging rivals. While the estimated ATT are insignificant for the first two post-merger periods, they are economically and statistically significant three and four years after the merger. Panel C and Panel D of Table 10 investigate the role of heterogeneous effects for the merged entity and non-merging competitors. For this purpose, merger dummies are interacted with the absolute value of the pre-merger differences between acquirer's and target's logarithmic patent stock, $\Delta(acq - target)$. This variable is related to b, the competitive disadvantage of target firms, in our theoretical model. We also interact the merger dummies with a pre-merger measure of innovation at the industry-level, the median patent stock in the market. This measure is inversely related to k, a market's research intensity in our theoretical model. Interestingly, the results show that not all

[22] As in previous regressions, acquirers and targets were treated as one firm before and after the merger.

mergers seem to cause negative effects on innovation output. This only seems to be the case if pre-merger differences between acquirer and target are sufficiently large or if, in the case of non-merging rivals, the market's research intensity is sufficiently high. These results are in line with the hypotheses derived from our theoretical model. The negative interaction term between merger incidence and pre-merger firm heterogeneity (b) is predicted by hypothesis 3 for the case of a research intensive industry (low k) – which arguably applies to most pharmaceutical markets. Further, hypotheses 2 and 5 state that outsiders only reduce innovation if both the market's innovation intensity is high (k is low) and pre-merger differences between acquirer and target are large (b is high). In contrast to our theoretical model, our empirical results do not indicate a significant effect of a market's research intensity on post-merger innovation in the merged entity. A possible explanation is that our sample mainly consists of markets with a relatively high innovation intensity. All in all, our empirical results are consistent with several predictions of our theoretical model and indicate that the observed decrease in innovation outcomes after mergers is related to a reduction in competition. In contrast to previous work that focuses on innovation outcomes within the merged entity, we can rule out alternative explanations such as post-merger integration problems and elimination of duplicated research activities since these would not apply to non-merging competitors.

7 Conclusion

While merger policy in both the EU and the US occasionally discusses the effects of mergers on innovation, the focus has, until now, almost exclusively been on the effect on the merging parties' innovation activities. This holds also true for the sparse academic literature that analyses mergers and innovations - a heavily under-researched field in general. Our paper intends to shift that focus to also draw attention to the effects that mergers can have on rival firms' innovation activities.

As we have shown, mergers can indeed not only have a negative impact on the merged firms' innovation activities, but also on rivals. This finding is especially relevant for research intensive industries. In order to analyse the effects of horizontal mergers on innovation of both the merged entity and its non-merging competitors, we have developed an oligopoly model with heterogeneous firms that yields empirically testable predictions. The main implication of our theoretical model is that in research intensive markets a merger reduces not only innovation activities of the merged entity, but a merger also has negative effects on outsiders' innovation expenditures if the merger involves a relatively small firm. Moreover, the negative effect on outsiders' innovation activities is the more likely to occur the smaller the acquired target is.

Using a data set of mergers in the pharmaceutical industry that affected European product markets. we have tested these predictions. We find that after a merger, patenting and R&D expenditures decline in the merged entity and among non-merging rivals. The results are robust towards alternative specifications, using an instrumental variable strategy and a propensity score matching approach. In line with our theoretical model, we also find that the negative effects of mergers on innovation are concentrated in markets with high pre-merger R&D intensity and a high degree of firm heterogeneity. As a consequence we suggest that merger policy should pay closer attention to the effects that mergers can have on innovation incentives, not only of the merger entity, but also on rivals in the market. Focusing only on the merged entity's innovation activities may well underestimate the negative effects that mergers can have on innovation.

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8 Tables

Table 1: Summary statistics - pre-merger

Variable		acquirer	target	competitor	compare	all
patents	# patents	50.10	20.86	45.70	2.71	12.81
		(121.5)	(63.3)	(161.5)	(17.2)	(78.9)
citations	# citation-weighted patents	152.78	62.74	141.75	7.28	38.81
		(367.3)	(221.3)	(508.7)	(52.3)	(247.9)
patent stock	cumulative # of patents	256.84	91.85	219.16	21.92	68.35
	(15% yearly depreciation)	(666.6)	(248.8)	(788.9)	(203.4)	(417.9)
citation stock	cumulative # citations	814.64	295.61	706.55	39.75	196.76
	(15% yearly depreciation)	(1969)	(891)	(2444)	(288)	(1204)
R&D	R&D expenditures	1685.1	967.2	1551.5	574.1	712.5
	(Euro million)	(1476)	(1397)	(1500)	(1080)	(1198)
Sales	Sales	5664.7	3857.6	3864.8	3093.1	3375.9
	(Euro million)	(9788)	(8668)	(8924)	(7265)	(7842)
Profitability	Gross profits / sales	0.11	0.06	0.11	0.10	0.10
		(0.19)	(0.19)	(0.18)	(0.22)	(0.21)
tech.proximity rivals	average technological	0.29	0.30	0.31	0.05	0.17
	proximity between firm's rivals	(0.27)	(0.28)	(0.22)	(0.14)	(0.23)
tech.proximity(i)	technological proximity	-	0.33	0.31	0.09	0.22
	to potential acquirers	-	(0.38)	(0.35)	(0.25)	(0.35)
co-location	= 1 if share of	0.44	0.43	0.79	0.29	0.39
	co-lated rivals > 1	(0.50)	(0.50)	(0.41)	(0.45)	(0.49)

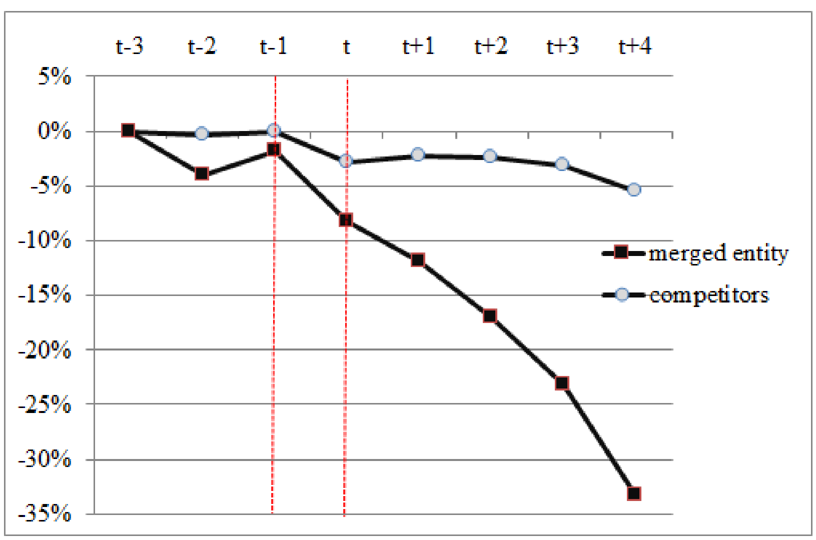
Notes: Tables shows mean values with standard deviations in parentheses. Statistics based on pre-merger observations of acquirers, targets and rivals.

Table 2: Pre- and post-merger levels of patenting activity

	t-1 merged entity	t+4 merged entity	t-1 competitor	t+4 competitor
patents	103.40	82.63	61.95	51.60
citations	325.02	292.88	208.39	168.92
patent stock	567.11	613.73	313.78	373.393
citation stock	1657.05	1948.57	959.73	1138.88

Notes: Tables shows mean values of patent outcomes one year before and 4 years after a merger which takes place in year t. For the merged entity, all patents in which either the acquirer, the target or the new entity appear as applicants are counted.

Figure 1: Relative deviations from predicted patent stock



Notes: Graph shows relative deviation of average observed values of patent stocks from patent stocks predicted by lagged stocks and growth rates of non-merging firms in the same region. t denotes the time period in which the merger takes place.

Table 3: Fixed Effects Regressions

	(1)	(2)	(3)	(4)	(5)
	patents	citations	R&D	profitability	ln(sales)
$POST_{acq,t-1}$	-0.3606***	-0.3424***	-0.4850***	0.0721***	-0.5614**
	(0.0080)	(0.0044)	(0.0978)	(0.0238)	(0.2822)
$POST_{comp,t-1}$	-0.0927***	-0.0777***	-0.1730***	0.0155*	0.3155***
	(0.0044)	(0.0025)	(0.0609)	(0.0092)	(0.0984)
N	33953	24016	9525	9525	9525

Notes: Tables shows the results of fixed effects regressions. Columns (1) and (2) contain results of Poisson fixed effects regressions, columns (3)-(5) contain results of linear fixed effects regressions. $POST_{acq,t-1}$ and $POST_{comp,t-1}$ are indicator variables which take a value of 1 in all post-merger periods for the merged entity and non-merging competitors, respectively. Variables are based on consolidated companies before and after M&As. All regressions include time dummies. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Dynamic models

	(1)	(2)	(3)	(4)
	patents	patents	patent citations	patent citations
$MA_{acq,t-1}$	-0.1686***	-0.1807***	-0.1916***	-0.1058
	(0.0450)	(0.0483)	(0.0691)	(0.0706)
$MA_{acq,t-2}$	-0.2538***	-0.3039***	-0.3069***	-0.3378***
	(0.0390)	(0.0524)	(0.0592)	(0.0734)
$MA_{acq,t-3}$	-0.3065***	-0.4127***	-0.2506***	-0.3432***
	(0.0505)	(0.0585)	(0.0507)	(0.0647)
$MA_{acq,t-4}$	-0.1705**	-0.2788***	-0.3382***	-0.2832***
	(0.0732)	(0.0892)	(0.0795)	(0.0885)
$MA_{comp,t-1}$	-0.1294***	-0.1231***	-0.1103***	-0.1230***
	(0.0264)	(0.0256)	(0.0377)	(0.0416)
$MA_{comp,t-2}$	-0.2250***	-0.2283***	-0.2569***	-0.2715***
	(0.0244)	(0.0297)	(0.0337)	(0.0353)
$MA_{comp,t-3}$	-0.2006***	-0.2258***	-0.2129***	-0.2759***
	(0.0279)	(0.0259)	(0.0355)	(0.0408)
$MA_{comp,t-4}$	-0.1053***	-0.1739***	-0.1324***	-0.1888***
	(0.0310)	(0.0346)	(0.0357)	(0.0419)
log patents(t-5)	0.7250***		0.6214***	
	(0.0439)		(0.0390)	
D(patents(t-5)> 0)	0.1846		0.8853***	
	(0.1520)		(0.0832)	
log patent stock(t-5)		0.6846***		0.6856***
		(0.0475)		(0.0510)
D(patent stock(t-5)>0)		-0.6014*		0.0467
		(0.3437)		(0.1984)
log pre sample patents	0.0514***	0.0012	0.0770***	-0.0450*
	(0.0157)	(0.0206)	(0.0168)	(0.0236)
D(pre sample patents> 0)	-0.7470***	-0.6981**	-0.7179***	-0.3838***
	(0.1853)	(0.3241)	(0.1224)	(0.1424)
log sales(t-5)	0.0805**	0.0875**	0.0773*	0.0781
	(0.0352)	(0.0446)	(0.0441)	(0.0498)
N	27512	27512	27512	27512

Notes: Tables shows results from count data regressions. $MA_{acq,t-k}$ ($MA_{comp,t-k}$) take a value of 1 if a firm has been affected by a merger in time period $t-k$ directly (indirectly as competitor). All regressions include time dummies and indicator variables for firms which ever merge or are affected by a merger during the sample period. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: First stage and reduced form regressions

	(1)	(2)	(3)	(4)
	First stage	Reduced form	Reduced form	First stage
Sample period:	1990-2008	1990-2008	1982-1989	1990-2008
Dependent variable:	MA_{comp}	patents	patents	MA_{comp}
tech.proximity rivals(t-5)	0.4955***	-0.1315**	0.0970	0.4895***
	(0.0272)	(0.0644)	(0.1219)	(0.0276)
co-location				0.0178**
				(0.0080)
tech.proximity(i,t-5)	-0.0291	0.1199**	-0.1742	-0.0294
	(0.0195)	(0.0551)	(0.1166)	(0.0195)
log patents(t-5)	0.0168***	0.6359***	0.4545***	0.0169***
	(0.0021)	(0.0073)	(0.0269)	(0.0022)
D(patents(t-5)>0))	-0.0876***	-0.2362***	0.4161***	-0.0877***
	(0.0075)	(0.0267)	(0.0708)	(0.0075)
log pre sample patents	-0.0101***	0.1076***	0.4508***	-0.0101***
	(0.0030)	(0.0100)	(0.0228)	(0.0030)
D(pre sample patents>0)	-0.0466***	-0.3759***	0.0347	-0.0467***
	(0.0111)	(0.0338)	(0.0270)	(0.0110)
number of firms	-0.0051***	-0.0001	-0.0005	-0.0055***
	(0.0003)	(0.0009)	(0.0011)	(0.0004)
log sales(t-5)	0.0014	0.0266***	0.0163***	0.0012
	(0.0009)	(0.0028)	(0.0033)	(0.0009)
N	12374	12374	5843	12374
F-Test 1st stage	227.08	1619.16	1597.32	211.64
Kleinbergen-Paap rk Wald F	298.32	-	-	120.83
R squared	0.342	0.778	0.804	0.354

Notes: Table shows the results of OLS regressions. All regressions include time dummies and indicator variables for firms which ever merge or are affected by a merger during the sample period. Robust standard errors in parentheses.

*p <0.1, **p <0.05, ***p < 0.01.

Table 6: IV second stage estimates

	(1) GMM	(2) GMM	(3) Linear IV (2nd stage)	(4) Linear IV (2nd stage)
MA_{comp}	-0.6221***	-0.8461***	-0.2655**	-0.2766**
	(0.2321)	(0.1375)	(0.1309)	(0.1299)
log patents(t-5)	0.8130***	0.8031***	0.6403***	0.6404***
	(0.0175)	(0.0155)	(0.0072)	(0.0072)
D(patents(t-5)>0)	0.5953***	0.5889***	-0.2595***	-0.2605***
	(0.0866)	(0.0868)	(0.0290)	(0.0289)
log pre sample patents	0.0238**	0.0275***	0.1049***	0.1047***
	(0.0101)	(0.0103)	(0.0102)	(0.0102)
D(pre sample patents>0)	-0.8958***	-0.9425***	-0.3882***	-0.3885***
	(0.0924)	(0.0826)	(0.0339)	(0.0339)
number of firms	-0.0016	-0.0008	-0.0014	-0.0014
	(0.0015)	(0.0014)	(0.0012)	(0.0012)
technological proximity(i,t-5)	-0.1134***	-0.0876**	0.1121**	0.1145**
	(0.0410)	(0.0371)	(0.0527)	(0.0527)
log sales (t-5)	0.0893***	0.1061***	0.0317***	0.0317***
	(0.0195)	(0.0135)	(0.0028)	(0.0028)
N	12,374	12,374	12,374	12,374
Hansen (p-value)	-	1.224 (0.265)		0.631 (0.427)

Notes: The dependent variables is the number of patent applications per year in column 1 and 2 and the log of (the number of patent applications plus 1) in columns 3 and 4. MA_{comp} takes a value of one if a firm has been affected by a merger among its competitors between time period $t-1$ and $t-4$. All regressions include time dummies and indicator variables for firms which ever merge or are affected by a merger during the sample period. Robust standard errors in parentheses.

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

Table 7: Estimation of propensity score

	(1)	(2)
	merged entity	rivals
log patents	0.2419***	0.1285***
	(0.0452)	(0.0294)
citations per patent	0.0146	0.0168
	(0.0180)	(0.0105)
log pre sample patents	0.3885***	0.1534***
	(0.0568)	(0.0265)
D(pre sample patents>0)	1.7954***	1.2417***
	(0.2133)	(0.0744)
log sales	-0.0418*	0.0347***
	(0.0252)	(0.0112)
profitability	0.1341	-0.1237
	(0.2681)	(0.1533)
N	13299	7350
pseudo R-sq	0.328	0.163

Notes: Table shows the result from Probit regressions. Dependent variable takes on value one in the case of a merger. Time-varying regressors are lagged one year relative to the merger decision. Regressions include time dummies. Robust standard errors in parentheses.

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

Table 8: Balancing property merged entity

Variable	Sample	Treated	Control	%bias	%bias red.	t-test	p-value
propensity score	Unmatched	0.0787	0.0037	113.6		28.07	0.000
	Matched	0.0787	0.07899	-0.5	99.6	-0.02	0.986
log patents	Unmatched	3.8538	0.63715	228.8		20.31	0.000
	Matched	3.8538	3.879	-1.8	99.2	-0.08	0.937
citations per patent	Unmatched	2.5407	1.7167	32.5		1.97	0.049
	Matched	2.5407	2.8308	-11.4	64.8	-0.91	0.367
pre sample patents	Unmatched	2.8339	0.22759	187.9		25.36	0.000
	Matched	2.8339	2.7467	6.3	96.7	0.24	0.807
D(pre sample patents>0)	Unmatched	0.90909	0.20457	200.5		12.94	0.000
	Matched	0.90909	0.94545	-10.3	94.8	-0.73	0.467
log sales	Unmatched	7.4461	4.2861	142.7		9.27	0.000
	Matched	7.4461	7.6817	-10.6	92.5	-0.65	0.519
profitability	Unmatched	0.27397	0.565	-4		-0.21	0.834
	Matched	0.27397	0.25591	0.0	99.7	0.26	0.796

Note: Table shows mean differences between merging firms and the control group before and after matching.

Table 9: Balancing property rivals

Variable	Sample	Treated	Control	%bias	%bias red.	t-test	p-value
propensity score	Unmatched	0.1059	0.02105	108		40.35	0.000
	Matched	0.1059	0.10611	-0.3	99.7	-0.03	0.976
log patents	Unmatched	1.9753	0.80898	63.7		16.94	0.000
	Matched	1.9753	2.1433	-9.2	85.6	-1.13	0.26
citations per patent	Unmatched	2.4228	1.8147	24.9		4.44	0.000
	Matched	2.4228	2.4928	-2.9	88.5	-0.41	0.685
log pre sample patents	Unmatched	1.3778	0.76931	42.8		12.77	0.000
	Matched	1.3778	1.4664	-6.2	85.4	-0.72	0.47
D(pre sample patents>0)	Unmatched	0.35635	0.09893	64.5		17.74	0.000
	Matched	0.35635	0.34521	2.8	95.7	0.35	0.727
log sales	Unmatched	6.3663	4.5003	72.8		15.76	0.000
	Matched	6.3663	6.5194	-6	91.8	-0.89	0.376
profitability	Unmatched	0.1557	0.4340	-3.6		-0.52	0.603
	Matched	0.1557	0.12117	0	99.2	1.54	0.125

Note: Table shows mean differences between firms affected by a merger of its competitors and the control group before and after matching.

Table 10: Average treatment effects from propensity score matching

	(1) patents(t+1)	(2) patents(t+2)	(3) patents(t+3)	(4) patents(t+4)
Panel A:merged entity				
MA_{acq}	-0.0432	-0.1231	-0.4284**	-0.5791**
	(0.1661)	(0.1862)	(0.2190)	(0.2868)
N	104	104	104	104
Panel B: Competitors				
MA_{comp}	0.0944	0.0592	-0.1824**	-0.2981***
	(0.0712)	(0.0727)	(0.0807)	(0.1080)
N	636	636	636	636
Panel C: merged entity				
MA_{acq}	0.4018	0.4735	0.3837	0.9672
	(0.3508)	(0.3837)	(0.5009)	(0.6243)
$MA_{acq} \times \Delta(acq - target)$	-0.8642*	-0.9672*	-1.3915**	-2.5636***
	(0.4543)	(0.4999)	(0.5760)	(0.7814)
$MA_{acq}\times$ industry-innovation	0.0012	0.0001	0.0006	0.0009
	(0.0010)	(0.0007)	(0.0008)	(0.0010)
N	104	104	104	104
Panel D: Competitors				
MA_{comp}	0.0028	0.2955	0.2223	0.4734**
	(0.1567)	(0.1909)	(0.1748)	(0.2110)
$MA_{comp} \times \Delta(acq - target)$	0.1371	-0.3483	-0.5013**	-0.9096***
	(0.2025)	(0.2313)	(0.2254)	(0.2865)
$MA_{comp}\times$ industry-innovation	-0.0003	-0.0009	-0.0024**	-0.0048***
	(0.0007)	(0.0008)	(0.0011)	(0.0017)
N	636	636	636	636

Notes: Table shows regressions based on the matched sample after propensity score matching. The dependent variable is the change in the log of (number of patents + 1) between $t+k$ and $t-1$ where t refers to the year of the merger. Robust standard errors in parentheses. MA_{acq} (MA_{comp}) is an indicator variable which takes on a value of one if a firm has been affected by a merger directly (indirectly as competitor). $industry-innovation$ is the median value of the patent stock within markets in the pre-merger period. $\Delta(acq - target)$ measures the absolute value of pre-merger differences in patent stocks between acquirer and target normalized by the sum of both firms' pre-merger patent stock.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

9 Appendix

Proof of Proposition 1: (i) In order to compare the post-merger profit of firm 1 and the pre-merger joint profit of firms 1 and 3, note that $\pi_1^{Post} = k((9k-8)/((9k-4)^2))$ and $\pi_1^{Pre} + \pi_3^{Pre} = (1/2)k(8k-9)(2b+2k-3)^2/(9-12b-30k+16bk+16k^2)^2 + (1/2)(b+k)(2k-3)^2(8b+8k-9)/(9-12b-30k+16bk+16k^2)^2$. The post-merger profit level exceeds the pre-merger profits for $b > b^*$ with $b^* \equiv -(1/2)(2k-3)/(576k^4-4292k^3+7624k^2-4992k+1152)(432-2424k+4651k^2-3590k^3+576k^4+(27k-12)\sqrt{(36k^4-356k^3+3809k^2-4104k+1296)})$, which is non-positive for $3/2 < k < 3.9954$. Hence, for all $b > 0$ it must be true that $b > b^*$ for $3/2 < k < 3.9954$ so that $\pi_1^{Post} > \pi_1^{Pre} + \pi_3^{Pre}$. (ii) For $3.9954 \leq k < 5.2196$, b^* has positive values which are increasing in k. For $b > b^*$ we obtain $\pi_1^{Post} > \pi_1^{Pre} + \pi_3^{Pre}$. (iii) For $k = 5.2196$ we have $576k^4 - 4292k^3 + 7624k^2 - 4992k + 1152 = 0$, so that $b^* \to \infty$ as $k \to 5.2196$, while for $k > 5.2196$ we obtain $\pi_1^{Post} < \pi_1^{Pre} + \pi_3^{Pre}$ for all $b > 0$.

Proof of Proposition 2: In order to compare the outside rival's innovation expenditures note that $I_2^{Post} = k(4/(9k-4))^2$ and $I_2^{Pre} = k((6b+6k-9)/(16bk-30k-12b+16k^2+9))^2$. Also note that $I_2^{Post} \geq I_2^{Pre}$ if $b \leq b^+$ with $b^+ \equiv (10k^2-15k)/(24-10k)$, which has strictly positive values for $3/2 < k < 12/5$ (case i). For $k > 12/5$, b^+ has negative values. Hence, for $b > 0$ it follows that $b > b^+$ for $k > 12/5$. Hence, $I_2^{Post} \geq I_2^{Pre}$ for $k > 12/5$ (case ii).

Proof of Proposition 3: In order to compare the merged entity's innovation expenditures note that $I_1^{Post} = k(4/(9k-4))^2$ and $I_1^{Pre} + I_3^{Pre} = k((6b+6k-9)/(16bk-30k-12b+16k^2+9))^2 + (k+b)((6k-9)/(16bk-30k-12b+16k^2+9))^2$. (i) Note that $(4/(9k-4))^2 < ((6b+6k-9)/(16bk-30k-12b+16k^2+9))^2 + ((6k-9)/(16bk-30k-12b+16k^2+9))^2$ implies that $I_1^{Post} < I_1^{Pre} + I_3^{Pre}$. The former inequality can be reduced to $12b-45k-5bk+22k^2+18 > 0$, where the left-hand side is strictly increasing in b for $k < 12/5$. For $b = 0$ the left-hand side has strictly positive values for $k > 3/2$ which is given by Assumption 1. Hence, $I_1^{Post} < I_1^{Pre} + I_3^{Pre}$. (ii) For $k > 12/5$ we have $k(4/(9k-4))^2 > k((6b+6k-9)/(16bk-30k-12b+16k^2+9))^2 + (k+b)((6k-9)/(16bk-30k-12b+16k^2+9))^2$ if $\Omega \equiv -1180b^2k^3 + 3552b^2k^2 - 1728b^2k + 556bk^4 - 3768bk^3 + 7713bk^2 - 5832bk + 1296b + 1736k^5 - 7320k^4 + 10818k^3 - 6480k^2 + 1296k < 0$. Note that $\Omega = 0$ for either $b = b_1 \equiv (1/2)(2k-3)/(1180k^3-3552k^2+1728k)(278k^3-1467k^2+1656k-432+(36-81k)\sqrt{(324k^4-1156k^3+1081k^2-456k+144)})$ or $b = b_2 \equiv (1/2)(2k-3)/(1180k^3-3552k^2+1728k)(278k^3-1467k^2+1656k-432+(81k-36)\sqrt{(324k^4-1156k^3+1081k^2-456k+144)})$. Note that b_1 only takes on negative values for $k > 3/2$, while b_2 has strictly positive values for $k > 3/2$. Hence, for $b > b_2 \equiv b^{++}$ we have $I_1^{Post} > I_1^{Pre} + I_3^{Pre}$.

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