Mergers and Innovation: Evidence from Patent Intensive Industries

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Abstract

The scope of this article is to increase the awareness about the potential effects of mergers on innovation. Initially, this is done by means of a review of the existing literature. Particular attention is given to the scholarly discussion which followed the European Commission decision on the *Dow/DuPont* case of 2017. In these regards, it is argued that the theoretical foundations of the so-called 'Innovation Theory of Harm' are too fragile to be the basis for changes in antitrust policy. In addition, this work provides evidence to the debate by considering the effects of mergers on patent proliferation in the chemical and the pharmaceutical sectors for the years 1995 - 2010. My findings pose a challenge to the view that mergers have a positive impact on innovation in patent-intensive industries. At the same time, they also cast doubts on some of the theoretical arguments underpinning the Innovation Theory of Harm.

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1 Introduction

In the Antitrust literature and practice, a merger is any decision by independent companies to put their assets together. When a merger takes place, a market player virtually disappears, as it is incorporated into the merged entity; eventually, the market structure is changed.

A new market structure can in turn determine two mutually exclusive classes of effects: coordinated effects and unilateral effects. Coordinated effects arise whenever the market structure has been shaped in such a way that collusive agreements between the remaining players are easier to sustain. On the other hand, unilateral effects may arise when firms continue to interact in an oligopoly, preserving their competitive behaviour and yet adapting their strategies to the new market structure.

In the latter case, threats to market well-functioning come unilaterally from within the merged entity, and not from a sub-group of coordinating firms. Although this definition of unilateral effects may seem outstretched, it is yet the most accurate: it goes beyond the simple ability of the merged entity to exercise market power, and accommodates for the different ways through which unilateral effects may unfold.

All unilateral effects stem from the fact that, after the transaction, merging firms that once competed can coordinate. As a result, they can in the first place internalize the negative externalities previously exerted on each other, and avoid the production of unprofitably high outputs. This coordination of strategies is paired with a coordination of assets: bigger firms can better allocate the production of output, attaining lower marginal costs. Moreover, the combination of different productive assets working synergistically may generate economies of scale and scope, which in turn entice efficiency.

While several academic inquiries have allowed us to achieve a high degree of understanding of these three static effects, there is a fourth channel whose importance has been acknowledged only recently: the relationship between mergers and innovation.

In principle, the coordination of technological knowledge between merging firms can significantly shape firms' incentives to invest in research and development. Yet, explicit considerations of any long-run assessment of dynamic efficiency have been unseen for long times in the practice of Antitrust Authorities. This is very surprising, especially if one considers the importance of innovation as a driver of economic growth and social welfare.

The scope of this article is to increase the awareness about the potential effects of mergers on innovation. This is done in two ways: by reviewing in detail the literature devoted to the topic, and by providing empirical evidence.

The work is hence organized in two main parts. Section 2 presents the topic from a theoretical perspective; special attention is devoted to the so-called 'Innovation Theory of Harm', a new approach to the issue of dynamic efficiency established by the European Commission with the *Dow/DuPont* case of March 2017. Section 3 provides additional evidence to the theoretical debate.[1] In particular, the empirical study is conducted for the case of two patent intensive industries: the chemical and the pharmaceutical sectors for the period 1995-2010. Strong emphasis is given to the construction of new variables starting from raw patent statistics, and to the solutions found for the identification challenges inherent to mergers.

The results of this paper pose a challenge to the view that mergers have a positive impact on innovation performances in patent intensive industries. At the same time, some of the claims put forth by the European Commission in its Innovation Theory of Harm are strongly questioned. Some concluding remarks, pointing also to the policy implications of the results obtained, are presented in Section 4.

[1] The empirical part of this article is inspired by and builds on the work of Carmine Ornaghi '*Mergers and innovation in big pharma*' (2009)

2 Mergers and Innovation in the Economic Literature

In the academic field of competition and innovation, the works of Schumpeter (1942) and Arrow (1962) still constitute a landmark today.

On one side of this debate, the Schumpeterian view contends that market power can promote innovation for the simple reason that higher profits make investments more financially sustainable. Instead, according to Arrow and subsequent works in his tradition, this is true in a limited number of circumstances; for example, when a monopolist faces the threat of an innovative entrant, and decides to protect its monopoly rent by innovating (Gilbert and Newberry, 1982). In Arrow's view, the ultimate driver of innovation is instead the difference between post-innovation and pre-innovation profits; because a monopolist is making substantial profits even in the absence of innovation – while a competitive firm makes none –, this quantity is lower under monopoly than under competition.

In more recent years, new influential literature has explored the relationship between concentration and innovation (notably, Aghion et al., 2005; Gilbert, 2006), rising the attention for the issue of dynamic efficiency. Although it is debatable whether the findings are directly applicable to the case of mergers (Shapiro, 2012), even antitrust merger practice has been influenced by this new level of awareness. In the US, antitrust agencies mention innovation effects in over one third of the mergers challenged since 2004 (Gilbert and Greene, 2015). In the EU, competition commissioner Margrethe Vestager stated in April 2016: "*When we look at high-tech mergers, we do not just look at whether they might raise prices. We also assess whether they could be bad for innovation.*"[2]

[2] See Vestager, M.: "Competition: The mother of invention", speech delivered at the European Competition and Consumer Day, 18 April 2016, https://ec.europa.eu/commission/commissioners/2014-2019/vestager/announcements/competition-mother-invention_en.

A turning point in the practice has been established with the *Dow/DuPont* case. In this ground-breaking merger case from 2017, two major companies in the chemical sector – Dow and DuPont – were willing to constitute a single entity with a market capitalization of 130 billion USD, which would have resulted in the world largest player in the crop protection industry, and the second largest player in the seeds global market. According to the European Commission, beside raising competition concerns in the markets for pesticides and for petrochemical products, the transaction would have fostered a significant reduction in innovation competition.

The approach with which the innovation segment of the case was argued presented many novelties; first and foremost, the Commission's investigation into the innovation concerns did not only involve products which were ready to be marketed, and was extended to the research activity of the involved firms as a whole (Petit, 2017).

In the policy debate, this approach has come to be known as the 'Innovation Theory of Harm'.

2.1 The Innovation Theory of Harm

The Innovation Theory of Harm emerging from the *Dow/DuPont* decision generally poses a negative presumption upon the relationship of mergers and innovation:

> *The merger between* [two firms] *will result in internalization by each merging party of the adverse effect of the R&D projects on* [...] *the other merging party; hence,* [...] *it will reduce investment in the competing R&D projects. The innovation competition effect* [of a merger] *follows the basic logic of unilateral effects, which is equally applicable to product market competition and to innovation competition.*[3]

[3] Annex 4, §145 of Commission Decision of 27/03/2017 declaring a concentration compatible with the internal market and the functioning of the EEA Agreement (Case M.7932 — Dow/DuPont) according to Council Regulation (EC) No 139/2004.

More in detail, the theoretical arguments underpinning this position refer to the presence of three main channels.

The first channel relates to the basic principles of merger theory: when a merger takes place, the internalization of negative externalities, together with a milder competition, always results in an increase of the insiders' profits. At the same time, it is reasonable to assume that innovation also increases a firm's profit, whether they underwent a merger or not. However, if the increase in profits due to innovation is smaller for merged firms than it is for unmerged ones, then their incentive to innovate is evidently smaller. In other words, the increase in profits due to the merger alone may decrease the attractiveness of new profits due to innovation.

In the papers which are often regarded as providing the theoretical foundations of the Innovation Theory of Harm, Federico, Langus and Valletti (2017, 2018) recognize that this 'product market competition channel' may also spur innovation: this is the case whenever merged firms gain from innovation more than un-merged ones. Ultimately, the final effect of this channel depends on the nature of competition.

A second channel which is particularly relevant to this article is related to the business-stealing effects of successful innovation: cheaper and better products are likely to steal customers from competitors, therefore firms with similar research projects engage in a competition that drives innovation efforts up. When two firms merge, they automatically stop exerting this negative externality on each other.

Federico et al. (2017) consider this case of 'duplicative research' in a two-stage game: in stage one, each firm chooses the effort to put in innovation; in stage two, they observe the outcomes of the innovation process and receive payoffs accordingly. Eventually, their model predicts that firms to a transaction solve the externality issue by jointly reducing their research efforts, so that in a sense each firm 'cannibalizes' the other's projects.

Finally, the third channel makes considerations onto the appropriability of findings: if an innovation can be easily imitated by competitors at the expenses of the innovating firms, a merger reduces the number of potential imitators, hence it increases the expected profits of an innovating firm.

As it appears from the discussion of each channel, the predictions of the Innovation Theory of Harm on the net total effect of mergers should not be ex-ante determined: the 'cannibalization channel' has negative impact, the 'appropriability channel' is instead positive, while the 'product innovation channel' has an effect which ultimately depends on the degree of market competition. Nevertheless, the theory of harm articulated by the Commission in the *Dow/DuPont* decision contends that mergers generally stifle innovation, and a negative presumption is justified. There is one important consequence to this view: if the presumption posed by the Commission is correct, even mergers whose static effects are benign could then be regarded as anticompetitive in a dynamic perspective.

2.2 The Innovation Theory of Harm – Discussion

The unprecedented policy implications of the *Dow/DuPont* decision soon raised discussion among scholars. In the following years, a large piece of literature was developed to assess the theoretical foundations of the Innovation Theory of Harm.

In a 2018 paper, Jullien and Lefouili shed some more light onto the functioning of the 'product competition channel'. In their view, the effect of this channel is largely driven by the objectives that the firms' management wants to achieve through innovation. If a firm's objective is to increase its margins, then the fact that a merger itself increases market prices will lower the incentives to innovate. On the other hand, if a firm wants to innovate in order to boost its sales, then the fact that a merger reduces the quantity sold by each firm will increase the incentive to invest in demand enhancing innovations.

As far as the 'innovation externality channel' is concerned, some academics believe that it does not necessarily have the negative impact predicted by Federico, Langus and Valletti. In 2017, the work of Motta and Tarantino had already pointed out that, in the presence of research synergies, mergers may boost innovation. More articulately, Denicolò and Polo (2018a) show that a joint reduction of research efforts is the post-merger equilibrium only in specific cases: firms may also opt for a more efficient allocation and better coordination of their R&D practices. In practical terms, the latter strategy may amount to the shutdown of one of the firm's labs, so that the risk of duplication is eliminated ab origine, and efforts can be exerted more narrowly and effectively.

The prevalence of 'cannibalization' over 'rationalization' ultimately depends on the returns of R&D expenditure: if they decrease very fast, the only way to optimally internalize the negative externality is to reduce R&D expenditure. Intuitively, rationalization would not be a successful solution: even if the firm concentrated its effort in one lab, the increased expenditure would give less returns.

Finally, some important contributions were made also with regards to the 'appropriability channel'. For example, Burreau, Jullien and Lefouili (2018) point out that even in the case of partial appropriability, technological spillovers benefiting the rivals are positive for innovation. Relatedly, Denicolò and Polo (2018b) notice that, after a merger, technological spillover between merging firms is in a sense automatic: parties to a transaction always share their discoveries with their partners, because the application on a wider set of assets is beneficial. They model this 'innovation sharing' effect with a two-step process: first, firms discover an intermediate innovation, then they apply it to improve research on the final product. In this setting, mergers are always beneficial to innovation because a merged entity can employ two labs in the research of the intermediate discovery; once the discovery is made – even by just one of the two labs –, it can be effectively applied to both.

'Innovation sharing' is particularly important in the case of process innovation. Intuitively, innovations of process are proportionally linked to the quantity of output produced by a firm; since a merged entity produces more output than the single parties, the incentive to process innovation is stronger for a merged firm. Moreover, it may even lead to a virtuous cycle: in general, incremental innovation decreases marginal costs, consequently it increases output, and more output eventually fosters more innovation in the productive process.

Table 1
Predicted effects of M&As on innovation

Channel	**Innovation Theory of Harm**	**New literature**
Product market competition	?	?
Innovation externality	-	?
Appropriability	+	+
Innovation sharing		+
Total effect	?	?

Taken together, the literature subsequent to the *Dow/DuPont* case poses serious challenges to the validity of the Innovation Theory of Harm: the negative presumption towards which it leant seems unjustified from a theoretical point of view. At the same time, some of the channels presented eventually maintain an undetermined effect, so that even a positive presumption would not be correct.

At the current stage of knowledge, merger control should continue to consider the impact of horizontal mergers on innovation with a case by case approach, bearing in mind that the effect can go either way.

3 Evidence from Patent Intensive Industries

The aim of this section is to provide empirical evidence to the theoretical debate started after the *Dow/DuPont* decision. This is done through the study of a series of mergers in the chemical industry and the pharmaceutical sector for the period 1995-2010.

The choice of these industries is driven by several reasons: first, these are two of the sectors with the most intense R&D practices, where innovation has a crucial role in the competition among firms. At the same time, because they both are patent intensive industries, said innovation can be reasonably measured by patent proliferation. Secondly, chemical and pharmaceutical firms have been central in the wave of international mergers of the first decade of the century (Harford, 2005). Thirdly, the choice of the chemical sector is also consequential to the fact that it is the industry involved in the *Dow/DuPont* case.

The analysis is restricted to mergers between the largest companies, those which generated transactions of at least 1 billion EUR in size. This seems like a reasonable choice, as only these types of transactions are able both to influence the incentives of the merging firms, and to reshape the structure of the industry. In addition, mergers between large companies are the operations more likely to rise anticompetitive concerns inquired by Antitrust Authorities.

This work adds to a field where empirical literature is scarce. Schulz (2007) provides an excellent summary of early literature, his conclusion being that results are mixed. More recently, Szücs (2014) finds that target firms substantially decrease their R&D post-merger; while Danzon, Epstein and Nicholson (2007), Ornaghi (2009) and Haucap and Stiebale (2016) all find that mergers in the pharmaceutical sector have negative impacts on innovation. On the contrary, other studies find no evidence of a decrease in post-merger R&D activity; notably, the study by Bennato, Davies, Mariuzzo, and Ormosi (2019) focuses on the HDD industry.

3.1 Data and Variables

To answer the questions of the investigation, a new dataset needed to be constructed.

Patent data for the EU have been obtained from the publicly available Patents-ICRIOS Database, described by Coffano and Tarasconi (2014). Similarly, patent data for the US have been retrieved from PatentsView, a platform supported by the Office of Chief Economist in the US Patent & Trademark Office (USPTO). Several files of both databases were used in order to collect data on the assignee and the applications. In general, all patents statistics have been computed only for granted patents, using the application date as point of reference.

Patents of the two databases had already been classified according to the IPC system[4]. This classification system, consisting of about 600 main patent classes and almost 70,000 sub-classes, allows to identify the technological area to which a patent belongs. Although very detailed, it is sometimes too elaborate and impractical, especially when reconducting each patent to an industry. To do so, I have used Eurostat official documents and univocally connected each IPC code into the much broader NACE[5] classes. In the case of the chemical industry, the NACE class comprises 67 patent main classes; for the pharmaceutical sector, it consists of 9 main classes and about 200 sub-classes. The NACE classification is especially important in the case of mergers involving highly diversified firms, because it allows to consider only the research activity in the sector of interest.

Patents classification also allows to infer significant information on a firm's technological position. Following Jaffe (1986), one could think that because each IPC class comprises discoveries with similar technical features, there exist as many research areas

[4] The International Patent Classification (IPC), established by the Strasbourg Agreement 1971, provides a hierarchical system of language-independent symbols for the classification of patents according to the different areas of technology to which they pertain.

[5] NACE (for the French term "Nomenclature statistique des Activités économiques dans la Communauté Européenne"), is the industry standard classification system used in the European Union. The current version is revision 2 and was established by Regulation (EC) No 1893/2006.

as the number of IPC classes. The "technological position" of a firm's research program can hence be defined by a vector $S = (s_1, \ldots, s_K)$, where K is the number of IPC classes and s_i is the fraction of patents held by the firm in the IPC class i. The correlation between the research programs of two firms α and τ, is then defined by:

$$\text{PatCr} = \frac{(S_\alpha S'_\tau)}{(S_\alpha S'_\alpha)^{\frac{1}{2}}(S_\tau S'_\tau)^{\frac{1}{2}}}$$

In the last part of the paper, this measure is also used as a measure for the extent to which the research activities of the merging parties are duplicative. In light of the debate about the direction of the 'innovation externality channel', it is particularly interesting to test whether highly duplicative research projects always lead to 'cannibalization' as proposed by Federico et al. (2017, 2018), or 'rationalization' may also happen, as suggested by Denicolò and Polo (2018a).

Another measure of research programs' overlap which has been used is the one conceived by Marco and Rausser (2002): it is constructed by looking at the overlap between the set of patents cited by the acquirer and the selected target:

$$\text{Over} = \frac{(\text{Number of Pat in } C_\alpha \bigcap C_\tau)}{(\text{Number of Pat in } C_\tau)}$$

The Citation files, which record the citations received by each granted patent, have also been used to identify the "important" patents, P^{imp}. In industries like the chemical and the pharmaceutical ones, firms patent prolifically, and the number of patents may be a rather noisy measure of research activity. Arguably, a better measure is given by 'important patents', namely those belonging to the top decile of the citations ranking for their application year. Given that some years need to pass for a patent to receive a representative number of citations, the variable P^{imp} is constructed up to four years before the last update of the dataset (2015 for the American patents and 2013 for the European patents).

Finally, as regards the merger transactions, they are obtained from Zephyr, the M&A database edited by Bureau van Dijk, by filtering for the relevant NACE class and a deal size exceeding 1 billion EUR.

Table 2
Descriptive statistics by industry

		1994	1995 - 2000	2000 - 2005	2005 - 2010	2011
Chemical	Number of mergers	0	7	9	12	2
	Average deal value (€m)	–	5,750	3,400	3,120	2,350
	Average number of patents	–	9,274	5,322	14,318	5,998
Pharmaceutical	Number of mergers	1	10	11	6	0
	Average deal value (€m)	5,300	17,550	42,820	16,130	–
	Average number of patents	1,388	6,807	9,140	7,828	–

Notes: These figures refer to the sample used for the final estimation, i.e. after the matching procedure.

As shown by Table 2, for each industry, there are about 30 M&A operations considered. Despite the rather small size of the samples, it must be kept in mind that this paper focuses on two well-defined sets of firms and operations: in this sense, it includes the entire universe of chemical and pharmaceutical companies and the major transactions in which they are involved.

3.2 Empirical Specification

In order to determine the effects of a merger, it is necessary to predict what the performance of the merging firms would have been if they had not merged. This is not as easy as a task.

In general, any study on the merger phenomenon is inherently difficult for one simple reason: treatment and control groups are not easily identifiable. First, mergers may come in waves which involve many firms, making the availability of appropriate controls limited. Secondly, and most importantly, while the randomized control trial framework would require that the probability of being treated is not affected by the decision of other units to be treated, in the case of mergers this is often not the case: especially during 'merger waves', the decision to merge may be a competitive response to other firms merging; in any case, the decision to merge of a competitor always affects a non-merging firm's competitive strategy, notably in terms of R&D activity.

Another important challenge posed by mergers is the fact that some firms might decide to merge multiple times, making it hard to isolate pre- and post-treatment periods. According to the industry, the entity of this issue changes extensively; it is of relevant dimensions in the chemical and the pharmaceutical sector, where some major players like Pfizer and BASF merge almost every other year. To alleviate the issue, I evaluate the effect of merging on patent proliferation over the limited period of three years, so that any subsequent merger happening after the third year does not constitute a problem. If any observation is involved in a second merger within three years after the first, I accordingly shorten the period of study for that specific observation.

Bearing in mind these peculiarities, this article studies the effects of mergers on innovation using a difference-in-differences approach. The following econometric model is estimated:

$$\Delta\%P_{i,t} = \beta_1 \,\text{Time}_t + \beta_2 \,\text{Merger}_i + \beta_3 \,(\text{Time}_t \times \text{Merger}_i) + \varepsilon_{i,t} \qquad (1)$$

Some definitions are in order: $\Delta\%P_{i,t}$ indicates the percentage change (logarithmic difference) in the number of patents produced between two consecutive years[6]; '$\mathsf{Time_t}$' is a dummy variable taking value 1 in the year after the merger, while 'Merger_i' is a dummy variable taking value 1 for the merging firms. The coefficient of the interaction term '$\mathsf{Time}_t \times \mathsf{Merger}_i$' represents a difference-in-differences estimate which captures the excess outcome growth for consolidated companies compared to non-merging firms. Given that large deals as those considered in this paper are likely to produce their effects over several years, rather than entirely in any one year, Equation (1) is estimated for each of the three years subsequent to the merger date.

As clear as the approach above may seem, it still has a main drawback, for it does not account for any source of endogeneity of the merger process.

3.3 Identification strategy

The decision to merge and the potential innovation outcomes – the ones that would be observed absent the merger – are likely to be simultaneously determined by factors like the quality of research activity, the technological fields in which a firm is specialized, and the upcoming expiration of important patents. In order to better account for these sources of endogeneity, I increase the robustness of my identification strategy by combining the baseline difference-in-differences estimation with a matching procedure. As it is done in Ornaghi (2009), the matching procedure is done in two steps.

In the first step, the identification strategy relies on the parallel trend assumption: firms with no significant differences up to the moment of the merger should not differ in future performance, if it were not for the merger itself. Thus, I produce the counterfactual outcomes using a control group of non-merging firms which have pre-merger characteristics similar to those of the merging firms. Because two firms can differ along

[6] A model in growth rates has been chosen also in order to purge from the specification any unobserved heterogeneity among firms that is persistent over time.

many different dimensions, non-merging firms are identified using the propensity score method.

First introduced by Rosenbaum and Rubin in 1983, this method is generally used to assess the effects of an economic treatment on a single unit. Because mergers involve two different units, I account for this peculiarity by matching both acquirers and targets.[7] The combination of a matching technique with a difference-in-differences approach is not new to the study of non-experimental data, Blundell and Costa Dias (2000) affirm that "*... a non-parametric propensity score approach to matching that combines this method with diff-in-diffs has the potential to improve the quality of non-experimental evaluation results significantly*" (pg. 438).

In this article, the probability of being a merging firm is estimated with a probit regression that uses as predictors some of the factors that might simultaneously affect the decision to merge and the future R&D activities. In the chemical and pharmaceutical industries, two sets of variables can arguably play such a role: approaching patent expirations and the quality of pre-merger innovation activities.

When patents approach their expiration date, patent intensive firms usually expect a reduction in cash flows. In turn, this can be both a determinant of mergers, and a possible source of disruption in the research activity (Scherer, 2004). Similarly, firms that are experiencing poor R&D results might anticipate further deteriorations and decide to pursue a merger to soften these negative events (Ornaghi, 2009).

The variables used to estimate the probability of firm merging are hence the following: the number of active patents on the merger date, the average number of years to expiration of important patents, the percentage of patents approaching expiration, and the percentage of new discoveries patented in the three years before the merger.

[7] In the merger literature, propensity score matching has been used, among others, by Hall (1987), Danzon et al. (2007), Bertrand and Zitouna (2008) and Ornaghi (2009).

In the second step of the procedure, I consider the possibility that some mergers are a defensive move taken by firms that anticipate negative technological shocks in an important field of their research. If this was the case, a negative correlation between mergers and research outcomes may be found even in the absence of any causal relationship. To control for this possibility, after having identified the five closest neighbours of each treated unit[8], following Jaffe (1986) I compute the technological relatedness between the treated unit and each of the five candidates. Eventually, I choose as final control the firm with the highest $PatCr$ score.

At the end of the algorithm, each acquirer and target of the real merger is matched with one unique control, which is labelled as "control acquirer" or "control target" accordingly. Finally, I construct fictitious mergers by summing together the patents of the control acquirers and targets of each transaction. When Equation (1) is run using only these fictitious mergers as controls, the estimated coefficients should effectively capture the actual effects of mergers on patent production.

As a final remark, it is important to bear in mind that the matching procedure described above attempts to get the most information out of patent data and use it to predict the probability of merging. Although for both sectors it appears that most of the variables considered do in fact drive the decision to merge, an ideal matching would typically also use data on R&D expenditure, number of commercialized products, measures of product relatedness. To alleviate this shortcoming, I have always assessed whether treated and control units were comparable in terms of market size and core business. If they did not seem comparable from a qualitative standpoint, I matched the treatment manually with the second most technically related candidate control.

While this approach can mitigate the identification problems, a convincing strategy will be always hindered by the fact that econometricians cannot observe most of

[8] The five closest neighbours are selected as follows: the closest neighbour is always retained; another four candidates are retained provided that their absolute distance from the treated unit in terms of propensity score is below 0.2.

the information that merging firms employ in their decision. Accordingly, one cannot rule out the possibility that the correlation found does not pin down the causal effect of mergers on innovation.

3.4 Connections with the Innovation Theory of Harm

The empirical strategy outlined above can provide some useful insights onto the topic of dynamic efficiency, especially considered the scarcity of existing empirical work. Instead, the extent to which it can add knowledge to the most recent academic works is more debatable.

Notably, those works measure innovation as input, or R&D investments, and not as output, expressed by patent proliferation. In this sense, this work may consistently underestimate innovation: it does not capture any unsuccessful effort nor, more relevantly, any increase in effort which is beneficial to the firm and society, but does not lead to the immediate production of patents.

Moreover, it is evident that this strategy can only assess the net effect of the four channels presented in Section 1. It proves to be inadequate if one wanted to study each single one: such a task would require insights onto the merged entity's cost function, estimates of demand shapes and measures of the degree of appropriability.

As regards the interpretations of the obtained results, the theoretical channels may also to some extent have limited explanatory power. On the one hand, this is due to the fact that any interpretation based upon the 'product competition channel' would require insider information to be a solid argument; on the other, the 'innovation sharing' channel mainly applies to process innovation, which cannot be captured by patent production. Accordingly, the concluding remarks of this paper (Section 4) will necessarily interpret findings only through the 'innovation externality' and the 'imitation' channels. Yet, as far as the former is concerned, this article provides some further insights.

In light of the debate about innovation externalities, it is interesting to test whether higher levels of research duplication are associated to 'cannibalization' of research projects, as predicted by Federico et al. (2017, 2018), or a 'rationalization' of research practices is also a possible outcome, as proposed by Denicolò and Polo (2018a).

To this aim, patent data are particularly useful, as they can provide sophisticated measures of technological relatedness between two different firms. In particular, this article uses two different measures: Jaffe's variable *PatCr* (1986), which is based on the positions of two firms in the technological space defined by patents; and Marco and Rausser's variable *Over* (2002), based on patent citations.

Because the sample used needs to be restricted to the sub-sample of merging companies, this paper uses a "two-step" Heckman procedure (1976) in order to account for the possible selection problem. In its first step, this procedure prescribes that the probability of receiving the treatment is estimated using a probit model, as above.

In the second step, the following equation is estimated:

$$\Delta\%P_i = \beta_1 \, \mathrm{TR}_i \; + \; \delta\lambda(\mathrm{X}\beta)_i + u_i \qquad (2)$$

where $\lambda(\mathrm{X}\beta)$ is the inverse Mills ratio[9] constructed from the "first step" estimates, included as an additional explanatory variable; while the variable TR is alternatively given by *PatCr* or *Over*, computed using patent statistics of the acquirer and the target at the day of the merger. As before, the specification is estimated for each of the three years subsequent to the merger.

Despite the simplicity of the approach, Equation (2) can provide interesting evidence on a rather unexplored issue: in particular, the results obtained seem to contradict the idea that higher levels of technological relatedness between merging parties are always associated with worse post-merger outcomes.

[9] The inverse Mills ratio is defined as $\lambda(\mathrm{x})=\frac{\phi(\mathrm{x})}{\Phi(\mathrm{x})}$, i.e. the ratio between the standard normal probability density function and its cumulative distribution function, each evaluated at x.

3.5 Findings

3.5.1 The Chemical Industry

There are 30 M&As considered in this industry, their details are reported in Table 3.1.

Table 3.1
List of mergers in the chemical industry

Acquiror	Target	Year	Value (m)
Hoechst	Marion Roussel	1995	€ 7,121
Du Pont	ICI - Polyester Polymer	1997	€ 2,494
Ciba	Allied Colloids	1998	€ 2,012
Akzo Nobel	Courtaulds	1998	€ 2,641
Du Pont	Herberts (Hoechst)	1999	€ 1,605
Huntsman	ICI - Industrial Chemical	1999	€ 2,575
Hoechst	Rhone-Poulenc	1999	€ 21,683
Dow	Union Carbide	2001	€ 12,483
Degussa-Huls	Laporte	2001	€ 2,144
Dow	Rohm&Haas - Agricultural Chemicals	2001	€ 1,179
Procter Gamble	Clairol	2001	€ 5,605
Solvay	Ausimont	2002	€ 1,300
S.C. Johnson Commercial Markets	Diversey	2002	€ 1,742
Air Liquide	Messer North America	2004	€ 2,680
Lubrizol	Noveon	2004	€ 1,506
Lyondell	Millennium Chemicals	2004	€ 2,030
Cytec	Surface Specialties	2005	€ 1,425
Crompton	Great Lakes	2005	€ 1,469
Linde	BOC	2006	€ 12,215
PPG	Sigmakalon	2008	€ 2,200
Henkel	ICI - Adhesives	2008	€ 3,530
Yara International	Saskferco	2008	€ 1,069
Ashland	Hercules	2008	€ 2,643
Dow	Rohm&Haas	2009	€ 14,194
Mitsubishi Rayon	Lucite International	2009	€ 1,148
Basf	Ciba	2009	€ 4,022
Unilever	Sara Lee	2010	€ 1,200
Basf	Cognis	2010	€ 3,100
Solvay	Rhodia	2011	€ 3,322
Clariant	Sud-Chemie	2011	€ 1,381

Notes: This is the complete list of M&As considered for the chemical industry. The merger between Hoechst and Rhone-Poulenc in 1999 led to the creation of Aventis. Crompton and Great Lakes joined together to form Chemtura in 2005.

The identification strategy outlined above requires finding 60 controls, one for each firm involved in the transactions. This is done with a two-step strategy that eventually matches each firm to the candidate control with the highest *PatCr* score among the five nearest neighbours in terms of propensity score.

Table 4.1

Propensity score (probit regression model) for the chemical industry

Variable	Estimate	Additional information	
Number of patents owned at the merger date	$0.178 \cdot 10^{-4}$	Number of obs	547
	(0.0866)	Wald chi2(4)	281.25
Average years to expiration for important patents	-0.0002 ***	Prob > chi2	0.0000
	$(0.41 \cdot 10^{-4})$		
Percentage of patents approaching expiration[a]	0.0162 ***		
	(0.0054)		
Percentage of new patent applications[b]	-0.0084 *		
	(0.0045)		

Notes: Robust standard errors in parentheses. Significance levels: ***=1%; **=5%; *=10%.

[a] Number of patents expiring in the next three years over total number of patents owned at merger date.

[b] Number of patent applications in the previous three years over number of patents owned at merger date.

The propensity to merge is estimated using a probit regression whose results are shown in Table 4.1. While it seems that mergers are not driven by the absolute number of patents owned at the date of the merger, it is interesting to notice that Table 4.1 confirms the finding of Danzon et al. (2007), according to whom firms whose important patents are far from expiration are less likely to merge. This speculation is confirmed when considering the totality of patents, regardless of their importance, as it is done with the third variable. Moreover, the sign and statistical significance of the last variable confirm that innovative firms are less likely to merge.

Before proceeding with the actual estimation, one needs to check whether the matching strategy eventually worked, and that treated firms show no significant differences with respect to their controls up to the moment of the merger. This check is carried out in different manners: a prima facie control is done qualitatively, by checking whether the treated unit and its control are similar in term of size and core business.

Secondly, similarities in the patent production patterns are checked graphically: Figure 1.1 shows the average number of patents for merging firms and their matched controls from four years before the merger to three years after the merger.

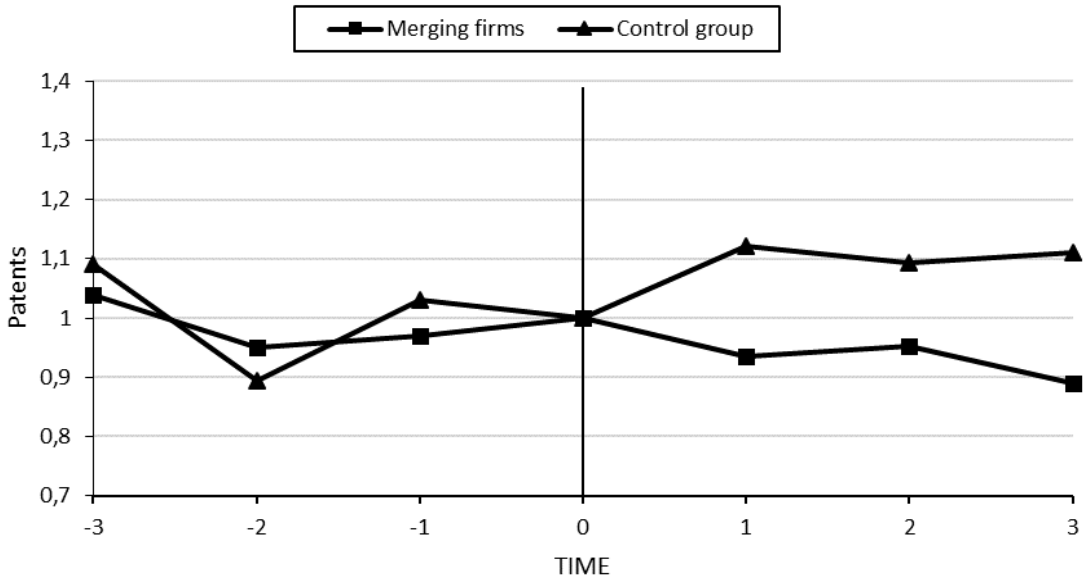

Fig. 1.1 The graph shows the average number of new patents of merging firms and the control group in the chemical industry. Notes: The control group is selected using the propensity score technique. Time on the horizontal axis refers to the number of years before or after the merger. Patents at the day of the merger are normalized to 1 to make the time series of the two groups easier

As it appears from the figure, the pre-merger number of patents of merging companies and controls follow a similar pattern up to the day of the merger, confirming that the matching algorithm was accurate. Divergence in innovation outputs begins only after the merger deal: while the post-merger research output of the latter continues to rise, consolidated companies keep their level of patent production below the level of the day of the merger.[10]

Finally, in Appendix A I formally test the parallel trend assumption by introducing a placebo merger.

Once that the soundness of the matching algorithm has been verified, the effects of mergers on innovation outputs are estimated using Equation (1). For each of the three years subsequent to the merger, I find that mergers have a highly statistically significant negative effect on the growth of innovation output.

[10] Notice that Patents at the date of the merger are normalized to 1 so that pre-merger and post-merger changes are easier to compare.

Table 5.1a
Effects of M&As on patents proliferation (chemical industry)

Variable	**t+1**	**t+2**	**t+3**
Time	0.0376 ***	0.0334 ***	0.0293 ***
	(0.0069)	(0.0067)	(0.0053)
Merger	0.0434 ***	0.0434 ***	0.0434 ***
	(0.0092)	(0.0092)	(0.0092)
Time × Merger	-0.0503 ***	-0.0414 ***	-0.0372 ***
	(0.0125)	(0.0127)	(0.0142)
$\mathbf{R^2}$	0.3392	0.3350	0.3381
Prob > F	0.0000	0.0000	0.0000

Notes: Robust standard errors in parentheses. Significance level: ***= 1%; **=5%; *=10%. The first two dependent variables are respectively a time dummy taking value 1 post-merger and 0 pre-merger, and a treatment dummy taking value 1 only for real mergers and 0 for fictional mergers.

As the interaction term displays a negative and highly significant coefficient, it is clear that the findings displayed in Table 5.1 contradict the idea that mergers can deliver relevant economies of scope and knowledge synergies. By and large, the findings are confirmed when restricting the analysis to the important patents, P^{imp}, as suggested by Table 5.1b in the Appendix B.

As interesting as the study of a global effect may be, the debate following the *Dow/DuPont* decision begs further questions on the direction of each of the channels identified by the theory. In the chemical sector it is hard to disentangle one effect from another; yet, this paper is able to provide some insights onto the discussion about the 'innovation externality' channel.

This is done by assessing whether high levels of research duplicability between merging entities are always associated with worse ex-post patents production. In Table 6.1a I estimate specification (2) using alternatively the variable *PatCr* or the variable *Over* as regressors. The inverse Mills ratio is computed using the probit model above.

Table 6.1a
Effects of Technological Relatedness on patents proliferation (chemical industry)

Variable	**t+1**	**t+2**	**t+3**	**t+1**	**t+2**	**t+3**
Inverse Mills Ratio	0.0159 ***	0.0122 ***	0.0335 ***	0.0261 **	0.0321 ***	0.0249 ***
	(0.0061)	(0.0021)	(0.0042)	(0.0125)	(0.0069)	(0.0076)
PatCr	0.2019 **	0.2866 *	0.0868 *			
	(0.0986)	(0.1529)	(0.0469)			
Over				0.115 **	0.0921 **	0.1713 ***
				(0.0467)	(0.0453)	(0.0612)
$\mathbf{R^2}$	0.4953	0.5299	0.3412	0.5910	0.5669	0.3361
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Robust standard errors in parentheses. Significance level: ***= 1%; **=5%; *=10%.

As it appears, the coefficients of the two TR variables are, although not highly statistically significant, all positive for the three years subsequent to the merger.[11] This finding is extremely interesting in light of the theoretical predictions made by Denicolò and Polo (2018a): duplicative research projects do not necessarily drive less innovation post-merger. Positive outcomes are also possible, and ultimately the result will depend on factors that are not contemplated in this model, like the returns of R&D expenditure and management ability to create dynamic synergies between the merging firms.

In the case of the chemical industry, it appears that the negative externality exerted on each other by innovative merging firms is solved by means of a rationalization, which eventually leads to an increased production of innovation outputs. This outcome is however not always the case, as it appears when studying the pharmaceutical sector.

[11] See Table 6.1b in Appendix C for important patents.

3.5.2 The Pharmaceutical Sector

The M&As considered in the pharmaceutical sector are reported in Table 3.2.

Table 3.2
List of mergers in the pharmaceutical industry

Acquiror	Target	Year	Value (m)
Roche	Syntex	1994	€ 5.307
Glaxo	Wellcome	1995	€ 14.284
Hoechst	Marion Roussel	1995	€ 7.121
Pharmacia	Upjohn	1995	€ 50.000
Rhone Poulenc	Fisons	1995	€ 2.888
Ciba	Sandoz	1996	€ 27.000
Roche	Corange	1997	€ 10.200
Amersham	Nycomed	1997	€ 1.568
Astra	Zeneca	1999	€ 30.936
Sanofi	Synthelabo	1999	€ 9.811
Hoechst Marion Roussel	Rhone Poulenc	1999	€ 21.683
Pfizer	Warner-Lambert	2000	€ 93.409
Glaxo Wellcome	Smithkline Beecham	2000	€ 189.951
Pharmacia Upjohn	Monsanto	2000	€ 27.765
Johnson & Johnson	Alza Corporation	2001	€ 12.257
Bristol-Myers Squibb	DuPont Pharmaceuticals	2001	€ 8.487
Abbott	Knoll (Basf)	2002	€ 7.380
Amgen	Immunex	2002	€ 15.945
Pfizer	Pharmacia	2003	€ 55.578
Teva Pharmaceuticals	Sicor	2004	€ 2.703
UCB	Celltech	2004	€ 2.252
Sanofi-Synthelabo	Aventis	2004	€ 55.300
Amgen	Abgenix	2006	€ 2.187
Bayer	Schering	2006	€ 17.000
Abbott Laboratories	Kos Pharmaceuticals	2006	€ 2.803
UCB	Schwarz Pharma	2006	€ 3.805
Pfizer	Wyeth	2009	€ 45.536
Merck & Company	Schering-Plough	2009	€ 25.487

Notes: This is the complete list of M&As considered for the pharmaceutical industry. The merger between Ciba and Sandoz in 1996 led to the creation of Novartis. Hoechst and Rhone-Poulenc joined together in 1999 to form Aventis.

Table 4.2 shows the results of the probit regression which has been used to match each merging company with a control. As above, it appears that the incoming expiration of important patents is a driver of merger decisions. At the same time, firms who are already innovating are less likely to merge. Contrary to the chemical industry, the absolute number of active patents also seem to play a role in determining the probability to merge.

Table 4.2

Propensity score (probit regression model) for the pharmaceutical sector

Variable	Estimate	Additional information	
Number of patents owned at the merger date	0.0001 *	Number of obs	479
	(0.00006)	Wald chi2(4)	223.12
Average years to expiration for important patents	-0.0002 ***	Prob > chi2	0.0000
	($0.216 \cdot 10^{-4}$)		
Percentage of patents approaching expiration[a]	0.0302 ***		
	(0.0063)		
Percentage of new patent applications[b]	-0.00211 ***		
	(0.0007)		

Notes: Robust standard errors in parentheses. Significance levels: ***=1%; **=5%; *=10%.

[a] Number of patents expiring in the next three years over total number of patents owned at merger date.

[b] Number of patent applications in the previous three years over number of patents owned at merger date.

Figure 1.2 confirms the correct functioning of the matching algorithm, as the pre-merger number of patents of merging companies and controls follow a similar pattern up to the day of the merger, and differences arise only post-merger. This is also confirmed by the placebo analysis presented in the Appendix.

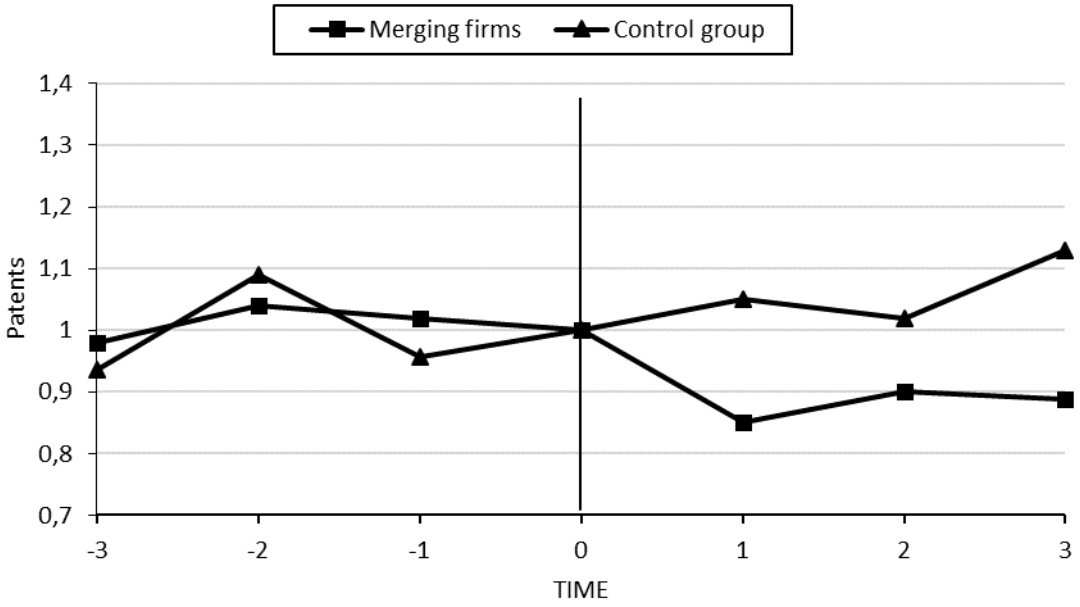

Fig. 1.2 The graph shows the average number of new patents of merging firms and the control group in the pharmaceutical sector. Notes: The control group is selected using the propensity score technique. Time on the horizontal axis refers to the number of years before or after the merger. Patents at the day of the merger are normalized to 1 to make the time series of the two groups easier to compare.

Table 5.2a displays the results for the estimation of Equation (1) when considering the pharmaceutical sector:

Table 5.2a
Effects of M&As on patents proliferation (pharmaceutical sector)

Variable	**t+1**	**t+2**	**t+3**
Time	0.0526 ***	0.0526 ***	0.0340 ***
	(0.0092)	(0.0097)	(0.0071)
Merger	0.0726 ***	0.0726 ***	0.0726 ***
	(0.0078)	(0.0078)	(0.0078)
Time × Merger	-0.0568 ***	-0.0722 ***	-0.0456 ***
	(0.0159)	(0.0147)	(0.0136)
$\mathbf{R^2}$	0.3984	0.3836	0.3381
Prob > F	0.0000	0.0000	0.0000

Notes: Robust standard errors in parentheses. Significance level: ***= 1%; **=5%; *=10%. The first two dependent variables are respectively a time dummy taking value 1 post-merger and 0 pre-merger, and a treatment dummy taking value 1 only for real mergers and 0 for fictional mergers.

As in the chemical industry, the results show that mergers have negative effects on the growth of innovation output.

Finally, I estimate specification (2) for the pharmaceutical sector in other to assess whether technological relatedness between merging firms has any effect on patent production in the three years subsequent to the merger.[12]

Table 6.2a
Effects of Technological Relatedness on patents proliferation (pharmaceutical sector)

Variable	**t+1**	**t+2**	**t+3**	**t+1**	**t+2**	**t+3**
Inverse Mills Ratio	0.0489 **	0.0655 ***	0.0478 ***	0.1023 ***	0.0932 ***	0.0869 ***
	(0.0193)	(0.0241)	(0.0087)	(0.0364)	(0.0302)	(0.0193)
PatCr	-0.0354 **	-0.0097 ***	-0.0215 *			
	(0.0151)	(0.0032)	(0.0126)			
Over				-0.7376	-0.3818	-0.5223
				(0.9903)	(1.004)	(0.848)
$\mathbf{R^2}$	0.5853	0.6302	0.5619	0.5583	0.6291	0.5643
Prob > F	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000

Notes: Robust standard errors in parentheses. Significance level: ***= 1%; **=5%; *=10%.

[12] For both estimations, results for "important" patents are available in the Appendix.

As anticipated, in the case of the pharmaceutical sector one observes that higher levels of Technological Relatedness (as measured by *PatCr*) are associated with lower levels of patent production.

The recent work of Cunningham, Edere and Ma (2019) can provide some interesting interpretations of this result. In their work, the three economists challenge the common view according to which participants to a transaction always aim at integrating their research projects and increase efficiency. Instead, an incumbent firm may acquire an innovative target in order to terminate the development of the its innovations and pre-empt future competition. This is what they call a 'Killer Acquisition'.

Relevantly to this article, they find that projects that are common to the merging parties are 4.9% more likely to be discontinued compared to non-overlapping projects. Despite the different empirical strategy, the findings of Cunningham et al. are confirmed in this work: in the pharmaceutical industry, higher levels of relatedness between the merging firms are associated with lower innovation output.

Nevertheless, one must exert caution when using the lenses provided by the work of Cunningham et al. to interpret the findings of this article. Firstly, because their measure of relatedness is based on product characteristics rather than patents; secondly, because they do not have any deal-size threshold, and mainly focus on mergers involving projects at a nascent stage.

3.6 Limitations

It might seem that the sole use of patent data inherently limits the validity of my work, I here clarify why this is not the case.

One first possible limitation is related to the matching procedure: indeed, it could be argued that the algorithm described above should also use information on R&D expenditure, number of commercialized products and measures of product relatedness.

Although I acknowledge that this would be an ideal solution, I also claim that the results of the matching procedure used in this work are already satisfactory. For each industry, the validity of the matching procedure has been checked in three different ways. First, the low number of observations allowed me to check manually whether treated units and controls were similar in a range of characteristics, including size and core business. Second, by plotting the number of new patents over years, I also ascertained that the outcome variable had a similar trend across the two groups up to the moment of the merger. Finally, in the Appendix I verify the validity of the parallel trend assumption by means of a placebo analysis. Together, these three methods point to the fact that the controls and treatments are similar except for the treatment itself.

A second class of doubts is related to the outcome variable chosen. Indeed, patent data alone may prevent from measuring innovation effectively. Following the theoretical framework developed by Bloom, Schankerman and Van Reenen (2005), a more robust test would use different innovation dimensions, covering also innovation inputs.

When brought to the empirical world, the pertinence of this remark changes extensively depending on the industry considered: for example, in the HDD industry, Bennato et al. (2019) indeed find that R&D expenditure is a better predictor of innovation than patent proliferation; on the other hand, studies on patent intensive industries as Ornaghi's (2009) or Haucap and Stiebale's (2016) all find results which are consistent across different measures of innovation. Hence, despite measuring one limited aspect of innovation, this study is not achieving misleading or partial results.

4 Conclusion

Mergers and innovation have become over the last few years more and more central in the academic debate. Especially after the European Commission decision on the *Dow/DuPont* case, several scholars have engaged in the discussion upon the topic of dynamic efficiency. This article adds to the existing literature in three ways: theoretical, empirical and methodological.

In its theoretical part, this work provides an organic review of the most recent papers devoted to the topic. After a detailed analysis of the theoretical arguments underpinning the Commission decision and the subsequent works in response, it is eventually pointed out that mergers do not have an ex-ante determined effect on innovation, hence any presumption – negative or positive – is unjustified.

The most important contributions of this article are however in its empirical content. Using a difference-in-differences approach, I find that mergers in the chemical and the pharmaceutical sectors in the years 1995-2010 have had a negative effect on innovation as measured by patent production. It may seem that the results of this article point towards a negative presumption, and are at odds with the approach prescribed in the first part of the paper. This would be a superficial interpretation. Like the works subsequent to the *Dow/DuPont* decision, this paper does admit the possibility that mergers may have negative effects on innovation, what instead is rejected is that mergers should *always* be regarded as inefficient from a dynamic prospective.

For patent-intensive industries, the presence of strong intellectual property rights may prevent the 'appropriability channel' from exerting its positive effect, it is therefore reasonable that the overall effect tends to be negative. The study of industries with different characteristics might well indicate a positive effect. It must also be kept in mind that a difference-in-differences approach measures an average effect, yet there is no such thing as an average merger: even within patent-intensive industries single

transactions might foster innovation. Furthermore, contrary to the Commission decision, this work rejects the idea according to which high level of relatedness are always associated with worse innovation outcomes post-merger.

One last general contribution is methodological: pinning down the effects of mergers on innovation performance is not a trivial exercise, because there are many characteristics that might simultaneously affect research activities and the decision to merge. This paper addresses this identification problem with a two-step procedure. First, I use a propensity score matching approach to select a group of companies whose pre-existing observable characteristics are similar to those of the merging companies. Second, in each group I select the firm with the highest technological relatedness with the treated unit. The results of this matching algorithm have been proved to be more than satisfactory, notwithstanding the fact that only patent data have been used.

In conclusion, the importance of innovation to long-term welfare, together with the empirical difficulties in assessing the causal effects of mergers on innovation, impose extreme caution in driving any radical change in Antitrust Authorities' practice. Although the empirical results of this paper cast some doubts on the view that mergers produce important advances in research productivity, this study focuses on the narrow cases of two patent intensive industries, and for a limited period of time. Given the paucity of empirical work, it is desirable to extend the analysis to other industries, especially those which are not patent-intensive.

These findings will hopefully stimulate the debate on the role of merger policy in research intensive industry; meanwhile, the current stage of theoretical knowledge and empirical evidence warrants that merger control continues to consider the dynamic impact of mergers with a case by case analysis.

References

Articles, working papers and lecture notes

Aghion, P., Bloom, N., Blundell, R., Griffith, R. and Howitt, P. (2005). "Competition and Innovation: An Inverted-U Relationship". *Quarterly Journal of Economics*, 120: 701-728.

Arrow, K. (1962). "Economic Welfare and the Allocation of Resources for Invention", in R. Nelson (ed.), *The Rate and Direction of Economic Activities: Economic and Social Factors*. Princeton University Press, 609-626.

Bennato, A. R., Davies, S. W., Mariuzzo, F. and Ormosi, P. L. (2019). *Mergers and Innovation: Evidence from the Hard Disk Drive Market*. Available at SSRN: https://ssrn.com/abstract=3190156.

Bertrand, O. and Zitouna, H. (2008). "Domestic versus cross-border acquisitions: which impact on the target firms' performance?", *Applied Economics* 40: 2221-2238.

Bloom, N., Schankerman, M. and Van Reenen, J. (2013). "Identifying technology spillovers and product market rivalry". *Econometrica* 81: 1347-1393.

Blundell, N. and Costa Dias, M. (2000). "Evaluation methods for non-experimental data". *Fiscal Studies* 21: 427-468.

Coffano, M. and Tarasconi, G. (2014). *Patstat Database: Sources, Contents and Access Rules*. CRIOS Working Paper Series 1. Center for Research on Innovation, Organization and Strategy, Milano.

Cunningham, C., Ederer, F. and Ma, S. (2019). *Killer Acquisitions*. Available at SSRN 3241707.

Danzon, P. M., Epstein, A. and Nicholson, S. (2007). "Mergers and acquisitions in the pharmaceutical and biotech industries". *Managerial and Decision Economics* 28: 307–328.

Denicolò, V. and Polo, M. (2018a). "Duplicative Research, Mergers and Innovation". *Economics Letters*, 166: 56–59.

Denicolò, V. and Polo, M. (2018b). *Mergers and innovation sharing.* Working paper.

Federico, G., Langus, G. and Valletti, T. (2017). "A Simple Model of Mergers and Innovation". *Economics Letters*, 157: 136-140.

Federico, G., Langus, G. and Valletti, T. (2018). "Horizontal Mergers and Product Innovation: An Economic Framework". *International Journal of Industrial Organization*, 59: 1-23.

Gilbert, R.J. (2006). "Looking for Mr. Schumpeter: Where Are We in the Competition-Innovation Debate?". *Innovation Policy and the Economy* 6: 159-215.

Gilbert, R.J. and Greene, H. (2015). "Merging Innovation into Antitrust Agency Enforcement of the Clayton Act". *George Washington Law Review* 83: 1919-1947.

Gilbert, R.J. and Newberry, D. (1982), "Preemptive Patenting and the Persistence of Monopoly". *American Economic Review* 72, 514-526.

Hall, B. (1987). *The effects of takeover activity on corporate research and development.* NBER Working Paper N. 2192.

Harford, J. (2005). "What Drives Merger Waves?". *Journal of Financial Economics* 77: 529–560

Haucap, J. and Stiebale, J. (2016). *How mergers affect innovation: Theory and evidence from the pharmaceutical industry.* DICE Discussion Paper no. 218.

Heckman, J. (1979). "Sample Selection Bias as a Specification Error". *Econometrica* 47(1), 153-161.

Jaffe, A. (1986). "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value." *The American Economic Review* 76: 984-1001.

Jullien, B. and Lefouili, Y. (2018). *Horizontal Mergers and Innovation.* Working paper. Toulouse School of Economics, Toulouse.

Marco, A.C. and Rausser, G.C. (2002). *Complementarities and Spill-overs in Mergers: An Empirical Investigation Using Patent Data.* Department of Agricultural & Resource Economics, UC Berkeley, Working Paper Series.

Motta, M. (2004). *Competition Policy: Theory and practice.* Cambridge: Cambridge University Press.

Motta, M. and Tarantino, E. (2017). *The effect of horizontal mergers, when firms compete in prices and investments.* Economics Working Papers 1579, Department of Economics and Business, Universitat Pompeu Fabra.

Ornaghi, C. (2009): "Mergers and innovation in big pharma". *International Journal of Industrial Organization* 27: 70–79.

Polo, M. (2018). *L13-15: Mergers.* Lecture Notes, 20628: Industrial Organization and Competition Policy, Università Commerciale L. Bocconi.

Rosenbaum, P. and Rubin, D. (1983). "The Central Role of the Propensity Score in Observational Studies for Causal Effects". *Biometrika* 70: 41-55.

Schulz, N. (2007). *Review on the Literature of Mergers on Innovation.* ZEW – Centre for European Economic Research Discussion Paper No. 07-061.

Schumpeter, J. A. (1942). *Socialism, Capitalism and Democracy.* New York: Harper and Brothers.

Shapiro, C. (2012). "Competition and Innovation: Did Arrow hit the bull's eye?". In: Lerner, J. and S. Stern (eds.), *The Rate and Direction of Inventive activity Revisited.* Chicago, IL: University of Chicago Press, pp. 361-404.

Szücs, F. (2013). *M&A and R&D – Asymmetric Effects on Acquirers and Targets?.* DIW Berlin Discussion Paper No. 1331.

Cases – Decisions of the European Commission

Commission Decision of 27/03/2017 declaring a concentration compatible with the internal market and the functioning of the EEA Agreement (Case M.7932 — Dow/DuPont) according to Council Regulation (EC) No 139/2004.

Databases

Patents-ICRIOS. Available at: http://download.unibo coni.it/ICRIOS2018/Icrios2018 06.rar. [last access: July 4th, 2019]

PatentsView. Available at: http://www.patentsview.org. [last access: July 5th, 2019]

Appendix

Appendix A

Tables A.1 and A.2 display the results of the placebo analysis for the chemical and the pharmaceutical sector respectively. The test is carried out by estimating Equation (1) for the three years previous to the merger. In this case however, the time lag is always

Table A.1
Placebo test for the chemical industry

Variable	**t-2**	**t-1**	**t**
Time	-0.0637 *	-0.0526 **	-0.0340 ***
	(0.0346)	(0.0256)	(0.0071)
Merger	0.0398 ***	0.0372 ***	0.0428 ***
	(0.0079)	(0.0082)	(0.0084)
Time × Merger	-0.0037	-0.0014	0.0097
	(0.0525)	(0.0217)	(0.0314)
$\mathbf{R^2}$	0.3836	0.3381	0.3984
Prob > F	0.0000	0.0000	0.0000

Notes: Robust standard errors in parentheses. Significance level: ***= 1%; **=5%; *=10%. The first two dependent variables are respectively a time dummy taking value 0 post-merger and 1 pre-merger, and a treatment dummy taking value 1 only for real mergers and 0 for fictional mergers.

Table A.2
Placebo test for the pharmaceutical sector

Variable	**t-2**	**t-1**	**t**
Time	-0.0693 ***	-0.0534 ***	-0.0376 ***
	(0.0078)	(0.0092)	(0.0097)
Merger	0.0592 ***	0.0652 ***	0.0634 ***
	(0.0048)	(0.0053)	(0.0046)
Time × Merger	-0.0568	-0.0722	0.0456
	(0.1463)	(0.1536)	(0.1645)
$\mathbf{R^2}$	0.3841	0.3392	0.3350
Prob > F	0.0000	0.0000	0.0000

Notes: Robust standard errors in parentheses. Significance level: ***= 1%; **=5%; *=10%. The first two dependent variables are respectively a time dummy taking value 0 post-merger and 1 pre-merger, and a treatment dummy taking value 1 only for real mergers and 0 for fictional mergers.

one year: in other words, in the first estimation '$\mathsf{Time_t}$' takes value 1 in $t-2$ and 0 in the previous period, in the second estimation takes value 1 in in $t-1$ and 0 in t , while in the third it takes value 1 in t.

It is interesting to notice that I fully reject the hypothesis of no parallel trends in the years before the merger date, meaning that receiving the treatment in the future does not affect the number of new patents in the previous years, and the controls have been chosen by and large correctly.

Appendix B

The following two tables display the effects of mergers on the proliferation of important patents (i.e. those belonging to the top decile of the citations ranking for their application year) in the chemical industry and the pharmaceutical sector respectively.

Table 5.1b
Effects of M&As on important patents proliferation (chemical industry)

Variable	**t+1**	**t+2**	**t+3**
Time	0.0245 ***	0.0497 *	0.0397 **
	(0.0082)	(0.0260)	(0.0173)
Merger	0.0454 ***	0.0454 ***	0.0454 ***
	(0.0145)	(0.0145)	(0.0145)
Time × Merger	-0.0687 ***	-0.0414 ***	-0.0522 ***
	(0.0230)	(0.0127)	(0.0174)
$\mathbf{R^2}$	0.2148	0.1549	0.1881
Prob > F	0.0000	0.0000	0.0000

Notes: Robust standard errors in parentheses. Significance level: ***= 1%; **=5%; *=10%. The first two dependent variables are respectively a time dummy taking value 1 post-merger and 0 pre-merger, and a treatment dummy taking value 1 only for real mergers and 0 for fictional mergers.

Table 5.2b
Effects of M&As on important patents proliferation (pharmaceutical sector)

Variable	**t+1**	**t+2**	**t+3**
Time	0.0718 ***	0.0496 ***	0.0308 ***
	(0.0196)	(0.0116)	(0.0102)
Merger	0.0862 ***	0.0862 ***	0.0862 ***
	(0.0297)	(0.0297)	(0.0297)
Time × Merger	-0.1061 ***	-0.0908 ***	-0.0764 **
	(0.0372)	(0.0329)	(0.0333)
$\mathbf{R^2}$	0.2152	0.2017	0.1745
Prob > F	0.0000	0.0000	0.0000

Notes: Robust standard errors in parentheses. Significance level: ***= 1%; **=5%; *=10%. The first two dependent variables are respectively a time dummy taking value 1 post-merger and 0 pre-merger, and a treatment dummy taking value 1 only for real mergers and 0 for fictional mergers.

Appendix C

The following two tables display the effects of technological relatedness (as measured alternatively by *PatCr* or *Over*) on the production of important patents. The population considered is that of (real) merged entities.

Table 6.1b
Effects of Technological Relatedness on important patents (chemical industry)

Variable	**t+1**	**t+2**	**t+3**	**t+1**	**t+2**	**t+3**
Inverse Mills Ratio	0.0126 ***	0.0134 ***	0.0399 ***	0.0326 **	0.0527 ***	0.0332 ***
	(0.0015)	(0.0017)	(0.0052)	(0.0165)	(0.0095)	(0.0123)
PatCr	0.2008 **	0.3075 **	0.0843			
	(0.0908)	(0.1523)	(0.0659)			
Over				0.1632 ***	0.0765 **	0.167 ***
				(0.0522)	(0.0347)	(0.0451)
$\mathbf{R^2}$	0.4862	0.4927	0.4313	0.6004	0.5758	0.4352
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Robust standard errors in parentheses. Significance level: ***= 1%; **=5%; *=10%.

Table 6.2b

Effects of Technological Relatedness on important patents (pharmaceutical sector)

Variable	**t+1**	**t+2**	**t+3**	**t+1**	**t+2**	**t+3**
Inverse Mills Ratio	0.0523 ***	0.0567 ***	0.0358 ***	0.0993 **	0.0877 **	0.0796 ***
	(0.0062)	(0.0093)	(0.0082)	(0.0435)	(0.0398)	(0.0256)
PatCr	-0.0312 **	-0.0123 **	-0.0274 *			
	(0.0147)	(0.0058)	(0.0153)			
Over				-0.6779	-0.6734	-0.1937
				(1.1034)	(1.0082)	(0.9189)
$\mathbf{R^2}$	0.5853	0.6302	0.5619	0.5583	0.6291	0.5694
Prob > F	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000

Notes: Robust standard errors in parentheses. Significance level: ***= 1%; **=5%; *=10%.