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Mergers and Innovation: the Case of the Pharmaceutical Industry

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Abstract

This paper takes a new look at the effects of mergers on innovation by analysing the relationship between ex-ante technological (and product) relatedness of acquirers and targets and post-merger performances. The analysis is conducted using data on consolidations in the pharmaceutical industry for the period 1988-2004. Empirical results show that merger deals are more likely to be signed between firms with related technologies and drug portfolio. I find that merged companies have on average, worst performances than the group of non-merging firms and that, contrary to what may be the common wisdom, higher levels of technological relatedness are associated with poorer performances. Finally, consolidations between large pharmaceutical companies seem to have a detrimental impact on the incentives of competitors to undertake research in those therapeutic areas where both acquirer and target are active players.

JEL classification: L66, O31, O32.

Keywords: M&A, innovation, product relatedness, technological relatedness.

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1 Introduction

According to Brealy and Myers (2003), merger waves are one of the ten unsolved puzzles in economics and finance. At present, there is not an accepted theory that can simultaneously explain why firms merge, what are the characteristics of merging firms and, more importantly, what are the effects of these operations on firms' performance. At the same time, empirical works on these issues have been quite inconclusive in explaining the drivers and the effects of the merger waves of the last decades. Mueller (1996) and Andrade, Mitchel and Stanford (2001) provide an excellent summary of the existing literature.

Among the many limitations of these empirical works, three are worth to point out. First, recent findings show the existence of industry clustering in merger activity (Andrade, Mitchel and Stanford, 2001). This suggests that the use of cross-industry data might be responsible for the inconclusiveness of previous studies and calls for an analysis that is based on a well-defined industry. Second, although there is a vast literature studying the short-run effects of M&As on firms' prices, profits and market value, little attention has been devoted to the long-run assessment of dynamic efficiency. The traditional static analysis of the effects of mergers on firms' market power and efficiency shows some important limitations when applied to those R&D intensive industries where both margins and costs are largely determined by innovation. Finally, there has been little effort to link the ex-post effects of mergers to the ex-ante observable characteristics of merging firms. But it is likely that the degree of successful of a merger depends largely on these

characteristics.

This study takes a new approach to the study of mergers that tries to overcome these limitations. To my data set, whose structure is briefly illustrated next and then detailed in Section 3, I ask the following two questions: i) What are the effects of mergers on the long-run performance of firms? In particular: Do they have a positive effect on the innovative ability of the firms involved, as their proponents often claim?[1] And do they have any relevant impact on the innovation efforts of competing firms? ii) Is there any relationship between the ex-ante technological and product relatedness of merging parties and the ex-post effects of the mergers?

The analysis is conducted for the case of the Pharmaceutical Industry for the period 1988-2004 and it is confined to M&As among the largest drug makers. There are different reasons that justify the choice of the pharmaceutical industry. First, pharmaceutical firms have played a prominent role in the wave of international M&As, accounting for some of the largest mergers of the last decade.[2] Second, this is one of the sectors with the highest intensity in R&D and innovation is clearly the most important dimension of competition among firms. At the same time, the analysis is restricted to the mergers between the largest drug companies because these are the only transactions that can both influence the incentives and abilities of the merged entities and reshape the structure of the industry, at least for some of its therapeutic areas. Needless to say that mergers between large companies

[1] As suggested by Lawrence White (1987, p. 18) "*Efficiencies are easy to promise, yet may be difficult to deliver*".

[2] Examples include Glaxo-Smithkline and Pfizer-Pharmacia Corp., until the recent acquisition of Aventis by Sanofi-Synthelabo.

are the operations more likely to rise anticompetitive concerns.

The dataset used gathers different sources of information. First, financial data for large pharmaceutical firms (SIC code 2834 and 2835) are retrieved from the Standard & Poor's Compustat and the Bureau van Dijk's Osiris. This set of data is matched with the patent statistics of the NBER Patent data, that comprise detailed information on all US patents granted between 1963 to 2002. Information on the drugs produced by the pharmaceutical firms are retrieved from the British National Formulary and the Orange Book of the Food and Drug Administration (FDA). Finally, merger transactions data for the period 1988-2004 are extracted from the Mergers Year Book. All these different pieces of information have been cross-checked with several sources available on the internet.

This study shows that merger deals are more likely to be signed between companies with related technologies and drug portfolio. Results obtained suggest that mergers do not seem to deliver any important efficiency gain to the firms involved. On average, merged companies are found to have worst innovation performances than the group of non-merging firms. But as there is no such a thing as an "average merger", this paper advances our understanding of the effects of mergers by analysing the relationship between ex-ante similarities of acquirers and targets and the post-merger performance. Indeed, the paper shows that, contrary to what may be the common wisdom, higher levels of technological relatedness are associated with poorer performances. Finally, consolidations between large pharmaceutical companies seem to have a detrimental impact on the incentives of competitors to undertake research in those therapeutic areas where both acquirer and target

are active players.

This study is close to the papers by Danzon, Epstein and Nicholson (2004), Ahuja and Katila (2001) and Cassiman, Colombo, Garrone and Veugelers (2004).[3] Danzon *et al.* (2004) examines the determinants of M&A in the pharmaceutical and biotech industry and, in turn, their effects on firms' performance. For large firms, they find that mergers are a response to excess capacity due to anticipated patent expirations and gaps in the company's product pipeline. In contrast with the results of this paper, they find that large firms that merged experience similar changes in enterprise value, sales, employees and R&D relative to similar firms that did not merge. The paper by Cassiman *et al.* (2004) show that the impact of M&As on R&D and innovation depends on the technological and market relatedness of acquirers and targets. They find that R&D level increases (decreases) when the ex-ante technology of the merged entities are complementary (substitutive). At the same time, there seem to be a more prominent increase in research efficiency when the merged parties have complementary technology.[4] Finally, Ahuja and Katila (2001) analyse the effects of mergers on the acquirers' performance, as measured through the number of patents obtained after the merger, in the chemicals industry. They construct a measure of technological relatedness based on the number of common patent citation made by the merging entities. They find significant evidence of a non-linear impact of relatedness on innovation output, where both too close and too distant cases

[3]Katz and Shelanski (2004) present an exhaustive discussion of the challenges that innovation poses to antitrust policy, with particular attention to the ways that innovation may factor into merger analysis.

[4]The paper by Cassiman *et al* (2004) also gives an exhaustive survey of the existing literature on the impact of M&As on R&D.

have detrimental effects.

Compared to the studies above, this paper differs in several important ways. First, the analysis builds on the main insights into the forces that drive the dynamics of R&D investment decisions provided by industrial organization literature. Interpretation of some empirical findings is difficult without a proper understanding of these forces. Second, I analyse the effects of mergers on different dimensions of innovation activities: inputs and outputs, as measured through R&D expenditure and number of patents, respectively, as well as research productivity, captured by the ratio of patents to R&D expenditure. As the effects of innovation are likely to materialise over a number of years, rather than entirely in any one year, the empirical specification measures the impact of acquisitions up to 3 years after the transactions. Moreover, the relationship between ex-post effects and ex-ante similarities between acquirers and targets is explored by computing different highly detailed measures of relatedness, both for technology and products portfolio. Finally, this paper tries also to extend the analysis of the effects of M&As on the innovation incentives of competing drug makers. By reinforcing the position of acquirers in some therapeutic fields, mergers might reduce the incentives of the other participants to actively compete in innovation races.

The article is organized as follows. Section 2 presents the theoretical underpinnings of our research questions together with the empirical methodology used to investigate these questions. Section 3 presents the data set and variables used, with particular emphasis on the construction of patent statistics from the original raw data. Empirical results are summarized in Section 4. Section 5 presents some concluding remarks, pointing also to the

policy implications of the results obtained.

2 Methodology

2.1 Theoretical Analysis

This section aims at exploring whether mergers among companies with similar characteristics are more likely and to what extent these operations effect the firms' *ex-post* innovation outcomes. As anticipated above, this paper does not treat these two issues as separate questions but try to explore possible links between post-merger research performance and the *ex-ante* characteristics of the two merging partners. Although I do not directly address the question of why firms decide to merge, the findings of this paper also shed some light on this issue.

a) Choice of a merging partner

The seminal paper of Becker (1973) about marriage provides a sound theoretical framework to show why "*positive assortive mating - a positive correlation between the values of the traits of husband and wives - is generally optimal*". At the same time, there are several evidences in social science literature that mating of likes (whether measures by intelligence, age, skin colour, religion or other traits) is very common. But surprisingly enough, empirical evidences on the importance of complementarity among merged firms' characteristics are rather scarce.

In this section, I define a simple theoretical framework to explain why managers might favour mergers between firms with similar technology and

products. To this purpose, let assume that the market value of a pharmaceutical company, V_i, depends both on the revenues from the portfolio of the m-drugs already sold in the market, R^m, and the expected revenues from the k-compounds that are still under investigation in its laboratories, R^k. Accordingly, it can be written that:

$$V_i = v\left(R_i^m, R_i^k\right) \tag{1}$$

Revenues R^m are assumed to be net of manufacturing and advertising costs while R^k are net of research costs.

Cutting of cost and adding marketed products to improve capacity utilization are generally considered the main drivers of mergers in the pharmaceutical industry (Ravenscraft and Long, 2000). Any merger between big pharmaceutical companies implies a reinforcement of their drug portfolio. But deals between firms with high product relatedness, PR, might increase their market power and in turn, revenues R^m. At the same time, a significant overlapping in the marketed drugs allows to achieve larger economies of scale in production and advertising, with again an increase of the net revenues R^m. It can be then assumed that $\partial V_i/\partial PR > 0$. Using a parallel argument, one can assume that there is a positive relationship between technological relatedness, TR, and market value, i.e. $\partial V_i/\partial TR > 0$, because of possible economies of scale in research and less competition in the innovation market (both of which increase the expected revenues R^k).

The discussion above suggests that managers might anticipate (correctly or not) that mergers between companies with high relatedness in products and research projects are optimal. Using Becker's terminology, hereafter I

will refer to this hypothesis as "positive assortive merging". The section below shows that the complexity of the research activity is such that it is difficult to anticipate the true relationship between technological relatedness and innovation outcomes and in turn, firms' value.

b) Effects of mergers on innovation

The aim of this section is to highlight the channel through which mergers can affect the optimal level of R&D expenditures and the consequent innovation performance. In the second part, the analysis is extended to consider the role of "technological relatedness" and "product relatedness".

The research process of pharmaceutical firms can be divided into two main phases: discovery and development. The discovery phase is aimed at detecting new compounds, also known as new chemical entities (NCEs). Once a new promising compound is found, firms apply for a patent to assure themselves the right of exploiting any potential economic return from the discovery. The second phase consists in a series of pre-clinical and clinical development work to test the safety and efficacy of the NCEs, before obtaining marketing approval.[5] Because of the nature of my data set (i.e. patent data), this paper is mainly concerned with the effects of M&As on the discovery of NCEs. Nevertheless, the empirical findings of Section 4 give some interesting insights on the causal effect of mergers on the overall innovation

[5]Failure rates during development are very high: for each new compound that is finally approved, roughly five enter human clinical trials and 250 enter pre-clinical testing (Danzon, Nicholson and Pereira, 2003). The time that is usually necessary to take a new compound through development and regulatory approval is about 8 years. This means that on average firms can benefit from patent protection on drugs approved only for 10 years. See Henderson and Cockburn (1996) for a detailed description of research and development of compounds.

activity.

The inputs in the discovery activity include the variable cost of funding different research projects, *R&D*, as well as a certain exogenous amount of fixed costs, F, that a firm incurs independently of the number of projects under way, e.g. lab buildings and equipments, libraries, etc. The outcome of the discovery activity is defined by the number of patent grants over newly discovered compounds, P. This is assumed to depend on the firm's R&D expenditure above the fixed costs, *R&D,* and on the level of knowledge acquired by the firm in that therapeutic field, Z.[6] Accordingly, I assume that the innovation function can be written as:

$$P_{i,t} = \theta_{i,t} * R\&D_{i,t}^{a} * Z_{it}^{b} \tag{2}$$

where θ is a random term that models the uncertainty in the relationship between the efforts that a firm makes and the actual progress towards the discovery of a new compound. This is assumed to be drawn from a uniform distribution $[0, 2\varsigma]$.[7]

The optimal level of R&D expenditure is determined by the firm solving the maximization problem:

$$\max_{R\&D} R_i(N) * \underbrace{\varsigma * R\&D_{i,t}^{a} * Z_{i,t}^{b}}_{P_{i.t}} - \varrho(R\&D_{i,t} + F_{i,t}) \tag{3}$$

where R refers to the average expected revenue from a patent, which is

[6]Note that the level of Z depends not only on the firm's past investments in research activity but also on the competitors' knowledge that spill over to the firm.

[7]Note that, as I do not observe investments at the level of individual research projects, the analysis refers to the set of compounds investigated by the firm as a unit.

assumed to depend, among other factors, on the number of competitors N in the market; ϱ is the cost of financing total research investments $(R\&D + F)$. As external finance for R&D is more expensive than internal finance, it is assumed that $\varrho = 1$ if firms use internal funds and $\varrho > 1$ for external capital.[8] Note that the random parameter θ has been replaced by its expected value ς. Straightforward calculation leads to the following equation:

$$R\&D^*_{i,t} = \left(\frac{a * R_i(N) * \varsigma * Z^b_{i,t}}{\varrho} \right)^{\frac{1}{1-a}} \tag{4}$$

This equation is useful to analyse the different channels through which mergers can affect the optimal R&D expenditure and in turn, innovation output. First, by unifying the expertise of the acquirer, Z_α, and the target, Z_τ, mergers might create large knowledge synergies. The new company can then rely on a knowledge base above those of the two merged entities, $Z_{\alpha+\tau} > Z_\alpha + Z_\tau$. According to equation (4), this would imply an increase in the R&D expenditure and, *ceteris paribus*, in the innovation output. However, this argument tend to overlook that the knowledge Z is embodied in the firms' biologists and chemists. The large reduction in the number of researchers that often follows the conclusion of a merger deal can then reduce the actual know-how of the newly formed company, i.e. $Z_{\alpha+\tau} < Z_\alpha + Z_\tau$.[9]

[8] Hall (2002) affirms that there are three main reasons why there might be a gap between the external and internal costs of capital: (i) asymmetric information problems (ii) moral hazard problems and (iii) tax treatments of external finance vs. finance by retained earnings.

[9] This assumption is confirmed by anecdotal evidence. After the merger in 1996 GlaxoWellcome closed Wellcome's main U.K. research facility in Becenham (1500 sceintists and staff). Several experts suggested that GlaxoWellcome lost more talent than they expected (Ravenscraft and Long, 2000). Similar situation for Aventis where R&D projects were cut and one R&D facility closed.

Moreover, cultural dissonances and other integration problems might disrupt innovation outcomes, therefore reducing the expected probability of successful innovation below ς.[10]

Second, mergers between large pharmaceutical companies may trigger strategic interaction between competitors. The paper on research joint venture by Kamier, Mueller and Zang (1992) shows that the internalization of technological outflows that were previously captured by competitors leads to an increase in R&D investments. Moreover, mergers not only implies the disappearance of one competitor but they might also induce a reduction in the R&D investments of those firms that find themselves well behind the newly formed company in the on-going patent races.[11] Under this scenario, merged companies can anticipate higher value of $R_i(N)$ and this might amplify the R&D expansion encouraged by the internalization of spillovers.[12]

Third, since part of the research expenditure consists of fixed costs, large economies can be realized by spreading these expenses. Mergers might then lead to a substantial reduction in research costs by avoiding useless duplica-

[10] In an interview with Financial Times, Joshua Boger, once top scientist in Merck and then founder of Vertex Inc., affirmed that "size is an advantage in times of stability and a disadvantage in times of change. If you have got 7,000 to re-engineer, it's much harder than if you have've got 300. GlaxoSmithkline has 16,000" ("Just what the drugs industry ordered", Financial Times, 24^{th}January 2001). Cultural clashes are cited as one of the main causes for the bad performance of Pharmacia, where US, Swedish and Italian subcultures were continued after the merger. Aventis faced the challenge of integrating German, French, and American business cultures ("Innovation in the Pharmaceutical Sector", 8^{th}November 2004, Charles River Associate, p.112)

[11] Using a stochastic race model, Harris and Vickers (1987) show that the follower makes less efforts when the gap from the leader increases.

[12] Despite the theoretical appeal of patent race models, Cockburn and Henderson (1994) find that research investments are weakly correlated across firms once common responses to exogenous shocks are considered. They suggest that strategic interections is not a main driver of the investment behaviour in the industry.

tion (i.e. $F_{\alpha+\tau} < F_\alpha + F_\tau$).

Finally, sizable consolidations as those considered in this study are largely financed with internal capital flows, partially diverted from the research activity. The cost of funding research projects, ϱ, might then increase if the firms have to raise more capitals from external sources. Equation (4) shows that this may imply a reduction in the level of R&D expenditure.

This framework suggests that it is not possible to predict the sign of the net effect of mergers on total R&D expenditures, $(R\&D + F)$, the observed measure of research inputs in this study. But if the effect of mergers is to increase innovation through knowledge synergies (i.e. $Z_{\alpha+\tau} > Z_\alpha + Z_\tau$), we would find an increase in both the number of patents, P, and the innovation productivity, as measured by the ratio of patents and research expenditure, $P/C(F, R\&D)$.

Most of the changes in R&D inputs and outputs defined above are driven by forces whose magnitude depends on the ex-ante technological relatedness, TR, and product relatedness, PR, of the merged parties. The remaining of this section is aimed at shedding some light on these rather unexplored issues.

First, post-merger knowledge synergies are likely to be greater when the research activities of two firms are closer, given that there are less opportunities for cross-fertilization of ideas when these activities fall too far apart. The knowledge base might then be a positive and increasing function of technological relatedness, i.e. $\partial Z_{\alpha+\tau}/\partial TR > 0$. This implies that, *ceteris paribus*, there is a positive relationship between innovation inputs/outputs and technological relatedness. As suggested above, this line of reasoning

can be misleading if firms' knowledge largely rests in the human capital of their personnel. In this case, a larger overlap of research activities might imply a greater scope for reduction of employees. Under this alternative view, technological relatedness might be associated with a greater dissipation of knowledge (i.e. $\partial Z_{\alpha+\tau}/\partial TR < 0$) and in turn, a reduction of the expected revenues from compounds under investigation (i.e $\partial V_i/\partial TR < 0$) .

Second, although mergers between technological related companies can reinforce their competitive advantage in research and development, the creation of "innovation monopolies" can reduce the incentives of other companies to invest in research. We might then observe an overall reduction of the innovation pace in some therapeutic areas. I come back to this point in the next subsection when I present an empirical specification aimed at assessing the impact of mergers on third parties.

Finally, the extent of technological relatedness affect the actual savings in research fixed costs. For instance, companies working in similar therapeutic areas are more likely to reunite their researchers in a single lab and divest redundant facilities. We can than assume that overall R&D expenditures are a decreasing function of TR.

As it is not possible to define unequivocal theoretical predictions about the causal effect of technological relatedness on innovation activities, empirical analysis is the only way to assess the actual relationship between the two variables in the pharmaceutical industry.

So far I have considered only the direct effect of mergers on innovation. But we cannot ignore the possibility that these transactions will impact the R&D activities indirectly through changes taking place in the market equi-

libria for approved drugs. Closer product relatedness between the two firms may imply a greater market power in case of merger, at least for some therapeutic areas.[13] As discussed in the previous section, this must lead to an increase in the market value of the firm, i.e. $\partial V_i/\partial PR > 0$. But, by increasing the available cash flows of the firm, this can also reduce the actual cost of funding research activities, ϱ, and in turn, increase the R&D expenditures (see equation (4) above). While it is interesting to assess the impact of technological relatedness and product relatedness on post-merger firms' performances, the latter is expected to play only a minor role in reshaping innovation activities.

The theoretical analysis presented in this section suggests that there are three empirical questions that are worth exploring. The first is whether acquirers usually target firms that are close in the space of chemical entities and product portfolio, i.e. "positive assortive merging". The second concerns the post-merger performances of consolidated firms compared to the other drug companies. The third is whether technological relatedness and product relatedness can explain post-merger differences in the performance of merged companies.

2.2 Empirical Specifications

In this section, I introduce the empirical specifications that are used to assess the effects of mergers on innovation, also in the light of the ex-ante

[13] Part of this marke power might arise from the ability of the merged companies' sales force to gain access to more doctors. For instance, in the Aventis merger the combination of the marketing organisations of the companies was hoped to lead to a much stronger presence in the United States ("Innovation in the Pharmaceutical Sector", 8^{th}November 2004, Charles River Associate, p.107)

technological and product relatedness of the merging parties

Mergers, in particular large deals as those considered in this paper, are likely to produce their effects over a number of years, rather than entirely in any one year. Therefore, the effects of mergers are analysed with the following econometric approach:

$$\Delta\%Y_{it} = \beta_0 D0 + \beta_1 D1 + \beta_2 D2 + \beta_3 D3 \ + \gamma_1 T + u_{i,t} \tag{5}$$

where $\Delta\%Y$ indicates the percentage change (i.e. logarithmic difference) of one of the innovation measures (e.g. R&D expenditure, number of patents, *etc.*) between two consecutive years, T is a complete set of time dummies for the period 1988-2004 and u is a random disturbance term. $D0$, $D1$, $D2$ and $D3$ are dummy variables that take on value of 1 if the firm i goes through a merger in period t, in period *t-1* (i.e. one-year ago), in *t-2* or in *t-3*, respectively. In this way, I can access the impact of mergers for up to 3 years after the deal is closed.[14]

In addition to innovation inputs and outputs, interesting insights on the effects of mergers can be inferred from estimating the change of V through specification (5). The stock market value, V, can be used as overall indicator

[14]Note that for the merged firms, the estimation of equation (5) requires that both the acquirer and the target are recorded in the dataset. For instance, to compute correctly the variable $\Delta\%R\&D$, it is necessary to know the R&D expenditures of acquirer and target in the year prior to the merger. This would not be necessary using the approach in Danzon *at al.* (2004), where the impact of a merger is measured by considering the change in a certain performance from *t+1* to *t+2* and *t+2* to *t+3*. The main advantage of this alternative approach is that one can rely on a larger number of observations, given that only the records of the acquirer are needed to compute the outcome of interests. But this approach makes the strong assumption that there are no important effects in the same year of the merger and in the following one. For instance, if a merger takes place at the beginning of year t, it is hard to imagine that the management will wait until the second year to cut any duplication of R&D expenditures.

of the effects of the mergers on the performance of these companies, including the impact on the development of new compounds covered by patents and the sales of approved drugs.

To assess the role of technological relatedness in reshaping the innovation activities of the merged companies, the following regression model is estimated:

$$\Delta\%Y_{i,t} = \beta_0 TR_{t-1} + \beta_1 TR_{t-2} + \beta_2 TR_{t-3} + \beta_3 TR_{t-4} + \gamma_1 T + u_{i,t} \qquad (6)$$

where TR refers to one of the measures of technological relatedness between acquirers and targets explained in the following section**.** As for equation (5), this specification allows us to study the role of similarities up to three years after the merger. Illustrately speaking, for each merger deal signed in 1995, the independent variable is computed using patent statistics of acquirer and target in the year before the merger, TR_{1994}. This is then used to assess the impact of relatedness on the selected dependent variables, $\Delta\%Y$, in the year of the merger (1995) and in the following 3 years (until 1998). Therefore, TR_{t-1} takes positive values for the firms that sing a merger deal in year t (as the dummy $D0$ takes on value 1 in period t), TR_{t-2} takes positive values for those companies that completed the deal one year ago while TR_{t-4} is defined for those firms that merged 3 years ago. A similar specification is used to compare the importance of technological relatedness, TR, versus product relatedness, PR, in affecting the research activities.

To get further evidences on the impact of M&As on the innovation abilities of the firms involved, I propose an alternative empirical test based on patent citation data. If the combination of the research experience of acquir-

ers and targets creates large knowledge synergies, their established knowledge will be more effective in producing major therapeutic breakthroughs. Given that a patent has to report citations to previous patents whenever the innovation relies on prior technology, it is possible to test whether important discoveries of NCE, as measured by the number of citations received by the patents obtained after a merger,[15] are actually built on the established knowledge of acquirers and targets. Accordingly, the following Poisson regression model can be estimated:

$$C_{\alpha,,j} = \exp(\beta_4 D4 + \beta_5 D5 + \beta_6 D6) + u_j \tag{7}$$

where C refers to the number of citation received by any patent j granted to the acquirers α after the merger, while the fictional variables $D4$, $D5$ and $D6$ take on value of 1 if patent j cites previous patents of the acquirer (only), target (only) and both the acquirer and the target, respectively. The existence of knowledge synergies would imply that all the β coefficients in the equation above, and in particular β_6, take positive values.

Finally, this paper advances the analysis of M&As and innovation by exploring the effects of these operations on third parties. Models of patent races show that a firm i can be deterred from undertaking further efforts in innovation, when one of the competitors is in a position to outdo any moves made by this firm to win the race (Harris and Vickers, 1985). Merged firms are more likely to "leapfrog" other competitors in those therapeutic areas where both acquirers and targets do active research. The following Poisson

[15] The number of citations is the measure generally used in the literature to capture the importance of a patent. Trajtenberg, Henderson and Jaffe (1997) represent one of the first empirical examples.

model is then specified:

$$G_{i,j} = \exp(\beta_7 D7 + \beta_8 D8 + \beta_9 D9 + \gamma_2 G^{bm}_{i,j}) + u_j \tag{8}$$

where G is the total number of citations received by patent j granted to any pharmaceutical firm i and cited by at least one of the merged parties (acquirers or targets) while G^{bm} is the number of citations received by patent j before the first merger among those considered in this study takes place.[16] This variable measures the differences in forward citations received by patent j before a deal is consumed. Finally, $D7$, $D8$ and $D9$ are dummy variables that assume value 1 if patent j is cited by (only) the acquirer, (only) the target, or both of the two, respectively. If competitors are actually deterred from doing research only in those fields where both the merged parties are active players, we expect to find a negative value for the coefficient β_9.

3 Data and Variables

To answer all the questions of this investigation a new dataset is constructed by gathering different sources of information. To minimize measurement errors, most of the data are cross-checked with information available on the internet.

The main financial data come from Compustat and Osiris, published by Standard and Poors and Bureau van Dijk, respectively. The variables

[16] For instance, suppose that patent j is granted in year 1995 and it is subsequently cited by Zeneca and Smithkline Beecham. As Zeneca is involved in a merger in 1999, one year before Smithkline's merger (see Table 2B), G^{bm} refers to the number of citation received by patent j until year 1998.

retrieved are revenues from approved drugs, R, total R&D expenditures, $(R\&D+F)$, and stock market value, V, for the period 1988-2004. For ease of notation, hereafter I will refer to total research investments (including fixed costs) as simply $R\&D$. All monetary values are adjusted for inflation using the US domestic manufacturing Producer Price Index (with index year 1987). The analysis is restricted to the largest pharmaceutical firms, those with a stock market value exceeding $1 billion at least once during the relevant period, including also Japanese companies. For those companies with relevant interests outside the pharmaceutical industry, such as BASF, Bayer and Monsanto, annual reports (available on the internet) are used to find the relevant information concerning their pharmaceutical arms. Large companies specialized in the production of generic drugs (such as Ivax, Mylan or Teva) are not included in the sample. Financial data reported in the original Compustat and Osiris data sets are edited to consider relevant spin-offs, such as Merck's divesture of the "pharmaceutical benefits management" company Medco in year 2003.

Patent statistics were obtained from the publicly available NBER Patent data, described by Trajtenberg, Jaffe and Hall (2001). This dataset comprises detailed information on all US patents granted between 1963 to 2002.[17] Two different files of this patent data bank are used in this investigation: the Patent Data file and the Citation Data file. The information retrieved from the first file are the patent number, the application year and the year the patents are granted, the assignee identifier and the patent class and subclass.

[17] I thank B. Hall for providing me complementary data on patent sub-classes that are not available in the original data bank.

The US Patent Office has developed a highly elaborate classification system for the technologies to which the patented inventions belong, consisting of about 400 main patent classes, and over 120,000 patent subclasses. Following the classification in Trajtenberg *et al.* (2001), our data include only patents recorded in the technological category "Drugs and Medical", made of 14 main patent classes.[18] The Citation Data file records the citations made for each patent granted. Given that pharmaceutical companies patent prolifically, the number of patents is a rather noisy measure of research success. It is then useful to count also the "important" patents, P^{imp}, where the importance is inferred by the number of citations that a patent receives. More precisely, all the patents granted in year t are ordered by the number of citations received and then grouped in quintiles. A patent is considered an "important" patent if it belongs to one of the top two quintiles of the citations ranking.[19]. Basic statistics for the main variables used to study the effects of mergers are reported in Table 1:

INSERT TABLE 1 ABOUT HERE

Using the compendium of drugs published by the National British Formulary and the data in the Orange Book of the FDA, together with complemen-

[18] This category is divided in the following sub-category: (1) Drugs: patent classes 424 and 514; (2) Surgery and Medical Instruments: 128, 600, 601, 602, 604, 606 and 607; (3) Biotechnology: 435 and 800; (4) Miscellaneous-Drug and Medicals: 351, 433 and 623. This makes a total of 14 patent classes.

[19] Results presented in the following section are robust to changes in the definition of "important" patent, for instance considering only patents in the top quartile in terms of citations received. Note that this variable has not been computed for year 2001 and 2002 since the number of citations for patents of these two years is very small (in most of the cases, zero).

tary information from different internet sites, a complete panel of proprietary drugs produced by the pharmaceuticals companies included in this study is added to the resources described above. Medicines are divided into therapeutic classes according to the "Anatomical Therapeutic Chemical" classification (ATC). The ATC provides four levels of classification. The first level (ATC 1) is the most general, with 14 anatomical groups and the fourth (ATC 4) the most detailed, with more than 400 chemical/pharmacological subgroups. To construct our measure of product relatedness, I will use the ATC 2 and the ATC 3 classification.[20]

Finally, the most important mergers transactions among pharmaceutical companies for the period 1988-2004 are obtained from The Mergers' Year Book published by Thomson Financial Service. To the best of my knowledge, this paper is the first that uses a dataset that gathers financial variables, patent statistics and product information.

Table 2A reports the number of mergers and acquisition over the period 1988 to 2004 together with the number of firms in the sample used for this study. Apart from year 1989, the wave of mergers between large pharmaceutical companies starts in 1994 and it extends to the end of the sample period. Overall, there are 27 M&As considered in this study,[21] whose details are reported in Table 2B. Despite the rather small size of the sample, it must be kept in mind that this paper focuses on a well-defined set of

[20]For instance, the ATC1 anatomical group "C", cardiovascular system, is divided at the second level in the following groups: cardiac therapy, antihypertensives, diuretics, peripheral vasodilators, vasoprotectives, beta blocking agents, calcium channel blockers, agents acting on the renin-agiotensin system and serum lipid reduction agents. Each of these subgroups is further divided in more detailed sub-groups at the 3^{rd} level.

[21]Note that, for the 3 operations taking place in year 2004, we can only assess the "immediate" impact of the merger but not the effects in the following years.

firms and operations: in this sense, this study includes the entire universe of large pharmaceutical companies and the major transactions in which they are involved. Moreover, the data used provide in-depth information on each company, including also fine indicators of technological and product relatedness. Table 2A reports also the average revenues, R&D expenditure and number of patents over the sample period. Note that the average number of patents obtained decreases considerably in the last years because of the truncation problem: as we approach the last year of data, patent statistics (computed according to the application date) will increasingly suffer from the delay imposed by the review process.

INSERT TABLE 2A and 2B ABOUT HERE

Using the *NBER* patent data, including the patent citation file, I construct four different measures of technological relatedness between acquirers and targets: the correlation between patents' technological classes ($PCorr$), the overlap between the list of patents cited ($Over$) and the importance of cross-citations from acquirers to targets (Cit) and viceversa ($Spill$). To test the "positive assortive merging" hypothesis, these four variables are computed not only for the true pair of acquirer and target, but also for all the possible pairs that can be defined by matching the actual acquirer with the other firms in the sample.[22]

[22]The idea is that these are the other firms that the acquirer could have considered as potential targets. For instance, in year 2004 the sample includes 33 firms and 3 deals. I then compute the 4 variables of technological relatedness between the "true" acquirers and targets (e.g. Sanofi and Aventis). Moreover, I compute the same measures for the acquirer and the other 32 possible targets (e.g. Sanofi and Astrazeneca).

Following Jaffe (1986), one could think that if there are K chemical areas in which pharmaceutical firms can do research, the "technological position" of a firm's research program can be defined by a vector $S=(S_1, ..., S_K)$, where S_k is the fraction of patents in area k. As there are only 14 patent classes in the technological category "Drugs and Medical", it would be difficult to characterize properly the vector S. I then use the finer classification based on patent sub-classes.[23] Each sub-class comprises compounds with similar chemical structure so that each firm is given a place in the space of chemical entities. The correlation between the research programs of acquirer α and (actual or potential) target τ is defined by:

$$PCorr = \frac{\sum_k S_{\alpha k} * S_{\tau k}}{\sqrt{\sum_k (S_{\alpha k})^2 * (S_{\tau k})^2}}. \tag{9}$$

Alternative measures of the proximity between the research activities of the firms can be computed using the patent citations data. Let P_α (P_τ) and $B_\alpha(B_\tau)$ be, respectively, the sets of patents owned and cited by the acquirer (target). The variable *Over* is computed by looking at the overlap between the set of patents cited by the acquirer and the selected target (see Marco and Rausser, 2003):

$$Over = \frac{(Number\ of\ Pat\ in\ B_\alpha \cap B_\tau)}{(Number\ of\ Pat\ in\ B_\tau)},$$

where firm α is the acquirer while firm τ is either the actual target or one of the fictional targets that are matched to α.

[23] Although there are more than 3000 sub-classes in the category "Drugs and Medical", I recoded them in order to get a more tractable classification of about 200 sub-classes.

The variable *Cit* computes the percentage of patents owned by the (actual or fictional) target τ that are cited by the acquirer α:

$$Cit = \frac{(Number\ of\ Pat\ in\ B_\alpha \cap P_\tau)}{(Number\ of\ Pat\ in\ P_\tau)}.$$

On the contrary, the variable *Spill* measures the number of the acquirer's patents that are cited by the target firm (normalized by the total number of target's citations) and it can be interpreted as a measure of the knowledge that spill from the acquirer over to the target:

$$Spill = \frac{(Number\ of\ Pat\ in\ P_\alpha \cap B_\tau)}{(Number\ of\ Pat\ in\ B_\tau)}.$$

The last two variables, *Cit* and *Spill*, are defined using cross-citations data and they measure direct linkages between firms rather than placing them in a certain technology space.[24]

As for product relatedness, I construct two measures of correlation between the acquirer and the (actual or potential) target, using a modified version of equation (9) where the vector $S=(S_1, ..., S_K)$ lists the fraction of medicines in the therapeutic area k, according to the categories of the ATC 2 and ATC 3. These two variables are labelled *AT2Corr* and *AT3Corr*, respectively.

[24] Two things need to be noticed. First, the four variables have been computed using all the patents owned by the firms (not only "important" patents), given that any patent is useful to define the "technological" position of the firm. Second, the normalization of the variables *Over*, *Cit* and *Spill* is always done with respect to the patent statistics of the actual or potential target, in order to take into account the size of the target in terms of patents holdings.

Table 3A provides descriptive statistics and correlations of the six measures of technological and product relatedness described above. The table shows that these variables differ from each other and, interestingly enough, are characterized by a low correlation, the only exception being the pair *AT2Corr* and *AT3Corr.*

INSERT TABLE 3 ABOUT HERE

4 Results

This section discusses the empirical results concerning the effects of M&As on the innovation activity of merged firms, and the ex-ante technological and product relatedness of acquirers and targets.

Table 4 shows the results of two different tests of the "positive assortive merging" hypothesis. The first is a simple t-test of the hypothesis that the 6 variables of relatedness defined above have the same mean between the group of true merged pairs and the group of fictional pairs. The second test is the van der Waerden *X-test* (Waerden, 1965). This consists of ranking the values of each measure of relatedness and testing whether the rank of actual pairs is statistically higher than the average rank of the fictional pairs.[25] In all the

[25]This is a nonparametric rank test, thus there is no hypothesis for the underlying distribution of the observations. The null hypothesis is that the observations in the two groups are drawn from the same distribution to test against the hypothesis of a "location alternative". This test is very close in spirit to the well-known "Wilcoxon" rank test (also known as Mann-Whitney-U-Test). The advantage of the *X-test* is a higher asymptotic efficiency. Moreover, "Wilcoxon" test requires more than 3 observations per group (which is not satisfied in our case since we compare the unique observation of the actual pair of merging firms against several arbitrary pairs).

cases, the two tests reject the null hypothesis that the computed measures of relatedness (or their corresponding ranks) have the same means within the two groups. This gives strong support to the hypothesis that acquirers tend to choose targets with similar research programs and product portfolio.

INSERT TABLE 4 ABOUT HERE

Table 5, Panel I, shows the effects of mergers on different aspects of firms' research activity, estimated using equation (5). Research inputs ($R\&D$) and outputs (P and P^{imp}) are found to decline in the same year and all the years after the deals. Mergers have a negative effect on the R&D intensity too: although none of the coefficients is statistically significant, the hypothesis that the sum of these coefficients is not statistically different from zero has be rejected (p-value 0.078). The reorganization of the merged entities implies a reduction in R&D investments that is above the reported decrease in revenues. As for the research productivity, measured by the ratio of patents and R&D expenditures ($P/R\&D$) and ($P^{imp}/R\&D$), most of the estimated coefficients have a negative sign, although they are not precisely estimated. Finally, the prevalence of negative coefficients in the last column of the table suggests that mergers have on average a negative impact on firms' performance.[26] Although there is not a (statistically) significant reduction of the

[26]It might be the case that the merging firms' market value in *t-1* already discounts the possibility that these firms decide to merge. I then use the average market value in *t-1* and *t-2* to soften the problem. This alternative approach gives similar results to those presented in Table 5. Moreover, it must noticed that the estimated effects of mergers on market value in the following three years are not affected by this problem.

variable V in any of the years considered, overall returns for shareholders after the merger are clearly below those of other pharmaceutical firms (p-value 0.064).[27]

To determine the effects of a merger, it is necessary to predict what the performance of the merging firms would have been in the absence of the merger. In Table 5, this counterfactual is computed using the entire sample of non merging firms as "control" group. A recognized weakness of this method is that, in many studies, only a few firms in the control group are comparable to merged firms. This issue is explored at length in the Appendix.

The rest of Table 5 analyses the relationship between the effects of mergers and the similarities of merged parties, as specified in equation (6) above. The measures of technological and product relatedness used are the patent correlation, *PCorr*, and the drug therapeutic equivalence according to the ATC2, *AT2Corr*, respectively. Panel II shows that the greater is the technological relatedness of the merged parties, the worse the effects of mergers on R&D inputs and outputs are. This finding is confirmed when the outcome considered is the research productivity, as measured by ($P^{imp}/R\&D$) or the market expectation about the firms' future performance (V). In Panel III, I estimate the simultaneous impact of technological and product relatedness on the different firms' outcomes already discussed. As expected, technological relatedness has a greater impact on innovation than product relatedness. Once technology is taken into account, similarities in the product portfolio

[27] An article recently appeared on the Wall Street Journal ("The big drug mergers can be hard to swallow", April 1^{st} 2004) points out that the stocks of pharmaceutical companies that have merged over the past five years have lost on average 3.7% of their stock-market value since their deals have been completed, compared with stocks in the Standard & Poor's pharmaceuticals index, which have risen by 7.2% on average.

have generally little explanatory power for the post-merger effects. The only interesting exception concerns the stock market value. While there is a negative correlation between *PCorr* and *V,* I find that companies with closer product portfolios have more prominent increases of their stock market values. This confirms the assumption that $\partial V_i/\partial PR > 0$. As advanced in Section 3, one possible explanation of this finding is that the increase in enterprise values mirrors the increase in market power accruing to the merged parties with similar drugs (Duso, Neven and Roller, 2003).

INSERT TABLE 5 ABOUT HERE

These findings already cast some serious doubts on the potential innovation synergies that can be realized within mergers. Estimation of equation (7) above can shed some further light on this issue. If M&As actually improve the knowledge of merged firms because each party learns something about the others' experience, major therapeutic breakthroughs are more likely to be the outcome of the combined past research activities of acquirers and targets. The results in Table 6 do not seem to support this hypothesis. Discoveries that rely on the past experience of acquirers and targets (alone) are less important than those innovations without a direct link to their prior patents. At the same time, patents that rely on past research of both acquirers and targets are not more important.

Finally, estimation of equation (8) can help us to understand whether mergers reduce the innovation incentives of competing firms. As suggested in Section 2, the maintained hypothesis is that mergers may deter other pharmaceutical companies from pursuing further research in those fields where

both acquirers and targets are active players. Figures in Table 7 seems to support this hypothesis. Patents that are cited by both the acquirer and the target received fewer citations than other patents after the deal between the two parties is closed. Competing firms seem then discouraged to develop new compounds in those chemical areas where the merged parties have overlapping activities.[28]

INSERT TABLE 6 and 7 ABOUT HERE

5 Conclusions

This paper explores the effects of mergers on innovation in the pharmaceutical industry. Consolidations among large pharmaceutical companies are found to have a negative impact on firms' innovative performance, possibly because of the post-merger dissipation of human capital and integration problems.

As for other studies, the difficulty of defining a correct counterfactual would suggest extreme caution in drawing conclusions for competition policy purposes. However, alternative evidence based on patent citation data seems to confirm that there are no knowledge synergies delivered by these operations. In addition, mergers are found to discourage third parties' research in those therapeutic areas where acquirers and targets are active players, thus raising the suspects that these operations can harm innovation competition.

[28] This finding is consistent with third parties' allegation that mergers "*would discourage any tentative research and development attempts by third parties ...and that a new but substantially smaller player would have difficulties in penetrating the market*" - EU merger case No. COMP/M.1846 - Glaxo Wellcome / Smithkline Beecham (par. 96).

Although these findings suggest that on average, mergers do not deliver any innovation efficiency, we have to keep in mind that there is no such a thing as an "average merger". To this aim, this paper advances our understanding of the effects of mergers by analysing the relationship between ex-ante similarities of acquirers and targets and the post-merger performance. This further step of the analysis raises another important concern. A higher level of technological relatedness between merged parties is associated with poorer innovation performances. That is, the operations that are more likely to raise anti-competitive concerns, are exactly those that seem to deliver less efficiency gains. As the reduction of R&D personnel is likely to be positive related to the merging firms' technological relatedness, human capital loses may be the cause of this interesting finding.

Beyond the contingent implication that technological relatedness can have for mergers in the pharmaceutical industry, this paper clearly shows that the analysis of the ex-ante similarities of merging parties might be helpful to shed lights on the effects of mergers on efficiency, market power and innovation performances. Partners' relatedness can possible explain why some mergers are a failure and others a success. Given the paucity of empirical work on this issue, it is then desirable to extend the present analysis to other industries and countries.

Appendix

Results of Table 5 - Panel I can be interpreted as the effects of mergers on innovation only under the assumption that in the absence of the consolidation, merged parties would perform as the control group of non-merging firms. The aim of this Appendix is to explore whether there are true causal

effects of mergers on innovation or whether the results are driven by an incorrect sample selection to model the counterfactual outcome.

To understand the nature of the problem is useful to estimate equation (5) for revenues, R, and number of employees, E. Table A1 shows that there is a sensible reduction in the revenues and the labour force of merged companies compared to the control group. In this case, it is not possible to affirm that these outcomes are caused by mergers. The work of Danzon *et al.,* 2004 shows in fact that mergers among large firms are a response to excess capacity due to anticipated patent expirations. This means that merged companies would experience a sensible reduction in their sales and in turn, a cut of their employees even in the absence of the merger.

By the same talk, the suggested causal relationship between mergers and innovation is undermined if merged entities anticipate a deterioration of their innovation performances, perhaps because of recent research failures. But this thesis is harder to defend. The stochastic nature of the research activity implies that the future outcomes are difficult to predict. Moreover, statistics in Table A2 below show that there are no ex-ante significant differences in the R&D intensity and innovation productivity (Patents/R&D) of acquirers or targets and the control group. The only statistically significant difference is that acquirers are larger than non-merging firms.

Table A2 confirms that the sample used in the present work is rather homogenous. Nevertheless, I check the robustness of the estimates when covariates are added to equation (5) to control for any remaining heterogeneity between firms. Specifically, I use each of three main financial variables available in this study (research expenditure, $R\&D$, revenues, R, and market

value, V) and different combinations of them. The coefficients reported in Table A3 below are estimated adding the market-value sales ratio, V/R, as control for ex-ante heterogeneity. Results with the other variables are substantially similar. The choice of V is due to the fact that the pre-merger market value should encompasses the expected performance of the firms in the absence of the merger. So, any pre-merger differences between firms should be captured by this variable. At the same time, by normalizing the market value for products sales, more emphasis is given to the firm value accruing from compounds under investigation. This covariate can be useful to partial out unobservable differences in innovation across firms prior to the merger.

Despite this approach implies a reduction in the number of observations available for estimation, Table A3 confirms the main findings in Panel I of Table 5: a strong reduction in R&D expenditures and a decrease in both research outputs and market value.

INSERT TABLE A1, A2 and A3 ABOUT HERE

Two final points are worth stressing. First, compared to other studies aimed at assessing the effects of an economic "treatment" (for instance, effects of a training program on unemployment), mergers have the peculiarity that two units (acquirers and targets) are involved in the process. Therefore, a control group selected on the base of acquirers' ax-ante characteristics will always be fallacious. Second, the correct assessment of the counterfactual relies on the assumption that the "treatment" applied to one unit do not affect the outcome of another unit (the so-called "stable unit treatment value

assumption"). It is clear that this assumption is unlikely to hold in the case of large merges. Despite I acknowledge the importance of these issues, it is beyond the scope of this paper to provide a solution to them.

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Table 1: Sample Statistics for Main Variables

Variable Description	Variable Name	Mean	Standard Deviation
Revenues, $million	R	5,595	5,802
	$\Delta\%R$	0.068	0.134
Firm market value, $million	V	24,725	33,971
	$\Delta\%V$	0.098	0.331
Total R&D expenditures, $million	$R\&D$	703	782
	$\Delta\%R\&D$	0.094	0.154
R&D intensity, (R&D/Revenues)	$R\&Dint$	0.13	0.05
	$\Delta R\&Dint$	0.003	0.015
Employment, thousands	E	31.6	28.7
	$\Delta\%E$	0.026	0.143
Number of new patents	P	48.8	56.1
	$\Delta\%P$	-0.133	0.765
Number of new important patents	P^{imp}	12.7	13.8
	$\Delta\%P^{imp}$	-0.113	0.737

Notes: $\Delta\%$ stands for growth rate, computed as logarithm differences between two consecutives years, while Δ indicates the simple difference between two consecutive years

Table 2A: Mergers and Acquisitions by Year

	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Number of Firms:	30	28	28	37	42	43	44	46	49	47	47	45	41	39	38	36	33
Number of Mergers:	0	4	0	0	0	0	2	4	1	2	0	2	4	3	2	0	3
Average Revenues ($million):	2928	3274	3547	3555	4135	4178	4466	4689	5006	4775	5347	5920	6353	6897	7615	8534	9184
Average R&D ($million):	258	299	341	374	450	484	514	568	612	618	712	777	871	945	1093	1241	1414
Average Number of Patents:	35	35	40	37	43	45	55	83	49	66	57	56	44	22	2		

Notes: These figures refer to the sample used for the estimation of the effects of mergers on research inputs and outputs, after dropping all time-firm observations that are not available. The number of observations for some variables such as market value is actually smaller (as indicated in Table 5). Firms included in the sample are those with stock market value exceeding $1 billion at least once during the period 1988-2004. This sample is representative of the entire universe of big pharmaceutical companies. Big companies specialized in the production of generic drugs (such as Ivax, Mylan or Teva) are not included in the sample. The NBER Patent data extends from 1964 though 2002. The average number of patents in any year is computed using the application date (and not the grant date).

Table 2B: List of Mergers

Acquirer	Target	Year	Value ($m)
Bristol Myers	Squibb	1989	12,500
Novo	Nordisk	1989	-
Smithkline Beckman	Beecham	1989	8,276
American Home Product	Robins	1989	3,190
American Home Product	Lederle (Amer. Cynamid)	1994	9,560
Roche	Syntex	1994	5,307
Glaxo	Wellcome	1995	14,284
Pharmacia AB	Upjohn	1995	-
Hoechst	Marion Roussel	1995	7,121
Rhone Poulenc	Fisons	1995	2,888
Ciba	Sandoz	1996	27,000
Amersham	Nycomed	1997	-
Roche	Corange	1997	10,200
Sanofi	Synthelabo	1999	-
Astra	Zeneca	1999	34,636
Hoechst Marion Roussel	Rhone Poulenc Rorer	2000	21,918
Glaxo Wellcome	Smithkline Beecham	2000	76,000
Pfizer	Warner Lambert	2000	87,413
Pharmacia Upjohn	Searle (Monsanto)	2000	26,486
Johnson & Johnson	Alza	2001	11,070
Abbott	Knoll (Basf)	2001	6,900
Bristol-Myers Squibb	Du Pont pharmaceuticals	2001	7,800
Pfizer	Pharmacia	2002	59,515
Amgen	Immunex	2002	16,900
Sanofi-Synthelabo	Aventis	2004	65,000
Yamanouchi	Fujisawa	2004	7,700
UCB	Celltech	2004	2,250

Notes: This is the complete list of M&As reported in Table 1A. Ciba and Sandoz join together in 1996 to form Novartis. The merger between Hoechst Marion Roussel and Rhone Poulenc Rorer in 2000 leads to the creation of Aventis. Finally, Astella is the resulting company from the merger between Yamanouchi and Fujisawa.

Table 3: Technological and Product Similarities
(Means and Correlations of Variables)

	Mean	**1**	**2**	**3**	**4**	**5**	**6**
PCorr	0.221	1					
	(0.295)						
Over	0.032	0.268	1				
	(0.058)	(0.221)					
Cit	0.023	0.149	0.619	1			
	(0.043)	(0.369)	(0.782)				
Spill	0.007	0.213	0.627	0.225	1		
	(0.011)	(0.202)	(0.549)	(0.587)			
AT2Corr	0.167	0.315	0.061	0.091	0.027	1	
	(0.255)	(-0.140)	(-0.213)	(-0.037)	(-0.146)		
AT3Corr	0.088	0.334	0.092	0.138	0.078	0.780	1
	(0.129)	(0.105)	(-0.126)	(0.174)	(0.018)	(0.828)	

Notes: In parenthesis, means and correlations of the variables for the "true" merged pairs.

Table 4: Technological and Product Similarities
(Test of Differences between "True" and "Fictional" Pairs)

Variable	***t*-test statistics [a]**	**X-test statistics [b]**
PCorr	-2.92	-4.03
	(0.00)	(0.00)
Over	-3.57	-3.91
	(0.00)	(0.00)
Cit	-1.85	-2.87
	(0.03)	(0.00)
Spill	-1.73	-2.92
	(0.04)	(0.00)
AT2Corr	-2.80	-2.59
	(0.00)	(0.00)
AT3Corr	-2.02	-1.94
	(0.02)	(0.03)

Notes: p-values in parenthesis

[a] *t*-test of the difference between mean values; the null hypothesis is that the mean of the variable for the "true" merged pairs is equal to the mean of the variable for the "fictional" pairs. The alternative hypothesis is that the mean for the "true" pairs is lower (one-tail test).

[b] The X-test statistics is distributed as *N(0,1)*. The null hypothesis is that the rankings of "true" merging pairs is equal to the ranking of "fictional" pairs. The alternative hypothesis is that the mean for the "true" pairs is lower (one-tail test).

Table 5: Effects of M&As

Panel I Dependent Variable:	$\Delta\%R\&D$	$\Delta R\&Dint$	$\Delta\%P$	$\Delta\%P^{imp}$	$\Delta\%\left(\frac{P}{R\&D}\right)$	$\Delta\%\left(\frac{P^{imp}}{R\&D}\right)$	$\Delta\%V$
Merged in *t*	-0.051**	-0.005	-0.167*	-0.308**	-0.115	-0.348***	-0.025
	(0.023)	(0.003)	(0.092)	(0.140)	(0.102)	(0.125)	(0.074)
Merged in *t-1*	-0.038*	-0.001	0.064	0.039	0.087	0.044	-0.076
	(0.023)	(0.003)	(0.151)	(0.072)	(0.153)	(0.078)	(0.051)
Merged in *t-2*	-0.060***	-0.003	-0.128	-0.081	-0.051	0.033	-0.066
	(0.018)	(0.002)	(0.113)	(0.139)	(0.117)	(0.143)	(0.041)
Merged in *t-3*	-0.076***	-0.002	-0.31***	-0.212**	-0.261**	-0.134	-0.046
	(0.025)	(0.003)	(0.117)	(0.095)	(0.120)	(0.090)	(0.037)
P-value [a]	0.000	0.078	0.037	0.025	0.203	0.100	0.064
N. of Obs.	640	632	694	617	520	445	495

Panel II Dependent Variable:	$\Delta\%R\&D$	$\Delta R\&Dint$	$\Delta\%P$	$\Delta\%P^{imp}$	$\Delta\%\left(\frac{P}{R\&D}\right)$	$\Delta\%\left(\frac{P^{imp}}{R\&D}\right)$	$\Delta\%V$
$PCorr_{t-1}$	-0.152**	-0.017*	-0.71***	-1.05***	-0.546**	-1.09***	0.014
	(0.062)	(0.010)	(0.227)	(0.399)	(0.262)	(0.425)	(0.219)
$PCorr_{t-2}$	-0.129***	-0.004	0.328	0.061	0.392	0.080	-0.247**
	(0.049)	(0.006)	(0.441)	(0.199)	(0.443)	(0.204)	(0.107)
$PCorr_{t-3}$	-0.187***	-0.013**	-0.454	-0.791	-0.231	-0.440	-0.258*
	(0.043)	(0.007)	(0.348)	(0.532)	(0.374)	(0.601)	(0.139)
$PCorr_{t-4}$	-0.222***	-0.004	-0.646	-0.614	-0.532	-0.366	-0.162
	(0.068)	(0.010)	(0.441)	(0.397)	(0.443)	(0.359)	(0.130)
P-value [a]	0.000	0.031	0.059	0.006	0.259	0.050	0.038
N. of Obs	640	632	694	617	520	445	495

Table 5 (Continued)

Panel III Dependent Variable:	$\Delta\%R\&D$	$\Delta R\&D\ int$	$\Delta\%P$	$\Delta\%P^{imp}$	$\Delta\%\left(\frac{P}{R\&D}\right)$	$\Delta\%\left(\frac{P^{imp}}{R\&D}\right)$	$\Delta\%V$
$PCorr_{t-1}$	-0.169*	-0.033***	-0.75***	-1.374**	-0.539*	-0.613	-0.338
	(0.087)	(0.011)	(0.269)	(0.549)	(0.319)	(0.410)	(0.327)
$PCorr_{t-2}$	-0.161**	-0.009	0.481	-0.119	0.596	-0.042	-0.369***
	(0.069)	(0.008)	(0.523)	(0.268)	(0.513)	(0.204)	(0.109)
$PCorr_{t-3}$	-0.215***	-0.016**	-0.807*	-1.306**	-0.619	-1.008*	-0.275
	(0.054)	(0.007)	(0.470)	(0.512)	(0.510)	(0.579)	(0.193)
$PCorr_{t-4}$	-0.144**	0.006	-0.023	-0.111	0.072	0.038	-0.272*
	(0.071)	(0.012)	(0.325)	(0.452)	(0.351)	(0.415)	(0.158)
$AT2Corr_{t-1}$	0.029	0.032***	0.148	0.524	0.096	-1.103**	0.445
	(0.151)	(0.010)	(0.201)	(0.829)	(0.439)	(0.485)	(0.308)
$AT2Corr_{t-2}$	0.047	0.009	-0.393	0.220	-0.484	0.096	0.273**
	(0.086)	(0.011)	(0.695)	(0.144)	(0.586)	(0.231)	(0.105)
$AT2Corr_{t-3}$	0.059	0.004	0.471	0.77***	0.552	0.879***	0.077
	(0.081)	(0.008)	(0.394)	(0.273)	(0.376)	(0.311)	(0.169)
$AT2Corr_{t-4}$	-0.103	-0.017	-0.793	-0.420**	-0.773	-0.305*	0.135
	(0.098)	(0.011)	(0.525)	(0.203)	(0.554)	(0.172)	(0.088)
P-value [b]	0.000	0.010	0.190	0.002	0.577	0.073	0.001
P-value [c]	0.877	0.161	0.556	0.220	0.515	0.483	0.009
N. of Obs.	633	625	689	612	515	440	489

Notes: Robust standard error in parentheses. Time dummies are included in all the regressions. The variables *PCorr* and *AT2Corr* are computed using patent and product data of acquirers and targets in the year before the merger (e.g. for a deal signed in 1995, the two variables are computed with data of 1994). These two variables take a value of zero for non-merging firms. The compute innovation output and productivity, a patent is added to the original number of patents so that that ln(patent)=0 when patent=0.

*** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level

[a] P-values of the *Wald*-test of the null hypothesis that the sum of the 4 coefficients is statistically different from zero.

[b] P-values of the *Wald*-test of the null hypothesis that the sum of the first 4 coefficients (i.e. those concerning *PCorr*) is statistically different from zero.

[c] P-values of the *Wald*-test of the null hypothesis that the sum of the last 4 coefficients (i.e. those concerning *AT2Corr*) is statistically different from zero.

Table 6: Mergers and Synergies

Dependent Variable:	Number of Citations Received by any patent *j* granted to the acquirer within 5 after the merger
Patent *j* cites patents of Acquirer (only)	-0.248***
	(0.088)
Patent *j* cites patents of Target (only)	-0.509***
	(0.066)
Patent *j* cites patents of Acquirer and Target	-0.001
	(0.592)
Number of Obs.	6,500

Notes: Robust standard error in parentheses. Complete set of time dummies included.
*** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level

Table 7: Effects of Mergers on Competing Firms

Dependent Variable:	Number of Citations Received by any patent *j* granted to any firm in the last 5 years before the merger
Patent *j* is cited by patents of Acquirer (only)	-0.011
	(0.045)
Patent *j* is cited by patents of Target (only)	-0.017
	(0.069)
Patent *j* is cited by patents of Acquirer and Target	-0.140**
	(0.070)
Number of Citations Received by patent *j* until *t-1*	0.017***
	(0.002)
Number of Obs.	12,662

Notes: Robust standard error in parentheses. Complete set of time dummies included.
*** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level.

APPENDIX

Table A1: Revenues and Employment

Dependent Variable:	*Δ%R*	*Δ%E*
Merged in *t*	-0.016	-0.039
	(0.018)	(0.028)
Merged in *t-1*	-0.032	-0.083***
	(0.026)	(0.027)
Merged in *t-2*	-0.042***	-0.075***
	(0.015)	(0.019)
Merged in *t-3*	-0.064***	-0.036**
	(0.017)	(0.014)
P-value [a]	0.000	0.000
Number of Obs.	638	538

Notes: Robust standard error in parentheses. Time dummies are included in all the regressions.
*** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level
[a] P-values of the *Wald*-test of the null hypothesis that the sum of the 4 coefficients is statistically different from zero.

Table A2: Ex-ante Differences between Merging and Non-merging Firms

Variable	Mean for Acquirers/Target	Mean for control group	P-value (diff. in means)
ln (Stock Market Value)	10.4	9.02	0.00
in millions of $	9.25	9.08	0.53
ln (R&D expenditure)	6.77	5.91	0.00
in millions of $	6.00	6.03	0.91
R&D intensity	0.134	0.130	0.68
	0.139	0.130	0.43
ln(Patents)	4.05	2.99	0.00
	3.55	3.02	0.14
Patent / R&D exp.	0.09	0.13	0.38
	0.11	0.13	0.75

Notes: The first line refers to the mean for acquirers while the second line to the mean for targets. The mean value for acquirers and targets is computed one year before the merger. The control group for acquirer (target) is formed by all those firms that do not acquire another firm (are not acquired by another firm) in any of the following three years.

Table A3: Effects of M&As controlling for Heterogeneity

Panel I Dependent Variable:	$\Delta\%R\&D$	$\Delta\%P$	$\Delta\%P^{imp}$	$\Delta\%\left(\frac{P}{R\&D}\right)$	$\Delta\%\left(\frac{P^{imp}}{R\&D}\right)$	$\Delta\%V$
Merged in *t*	-0.071***	-0.108	-0.468***	-0.020	-0.396***	-0.021
	(0.026)	(0.100)	(0.136)	(0.105)	(0.141)	(0.074)
Merged in *t-1*	-0.051**	-0.000	0.011	0.062	0.071	-0.063
	(0.024)	(0.178)	(0.119)	(0.179)	(0.128)	(0.053)
Merged in *t-2*	-0.068***	-0.190	-0.159	-0.126	-0.044	-0.056
	(0.024)	(0.145)	(0.215)	(0.150)	(0.202)	(0.048)
Merged in *t-3*	-0.096***	-0.443***	-0.351***	-0.386**	-0.249**	-0.051
	(0.031)	(0.147)	(0.106)	(0.160)	(0.107)	(0.021)
Control: *V/R*	0.045***	-0.011	-0.026	-0.042	-0.054	-0.031
	(0.009)	(0.038)	(0.037)	(0.035)	(0.038)	(0.021)
P-value [a]	0.000	0.018	0.001	0.145	0.041	0.108
N. of Obs.	483	391	325	381	316	473

Notes: Robust Standard Error in parentheses. Time dummies included in all the regressions.
*** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level
[a] P-values of the *Wald*-test of the null hypothesis that the sum of the 4 coefficients is statistically different from zero.