Mergers and Innovation in Big Pharma

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Abstract

The aims of this paper are to study the effects of mergers on the R&D activity of consolidated firms and to explore the relationship between ex-ante relatedness of merging parties and their ex-post performances. The analysis is conducted using data of the pharmaceutical industry for the period 1988-2004. The empirical results suggest that merged companies have on average, worst performances than the group of non-merging firms. This result is confirmed when I account for the endogeneous formation of mergers using the propensity score method and when I control for technological relatedness in selecting the control group. Finally, I find that higher levels of technological relatedness are not associated with better R&D outcomes.

JEL classification: L66, O31, O32.

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

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1 Introduction

Antitrust authorities on both sides of the Atlantic have been rather reluctant to consider explicitly long-run effects of mergers on innovation: their analysis is traditionally focused on the short-term effects of mergers on market structure, leaving little role for any long-run assessment of dynamic efficiency. The traditional static analysis of the *ex-ante* foreseeable implications 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. On the one hand, by joining the research expertise of the two companies, M&As can profoundly improve the research performance of the firms involved: new and better products can be developed in the research labs of the new company, with clear positive effects on consumer welfare. On the other hand, acquirers may decide to target those firms that are developing products with similar technological contents in order to soften competition and to avoid any negative impact on their future growth. This can have two negative consequences: higher consumer prices in the short run and, even more importantly, less incentives to innovate in the long-run.

If the difficulties involved in assessing the effects of mergers on innovation can partially justify the conservative attitude showed by antitrust authorities, it is nevertheless surprising that little academic research has been devoted to this issue.[1] The aim of this paper in then to produce new general evi-

[1] Most of the empirical evidence produced by researchers focuses on the effects of mergers on profits, sale, market shares and market values. Mueller (1996) and Andrade, Mitchel and Stanford (2001) provide an excellent summary of the existing literature. One of the earliest studies of the impact of mergers on innovation is the paper by Hall (1987). Cassi-

dence on this under-investigated topic. 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 performances of firms? In particular: Do they have a positive effect on the innovative ability of the firms involved, as their proponents often claim?[2] ii) Is there any relationship between the ex-ante technological and product relatedness of merging parties and the ex-post effects of 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.[3] 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 are the operations more likely to rise anticompetitive concerns.

The data set used gathers different sources of information. First, financial

man, Colombo, Garrone and Veugelers (2004) provide an exhaustive survey of the existing literature on M&As and R&D.

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

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

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.[4]

This study shows mergers do not seem to deliver any important efficiency gains to the firms involved. On average, merged companies have worst innovation performances than the group of non-merging firms. These findings are confirmed when I account for endogeneity and selection issues using the propensity score method or when I control for the technological relatedness of the firms in selecting the control group. Finally, empirical results seem to contradict the idea that higher levels of technological relatedness between merging parties are associated with better post-merger outcomes.

Compared to previous studies, this paper differs in at least two important ways. First, 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. In the absence of a full structural model, the analysis of multiple outcomes (input and output)

[4]This large among of data has been carefully cross-checked with several sources available on the internet in order to minimize measurement errors. For instance, some financial data in compustat did not match with the correspoding annual reports available in the EDGAR database of the U.S. security and exchange commission (www.sec.gov).

provides a more robust test of the effects of M&As compared to the use of a single indicator.[5] The importance of this approach is confirmed by the theoretical framework developed by Bloom, Schankerman and Van Reenen (2005) in their study of technology and product market spillovers. Second, 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 product portfolios.[6]

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 Theory and Empirics

2.1 Theoretical Considerations

This section aims at exploring how mergers can affect the firms' post-merger innovation performances and to what extent these outcomes depend on the

[5] Danzon, Epstein and Nicholson (2004) examine the determinants of M&A in the pharmaceutical and biotech industry and, in turn, their effects on firms' performances, including enterprise value, sales, employment and R&D expenditure. Their analysis is not focused on the effects of mergers on innovation.

[6] Cassiman *et al.* (2004) also study the relationship between innovation and technological and market relatedness of acquirers and targets. But their analysis is based on mergers in industries with different R&D intensities and their measures of relatedness rely upon qualitative data collected through a questionaire.

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) Effects of mergers on innovation

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 tests to check the safety and efficacy of the NCEs, before obtaining marketing approval.[7] 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 activity.

Research expenditures ($R\&D$) include the variable cost of funding different projects, as well as the fixed costs that a firm incurs independently of the number of projects under way, e.g. lab buildings and equipments, libraries, etc. The outcome of the research activity is measured by the number of patent grants over newly discovered compounds (P). It is very difficult to define a functional relationship between research inputs and outputs. The

[7]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. See Henderson and Cockburn (1996) for a detailed description of research and development of compounds.

complexity of the research implies in fact a high degree of uncertainty on the actual progress towards the discovery of new compounds.

Mergers can affect the optimal R&D expenditure and in turn, innovation output through different channels. First, as part of the research expenditure consists of fixed costs that all the firms need to sustain independently of the number and focus of their research, mergers might lead to a substantial reduction in research costs by avoiding useless duplication.

Second, by unifying the expertise of two companies, mergers might create large knowledge synergies. Discoveries made by scientists in one program can stimulate the research activity of their colleagues in another field through cross-fertilization of ideas. Differently from pure economies of scope, knowledge synergies imply an increase in the research performance of the firms, irrespective of any change in R&D inputs.[8]

Third, deals studied in this paper imply the disappearance of one important competitor. It is then possible that the internalization of technological outflows that were previously captured by rivals can further stimulate the R&D investments of the new company (Kamier, Mueller and Zang, 1992).

The analysis above suggests that mergers have a positive impact on research productivity, as measured by some ratio of research outputs and inputs. Nevertheless, it tends to overlook that most of the firms' knowledge is embodied in their biologists and chemists. The large reduction in the number of researchers that often follows the conclusion of a merger deal can then

[8] On this point, Henderson and Cockburn (1996) argue that "*economies of scope relate to research expenditures, whereas internal knowledge spillovers affect output irrespective of expenditures*".

reduce the actual know-how of the newly formed company.[9] Moreover, cultural dissonances and other integration problems might disrupt innovation outcomes, therefore hampering the probability of a successful innovation.[10] Under this scenario, it is not possible to predict the sign of the net effect of mergers on the research process.

Table 1 summarizes all the arguments above. It shows that mergers can either increase or decrease R&D inputs, output and performance depending on the forces that dominate the consolidation process. If mergers can deliver large economies of scale and knowledge synergies, we should anticipate an increase in both R&D output and performance.

INSERT TABLE 1 ABOUT HERE

b) Technology and product relatedness

Most of the changes in R&D inputs and outputs defined above are driven by forces whose magnitude depends on the technological relatedness, TR,

[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.

[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)

and the product relatedness, PR, of the merged parties. 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. By targeting firms that are working on similar technologies, acquirers can also soften competition and possibly, erect higher technology barriers that can negatively affect the innovation process of other firms.

Opportunities to use the inputs of one firm in the research projects of another company are more likely to arise when firms work on similar technology fields. Besides, post-merger knowledge synergies are 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. 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 and in turn, a deterioration of the post-merger performances. The complexity of the forces at work precludes defining unambiguous theoretical predictions on the relationship between TR and innovation performances.

Deals between firms with high product relatedness, PR, allow to achieve larger economies of scale in production, distribution and advertising while reinforcing the market power in those therapeutic area where both acquirer and target are active players. Given that human capital dissipation is less problematic in these areas, higher degree of product relatedness are likely to

deliver better post-merger outcomes.

The framework above suggests that technological relatedness and product relatedness can explain differences in the post-merger results of consolidated firms. The empirical results presented in Section 4 seem to confirm this perspective.

2.2 Empirical Specifications

As a first step, the effects of mergers are analysed using a dummy variable approach. Given that 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, I estimate the following econometric model :

$$\Delta\%Y_{it} = \beta_0 M0 + \beta_1 M1 + \beta_2 M2 + \beta_3 M3 \ + \gamma T + u_{i,t} \qquad (1)$$

where $\Delta\%Y$ indicates the percentage change (i.e. logarithmic difference) of one of the innovation measures (e.g. research expenditures $R\&D$, number of patents P, *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. $M0$, $M1$, $M2$ and $M3$ are dummy variables that take a 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.[11]

[11] Note that for the merged firms, the estimation of equation (1) 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

In addition to innovation inputs and outputs, interesting insights on the effects of mergers can be inferred using the change of the stock market value, $\Delta\%V$, as dependent variable in eq. (1). The stock market value can be used as overall indicator of the effects of the mergers on the performances of these companies, including the impact on the development of new compounds covered by patents and the sales of approved drugs.

Two matters need to be clarified about eq. (1). As the model is defined in growth rates, any unobserved heterogeneity among firms that is persistent over time (i.e. unobservable individual fixed effects) is purged from the specification. Second, the coefficient of $M0$ represents a difference-in-difference estimate of the performance changes due to the merger: it captures the excess outcome growth for consolidated companies compared to the control group of non-merging firms. The dummies $M1 - M3$ in turn assess whether there are lagged effects of consolidation in the following years. By testing whether the sum of the βs coefficients are statistically difference from zero, I can then evaluate whether mergers have a significant permanent effect on the level of the observed outcome.

A main drawback of this approach is that the endogeneity of the merger formation is not accounted for. The decision to merge is not an exogenous process but it is taken by the firms on the base of their specific characteristics, some of which can influence the post-merger outcome. In other words, the estimated coefficients of the M dummies do not assess the actual effect

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 mergers on innovation if most of the merged companies would have experienced poorer performance (compared to the control group) even in the absence of the merger. For instance, Danzon *et al.* (2004) find that firms with important drugs coming off patents are more likely to pursue a merger. But this same event affects also the future revenues of the firm. Therefore, one would find a negative correlation between mergers and growth of revenues, even in the absence of a causal effect of the first on the second.

Consider the following simple setup:

$$p(M = 1|X) = \Phi(\delta X) \tag{2A}$$

$$\Delta\%Y = \beta M + \delta X + v \tag{2B}$$

The first equation specifies the probability that a firm merges as a function of a variable X (e.g. patent expirations). The second equation assumes that changes in Y (e.g. revenues) depend not only on the decision to merge but also on X. If these two-equations model is replaced with the single equation $\Delta\%Y = \beta M + u$, X would enter the error term and the resulting correlation between M and u would bias the estimates of β.

Estimated coefficients of eq. (1) do not assess the causal effects of mergers on R&D inputs and output if firms that anticipate a deterioration of their R&D activities are more likely to merge. In this case, a correct identification of the β coefficients relies on the use of observables that can account for this selection. There are two set of variables that can play such a role in the pharmaceutical industry: pre-merger R&D performances and patent expirations. Firms that are experiencing poor R&D results might anticipate a further de-

terioration of their innovation performance; therefore they are more likely to pursue a merger as a way to soften these negative events. Similarly, patent expiration is a main determinant of mergers and a possible source of disruption in the research activity because of the reduction in internal cash flows it causes.[12]

As in other recent empirical works, I try to control for this selection problem using the propensity score method.[13] First, the probability that a firm i merges in year t is estimated conditional on some observables capturing pre-merger R&D performance and the approaching patent expiration (see eq.(2A) above). Then, each merging firm is matched with control firms endowed with similar propensity score. Under this approach, the control group is assumed to represent a good proxy of what the outcome of a consolidated company would have been if it had not merged. Estimated coefficients of eq. (1) should then capture the actual effects of mergers on the R&D inputs and output.[14]

The propensity score method is generally used to asses the effects of an economic "treatment" on a single unit (for instance, effects of a training program on people unemployed). Differently from these studies, mergers involve two different units: an acquirer and a target. In this study I account for this peculiarity by matching both acquirers and targets with the two firms

[12] Scherer (2004) suggests that the expectation of high (lower) profits increases (decreases) research-and-development outlays.

[13] See, among others, Bertand and Zitouna (2005) and Danzon *et al.* (2004) for further details on this methodology.

[14] This approach combines then difference-in-difference estimation with matching technique. 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*".

that have the closest probability to merge.

Besides the propensity score, a second approach is used in the empirical analysis to account for selection issues. Let's assume that most of the mergers considered in this study are driven by negative technological shocks that hit firms with similar research activities.[15] If this were the case, any negative correlations between mergers and innovation captured by the dummies in eq.(1) might be spurious, given that these variables are picking up the effects of these exogenous technology changes. Since any negative shocks should hit not only the merged companies but also those firms that have very similar technology, I check the robustness of the results when the control group is restricted to the firms that have the highest technology relatedness with the consolidated companies.[16]

Finally, to address the question of the relationship between the ex-ante technological and product relatedness of merging parties and the ex-post effects of mergers, the sample used has to be restricted to the sub-sample of merging companies. To account for the possible selection problem, I use the Heckman "two-step" procedure. First, the probability of being a merging firm is estimated using logit model, as in eq. (2A) above. Then, I estimate an equation of the form:

$$\Delta\%Y = \beta_1 TR + \beta_2 PR + \delta\lambda(X\beta) + u_{i,t} \tag{3}$$

[15] For instance, doctors have recently successfully transplanted insulin producing cells in diabetic patients, thus eliminating their dependence on insulin injections. This change in technology can negatively affect the performance of those firms with research projects in this therapeutic area.

[16] Note that it is not possible to control for technological relatedness by including a measure of TR in the propensity score equation. Differently from other variables (e.g. R&D expenditure) technology relatedness can be defined only in relative term so that, in each period, different values of TR can be computed.

where $\lambda(X\beta)$ is the inverse Mills ratio constructed from the "first step" logit estimates, which controls for the selection problem. As before, the specification is estimated up to three years after the merger. Illustratively speaking, for each merger deal signed in 1995, the independent variables TR and PR are computed using patent and product statistics of acquirer and target in the year before the merger, i.e. 1994. This is then used to assess the impact of relatedness on changes in performance, in the year of the merger ($\Delta\%Y_{1995}$) and in the following 3 years, until 1998 ($\Delta\%Y_{1998}$). Despite the simplicity of this approach, eq (3) can provide interesting evidence on a rather unexplored issue.

3 Data and Variables

To answer all the questions of this investigation a new data set is constructed by gathering different sources of information. The main financial data come from Compustat and Osiris, published by Standard and Poors and Bureau van Dijk, respectively. The variables retrieved are revenues from approved drugs, *R,* total R&D expenditures, *R&D*, and stock market value, *V*, for the period 1988-2004. 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 infor-

mation 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 data set 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. Patent statistics for period t are computed using the application year.

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 pro-

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

[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.

lifically, 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 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 2A:

INSERT TABLE 2A 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 complementary 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]

[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.

[20]For instance, the ATC1 anatomical group "C", cardiovascular system, is divided at the second level in the following groups: cardiac therapy, antihypertensives, diuretics,

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.

The first row of Table 2B reports the number of mergers and acquisition over the period 1988 to 2004. 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 2C. Despite the rather small size of the sample, it must be kept in mind that this paper focuses on a well-defined set of 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 2B 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 2B and 2C ABOUT HERE

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.

Using the *NBER* patent data, including the patent citation file, I construct four different measures of technological relatedness between acquirers and targets: the overlap between the list of patents cited (*Over*), the correlation between patents' technological classes (*PatCr*), the importance of cross-citations from acquirers to targets (*Cit*) and viceversa (*Spill*).

My preferred measure of technological relatedness is the variable *Over*, which is constructed with 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). *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.

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.[22] 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

[22] 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.

(actual or potential) target τ is defined by:

$$PatCr = \frac{(S_\alpha S'_\tau)}{(S_\alpha S'_\alpha)^{\frac{1}{2}}(S_\tau S'_\tau)^{\frac{1}{2}}}. \quad (4)$$

The remaining two measures of technological relatedness are computed using the patent citations data. 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:

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

These two variables measure direct linkages between firms rather than placing them in a certain technology space.[23]

[23] 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.

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 (4) where the vector $S=(S_1, ..., S_K)$ includes the fraction of medicines in the therapeutic area k, according to the ATC2 and ATC3 classification. These two variables are labelled *ATC2Cr* and *ATC3Cr*, respectively.

Table 3 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, some are characterized by low correlation. The t-test statistics rejects the null hypothesis that the relatedness among "true" merging pairs is similar to that of the "fictional" pairs. This suggest that mergers among firms with similar research activities and drug portfolio are more likely.

INSERT TABLE 3 ABOUT HERE

Before discussing the empirical results, a remark is required. Specifications are estimated using all the available observations in the dataset. As individual data for either R&D variables or stock market values are missing in some years, the size of the sample varies between specifications. Even though this makes the comparison of the results more difficult, the use of a unique sub-sample can negatively affect the consistency of the estimates because of the large number of observations that would be lost.

4 Results

a) Effects of mergers on innovation

Table 4, shows the effects of mergers on different aspects of firms' research activity, estimated using eq. (1). 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: the cumulated effect after three years implies a decrease of almost 1 percentage poin, which is statistically different from zero (p-value of the *Wald*-test is 0.05). The reorganization of the merged entities implies a reduction in R&D investments that is above the decrease in revenues observed in other studies (Danzon *et al.,* 2004).

As for the changes in research productivity, measured by ratio of patents to R&D expenditure, most of the estimated coefficients have a negative sign and, although some of them are not precisely estimated, the p-values in the last two columns show that the null hypothesis that changes over three year are not statistically different from zero has to be rejected. Finally, the prevalence of negative coefficients in the first column of the table suggests that mergers have on average a negative impact on firms' performances[24]: overall returns for shareholders up to three years after the merger are clearly below those of other pharmaceutical firms (p-value 0.06).[25]

[24] 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.

[25] 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

INSERT TABLE 4 ABOUT HERE

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 4, this counterfactual is computed using the entire sample of non merging firms as control group. A recognized weakness of this approach is that only a few firms in the control group might be comparable to merged firms. Hereafter, I check the robustness of the results using the propensity score method.

First, I estimate the propensity to merge using a logit regression. As explained above, I try to control for those factors that might simultaneously affect the decision to merge and the future R&D activities, namely percentage of drugs approaching patent expirations, percentage of new drugs launched into the market, and ex-ante (level and growth of) number of patents. The dependent variable is a dummy taking value 1 if a firm decides to merge and 0 otherwise.[26] All the explanatory variables of the logit model are measured one year before the merger decision. Table 5A confirms the finding in Danzon *et al.* (2004) that firms with drugs approaching patent expiration and without new drugs launched on the market are more likely to pursue a merger. Good recent performances in patent activities decreases the probability of a merger but this effect does not seem to be statistically significant.

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.

[26]Note that I use a unique probit regression for acquirers and targets. There are two reasons behind this choice. First, most of the transactions are best described as mergers of equal, so it would be difficult to say who is the acquirer and who is the target. Second, drivers of mergers seem to be similar among acquirers and targets (for instance, they both seem to face important patent expirations).

Second, acquirers and targets are each matched with the two companies that have the closest probability of merging. Table 5B shows that the ex-ante characteristics of the selected control group are very close to those of acquirers and targets: the null hypothesis that the difference in mean for each variable considered is not different from zero cannot be rejected.

Finally, the effects of the merger are estimated using the new control group. The first column in Table 5C shows that the overall market performance of consolidated companies is still worse than the matched control group but the difference is now smaller and not statistically significant. This result is somehow comforting since it softens findings in Table 4 that mergers consistently destroy stockholders' wealth. Looking at the R&D process, I still find that mergers have a statistically significant negative impact on the growth of inputs, output and productivity. For all research measures but R&D intensity, the null hypothesis that the overall change over three years is not statistically different from zero has to be rejected. Again, these findings contradict the idea that mergers can deliver relevant economies of scope and knowledge synergies. Qualitative similar results are obtained when changing the number of matched firms (from one up to three firms) for each acquirer and target or when merging parties are matched with the non-merging firms with closest market value one year before the merger.[27]

INSERT TABLE 5A, 5B and 5C ABOUT HERE

[27] The idea is that market value is the leading indicator of the expected performance of a firm. Therefore firms that have the closest market value to the acquirers and targets one year before the merger should represent a valid control group.

Table 3 shows that consolidations are more likely among firms with similar technology. As suggested in Section 3, a possible explanation for this finding is that mergers are a defensive move taken by firms that experience negative shocks in the common technological areas. If this were the case, the negative correlations between mergers and innovation described above might be spurious. I then check the robustness of the results when controlling for the technological relatedness of merging firms and control group. Table 6 confirms that consolidated companies have worst innovation outcomes even when compared to this alternative control group.

INSERT TABLE 6 ABOUT HERE

b) Ex-ante technology and product relatedness and ex-post innovation

Although these findings suggest that on average, mergers do not deliver the expected innovation efficiency, there is no such a thing as an "average merger". If some mergers turn out to be a failure, others are generally regarded as successful operations. The theoretical analysis in Section 2 suggests that both technology relatedness and product relatedness can possibly explain differences in post-merger R&D performances. To shed some light on this rather unexplored issue, I estimate specification (3) using the variable $Over$ and $ATC2Cr$, both separately and jointly. The inverse Mills ratio is computed using the estimates of the logit model in Table 5A above.

The outcomes considered are only the growth of R&D efforts, innovation productivity and market value. Table 7 shows that the estimated coefficients have a clear pattern, although some of them are not precisely estimated

(possibly because of the small number of observations that are used). The results suggest that product relatedness has a positive effect on the post-merger outcomes while technology relatedness seems to have a detrimental impact.

The most interesting finding concerns the change in stock market value. While *Over* and $\Delta\%V$ are negatively correlated, firms with similar product portfolios have more prominent increases in market value. A tentative interpretation of this finding is that managers correctly anticipate that mergers among companies with similar product portfolios increase stockholders' wealth (because of synergies in sales and marketing operations and/or increased market power). But by focusing (mainly) on drug portfolios, managers might underestimate or wrongly evaluate the disruptive effects that these operations might have on the research process of the firms. Overall, these results seem to contradict the idea that higher levels of technological relatedness are associated with better R&D outcomes.

INSERT TABLE 7 ABOUT HERE

5 Conclusions

This paper explores the effects of mergers on innovation in the pharmaceutical industry. I find that consolidations among large pharmaceutical companies have a negative impact on firms' innovative performance, possibly because of the post-merger dissipation of human capital and integration problems. This paper takes into accont the role of technology and product relatedness in two

ways. I first use relatedness to construct a control group that can provide a better counterfactual of what would be likely to occur in the absence of the merger. Then, I use it to explain differences in post-merger outcomes of consolidated companies. On this latter issue, the most interesting finding is that the growth in market value is positively correlated to product relatedness and negatively correlated with technology relatedness.

The findings of this paper can hopefully stimulate the debate on the role of the merger policy in R&D intensive industry. Mergers of alike can raise anti-competitive concerns given that consolidated companies might reinforce their market power in some technology area. When Glaxo and Smithkline merged in year 2000, the EU commission reported the allegation by third parties that the merger "*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). At the same time, results above cast serious doubts on whether mergers can deliver large dynamic efficiencies to offset these (possible) anti-competitive effects.

The importance of innovation to long-term welfare and the empirical difficulties in identifying the causal effects of mergers on innovation impose extreme caution in drawing any radical conclusion for competition policy purposes. Given the paucity of empirical work in this area, it is desirable to extend the present analysis to other industries and countries. Future empirical studies should also encompass the effects of mergers on the innovation efforts of competitors. At present, there is no evidence on whether mergers

increase or reduce the incentive of the other firms to innovate. But it is clear that this issue is of paramount importance for the competition authorities to take appropriate decisions.

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Table 1: Predicted Effects of M&As on the R&D activity

Effects of M&As on:	**R&D inputs**	**R&D output**	**R&D perfor**
Elimination of common R&D (avoid duplication of fixed costs)	-		+
Economies of scope and Knowledge Synergies	+	+	+
Internalization of Spillovers and Technology market power	+	+	+
Human capital dissipation and Cultural dissonances	-	-	-
TOTAL EFFECT	?	?	?

Table 2A: Sample Statistics for Main Variables

Variable Description	**Variable Name**	**Mean**	**Standard Deviation**
Revenues, $million	R	5,418	5,689
	$\Delta\%R$	0.082	0.165
Firm market value, $million	V	24,525	32,380
	$\Delta\%V$	0.124	0.389
Total R&D expenditures, $million	$R\&D$	694	756
	$\Delta\%R\&D$	0.104	0.216
R&D intensity, (R&D/Revenues)	$R\&Dint$	0.135	0.048
	$\Delta R\&Dint$	0.003	0.017
Employment, thousands	E	29.8	28.1
	$\Delta\%E$	0.042	0.171
Number of new patents	P	48.5	54.5
	$\Delta\%P$	-0.079	0.663
Number of new important patents	P^{imp}	10.6	12.2
	$\Delta\%P^{imp}$	-0.116	0.668

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 2B: Descriptive Statistics by Year

	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Number of Mergers:	0	4	0	0	0	0	2	4	1	2	0	2	4	3	2	0	3
Average Revenues ($million):	3367	3631	3935	3733	4217	4163	4451	4673	4720	4856	5331	5911	6218	6743	7821	8534	9661
Average R&D ($million):	278	347	380	384	462	491	515	568	590	629	713	778	853	925	1122	1241	1480
Average Number of Patents:	37	38	42	39	45	46	56	88	50	69	59	59	43	22	3		

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 2C: 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 2B. 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)

Variables		**Mean**	***t*-test statistics** [a]	**Correlation**					
				1	**2**	**3**	**4**	**5**	**6**
1	*Over*	0.033	-3.85	1					
		(0.058)	[0.00]						
2	*PatCr*	0.231	-3.19	0.287	1				
		(0.314)	[0.00]	(0.329)					
3	*Cit*	0.025	-1.76	0.689	0.131	1			
		(0.043)	[0.04]	(0.865)	(0.407)				
4	*Spill*	0.007	-3.30	0.637	0.276	0.305	1		
		(0.013)	[0.00]	(0.677)	(0.131)	(0.619)			
5	*ATC2Cr*	0.166	-2.84	0.091	0.343	0.109	0.074	1	
		(0.255)	[0.00]	(-0.189)	(-0.159)	(-0.064)	(-0.185)		
6	*ATC3Cr*	0.087	-2.06	0.119	0.365	0.154	0.132	0.780	1
		(0.129)	[0.02]	(-0.02)	(0.101)	(0.164)	(-0.012)	(0.828)	

Notes: In parenthesis, means and correlations of the variables for the "true" merged pairs.
[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). *P*-values in square brackets.

Table 4: Effects of M&As

Dependent Variable:	$\Delta\%V$	$\Delta\%R\&D$	$\Delta R\&Dint$	$\Delta\%P$	$\Delta\%P^{imp}$	$\Delta\left(\frac{P}{\ln R\&D}\right)$	$\Delta\left(\frac{P^{imp}}{\ln R\&D}\right)$
Merged in *t*	-0.025	-0.052**	-0.002	-0.029	-0.159	-2.60**	-0.567
	(0.059)	(0.023)	(0.003)	(0.070)	(0.151)	(1.22)	(0.585)
Merged in *t-1*	-0.047	-0.046*	-0.002	-0.119	0.003	-2.91*	-0.722
	(0.049)	(0.025)	(0.003)	(0.082)	(0.086)	(1.53)	(0.740)
Merged in *t-2*	-0.051	-0.048**	-0.003	-0.161	-0.021	-2.62*	-0.533
	(0.036)	(0.018)	(0.002)	(0.116)	(0.092)	(1.46)	(0.497)
Merged in *t-3*	-0.089*	-0.089***	-0.003	-0.325**	-0.241	-1.66	-0.432
	(0.051)	(0.025)	(0.003)	(0.124)	(0.130)	(1.13)	(0.281)
P-values [a]	0.06	**0.00**	**0.05**	**0.00**	**0.04**	**0.00**	**0.01**
N. obs	506	650	639	831	617	576	449

Notes: Robust standard error in parentheses. Time dummies are included in all the regressions. Control group of non-merging firms is formed by all firms available in the dataset.
*** = 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 not statistically different from zero. In bold, *P*-values below 0.05.

Table 5A: Propensity score
(Logit Regression Model)

Variable	(1)	(2)
Percentage of drugs approaching patent expiration [a]	0.037***	0.038**
	(0.013)	(0.018)
Percentage of new drugs introduced in the market [b]	-0.036***	-0.033*
	(0.012)	(0.018)
Revenues		0.635
		(0.593)
Growth of Revenues		-3.191**
		(1.459)
Number of New Patents		-0.212
		(0.439)
Growth of Number of New Patents		-0.564
		(0.574)
Year dummies	Included	Included
Number of Obs.	610	397

Notes: Robust standard error in parentheses.
*** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level
[a] Number of drugs with patents expiring in the next three years over total number of drugs.
[b] Number of drugs with launched in the last three years over total number of drugs.

Table 5B: Ex-ante Differences
(control group selected using propensity score)

Variable	Mean for Acquirers/Target	Mean for control group	P-value (diff. in means)
$\Delta\%V$	0.036	0.104	0.43
	0.068	0.236	0.13
$\Delta\%R\&D$	0.087	0.062	0.57
	0.086	0.038	0.26
$\Delta R\&Dint$	0.004	-0.003	0.44
	0.006	-0.003	0.31
$\Delta\%P$	-0.073	-0.184	0.54
	-0.279	-0.225	0.78
$\Delta\%P^{imp}$	-0.332	-0.235	0.62
	-0.391	-0.241	0.40
$\Delta\left(\frac{P}{\ln R\&D}\right)$	-0.552	-1.285	0.60
	-1.282	-0.147	0.38
$\Delta\left(\frac{P^{imp}}{\ln R\&D}\right)$	-0.466	-0.064	0.16
	-0.345	-0.140	0.36

Notes: All the variables are computed one year before the merger. For each variable, figures in the first line refer to the acquirers while figures in the second line refer to the targets. The control group is selected matching each acquirer and target with the two firms that have the closest propensity score. The control group is the same used for the estimates reported in Table 6C.

Table 5C: Effects of M&As
(control group selected using propensity score)

Dependent Variable:	$\Delta\%V$	$\Delta\%R\&D$	$\Delta R\&Dint$	$\Delta\%P$	$\Delta\%P^{imp}$	$\Delta\left(\frac{P}{\ln R\&D}\right)$	$\Delta\left(\frac{P^{imp}}{\ln R\&D}\right)$
Merged in *t*	-0.008	-0.040*	-0.002	-0.027	-0.126	-2.26*	-0.495
	(0.062)	(0.022)	(0.003)	(0.074)	(0.157)	(1.20)	(0.585)
Merged in *t-1*	-0.024	-0.040	-0.001	-0.092	-0.029	-2.19	-0.878
	(0.049)	(0.027)	(0.003)	(0.071)	(0.098)	(1.45)	(0.751)
Merged in *t-2*	-0.028	-0.015	-0.002	-0.068	-0.024	-1.81	-0.534
	(0.038)	(0.019)	(0.003)	(0.097)	(0.111)	(1.44)	(0.519)
Merged in *t-3*	-0.063	-0.064**	-0.004	-0.331***	-0.298**	-1.63	-0.548
	(0.046)	(0.029)	(0.003)	(0.105)	(0.120)	(1.18)	(0.258)
P-values[a]	0.33	**0.00**	0.08	**0.01**	**0.04**	**0.00**	**0.01**
N. obs.	337	442	442	377	278	371	272

Notes: Robust standard error in parentheses. Time dummies are included in all the regressions. The control group is selected matching each acquirer and target with the two firms that have the closest propensity score.
*** = 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 not statistically different from zero. In bold, *P*-values below 0.05.

Table 6: Effects of M&As
(control group selected using technology relatedness)

Dependent Variable:	$\Delta\%V$	$\Delta\%R\&D$	$\Delta R\&Dint$	$\Delta\%P$	$\Delta\%P^{imp}$	$\Delta\left(\frac{P}{\ln R\&D}\right)$	$\Delta\left(\frac{P^{imp}}{\ln R\&D}\right)$
Merged in *t*	-0.033	-0.055**	-0.003	-0.116	-0.231	-2.862**	-0.749
	(0.065)	(0.025)	(0.003)	(0.074)	(0.154)	(1.238)	(0.577)
Merged in *t-1*	-0.041	-0.038	-0.002	-0.187*	0.037	-2.818*	-0.689
	(0.053)	(0.027)	(0.003)	(0.098)	(0.083)	(1.483)	(0.718)
Merged in *t-2*	-0.025	-0.044**	-0.003	-0.211*	-0.041	-2.329	-0.541
	(0.045)	(0.021)	(0.003)	(0.126)	(0.101)	(1.518)	(0.486)
Merged in *t-3*	-0.113**	-0.086**	-0.000	-0.426***	-0.271*	-2.173*	-0.610**
	(0.052)	(0.035)	(0.004)	(0.140)	(0.142)	(1.277)	(0.288)
P-values[a]	0.11	**0.00**	0.17	**0.00**	**0.02**	**0.00**	**0.01**
N. obs.	284	349	331	301	222	293	214

Notes: Robust standard error in parentheses. Time dummies are included in all the regressions. The control group is constructed by choosing the 3 firms that have the highest technological correlation with the acquirer (using the variable *Over*).
*** = 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 not statistically different from zero. In bold, *P*-values below 0.05.

Table 7: Mergers and Technological/Product Relatedness

Dependent Variable:	$\Delta\%V$	$\Delta\%R\&D$	$\Delta\left(\frac{P}{\ln R\&D}\right)$	$\Delta\left(\frac{P^{imp}}{\ln R\&D}\right)$
Over	-1.113* (0.545)	-0.076 (0.216)	-24.73* (13.12)	-11.32*** (3.767)
ATC2Cr	0.362*** (0.124)	0.084 (0.051)	8.434** (3.858)	2.438 (1.591)
Over	-1.161** (0.417)	-0.071 (0.187)	-26.86 (17.69)	-12.98** (4.565)
ATC2Cr	0.369*** (0.090)	0.085 (0.052)	8.831** (3.299)	2.97** (1.125)
	Inverse Mills ratio included in all regressions			
N. Obs.	69	81	69	52

Notes: Robust standard error in parentheses.
*** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level