Mergers and Innovation: the Case of Pharmaceutical Industry

Carmine Ornaghi*
Universidad Carlos III de Madrid and IDEI

April 2004
PRELIMINARY VERSION

Abstract

The present paper takes a new look at the causes and effects of mergers by exploring the relationship between acquisitions and innovation. Although innovation represents the engine for the long run growth and success of firms, there are few empirical studies that have explored this relationship. Three different issues are investigated: the role played by R&D and innovation in the decision to merge, the importance of patents holdings in the search for merger partners and the effects of mergers on innovative performance of the firms. The analysis is conducted for the case of the pharmaceutical industry for the period 1989-2001. Two main novelties are introduced. On an empirical ground, I utilize a newly constructed dataset containing not only financial data but also firm-level patent records for publicly traded pharmaceutical firms. On a methodological ground, determinants of mergers are investigated using survival analysis, the choice of targets is explored using measure of similarities between research programs and merger effects are examined using propensity scores to control for endogeneity. The results of this study suggest that firms who experience troubles in replacing important drugs coming off patent with other new promising compounds are more likely to pursue a merger. Although acquirers tend to target firms with similar research programs,

*I would like to thank Brownyn Hall for kindly providing the dataset used in this paper. Valuable comments were received from seminar partecipants at University of Toulouse.

which should a priori maximise the synergies from a consolidation, these operations do not seem to deliver any important efficiency gain to the merging firms. On the contrary, they seem to further deteriorate the research performance of these companies.

1 Introduction

A significant body of economic research has addressed the issue of what are causes and the consequences of mergers and acquisitions (M&As). As far as the reasons driving consolidation are concerned, the hypothesis that have been formulated can be grouped in three main groups (Mueller, 1989 and 1996). A first stream of literature advocate that mergers are efficiency enhancing operations that allow the new company to achieve a sensible reduction in costs, because of economies of scale and scope of different nature. A second line of research stresses that the purpose of mergers is to create or reinforce the market power of the firms or that mergers are an instrument to facilitate collusion, because of the reduction in the number of competing firms in the market. Finally a third line of research highlights that mergers can be driven by managers' interests in being at the head of large and powerful organization.

Given that all these models give plausible theoretical explanation of why firm merge, empirical analysis acquires an important role to discern what theory can best explain the merger wases of the last decades. Unfortunately, applied works have not settled but fed the existing controversy. Apart from the bitter consideration that empirical regularities across studies are hardly found, there is an important flaw that needs to be considered. Empirical studies have tried to identify the determinants of mergers by examining whether acquirers and targets have some distinctive features. But pre-merger characteristics of merging firms may not have a unique interpretation in terms of determinants. For instance, the fact that consolidations usually involve acquirers with high-Q (the ratio of the market value of corporate assets to their replacement value) and targets with low-Q is generally interpreted as a sign that mergers are channels through which capital flows to better project and better management (efficiency reason). But given that payments are often done by exchange of shares, it is also possible that managers may take advantage of the high enterprise value to increase the size of their firms (e.g. empire-building motivation) even if they do not expect the operation to be

successful. The greatest contribution of empirical work to the understanding of merger activity probably rests in the analyses of the effects of mergers. Understanding the consequences of mergers not only is an interesting question on its own but it can also help to infer the reasons behind consolidations, given that the effects of mergers can be considered the realization of the ex-ante goals pursuit by managers (Gugler, Mueller, Yurtoglu and Zulehner, 2003).

The present paper takes a different look at the causes and effects of mergers by exploring the relationship between acquisitions and innovation. Although innovation represents the engine for the long run growth and success of firms, there are few empirical studies that have explored this relationship. The necessity to be at the frontier of the innovation may be a main driving force behind merger activity. At the same time, by joining the research expertise of the two companies, M&As can profoundly change the research strategy and innovation ability of the firms involved. The objective of this paper is to get some interesting insights on these rather unexplored issues. In particular, to our data set, whose structure is briefly illustrated next and then detailed in Section 3, I ask the following three questions: i) Do R&D and innovation play an important role in the decision of undertaking a merger? ii) Can patent statistics help to understand the choice of the target, thus to answer the question "who merge with whom"? iii) 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, as their proponents often claim? The analysis is conducted for the case of the Pharmaceutical Industry for the period 1989-2001.

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 biggest mergers of the last decade. Recent examples include Glaxo-Smithkline and Pfizer-Warner Lambert. Second, this is one of the sectors with the highest intensity in research and development (R&D). Not only innovation is the most important dimension of competition among firms, but there are no other sectors where innovation has such an important welfare impact on consumers, given that there are no goods as precious as health. Third, horizontal mergers account for almost the totality of the consolidations and there are not important examples of comglomerate mergers, i.e. pharmaceutical firms targeting at companies outside the industry or vice versa. This is an important characteristic given that it would be difficult to establish a causal link between the

consolidation and any evidence of changes in the innovation activity of the merging firms when these belong to completely different sectors. Finally, by focusing on a well-defined sector, the heterogeneity of the results that may derive from cross-industry studies can be eliminated.

In order to answer all the questions of this investigation a new dataset has been constructed by gathering three main data sources. First, financial data for firms with a primary biotechnology or pharmaceutical SIC code (2834, 2835 and 2936) have been retrieved from the Annual Industrial file of Standard & Poor's Compustat. This dataset has been matched with the patent statistics of the NBER Patent data, that comprise detailed information on all US patents granted between 1963 to 2002. Finally, merger transactions data for the period 1989-2001 are extracted from SDC International Mergers & Acquisitions Database, cross-checking the information with other sources, such as The Mergers Year Book or internet.

The results of this study suggest that firms who experience troubles in replacing important drugs coming out of patent with other new promising compounds are more likely to pursue a merger. Thus, a distinctive feature of acquirers is their poor research outcomes prior to the merger. Although acquirers tend to target firms with similar research programs, which should a priori maximise the synergies from a consolidation, these operations do not seem to deliver any important efficiency gain to the merging firms. On the contrary, they seem to further deteriorate the research performance of these companies. Specifically, I find that the number of "important" discoveries done by merged firms records a significant decrease after the merger while there is a sharp increase in the average expenditure per patent.

Although there is a vast literature assessing the causes and effects of M&As (Mueller, 1996; Andrade *et all*, 2001), there are few empirical papers that have explored the relationship of consolidation and innovation. This study is mainly close to Hall (1999), Marco and Rausser (2002) and Dazon, Epstein and Nicholson (2003). Hall (1999) explores the relationship between mergers and R&D investments, using a large sample of publicly traded manufacturing firms, that existed at some time between 1976 and 1995. Using a Cox proportional hazard model, she first examines the distinctive characteristics of firms going through different types of restructuring activity, including mergers. She then analyses the effects of mergers on R&D investments, selecting the control group of non merging firms by using the "propensity score" methodology of Rosenbaum and Rubin (1983 and 1984). Although she finds a slight hint that R&D expenditures may have declined

after mergers in the 1990s for firms with the highest propensity to merge, no significant effect of mergers on R&D are found for the sample as a whole. Marco and Rausser (2002) study the role of patent holdings in influencing firms' decisions to merge in agricultural biotechnology. They also use patent statistics in a logit model to investigate the matching of merger partners. They find that matches are more likely to occur when the patent portfolio of acquires and targets lie in similar technology spaces. Given that spillovers are more likely to occur between firms in the same technological field, their interpretation of this finding is that some of the merger activity may be explained by attempts to reduce technological outflows. Finally, Danzon *et all* (2003) examines the determinants of M&A in the pharmaceutical and biotech industry and, in turn, their effects on firms' performance using "propensity scores" as in Hall (1999). 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. They also 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.

Compared to the studies above, this paper differs in two important dimensions. First, it is the first, to the best of my knowledge, that uses a dataset constructed by merging a financial dataset, such as Compustat, with patent statistics. This allows me to analyses the relation between mergers and patent holdings, controlling for those financial variables, such as firms' size and market value, that have been the main focus in most of the previous studies on mergers. Second, it performs a complete analysis of the relation between mergers and innovation by investigating three separate issues: the role of R&D and innovation in the merger decision, the importance of patents holdings in the matching of merger partners and the effects of mergers on innovative performance of the firms. With this approach it is possible to have a better understanding of the relationship between innovation and consolidation because the results obtained in exploring these three questions are strictly complementary and, as we will see, somehow mutually supportive.

The article is organized as follows. Section 2 presents the methodology used to investigate our research questions. Section 3 presents the data set and variable 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 possible policy implications of the results obtained.

2 Methodology

Our investigation proceeds in three stages. First, I analyse the causes behind the merger activity by specifying a reduced form model for the probability with which firms will pursue acquisitions. In this first stage, our interest is in analysing whether acquirers have particular features that can explain their decision to make an acquisition. Next I study whether patent statistics can help to understand why acquirers decide to target a given firm among all possible choices. The pair-wise characteristics of merging parties are compared to those of arbitrary pairs defined by randomly matching the acquirer with other possible targets. Finally, I examine the effects of mergers on the firms' innovative performance. As in Hall (1999), the "propensity score" methodology is employed to select the control group of non merging firms.

Before explaining the details of each stage, it important to describe the main features of the research activity in the pharmaceutical industry. The research process 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 (NCE). 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 NCE, before obtaining marketing approval.[1] Our data on patents holdings are then mainly informative of the first phase of the research process. Even so, it can be assumed that *ceteris paribus*, the higher is the value that the market ascribes to drugs in the development face, the higher will be the ratio of market value to book value of firms' assets. Therefore, Tobin's Q can be used as an indirect measure of the potential returns from the pipeline of products, that is products not yet on the market but which are at an advanced stage of development.[2]

[1] Failure rates during the 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.

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

2.1 Duration Model for Acquirer Characteristics

To investigate the factors influencing the merger decision, duration analysis is employed. The probability that firm i will engage in an acquisition in year t is modelled as an hazard function $\lambda_{\mathrm{i}}(t)$ that depends on time varying covariates $\mathbf{x}_{\mathrm{i}}(t)$ and a set of 13 unknown constants λ_{t} for the period 1989-2001:

$$\lambda_{\mathrm{i}}(t) = k(\mathbf{x}_{\mathrm{i}}(t))\lambda_{\mathrm{t}} \text{ for } t = 1989, ..., 2001$$

Under this specification, generally known as Piecewise-Constant hazard, the underlying baseline hazard varies freely from year to year, wh16(d)11(e)9(9(a)10(y)12(i)6

patent protection on key products and that do not have promising replacements in their products pipeline to offset the drop in sales due to the patent expiration. This is what Danzon *et all.* (2003) describe as an expected excess capacity in firm's marketing and sales operation due to pipeline gaps. I define this hypothesis **as** "Expiration / Pipeline-Gap" and I use four variables to test whether it is an important driving force behind consolidation: the value of expiring patents ($VEPat$), the value of new patens ($VNPat$) , Tobin's Q (Q) and the R&D expenditures ($R\&D$). The hypothesis predicts a positive sign for the coefficient of the variable $VEPat$ and a negative one for $VNPat$. As already mentioned above, I can expect that a firm with large expected growth opportunities due to a promising pipeline of products will have a high Q value. Our hypothesis predicts therefore that mergers are negatively related to Q. Following basic economic theory, the optimal amount of R&D expenditure is determined by equalizing the (expected) marginal rate of return on research investment and the marginal cost of the capital (Grabowski and Vernon, 2000). Once controlled for other variables that can affect the optimal amount of R&D investments, in particular the size of the firm,[5] I would expect that firms with larger investments are those that anticipate higher returns from these investments because of promising research program. As for the Tobin's Q, the "Expiration / Pipeline-Gap" hypothesis predicts than a negative relationship between the probability of merger and the variable R&D. If the coefficient estimates of the four covariates introduced above confirm the prediction of the hypothesis, we will have a clear sign that innovation, **or better said**, the lack of promising research projects is an important driving force of consolidation in the pharmaceutical industry.

The other variables used in the "Logistic hazard" comprise the firm's sales ($Sales$) and stock market value, in levels ($StkMrk$) and growth rates ($\Delta\%StkMrk$).

2.2 Matching Acquirers and Targets

The duration model is useful to define some of the characteristics of acquiring firms but it does not help to understand the factors that make a given target more attractive than another one. In Marco and Rausser (2003) the

[5] Small firms can invest in a limited number of project since they have a tighter constrain on their overall expenditure in R&D. Moreover, size can also affect the cost of financing the investments.

decision to merge and the choice of the target are modelled as two independent decisions: first a firm decide to merge and then it chooses the target. But in some cases these two decisions may be simultaneous. Any acquirer could have possibly decided not to undertake any merger if it was not with that particular firm. Here I investigate whether patent statistics can help to understand who merge with whom.

Mergers may increase the efficiency of the research activity by reducing fixed costs in R&D, such as the costs of labs' buildings and equipments. But, more importantly, mergers they can raise the effectiveness of research as merging firms can share past experiences on which research process appear more or less promising, thus weeding out fruitless approaches more rapidly. Efficiency gains in innovation are more likely to emerge when the merging firms follow similar research path, given that they have more things to learn from each other. It is then an interesting empirical question to examine whether acquirers usually target firms with similar research activity. I define this hypothesis **as** "Attraction for Similarities".

Using information on patents' technological field and data from patent citation file, I construct four different variables to measure how close the research programs of the acquirer and the target are (see computational details in the following Section): the correlation between patents' technological classes (*Corr*), the overlapping between set of patents cited (*Over*) and the importance of cross-citation between acquires and targets (*Cit* and *Spill*). For each consumed acquisition, the same four variables are calculated for 50 arbitrary couple of firms defined by randomly matching the actual acquirer with other possible targets. Computed values of the variables above for the true pair of merging firms and the 50 random pairs are then ranked from 1 (for the highest value in terms of similarities between research processes) to 51 (for the lowest value). If acquirers do not have as favourite target firms in the same technology space, the rank of the actual acquirer-target pair will be on average around position 26. We than test whether the rank of actual pair is statistically different then those of the random pairs using the van der Waerden *X-test* (Waerden, 1965).[6]

[6]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

Finding empirical results supporting the "Attraction for Similarities" hypothesis has not a unique interpretation. While I suggested above that it can be an evidence in favour of the search for efficiency in the research activity, it is also possible that merging firms try to reinforce their market power, given that similarities in technological research mean also that the merging firms are likely to market drugs in analogous therapeutic areas.

2.3 Effects of Mergers

The third stage of the analysis concerns the effects of mergers on the research program of the firms. I focuses my attention on four different outcomes: the firms' growth in R&D investments ($\Delta\%R\&D$) and in stock market value ($\Delta\%StkMrk$), the average change in the number of patents ($\bar{\Delta}Pat$) and the average growth in R&D expenditure per patents ($\bar{\Delta}\%R\&D/Pat$).

Mergers are expected to reduce investments in R&D because of the avoidance of truly unnecessary duplication of part of the research costs. At the same time, they may raise the effectiveness of research programs and thus the marginal return from this type of investments; in the case, an increase in the research efforts of merging firms can be anticipated. As these two elements work in opposite direction, it is not possible to predict what will be the net effect of mergers on the total amount of R&D investments. More clear prediction can be drawn for $\bar{\Delta}Pat$ and $\bar{\Delta}\%R\&D/Pat$. If consolidations are efficiency enhancing operation that allow to increase the research performance of the parties involved, the two variables are expected to take relatively higher values for firms that merge. Finally, I use the change in enterprise value as a measure of the overall effects of the merger on the performance of the firms, thus including the impact on R&D. Some studies have valued the effects of mergers by using the abnormal returns in stock prices around the merger announcement date. The underlying assumption made is these prices quickly adjust to merger announcement, incorporating any expected value changes (Andrade *et all.*, 2001). I prefer to consider a longer window since it is difficult for investors to assess quickly the full impact of mergers on the innovation activity of the firms.

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

it is not satisfied in our case where we compare the unique observation of the actual pair of merging firms against those of 50 arbitrary pairs) while the normal approximation of the X-test holds if there are more than 50 observations in both groups.

merger. A common approach used in the empirical literature to compute this counterfactual is to use the entire sample of non merging firms as "control" group. A clear weakness of this method is that only a few firms in the control group are comparable to the merging firms and this can lead to a misleading definition of the counterfactual. For example, suppose that firms with poor performance of their research labs in recent years are more likely to merge compared to firms with new important research outcomes. Then, the subsequent performance of the merged firms may be still inferior to that of the entire sample of non merging firms but, nevertheless, better than that they would have achieved in the absence of the merger. Comparing the performance of merged firms to the average industry mean may give a bias estimate of the effects of mergers if the decision to merge is not random but is endogenously determined by the anticipated realization of that performance. A possible solution to this problem is to select the control group using the "propensity score" methodology of Rosenbaum and Rubin (1983 and 1984).[7] Under this approach the performance of the merged firms had they not merged can be identified by using as control group those units with similar vector of observable covariates X (which can comprise any variable that describes the firms prior to merging). By comparing merged and non-merged firms that do not systematically differ from each other in their characteristics, it is possible to get an unbiased estimate of the effects of mergers.

The "propensity score" methodology is here implemented in the following way. Suppose that we are interested in estimating the impact of the merger on the growth in R&D investments ($\Delta\%R\&D$). First, the propensity of merging, $p(M_i)$, that is the probability that a firm i will merge in year t conditional on its observed characteristics, is derived from the "Logistic hazard" model defined in the first part of this Section. Second, each single merged firm is matched to the control units with the closest propensity of merging. More specifically, for each merged firm with propensity score $p(M_i)$, I consider all the control units whose estimated probability of merger is within a radius of 0.025 from $p(M_i)$. Given that each merged firm has several controls satisfying this condition, the control sample is further restricted to those units with

[7] This methodology has been extensively used in evaluation of labour training programs where it has been proven successful in selecting the small subset of units comparable to the training participants and, hence, in alleviating the estimation bias for the effects of these programs (Dehejia and Wahba, 1998). The first application of this methodology to evaluate the effects of mergers is **in** Hall (1999).

similar value of the outcome variable under study, in this specific case the R&D investment. In particular, among all control firms that are within a radius of 0.025 from the merged firm i, I select those firms whose R&D investments are less than 10 percentage points greater or smaller than the R&D of firm i.[8] Finally, a resampling method is applied to the firms that are left in the control group in order to estimate the average impact of mergers on $\Delta\%R\&D$ and relative confidence intervals. This resampling consists in selecting at random two control firms for each merged firm and in estimating the outcome of interests on the resulting subsample. This process is iterated 50 times, so that an average outcome with relative confidence intervals can be obtained using the 50 estimations.

3 Data and Variables

To answer all the questions of this investigation a new dataset has been constructed by gathering three main data sources.

First, financial data for firms with a primary biotechnology or pharmaceutical SIC code (2834, 2835 and 2936) come from the Annual Industrial file of Standard & Poor's Compustat. Although Compustat contains data for United-States based publicly traded firms, all major European Drug Companies have their shares traded on the US Stock Market and are then included in the dataset. This is a clear sign that the Drug Companies work on a global scale and they work in almost any significant geographical market. The information retrieved from Compustat are the stock market value, sales and R&D expenditures for the period 1988-2002.[9]

Second, patent statistics were obtained from the publicly available NBER Patent data, described by Trajtenberg, Jaffe and Hall (2001). This dataset comprise detailed information on all US patents granted between 1963 to 2002.[10] Two different files of this patent data bank are used in this inves-

[8] Recall that several covariates are used to get the estimated propensity of merging, so that matching on $p(M_i)$ does not assure that merged firms and control units have R&D investments sufficiently close

[9] In order to investigate the determinats and the effects of mergers consumed between 1989-2001, I need to use data from 1988 to 2002. The explanatory variables used in the duration analysis are based on figures for the year before the acquisition to avoid endogeneity problems. At the same time, the analysis of the effects of mergers signed in year t requires to constract percentage changes between *t-1* and *t+1*.

[10] I thank B. Hall for providing me data from the period 2000 to 2002 and complementary

tigation: 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. The US Patent Office has developed a highly elaborated 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 all* (2001), our data include only patents recorded in the technological category "Drugs and Medical".[11] The Citation Data file records the citation made for each patent granted. This information is used used to construct the variables of the matching analysis. Given that pharmaceutical companies patent prolifically, the number of patents is a rather noisy measure of research success. It is then useful to count only "important" patents, where the importance of a patent is inferred by the number of citation that it receives. More precisely, all the patents granted in year t are ordered by the number of citation received and then grouped in quintile. A patent is considered an "important" patent if it belongs to one of the top two quintiles of the citation ranking.[12]

Finally, merger transactions data for the period 1989-2001 are extracted from SDC International Mergers & Acquisitions Database. The records contained in this dataset have been cross-checked and completed with information reported in The Mergers' Year Book published by Thomson Finacial Service and firms' documents gathered by the U.S. Securities and Exchange Commission.[13] The latter source has been particularly useful for trucking the exists from Compustat that are not explained by the merger transactions data described above.

Considerable effort was devoted to matching the names of firms in Compustat with those of the assignee recorded in the patent data . To the best of my knowledge, this paper is the first that uses a dataset constructed by merging these two data sources. This allows us to analyses the relation between mergers and patent holdings, controlling for relevant financial variables such

data on patent sub-classes that were not available in the original data bank.

[11] 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.

[12] Results presented in the following Section are robust to changes in the definition of "important" patent.

[13] This information is freely available on Internet at the web page www.sec.gov.

as sales or stock market value.

Table 1 reports the number of mergers and acquisition over the period 1989 to 2001 together with the number of firms in the sample used for the duration analysis. Starting from 1994, there has been a remarkable increase in the number of consolidations consumed in the pharmaceutical industry. Large number of mergers has been recorded untill 1999 while the arrival of the new millenium has been characterized by a clear decrease in the merger activity. Since mergers involving big pharmaceutical companies have a particular relevance for the drug industry, in all the three stages of the analysis I report separate results and figures for the sub-sample of large firms.[14]

INSERT TABLE 1 ABOUT HERE

Hereafter, I describe the variables used in each model. The first stage of the analysis focuses on the characteristics of acquirers. All the variables used are measured in the period prior to the (potential) acquisition. As explained in Section 2.1, the duration model include some financial variables that have been identified in the empirical literature as important determinants of consolidation, such as the firms' sales ($Sales$) and market value in levels ($StkMrk$) and growth rates ($\Delta\%StkMrk$). In order to test the "Expiration / Pipeline-Gap" hypothesis, four variables have been introduced: the value of expiring patents ($VEPat$), the value of new patens ($VNPat$) , Tobin's Q (Q) and the R&D expenditures ($R\&D$). The later variable is directly extracted from Compustat while Tobin's Q is constructed **as** to measure the market-to-book ratio of corporate assets.[15] In order to compute the variable $VEPat$, I first calculate the number of "important" patents alive in year t (those that have been granted 17 years ago or before) and the percentage of these patents that are close to expiration (those that have been granted between 15 and 17 years ago). Given that the forthcoming expiration of an important patent should lead to a reduction in the firms' market price, I assume that the value of the expiring patents can be computed multiplying the percentage of expiring patents for the change in stock market value, whenever this is negative:

[14] Large firms are those that record the $1 billion market value threshold in at least one year over the study period.

[15] Following Javanovic and Rousseau (2003), the market value of firm assets is computed adding the short and long term debt (items 34 and 9 of Compustat) and the book value of preferred stock (item 30) to the value of common equity at current share prices (the product of items 24 and 25). The book value is computed similarly but using the book value of common equity (item 60) instead of the market value.

$$VEPat = \%ExpPat * \Delta\%StkMrk * \Psi$$

where Ψ is a indicator function that takes value 1 if $\Delta\%StkMrk$ is negative and 0 otherwise.

In the same way, I compute the percentage of new patents as the ratio of "important" patents granted in the previous year over total number of patents alive, while their economic value is captured by any positive change in market value:

$$VNPat = \%NewPat * \Delta\%StkMrk * \Phi$$

where Φ is a indicator function that takes value 1 if $\Delta\%StkMrk$ is positive and 0 otherwise.

We also control for the total number of mergers ($TMer$) concluded by each firm since 1989 to see whether the probability of pursuing an acquisition is greater (or smaller) for those firms that have already experienced a merger.

Table 2 reports descriptive statistics for the variables used in the duration analysis.

INSERT TABLE 2 ABOUT HERE

The second stage of this analysis addresses the question "who merge with whom" by testing the "Attraction for Similarities" hypothesis. To this purpose, four different variables have been introduced: the correlation between patents' technological classes ($Corr$), the overlapping between set of patents cited ($Over$) and the importance of cross-citation between acquires and targets (Cit and $Spill$).

Following Jaffe (1986), one could think that if there are K areas in which pharmaceutical 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" (**see footnote 11**), it would be difficult to characterize properly the vector S. I then use the finer classification based on patent sub-classes.[16] The correlation between the research programs of firm i and j is defined by:

[16] 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

$$Corr_{\mathsf{it}} = \frac{\sum_{\mathsf{k}} S_{\mathsf{ik}} * S_{\mathsf{jk}}}{\sqrt{(S_{\mathsf{ik}})^2 * (S_{\mathsf{jk}})^2}}$$

Alternative measures of the proximity between the research activities of firm i and j can be drawn from patent citation data. Let P_i and B_i be the set of patents owned by firm i and the set of patents cited by firm i, respectively. The variable *Over* is computed by looking at the overlapping between the set of patents cited by the two firms (see Marco and Rausser, 2003):

$$Over = \frac{(number\ of\ patents\ in\ B_i \cap B_j)}{(number\ of\ patents\ in\ B_i)},$$

where firm j is the acquirer while firm i is either the actual target or one of the arbitrary target that have been randomly matched to j.

The variable *Cit* computes the number of patents owned by the (actual or random) target i that are cited by the acquirer j, normalized by the dimension of the target in terms of patent holdings:

$$Cit = \frac{(number\ of\ patents\ in\ B_i \cap P_j)}{(number\ of\ patents\ in\ P_j / \ total\ number\ of\ patents)}$$

On the contrary, the variable *Spill* measure the number of patents of acquirer j that are cited by the target i and it is computed as:

$$Spill = \frac{(number\ of\ patents\ in\ P_i \cap B_j)}{(number\ of\ patents\ in\ B_i)}.$$

The last two variables, *Cit* and *Spill*, are defined using cross-citation data and they measure direct linkages between firms rather than placing them in a certain technology space. The variable *Spill*, for example, can also be interpreted as a measure of the knowledge that spill from the acquirer over to the target.[17]

Finally, the impact of a merger in year t is measured with respect to four different outcomes: the firms' growth in R&D investments ($\Delta\%R\&D$) and in stock market value ($\Delta\%StkMrk$), the average change in the number

[17] 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 matched target, in particular to take into account the size of the target in terms of patents holdings.

of patents($\bar{\Delta}Pat$) and the average growth in R&D expenditure per patents ($\bar{\Delta}\%R\&D/Pat$). Two different values of $\Delta\%R\&D$ are computed. One for the growth in R&D expenditures between the year prior to the merger and year after the merger:

$$\Delta\%R\&D(1)=\ln(StkMrk_{t+1}/StkMrk_{t-1}).$$

The other for the growth in R&D recorded between the year before the merger and three years after the merger:

$$\Delta\%R\&D(3)=\ln(StkMrk_{t+3}/StkMrk_{t-1}).$$

The same procedure has been applied to compute the change in stock market value one year and three year after the merger. The variable $\bar{\Delta}Pat$ refers to the difference between the average value of "important" patents over the two years before the merger and its average value over the three years after the merger:

$$\bar{\Delta}Pat=Average(\text{“important” patents in } t+1,\ t+2,\ t+3) - Average(\text{“important” patents in } t-1,\ t-2).$$

Finally the percentage change in R&D expenditure per patents is computed as:

$$\bar{\Delta}\%R\&D/Pat=\ln\frac{Average(R\&D \text{ investment } t+1,t+2,\ t+3)}{Average(\text{“important" patents in } t+1,\ t+2,\ t+3)} - \ln\frac{Average(R\&D \text{ investment } t-1,t-2)}{Average(\text{“important" patents in } t-1,\ t-2)}.$$

Note that for the merged firms, the construction of the outcome variables defined above requires that both the acquirer and the target are recorded in the dataset.[18] This would not be necessary using the approach in Danzon *at all* (2003), where the impact of a merger is measured by considering the change in a certain performance from *t+1* to *t+2*, *t+2* to *t+3* and so forth. 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 overlooks all the effects of mergers that materialize in the 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 untill the second year to cut any duplication of R&D expenditures.

[18]For instance, to compute correctly the variable D%R&D, it is necessary to know the R&D expenditures of acquirer and acquiree in the year prior to the merger.

4 Results

The duration model defined in the first part of Section 2 is used to estimate whether and to what extent the covariates defined affect the probability of making an acquisition. Note that it is possible for any firm to undertake more than one acquisition over the sample period. In the sample used there are 31 firms that record two acquisitions and 20 firms with at least 3 transactions, with a maximum of 5 consumed acquisitions for ICN Pharmaceutical. The variable *TMer* computes the total number of acquisitions already consumed by the firm prior to year t and it is used to determine whether the probability of making an acquisition is higher when a firm has already gone through a merger.

Estimated coefficients of the duration model are reported in Table 3. The first three columns report results based on the sample that is left after dropping missing observations for relevant variables, while the last two columns focuses on the sub-sample of "large" firms. To test the robustness of the results, three different model specification are used: "Piecewise-Constant Logistic Hazard" in columns (1), "Piecewise-Constant Logistic Hazard" allowing for Unobserved Heterogeneity in column (1b) and Cox Proportional Hazard model in columns (2). The "rho" term in column (1b) is a measure of the statistically importance of the heterogeneity between firms. The reported value suggest that there is negligible unobserved heterogeneity. In fact, the coefficients of the covariates in the frailty model are almost the same as those in the corresponding basic "Logistic Hazard" model. Given that the results obtained with the Cox Proportional model are also no remarkably different, I focus my comments on the results reported in the two columns (1).

Size as measured either by firms' sales or stock market value has a positive effect on the probability of making an acquisition. This confirms the already known finding that acquirer tend to be larger than non-acquiring units in the same line of business (Ravenscraft and Scherer, 1987). At the same time, acquirers record a higher increase in the growth of their market value before the acquisition compared to the control group. Although this result is open to different interpretations, it is clear that if mergers are driven by the desire of executives to run larger companies, the likelihood of undertaking an unprofitable acquisition is higher when shareholders are satisfied with recent market performance achieved by the management. The fact that the point estimates are statistically significant only for the group of large firms is not surprising given that managers of large organizations usually enjoy more

discretion in their choices.

Once taken into account the size of the enterprise, the higher is the R&D expenditure of the firm, the lower is the probability of making an acquisition. Firms that are strongly committed to research are less likely to go through a merger. At the same time, the negative value of the coefficient for Tobin's Q suggests that firms with lower value of their intangible capital, that is with less promising pipeline of products, are more likely to undertake an acquisition. Once again, coefficients are more precisely estimated for the sub-sample of large firms. These two results seem to mutually support the idea that innovation, or better said the lack of innovation, is an important driving force behind merger activity. Strong support to the "Expiration / Pipeline-Gap" hypothesis is further provided by the coefficients of *VEPat* and *VNPat*. Firms with important patents close to expiration and with no relevant discovery of new compounds are more likely to acquire another firm, as predicted by the hypothesis. These findings cast some doubts on the reliability of the existence of true efficiency gains commonly claimed by managers to defend mergers. In fact, it is not clear why firms should realize of the existence of this efficiency only when they are experiencing troubles in their R&D programs and how the research projects of target firms can be better developed by firms that have been unable to produce major advances in drug research. Finally, there is not a significant evidence that firms that have already consumed an acquisition are more likely to pursue a new one.

INSERT TABLE 3 ABOUT HERE

Box Plots of the predicted probability derived from the "Logistic hazard" models for acquirers and control group of non-acquiring firms are shown in Figure 1 (complete sample) and Figure 2 (sub-sample of large firms). In both pictures, the boxes representing the first to third quartile ranges do not overlap, thus meaning that the covariates used in the duration model can actually separate the characteristics of acquirers from the remaining firms in the sample.

INSERT FIGURE 1 AND 2 ABOUT HERE

The finding presented above are very similar to those obtained by Danzon *et all* (2003). They find that mergers, in particular for among large firms, are a response to excess capacity due to anticipated patent expirations and gaps in a company's product pipeline.

The second stage of the analysis explore the question "who merge with whom", specifically the hypothesis that acquirers usually target those firms with similar research programs. Once again, I consider first a sample of 128 actual pairs of acquirers and targets and then I focus on the sub-sample of 19 actual pairs of large firms. As explained in Section 2, for each of the 128 pairs, I compute the relevant variables for 50 arbitrary couples by randomly matching the acquirer with any other possible firm that is alive in the year of the acquisition. The arbitrary pairs for large consolidations has been matched with a slightly different procedure. I first selected the largest firms in the sample (58 firms) and then, for each of the 19 large consolidations, I randomly matched the actual acquirer with all the other available targets. Note that as years pass, there are fewer available targets because some of the initial 58 firms have already been acquired.

The four variables constructed can be classified in two different groups. The variable *Corr* and *Over* define the correlation or overlapping between the technological fields of the merging firms while *Cit* and *Spill* measure direct linkages between firms instead of placing them in a particular technological space.

For each consumed merger (128 in the whole sample and 19 for large firms), I calculate the *X-statistics* by ordering the relevant variables of the actual pair and the random matches and comparing the ranking of these two groups. For the complete sample, there are 128 such statistics and 19 for the sub-sample of large firms, each following a standard normal distribution. Figures in Table 4 refers to the sum of these 128 statistics (19 for large firms). As the sum of normal distribution has still a normal distribution, the values reported have to be compared to the threshold value of -1.624 to test their statistical significance at 5% level.

The *X-statistics* for all the four variables clearly lie in the left tail of the standard normal distribution. The null hypothesis that the rank of true pairs are drawn from the same distribution of the control sample has to be rejected. Similarities in the research programs of actual pairs are statistically higher than those of the random matches, both for the complete sample and for the sub-sample of large consolidations.

There is a clear evidence that acquirers tend to choose targets with similar technological programs. The results obtained not only give support to the "Attraction for Similarities" hypothesis but they seem to suggest that mergers can be a tool to reduce technological spillovers. This is in fact a possible interpretation of the finding that two firms are more likely to merge

when they show a higher propensity to cite each other.

Two different implications derive from these results. From one point, it is clear that any positive effect of mergers due to elimination of duplication of research costs is amplified when the two merging firms work in the same technological fields. Moreover, by sharing their knowledge on therapeutic areas, merging firms can improve the performance of their research labs. But this possible positive effects can be counterbalanced by the fact that similarities in technological research mean also that the merging firms are more likely to market drugs in analogous therapeutic areas and this can lead to anti-competitive effects in the market.

INSERT TABLE 4 ABOUT HERE

Finally, Table 5 reports the results for the effects of mergers. Quite interestingly, there are few remarkable difference between the results obtained with the traditional approach of comparing the performance of merged firms to the whole sample of non-merged firms and those obtained with selecting the control group using the "propensity score" methodology, the only relevant variation being for the growth of R&D expenditures of large firms.

The effects of mergers and research efforts and enterprise value are not clear. There is a slight hint that mergers imply both a reduction in the R&D investments and in the stock market valuation but the estimated coefficients are in most of the cases not statistically significant. Only for large firms, a great and significant reduction in R&D expenditures is found using the "propensity score" methodology. This finding can have two different interpretations. It can be an evidence of the savings that can be achieved through the consolidation or it can suggest a reduction in the research commitments of pharmaceutical firms after the merger because resources may be diverted to finance the acquisition.

Stronger results are obtained for the variables that are more strictly linked to the innovation performance. There is a clear reduction in the average number of "important" patents obtained by merged firms compared to the control group while the average R&D expenditure per "important" patent records a drastic increase. This later result suggests that, even if we take into account possible cut in R&D expenditures, reduction in research inputs cannot account for the great deterioration of the research outputs. If consolidations are really meant to increase the research abilities of firms, these results suggest that managers should look to other way to reach this objective given

that the synergies aften claimed to defend conlidations do not seem to materialize. Results above shows that acquirers are more likely to be firms with poor research performance and lack of promising pipeline of products. We now find that the innovative performance of merged firms seems to further deteriorate after the consolidation.

INSERT TABLE 5 ABOUT HERE

5 Conclusions

In an article appeared on the 1st of April issue of the "Wall Street Journal", it is pointed out that big pharmaceutical mergers "haven't really paid off for investors because there doesn't seem to be a correlation between increased size and productivity". Stocks of companies in the drug industry 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. For example the GlaxoSmithKline is cited as a clear example of a merged company being "slow to deliver on shareholder value". Glaxo has been promising year after year better growth and more attractive products coming out of their pipeline but none of these expectations has actually materialized.

The results of this paper seem to point in the same direction. Acquirers are more likely to be firms with gaps in the pipeline of products and with an expected forthcoming drop in their sales due to important patent expiration. Given this precarious pre-merger situation, consolidations do not seem to deliver any important efficiency gain to the merging firms. On the contrary, they seem to further deteriorate the research performance of these companies. The number of "important" discoveries done by merged firms records a significant decrease while there is a sharp increase in the average expenditure per "important" patents. In light of these results, the finding that acquirers tend to target firms with close "technological" programs can hardly be interpreted as an attempt to maximise research synergies, while it can be the case that firms are looking for partners with similar approved drugs to increase their market power. With detailed data on products and prices, it would be interested to test this hypothesis. Unfortunately, the data used do not comprise this information, so that this remains an open issue for future research.

However, the results presented have still some interesting implication for competition policy. This paper shows that the efficiency gains in R&D commonly claimed to defend the consolidation do not actually materialize. And if there are doubtful efficiency gains from a merger, should this merger be authorized even in the absence of clear anticompetitive effects? On this point, I agree with D. Mueller (1996), who recommends a shift of the emphasis from a proof of anticompetitive impact to a proof of positive, net social welfare gains from increases in efficiency: "*[A] vigorously enforced antimerger policy that allowed only those mergers that promise measurable and substantial efficiency gains is the single most important policy step Europe could take to preserve and intensify competition, ...*". But this approach sets an interesting research question. Although our results suggest that, on average, mergers have not a positive impact on the innovative abilities of the firms, there are examples of consolidations that are successful experiences. Is there then a way to anticipate what mergers will prove to have a positive impact on firms' research performance? That is, apart from determining the mean effects of mergers, is it possible to explain what causes the variance in mergers' outcomes? Given that there is little empirical work on the long-run effects of mergers on R&D and innovation, it is desirable to extend the present analysis to other industries, countries and periods. At the same time, future works should try to investigate not only the average effects of mergers but also to understand what are the sources of variability between successful and unsuccessful consolidations.

References

[1] Andrade, G., M. Mitchell and E. Stafford (2001), "New Evidence and Perspectives on Mergers". *Journal of Economic Perspectives*, Vol. 15, pp. 103-120.

[2] Danzon, P.M., A. Epstein and S. Nicholson (2003), "Mergers and Acquisitions in the Pharmaceutical and Biotech Industries". *mimeo.*

[3] Danzon, P.M., S. Nicholson and N.S. Pereira (2003), "Productivity in Pharmaceutical-Biotechnology R&D: the Role of Experience and Alliances". *mimeo.*

[4] Dehejia, R.H. and S. Wahba (1998) "Propensity Score Matching Methods for Non-experimental Casual Studies". *NBER Working Paper N. 6829.*

[5] Grabowski, H. and J. Vernon (2000), "The Determinants of Pharmaceutical Research and Development Expenditures". *Journal of Evolutionary Economics*, Vol. 10, pp. 201-215.

[6] Gugler, K., D.C. Mueller, B.B. Yurtoglu and C. Zulehner (2003), "The Effects of Mergers: an International Comparison". *International Journal of Industrial Organization*, Vol. 21, pp. 625-653.

[7] Hall, B.H. (1999), "Mergers and R&D Revised". *mimeo.*

[8] Henderson, R. and I. Cockburn (1996), "Scale, Scope and Spillovers: Determinatnts of Research Productivity in Drug Discovery". *Rand Journal of Economics,* Vol. 27, pp. 32-59.

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

[10] Javanovic and Roussear (2003). *American Economic Review, Papers and Proceding*

[11] Marco, A.C. and G.C. Rausser (2002), "Complementarities and Spillovers in Mergers: An Empirical Investigation Using Patent Data". *mimeo.*

[12] Mueller, D.C. (1996), "Lessons from the United States' Antitrust History". *International Journal of Industrial Organization*, Vol. 14, pp. 415-445.

[13] Mueller, D.C. (1989), "Mergers: Causes, Effects and Policies". *International Journal of Industrial Organization*, Vol. 7, pp. 1-10.

[14] Ravenscraft, D.J. and F.M. Scherer (1987) "Mergers, Sell-offs and Economic Efficiency". *Brooking Institutions,* Washington, DC.

[15] Rosenbaum, P.R. and D.B. Rubin (1983), "The Central Role of the Propensity Score in Observational Studies for Casual Effects". *Biometrika*, Vol. 70, pp. 41-55.

[16] Rosenbaum, P.R. and D.B. Rubin (1984), "Reducing Bias in Observational Studies Using Subclassification on the Propensity Score". *Journal of the American Statistical Association*, Vol. 79, pp. 516-524.

[17] Hall, B.H., A.B. Jaffe and Trajtenberg, M (2001), "The NBER Patent Citation Data File: Lessons, Insight and Methodological Tools". *NBER Working Paper N. 8498*

[18] Waerden, B.L. van der (1965), "Mathematische Statistik". 2nd edition, Berlin-Heidelberg-New York

Figure 1: Box Plots of predicted probability of pursuing an acquisition (All Firms)

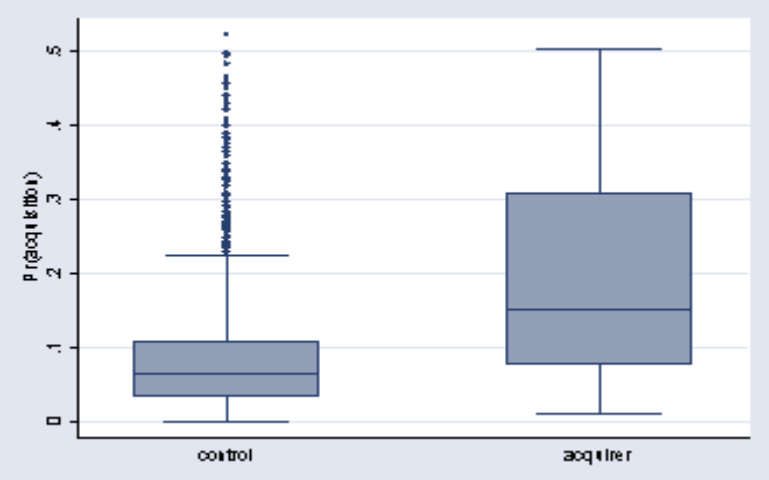

Figure 2: Box Plots of predicted probability of pursuing an acquisition (Large Firms)

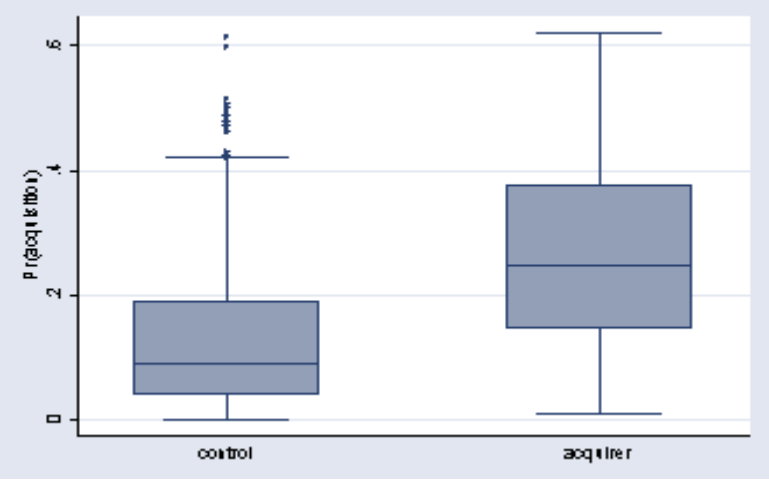

Table 1: Mergers and Acquisitions by Year

Year	All Firms		Large Firms	
	Number of Firms	**Number of Mergers**	**Number of Firms**	**Number of Mergers**
1989	78	7	44	6
1990	71	3	41	1
1991	79	5	44	4
1992	83	5	46	3
1993	105	4	53	4
1994	126	22	61	15
1995	144	22	63	15
1996	152	15	63	10
1997	167	22	66	11
1998	185	15	69	6
1999	170	20	63	15
2000	160	12	60	8
2001	162	14	62	11
Total	1682	166	735	109

Notes: This figures refers to the sub-sample used for the estimation of the duration model (Table 3), thus after dropping all time-firm observations for which all the covariates required for the estimation are not available. Large firms are those firms with stock market value exceeding $1 billion at least once during the sample period.

Table 2: Sample means and Standard Deviations (Duration Model)

Variable Description	**Variable Name**	All Firms		Large Firms	
		Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
Ln(sales), $million	*Sales*	3.60	3.07	5.91	2.69
Ln(firm market value), $million	*StkMrk*	5.76	2.35	7.66	2.11
Growth of firm market value (log difference)	*Δ%StkMrk*	-0.007	0.656	0.066	0.561
Ln(R&D expenditures), $million	*R&D*	2.90	2.06	4.44	1.82
Tobin's Q (Market-to-Book ratio of Firms Assets)	*Q*	5.07	10.37	4.96	4.88
Percentage of Important Patents close to Expiration	*%ExpPat*	4.37	10.40	7.41	10.71
Percentage of New Important Patents	*%NewPat*	14.18	24.22	13.19	19.97
Value of Important Patents close to Expiration	*VEPat*	0.694	4.15	0.89	2.97
Value of New Important Patents	*VNPat*	3.34	12.84	3.06	11.59
Cumulative Number of Mergers	*TMer*	0.48	0.88	0.71	1.06
Observations		1682		735	

Notes: This figures refers to the sub-sample used for the estimation of the duration model (Table 3), thus after dropping all time-firm observations for which all the covariates required for the estimation are not available. Large firms are those firms with stock market value exceeding $1 billion at least once during the sample period.

Table 3: Duration Analysis: Probability of making an Acquisition

	All Firms			Large Firms	
	(1)	**(1b)**	**(2)**	**(1)**	**(2)**
Sales	**.165**	**.197**	**.141**	.125	.107
	(.059)	(.084)	(.055)	(.105)	(.099)
StkMrk	.179	.213	.161	**.637**	**.497**
	(.117)	(.148)	(.110)	(.234)	(.193)
Δ%StkMrk	.399	**.354**	.336	**.617**	**.469**
	(.245)	(.210)	(.215)	(.323)	(.218)
VEPat	**.132**	**.140**	.110	**.225**	**.184**
	(.068)	(.068)	(.072)	(.088)	(.072)
VNPat	**-.052**	**-.054**	**-.046**	**-.054**	**-.045**
	(.018)	(.025)	(.014)	(.027)	(.018)
R&D	-.070	-.071	-.075	**-.415**	**-.334**
	(.083)	(.108)	(.079)	(.164)	(.115)
Q	-.045	-.045	-.041	**-.079**	**-.065**
	(.028)	(.035)	(.023)	(.041)	(.030)
TMer	.129	-.091	**.099**	.013	.015
	(.091)	(.203)	(.060)	(.113)	(.068)
Year dummies	**Included**	**Included**		**Included**	
Rho[(a)]		.132			
		(.108)			
Number of Obs.	1682	1682	1682	735	735

Duration Model: **(1)** Piecewise-Constant Logistic Hazard; **(1b)** Piecewise-Constant Logistic Hazard with Unobserved Heterogeneity (frailty term normally distributed); **(2)** Cox Proportional Hazard;
Notes: In bold, coefficient estimates significantly different from 0 at 10% level.
(a) The null hypothesis that rho=0 cannot be rejected at 5% level using likelihood ratio test, thus suggesting statistically significant frailty.

Table 4: Waerden X-test

	All Firms (128 pairs)	Large Firms (19 pairs)
Corr	-6.78	-3.14
Over	-7.65	-3.33
Cit	-7.41	-5.38
Spill	-3.19	-3.74

Notes: Given that the X-test statistics is distributed as *N(0,1)*, the values reported in the tables are in the left-tail of the normal distribution (5% of the observations of a normal distribution have values less than –

1.645). This means that the rank of "true pairs" is (statistically) significantly higher than those of random matches.

Table 5: Effects of M&As

	All Firms		Large Firms	
Control Sample:	All Non-Merged Firms	Matched on Propensity Score	All Large Non Merged Firms	Matched on Propensity Score
Δ%R&D(1)	**0.135**	**0.139**	0.065	**-0.244**
	(0.068)	(0.062)	(0.080)	(0.028)
Δ%R&D(3)	-0.071	-0.045	-0.050	**-0.259**
	(0.108)	(0.088)	(0.113)	(0.068)
Δ%StkMrk(1)	-0.028	0.047	-0.009	0.012
	(0.084)	(0.121)	(0.101)	(0.072)
Δ%StkMrk(3)	-0.146	-0.181	-0.035	-0.189
	(0.139)	(0.177)	(0.194)	(0.257)
ΔPat	**-9.80**	**-4.80**	**-15.98**	**-9.54**
	(1.684)	(0.642)	(3.13)	(1.04)
Δ%R&D/Pat	**0.65**	**0.68**	**0.49**	**0.35**
	(0.17)	(0.14)	(0.15)	(0.05)

Notes: In bold, point estimates of the effects of mergers significantly different from 0 at 10% statistical level or more.