

POSITIVE ASSORTIVE MERGING

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This paper addresses the following two questions: (i) Is there any evidence that firms, like human beings, prefer to partner with alike? (ii) Is there any relationship between the ex ante technological and product relatedness of merging parties and the postmerger performances? Using data of patent holdings and product portfolios of big pharmaceutical companies, I find that (i) merger deals are more likely to be signed between firms with related technologies and drug portfolios, and (ii) product relatedness and technology relatedness are positively and negatively correlated with postmerger performances, respectively. The analysis suggests that the negative effect of technology relatedness might be driven by a large human capital depreciation following consolidations. The results have important implications for competition policy, which are discussed in the concluding section.

1. INTRODUCTION

Empirical works on mergers and acquisitions (M&As) have been inconclusive in explaining the drivers of mergers and finding clear evidence of their effects.¹ Although data might suggest that merged firms perform, on average, worse than other companies, it is very difficult to establish a causal link between mergers and poor performances because of the difficulties in measuring the counterfactual outcomes had those firms

I thank Bruno Cassiman, Marc Ivaldi, Robin Mason, Ralph Siebert, Georges Siotis, Reinilde Veugelers, and Brownyn Hall for kindly providing the patent data. Valuable comments were received from seminar participants at Purdue University, the Universidad Carlos III de Madrid, the Universitat Pompeu Fabra, the University of Southampton, and the Fifth CEPR Conference in Applied Industrial Organization. Financial support from an educational grant awarded to the Universidad Carlos III de Madrid and Pompeu Fabra de Barcelona by the Merck Foundation, the philanthropic arm of Merck Co., Inc., White House Station, NJ, is kindly acknowledged.

1. Although mergers are generally regarded with favor among managers and businessmen, most economists seem to have a skeptical view of the benefits that mergers can deliver. A recent article of *The Economist* (February 3, 2005) sums up this skepticism by stating that “Despite claims that lessons had been learnt, the 1990s merger wave was as damaging as any before it.”

not merged. And even when mergers can be accountable for those poor outcomes, it must be remembered that there is no such thing as an “average merger” and differences in postmerger outcomes are still left unexplained.

This paper tries to advance our understanding of mergers by focusing on two (almost) unexplored questions. First, it investigates whether firms, like human beings, tend to partner with alike. Following the seminal paper of Becker (1973) on marriage, several studies have found positive correlation of traits, such as education, religion, or socioeconomic status, among spouses.² But, strangely enough, the evidence for “corporate unions” is rather scarce. Although the empirical analysis encompasses different measures of similarities, including geographic distance and “cultural” affinities, the main focus of this paper is on product relatedness and technology relatedness because these two dimensions can have strong and pervasive affects on synergies, efficiency gains, and market power. The second aim of this paper is then to investigate whether the extent of *ex ante* similarities can account for the differences in their *ex post* performances. It is important to note that these two questions are naturally interlocked. If there are strong theoretical arguments to sustain that mergers between companies that look alike might deliver better postmerger outcomes, we expect to find that at the same time (i) mergers are more likely to be signed among firms with similar characteristics, and (ii) there is a positive relationship between *ex ante* similarities and postmerger performances.

The questions above are explored using data of patents and products of big pharmaceutical companies for the period 1988–2006. Only merger deals in which both acquirers and targets are well-known, established drug makers are considered in this study. Restricting the analysis to the subset of big firms in this specific industry implies dealing with a small sample. But this choice also has some important advantages. First, as “Big Pharma” have a wide drug portfolio and tend to patent prolifically, it is possible to construct detailed measures of product relatedness and technological relatedness. The former is measured by the distribution of drugs across therapeutic areas and the latter by the distribution of patenting across different fields. Second, only large merger deals can have a significant impact on firms’ performance. If a big pharmaceutical company acquires a small laboratory, the operation is unlikely to produce any relevant effect (or, at least, any effect that is observable by an econometrician). Finally, because of the small number of firms included in this analysis, it is possible

2. Becker (1973) provides a sound theoretical framework to show why “positive assortive mating—a positive correlation between the values of the traits of husband and wives—is generally optimal.”

to cross-check all the relevant information with different sources, thus minimizing measurement errors and missing data.

To anticipate present results, this study shows that merger deals are more likely to be signed between firms with related technologies and drug portfolios. Empirical findings show the existence of a positive relationship between product relatedness and postmerger performance and a negative correlation between technological relatedness and performance. The analysis suggests that this latter result might be caused by a large human capital depreciation following consolidations.³

The main difficulty in studying the relationship between relatedness and postmerger outcomes is that relatedness is endogenous to the decision to merge. Unobservable firm management characteristics or exogenous changes in technology and regulations might affect both postmerger performance and the probability of merging with a similar partner. It is then possible that the correlation between relatedness and performances is spurious and does not reveal causation. This paper tries to account for the potential endogeneity of the partner choice using a matching technique and Heckman's selection model. The empirical findings above are confirmed under these alternative estimation methods.

This study is close to the papers by Marco and Rausser (2002) and Cassiman et al. (2005). Marco and Rausser (2002) investigate the issue of "who merges with whom" in the biotech sector. They also find that matches are more likely to occur when patents of acquirers and targets lie in similar technology spaces. Given that spillovers are more likely to occur between firms in the same technological field, they suggest that part of the merger activity may be explained by attempts to reduce technological outflows. Using a survey of 31 mergers in Belgium, Cassiman et al. (2005) find that the impact of M&As on R&D and innovation is affected by the technological and market relatedness of acquirers and targets: R&D levels are found to increase (decrease) when the *ex ante* technology of the merged entities are complementary (substitutive). At the same time, they find a more prominent increase

3. In a companion paper, Ornaghi (2009), I compare the innovation performances (i.e., R&D expenditure, patent output, and research productivity) of merging firms with those of a control group of nonmerging firms and find that consolidated companies have, on average, worse performance. The market value of the consolidated company is also found to be lower compared with the control group. This finding is similar to that reported in an article of the *Wall Street Journal* that points out that the stocks of pharmaceutical companies that merged in the previous 5 years have lost, on average, 3.7% of their stock market value since their deals have been completed, compared with an average increase of 7.2% of the Standard & Poor's pharmaceutical index (source: "The big drug mergers can be hard to swallow," April 1, 2004).

in research efficiency when the merged parties have complementary technology.⁴

There are three important contributions of this paper to the literature. First, this study tries to capture similarities among merging parties along different dimensions: cultural and geographic closeness and product and technology relatedness. Given the peculiarity of the pharmaceutical industry, the latter two variables can be constructed with a level of accurateness that is usually not found in other studies. Second, to the best of my knowledge, this is the first study that analyzes the similarities among acquirers and targets and the relationship between these similarities and postmerger performances simultaneously. The empirical findings make clear the importance of this approach to shed some lights on possible gaps between causes (i.e., the *ex ante* objectives pursued by managers) and consequences (i.e., the actual performances of merged companies) of mergers.⁵ Finally, this paper tries to uncover the reasons behind the negative correlation between technological relatedness and postmerger outcome by providing new evidence on the underinvestigated problem of human capital depreciation.

The article is organized as follows. Section 2 develops the research hypotheses and defines the empirical specification used to test them. After describing the data and the construction of the variables in Section 3, Section 4 outlines the empirical results. A discussion of these findings and their implications for competition policy is presented in the conclusion.

2. THEORY AND EMPIRICS

2.1 HYPOTHESIS FORMULATION

According to Ravenscraft and Long (2000), the main drivers of M&As in the pharmaceutical industry are the reduction of costs and the

4. This paper is also close in spirit to that of Podolny and Scott-Morton (1999). In an interesting study of shipping cartels, they find that a common background (i.e., same nationality and social status) significantly decreases the probability of a price war. Although the research questions of their study are different from those analyzed in this paper, there is a common effort to analyze economic decisions in a richer framework that tries to account for the similarities among economic actors. These measures are usually neglected in economic studies but are rather important in other social sciences.

5. It is often assumed in the literature that the analysis of the effects of mergers can shed light on the reasons that lead to these mergers, given that postmerger outcomes should be the materialization of the *ex ante* objectives pursued by the firm. But postmerger performances can be consistent with alternative motivations. For instance, in the case of poor results, it is difficult to discern the cases in which the acquiring firms' managers expect the acquisition to be profitable, but made a mistake, from those cases in which they knowingly undertake a merger for some alternative objectives.

strengthening of product portfolio to improve capacity utilization. This is consistent with the results by Danzon et al. (2004), who find that, for large firms, the anticipation of patent expirations and the associated shock to revenues and excess labor capacity are significant motives for acquisition. Although any merger may offer the potential to reduce costs through the elimination of duplicative function, and to minimize investments loss in human and physical capital through the selection of best projects and people, it is clear that the organization restructuring and, in turn, the postmerger outcomes are largely affected by the extent of similarities in products and technology of the two merging companies. This section analyzes a variety of theoretical results from industrial organization and management literature in order to derive testable predictions about the role of product relatedness, *PR*, and technological relatedness, *TR*, in mergers.

There are two main theoretical reasons why larger similarities in product portfolios of merging companies can deliver better postmerger outcomes. First, product relatedness allows for larger savings in costs of production and distribution through the elimination of duplicative functions. Second, market shares and market power of the consolidated company can increase in those therapeutic areas in which both acquirers and targets are active players. While premerger advertising efforts of acquirers and targets could undermine their respective impact on physicians' choice, possibly to the advantage of a third drug, the sales of the merged company can increase as they stop sending contradictory messages and start coordinating their marketing strategies. Moreover, a large drug portfolio allows merged companies orchestrating a migration of consumers away from molecules that experience generic entry toward branded products that still enjoy patent protection. No persuasive arguments on the negative impacts of *PR* on postmerger outcomes seem to have been raised in the literature.

The analysis of the effects of technological relatedness of postmerger performance is more complex as there are several forces through which mergers can affect the R&D activities of merged parties. First, firms working in similar technological areas are more likely to reunite their researchers in a single laboratory and divest redundant facilities, thus allowing for larger savings in research costs.

Second, the knowledge accumulated by the acquirer is more likely to be a fruitful input into the ongoing projects of the target firm if there is a certain overlapping between the researches activities of the two parties. Technology relatedness might stimulate greater knowledge synergies, through cross-fertilization of ideas, when scientists of merged companies work in related fields.

Third, mergers between pharmaceutical companies that are doing research in similar technologies may trigger important changes in R&D strategies. Kamien et al. (1992) show that the internalization of existing knowledge spillovers between acquirers and targets can lead to an increase in R&D investments of merged companies. Moreover, mergers between two competitors should increase the probability of the newly formed company to get better results in the ongoing "patent portfolio races." At the same time, higher technological relatedness between merged parties might imply a greater market power in the technology market (as a result, for instance, of patent thickets).⁶

Although the analysis above suggests that technological relatedness might deliver better postmerger performances, various studies in the management literature have found that the reduction in the number of researchers that often takes place during post-restructuring can negatively affect their know-how. In a study of 43 acquisitions, Ernst and Vitt (2000) find that many key inventors, identified on the basis of their patent output, leave their company during the restructuring period, a problem confirmed by anecdotal evidence for the pharmaceutical industry.⁷ It is possible that a large overlapping of research activities might imply a greater scope for reduction of researchers with similar skills, thus causing a more drastic dissipation of human capital.⁸

Although the focus of the paper is on technological and product relatedness, the empirical specifications presented in Section 4 also estimate the role of geographic and cultural distance between merged parties. Several studies in the management literature have documented how cultural dissonances and other integration problems disrupt the established routines of merging parties. Difficulties in forging a common corporate culture can prevent the full realization of synergies and

6. It must be noticed that patent race models produce no robust predictions about the effects of changes in market structure. For instance, although Lee and Wilde (1980) show that an increase in the number of firms increases the equilibrium individual R&D effort. Delbono and Denicolo (1991) demonstrate that by changing the assumptions used by Lee and Wilde, opposite conclusions are obtained: "an increase in the number of firms may result in a decrease in the equilibrium R&D effort of each firm". On an empirical ground, Cockburn and Henderson (1994) find that research investments of pharmaceutical companies are weakly correlated across firms once common responses to exogenous shocks are considered. They suggest that strategic interaction is not the main driver of the investment behavior in the industry.

7. After the merger in 1996, GlaxoWellcome closed Wellcome's main UK research facility in Becenham (1,500 scientists and staff). Several experts suggested that GlaxoWellcome lost more talent than what they expected (Ravenscraft and Long, 2000). A similar situation is seen for Aventis where R&D projects were cut and one R&D facility was closed.

8. A higher overlapping in product portfolios is likely to determine a higher reduction in the number of people employed in marketing and manufacturing activities. Given that the skills and knowledge necessary to perform these two activities are clearly less than those required for R&D, there are no concern of a greater dissipation of human capital for higher level of product relatedness.

seriously compromise the innovation performances of consolidated companies.⁹ Acquirers might then be more reticent to target companies with higher levels of cultural diversity. Similar considerations might lead to a higher probability of consolidations between companies located in the same country or border countries.

All the above arguments lead to the following hypotheses to be tested in this study:

Hypothesis 1: Acquirers are more likely to target firms that have similar technologies and products as well as cultural affinities. Using Becker's terminology, hereafter, I will refer to this hypothesis as "positive assortive merging."

Hypothesis 2: There is a positive relationship between product relatedness and postmerger performances and a negative relationship between cultural (or geographic) distance and postmerger performances.

Hypothesis 3: There is a positive (negative) relationship between technology relatedness and postmerger performances if synergy or market power effects are greater (lower) than capital destruction effects.

2.2 EMPIRICAL SPECIFICATIONS

To test the "positive assortive merging" hypothesis, it is assumed that each acquirer at the date of each actual acquisition τ could have targeted one of the other firms in the dataset. Variables capturing the technology relatedness, TR , and product relatedness, PR , are then computed for both the "true" acquirer–target pairs and the "fictional" pairs formed by matching the acquirer to the other firms in the dataset at time τ (see the following section for details on these variables).

The following probit model is then estimated:

$$P(\text{Pair} = 1 | X) = \Phi(\alpha_0 + \alpha_1 TR + \alpha_2 PR + \alpha_3 X), \quad (1)$$

where the dependent variable Pair takes value 1 for the true pairs and 0 otherwise, X is a vector of other explanatory variables, including cultural and geographic distance, and Φ is the cumulative distribution function of the standard normal.

9. In an interview with *Financial Times*, Joshua Boger, once a 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 got 300. GlaxoSmithkline has 16,000" (source: "Just what the drugs industry ordered," *Financial Times*, January 24, 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 (source: "Innovation in the Pharmaceutical Sector," November 8, 2004, Charles River Associate, p. 112).

To analyze postmerger performances of consolidated companies, this paper uses (yearly) changes in stock market value, ΔV . Although other measures of performance (such as revenues, profits, or market shares) might capture the postmerger effects related to the consolidation of marketed products, the stock market value depends not only on the costs and revenues of approved drugs but also on the successful development of new compounds. In this sense, V is the most comprehensive and accurate measure to investigate the effects of product relatedness and technology relatedness on consolidated companies.

Accordingly, the impact of TR and PR on the performance of a company i that merged in period τ is estimated as follows:

$$\Delta V_{i,\tau+x} = \beta_1 TR_{\tau-1} + \beta_2 PR_{\tau-1} + \beta_3 X + \beta_4 T + u_{i,\tau+x}, \quad (2)$$

where X is a vector of other explanatory variables, and T is a complete set of time dummies that capture cyclical stock market movements. The independent variables TR and PR are constructed using the distribution of patents and products of the acquirer and the target in the year before the merger, $\tau - 1$.

Equation (2) is estimated only for the subset of consolidated companies. 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. The use of growth rates instead of levels avoids at the same time the serial correlation problems found by Bertrand et al. (2004) in several studies of treatment effects.¹⁰

Because of the complexity involved in unifying the business and research activities of drug makers, big mergers are likely to affect the firms' performance over a long period of time. Our preferred specification includes yearly changes in stock market value ΔV (i.e., logarithmic difference) up to 3 years after the merger (i.e., for $x = 0, 1, 2, 3$). Illustratively speaking, for a merger signed in 2000, the independent variables are computed using data in 1999, TR_{1999} and PR_{1999} . These variables are then regressed on changes in market values in the year of the merger (ΔV_{2000}) and in the following 3 years until 2003 (ΔV_{2003}) so that four observations per merger are included in the estimation.¹¹

10. The authors test the significant of randomly generated placebo laws on female wages and find that the use of panel data with observations that are serially correlated causes: "an effect significant at the 5 percent level for up to 45 percent of the placebo interventions." Table 8 of their paper shows that zero percent of their placebo interventions are significant when they use changes in wages as a dependent variable. Differently from level series, first differences are generally not serially correlated.

11. Four clarifications are in place. First, in the year of the merger, ΔV is computed as the logarithm of the market value of the merged company minus the logarithm of the sum of the stock market value of acquirer and target in the previous period. Second,

3. DATA AND VARIABLES

Stock market data for the period 1988–2006 are retrieved from Compustat and Osiris, published by Standard & Poor and Bureau van Dijk. Financial data reported in these two datasets are edited to consider relevant spin-offs, such as Merck's divestiture of the "pharmaceutical benefits management" company Medco in 2003. To minimize measurement errors and missing data, financial data have been cross-checked using information available on the Web. Nominal 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, also including Japanese companies. Large companies specialized in the production of generic drugs (such as Ivax, Mylan, or Teva) are not included in the sample.

Patent statistics were obtained from the National Bureau of Economic Research (NBER) patent data, described by Trajtenberg et al. (2001). This dataset comprises detailed information on all US patents granted between 1963 and 2002. Following the classification in Trajtenberg et al. (2001), our data include only patents recorded in the technological category "Drugs and Medical."¹²

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, I construct a complete panel of proprietary drugs produced by the pharmaceutical companies included in this study. Each drug is assigned to a therapeutic class according to the "Anatomical Therapeutic Chemical" (ATC) classification. The ATC provides four levels of classification. The first level (ATC 1) is the most general, with 16 anatomical groups, and the fourth (ATC 4) is the most detailed, with more than 400 chemical/pharmacological subgroups. This paper uses two measures of product relatedness based on the ATC2 and the ATC 3 classification.¹³

only three observations can be used for mergers signed in 2004, given that available stock market data stop in 2006. Third, the standard errors of equation (2) reported in Section 4 are computed clustered observations by merger. Finally, none of the firms is involved in more than one merger per year. Pfizer is the only firm that experiences two mergers in a short period of time (with Warner Lambert in 2000 and Pharmacia in 2002).

12. Together with Patent data, the NBER provides a file to match patent holders to Compustat accounting data. After double checking that all the pharmaceutical companies used in this study were properly matched by the routine, I also look for the name of the main subsidiaries of these companies using Osiris and other external sources. For instance, accounting data of Johnson & Johnson are matched to the patents of more than 20 subsidiaries, including Janssen and Ortho McNeil.

13. For instance, the ATC1 anatomical group "C," cardiovascular system, is divided at the second level into the following groups: cardiac therapy, antihypertensives, diuretics,

TABLE I.
LIST OF “BIG PHARMA”

Abbott	Du Pont Pharma	Merck Kgaa	Serono
Allergen	Eisai	Nordisk	Shionogi
Alza	Élan	Novartis	Smithkline- Beck
Amesham	Ely Lilly	Novo	Squibb
Amgen	Fisons	Nycomed	Syntex
Astellas	Forest Laboratories	Organon	Synthelabo
Astra AB	Fujisawa	Pfizer	Takeda
Aventis	Genentech	Pharmacia	UCB
Bayer	Glaxo	Roche	Upjohn
Beecham	Hoechst	Rhone-Poulenc	Warner-Lambert
Boehringer Ingel.	Immunex	Sandoz	Wellcome
Bristol-Myers	Johnson & Johnson	Sankyo	Wyeth
Celltech	Knoll (BASF)	Sanofi	Yamanouchi
Ciba	Lederle (Am. Cynam)	Schering Ag	Zeneca
Corange	Marion Roussel	Schering-Plough	
Daiichi	Merck & Co	Searle (Monsan.)	

Notes: This is the list of big pharmaceutical companies included in this study. The table does not report consolidated companies whose name is similar to merging partners (e.g., Bristol-Myers Squibb, AstraZeneca, NovoNordisk, etc.), but it includes consolidated companies with new name: (i) Novartis formed in 1996 by Ciba and Sandoz, (ii) Aventis formed in 2000 by Hoechst Marion Roussel and Rhone Poulenc Rorer, and (iii) Astellas created in 2004 by Yamanouchi and Fujisawa.

The most important merger deals among big pharmaceutical companies for the period 1988–2004 are obtained from *The Mergers' Year Book* published by Thomson Financial Service. Overall, there are 27 M&As considered in this study. 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.

The list of big pharmaceutical firms and merger deals considered in this study are listed in Table I and II, respectively.

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 vice versa (*Spill*). To test the “positive assortive merging” hypothesis,

peripheral vasodilators, vasoprotectives, beta-blocking agents, calcium channel blockers, agents acting on the renin–angiotensin system, and serum lipid reduction agents. Each of these subgroups is further divided into more detailed subgroups at the third level.

TABLE II.
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

Note: American Home Product changed its name to Wyeth in 2002.

these four variables are computed not only for the true pair of acquirer and target but also for all the possible pairs.¹⁴

Let P_{acq} and B_{acq} be the sets of patents owned and cited by the acquirer, and P_{tar} and B_{tar} the corresponding variables for the target. Following the work by Podolny et al. (1996), the variable *Over* is computed by looking at the overlap between the set of patents cited by the acquirer and the selected target

$$Over = \frac{(\text{Number of Patents in } B_{acq} \cap B_{tar})}{(\text{Number of Patents in } B_{tar})},$$

14. For instance, in 2004, the sample includes 33 firms and three deals. I then compute the four variables of technological relatedness between the “true” acquirers and targets (e.g., Sanofi and Aventis). Moreover, I compute the same measures for the acquirer and the other 32 possible targets (e.g., Sanofi and Astrazeneca).

where subscript *tar* refers to either the actual target or one of the fictional targets that are matched to the acquirer.

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 $S = (S_1, \dots, S_K)$, where S_k is the fraction of patents in area k . Using the distribution of patents among subclasses of the category “Drugs and Medical,”¹⁵ the correlation between technological classes is computed as

$$PatCr = \frac{(S_{acq} S'_{tar})}{(S_{acq} S'_{acq})^{\frac{1}{2}} (S_{tar} S'_{tar})^{\frac{1}{2}}}. \quad (3)$$

As for *Over*, 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 that are cited by the acquirer

$$Cit = \frac{(\text{Number of Patents in } B_{acq} \cap P_{tar})}{(\text{Number of Patents in } P_{tar})}.$$

On the contrary, the variable *Spill* measures the number of the acquirer’s patents that are cited by the target firm

$$Spill = \frac{(\text{Number of Patents in } P_{acq} \cap B_{tar})}{(\text{Number of Patents in } B_{tar})}.$$

These two variables measure direct linkages between firms rather than placing them in a certain technology space. In particular, they can capture the knowledge that spills from targets over to acquirers and from acquirers over to targets, respectively. These two variables can then be used to see whether knowledge spillovers and asymmetries in incoming or outgoing knowledge flows play a role in mergers.¹⁶

A measure of product relatedness between the acquirer and the (actual or potential) target is constructed using a modified version of

15. This category is divided into the following subcategory: (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; and (4) Miscellaneous—Drug and Medicals: 351, 433, and 623. This makes a total of 14 patent classes. In order to have a finer measure of relatedness, these 14 classes are further divided into more than 200 subclasses (so that each of them refers to compounds with similar chemical structure). For any patent class, the construction of subclasses is done using the “mainlines” and the “indent level 1” described in the *Manual of Patent Classification* by US Patent and Trademark Office.

16. It must be noticed that 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.

equation (3) in which the vector $S = (S_1, \dots, S_K)$ includes the fraction of medicines in the therapeutic area k , according to either the ATC2 classification or the ATC3. These variables are labeled *ATC2Cr* and *ATC3Cr*, respectively.

Differences between the culture in which firms operate are captured with the Hofstede indices. Using factor analysis of 88,000 questionnaires of employees in 40 different countries, Hofstede (1980) finds that national cultures vary substantially along four dimensions (labeled individualism, masculinity, uncertainty avoidance, and tolerance of power distance). Hofstede defines then country-specific scores for each of these four dimensions. Following the procedure developed by Kogut and Singh (1988), the cultural distance (*CD*) between acquirer in country j and target in country k is calculated as follows:

$$CD_{j,k} = \sum_{n=1}^4 [(D_{n,j} - D_{n,k})^2 / V_n] / 4,$$

where $D_{n,j}$ ($D_{n,k}$) is the score for the acquirer (target) on cultural dimension n , and V_n is the variance of the index for cultural dimension n .¹⁷ Finally, geographic distance (*GD*) is computed as thousands of kilometers between the capitals of the nations where acquirer and target have their headquarters.

Table III provides descriptive statistics of the variables described above. Technology and product variables are expressed as percentage: they take values between 0 (no relatedness) and 100 (perfect relatedness). Quite interestingly, the correlation between the four measures of technological relatedness are low, suggesting that they capture different aspects of the research activities. Similarly, there is not a high correlation between the variables capturing technology relatedness and those measuring similarities in products.¹⁸

The *t*-test statistics in column 2 already reject the null hypothesis that the technology and product relatedness among “true” merging pairs is similar to that of the “fictional” pairs. They also suggest that both cultural and geographic distance of acquirers and targets are significantly lower than those computed for “fictional” pairs.

17. This measure has been extensively used in the business literature. See Gomez-Mejia and Palich (1997) among others.

18. The same disease can be treated using different technologies. For instance, Zantac and Losec are two well-known drugs used to reduce stomach acid segregation. Although they belong to the same ATC3 group, Zantac works by blocking the histamine receptors in acid-producing cells in the stomach (H_2 blocker), whereas Losec stops the production of acid by shutting down a system in the stomach known as the proton pump (proton pump inhibitor). There are also examples in which the same technology can be used to treat different diseases. For instance, the molecule duloxetine is used for the treatment of both depression and stress urinary incontinence.

TABLE III.
TECHNOLOGICAL AND PRODUCT SIMILARITIES
(MEANS AND CORRELATIONS OF VARIABLES)

Variables	Mean	<i>t</i> -Test Statistics*	Correlation							
			1	2	3	4	5	6	7	8
1 <i>Over</i>	3.27 (5.86)	-3.85 [<0.01]	1							
2 <i>PatCr</i>	23.08 (31.41)	-3.19 [<0.01]	0.287	1						
3 <i>Cit</i>	2.47 (4.55)	-1.76 [<0.01]	0.689	0.131	1					
4 <i>Spill</i>	0.67 (1.27)	-3.30 [<0.01]	0.637	0.276	0.305	1				
5 <i>ATC2Cr</i>	16.56 (25.47)	-2.84 [<0.01]	0.106	0.349	0.127	0.008	1			
6 <i>ATC3Cr</i>	8.73 (12.91)	-2.06 [0.02]	0.129	0.371	0.170	0.138	0.780	1		
7 <i>GD</i>	4.30 (1.54)	4.07 [<0.01]	0.009	-0.055	-0.008	0.071	-0.086	-0.052	1	
8 <i>CD</i>	1.43 (0.79)	2.08 [0.02]	-0.171	-0.032	-0.101	-0.111	-0.101	-0.095	0.345	1

Notes: In parentheses, the means of the variables for the “true” merged pairs. Variables measuring technology relatedness (*Over*, *PatCr*, *Cit*, and *Spill*) and product relatedness (*ATC2Cr* and *ATC3Cr*) can take values between 0 (no relatedness) and 100 (perfect relatedness). Cultural distance (*CD*) is a composite index constructed using Hofstede cultural attributes scores (Hofstede, 1980). Geographic distance (*GD*) is computed as thousands of kilometres between the capitals of the nations where acquirer and target have their headquarters (Frankfurt and New York are used for Germany and the United States, respectively).

**t*-test of the difference between the mean values; the null hypothesis is that the mean of the variable for the “true” merged pairs (in parenthesis) 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.

4. RESULTS

Table IV shows the results of the probit model specified in equation (1). Besides the variables described in Section 3, the empirical specifications include the number of patents owned by targets (*Target_NPat*) and the difference in the number of patents between acquirers and targets (*Diff_NPat*). The first variable is target-specific and allows controlling for size and patent holdings, whereas the latter captures differences between acquirers and targets along these two dimensions. Specifications also include a set of variables that control for targets’ technology speciality (*Pat_Classes*) and product speciality (*Prod_Classes*). More precisely, *Pat_Classes* (*Prod_Classes*) include 25 (16) different variables, each one measuring the number of patents (products) that matched targets have in that particular class. These two (set of) variables place each target in a particular technology and product space, thus assuring

that similarity (and not technology or product heterogeneity) is driving our empirical results. All the variables included in the probit regression refer to the year prior to the merger.

McFadden R^2 suggest that the specifications used have a fine goodness of fit. Columns 1 and 2 show that the coefficients of the variables *Over* and *ATC2Cr* or *ATC3Cr* are positive and significant: acquirers are more likely to target firms that have higher overlapping in technology and products. Although estimates in column 4 show that this positive relationship is confirmed when other measures of technology relatedness are used, the results in columns 3 and 5 suggest that *Over* clearly outperforms the other variables in capturing technology relatedness. Both cultural distance and geographic distance are found to decrease the probability of a match. Although the two variables are clearly interlinked, the fact that *GD* is more significant than *CD* may be due to the difficulty of computing a precise measure of cultural differences.

Overall, these results give strong support to the “positive assortive merging” hypothesis: mergers are more likely to be signed among companies with similarity in technologies, products, and culture whose headquarters are often in the same country or same continent.

Empirical evidence concerning the relationship between relatedness and postmerger outcomes is presented in Table V. Because of the small number of observations used, particular attention has been devoted to control for outliers and check the robustness of the results to alternative specifications. The results in column 1 suggest using *Over* and *ATC3Cr* as preferred measure of technology and product relatedness, being the two variables with a statistically significant correlation with changes in stock market values.¹⁹ Worse postmerger performances are found when geographic and cultural distances of merging parties increase, although the coefficients of these two variables are not statistically significant.

The estimated coefficients reported in column 2 show the existence of a negative correlation between *Over* and ΔV and a positive relationship between *ATC3Cr* and ΔV . A 1% increase in *Over* and *ATC3Cr* implies a change in market value of -1.6% and 0.5% , respectively.²⁰ The negative coefficient of the variable *Over* seems to question the effectiveness of acquirers’ strategy to search for partners with high

19. The small number of observations and possible problems of multicollinearity suggest to use a parsimonious specification with only one variable for *TR* and *PR*, as in column 2.

20. The mean values of *Over* and *ATC3Cr* for the 77 observations used to estimate the coefficients in column 2 are 4.8 and 10, respectively. At these mean values, the negative effect of *TR* is stronger than the positive effect of *PR*.

TABLE IV.
POSITIVE ASSORTIVE MERGING
(PROBIT REGRESSION MODEL)

Variable	(1)	(2)	(3)	(4)	(5)
<i>Over</i>	0.176 [<0.01]	0.162 [<0.01]	0.159 [<0.01]		0.155 [<0.01]
<i>PatCr</i>			0.014 [0.33]		
<i>Cit</i>				0.066 [<0.01]	0.032 [0.19]
<i>Spill</i>				0.199 [0.02]	-0.009 [0.93]
<i>ATC2Cr</i>	0.020 [<0.01]		0.019 [<0.01]	0.017 [<0.01]	0.020 [<0.01]
<i>ATC3Cr</i>		0.026 [0.03]			
<i>CD</i>	-0.126 [0.17]	-0.143 [0.15]	-0.139 [0.12]	-0.178 [0.03]	-0.131 [0.16]
<i>GD</i>	-0.163 [<0.01]	-0.161 [<0.01]	-0.164 [<0.01]	-0.152 [<0.01]	-0.163 [<0.01]
<i>Diff_NPat</i>	-0.0005 [<0.01]	-0.0005 [<0.01]	-0.0005 [<0.01]	-0.0005 [<0.01]	-0.0005 [<0.01]
<i>Target_NPat</i>	0.0001 [0.99]	0.0001 [0.95]	0.0001 [0.85]	0.0001 [0.85]	0.0001 [0.98]
<i>Pat_Classes*</i>	Included	Included	Included	Included	Included
<i>Prod_Classes*</i>	Included	Included	Included	Included	Included
McFadden R^2	0.456	0.443	0.460	0.429	0.459
No. of observations	950	950	950	950	950

Notes: Dependent variable takes value 1 for “true pairs” and 0 for “fictional pairs” (i.e., acquirers are randomly matched with third companies not involved in the merger). In square brackets, *p*-values computed using robust standard errors. Observations are assumed to be independent across clusters (i.e., an acquirer with matched targets) but not within clusters. In bold, estimated coefficients that are significant at 5% or more.

*Patents and products are divided in 25 and 16 groups, respectively. Patent classes (product classes) include then 25 (16) different variables, each one measuring the number of patents (products) that matched targets have in that particular class.

technological similarities. I will come back to this point after analyzing the robustness of the estimates.

It is important to note that competition authorities can oblige consolidated companies to divest one or more drugs in those therapeutic areas in which the combined market share of acquirers and targets is high enough to raise anticompetitive concerns. Given that larger divestitures are imposed when there is a higher level of overlapping between product portfolios, merger remedies can lead to a negative correlation between *PR* and ΔV . In this sense, the estimates in Table V can be considered a lower bound of the coefficient of product relatedness.

Column 3 uses the variables *Cit* and *Spill* to assess whether post-merger performances differ when there are asymmetries between the knowledge flows from targets to acquirers and from acquirers to targets. The estimated coefficients are both negative, but only the coefficient of *Cit* is significant at the 10% level. Column 4 estimates a specification in levels in which past values of the dependent variables are included as regressors. The positive correlation between product relatedness and postmerger performance and the negative correlation between technology and changes in market values are confirmed also using this alternative specification. Results (not reported here) similar to those in Table V are also obtained when using *ATC2Cr* to capture product relatedness or when other control variables are added to the specification, such as growth of sales. This latter is found to have no significant relationship with ΔV (p -value of the estimated coefficient is always above 0.8), thus confirming the difficulty in finding variables that can predict changes in stock market values.

As a further check of robustness of these findings, the Appendix shows that similar results are obtained when equation (2) is estimated using different time horizons (e.g., 3 years after the merger vs. 5 years after the merger) and when only one observation per merger is included in the estimation (e.g., growth rates between τ and $\tau + 3$ instead of three-yearly changes).

Figures in Table V confirm Hypothesis 2. At the same time, the negative correlation between technology relatedness and postmerger market value appears to suggest that a gap exists between the search for similarities pursued by managers and the actual consequences of this strategy. One possible explanation for the seeming contradiction is that, at the time of the announcement, financial markets overvalue the importance of technological relatedness in delivering value to shareholders and, in the following period, revise their expectations. This revision of overoptimistic forecasts can lead to the negative correlation shown in Table V, even in the presence of a positive effect of overlap on firms' performance. Another explanation might be that gains from technology similarities (e.g., synergy or market power) are offset completely by other effects, such as the destruction of human knowledge through turnover, that work in the opposite direction. This point will be investigated in more detail below.

There are two important issues that the results above raise. Can the correlations between technology and product relatedness and market value be interpreted as a causal effect of *ex ante* similarities on *ex post* performances? Is there any evidence that human capital dissipation is what causes worse postmerger performances for companies with higher levels of technology relatedness?

TABLE V.
TECHNOLOGICAL/PRODUCT RELATEDNESS AND MARKET VALUE

Dependent Variable Independent Variable	ΔV (1)	ΔV (2)	ΔV (3)	V (4)	ΔV^{norm} (5)*	ΔV (6) [†]
<i>Over</i>	-1.620 [0.02]	-1.648 [<0.01]		-1.433 [<0.01]	-1.657 [<0.01]	-1.251 [<0.01]
<i>PatCr</i>	-0.169 [0.28]					
<i>Cit</i>	-0.213 [0.75]		-1.420 [0.06]			
<i>Spill</i>	0.846 [0.39]		-0.445 [0.73]			
<i>ATC2Cr</i>	0.008 [0.95]					
<i>ATC3Cr</i>	0.573 [0.07]	0.546 [<0.01]	0.697 [<0.01]	0.554 [<0.01]	0.949 [<0.01]	0.728 [<0.01]
<i>CD</i>	-0.008 [0.72]	-0.023 [0.36]	-0.013 [0.58]	-0.035 [0.06]	-0.005 [0.74]	-0.013 [0.18]
<i>GD</i>	-0.001 [0.95]	-0.014 [0.24]	-0.018 [0.12]	-0.008 [0.44]	-0.023 [0.49]	-0.018 [0.32]
Lag of V				0.944 [<0.01]		
Inverse Mills ratio						0.073 [<0.01]
Time dummies	Included	Included	Included	Included	Included	Included
R^2	0.71	0.70	0.69	0.98	0.48	0.73
No. of observations	77	77	77	77	77	77

Notes: *p*-values computed using robust standard errors (observations clustered by merger) in square brackets. In bold, estimated coefficients that are significant at 5% or more. Diagnostic tests of sensitivity to individual observations show that estimates are not affected by the presence of outliers.

*Propensity score: I select the two firms with the closest probability of being chosen as targets to that of the "true" pair (as for the probit regression in column 2 of Table IV) and normalize the postmerger market value of each consolidate company with respect to the average market value of the two matched firms.

[†]Heckman sample selection: Inverse Mills ratio is computed using the probability of being acquired estimated in the probit regression of column 2 of Table IV. The variables *Diff_NPat*, *Target_NPat*, *Pat_Classes*, and *Prod_Classes* act as exclusion restriction for the selection model.

To give an affirmative answer to the first question, we have to analyze whether the correlation between *TR* and *PR* and ΔV is driven by some unobserved factors that command high level of technology (product) relatedness and poor (good) economic performances. In other words, as the level of relatedness is endogenous to the decision to merge, it may be the case that *TR* and *PR* are correlated with the error term in equation (2). For instance, it may be the case that some of the mergers considered in this study are driven by negative technological shocks that hit firms with similar technologies. If this were the case, the observed

negative correlation between TR and ΔV is spurious, and the *ex ante* similarities cannot be considered the cause of poor *ex post* outcomes.

To account for this endogeneity problem, I check the robustness of the estimates using two alternative procedures: matching estimator and Heckman's selection estimator. The first approach assumes that the performance of merged firms can be compared with that of a control group of nonmerged firms that have similar characteristics, in particular, in terms of technology and product portfolios. If high levels of relatedness among acquirers and targets are due to common negative exogenous shocks (e.g., changes in technology or legislation), the correlation between relatedness and market value should disappear when performances of consolidated are compared with those of companies with related technology. Using the results of the probit regression in column 2 of Table IV, I select the two firms with the closest probability of being chosen as targets to that of the "true" target and normalize the postmerger market value of each consolidated company with respect to the average market value of the two matched firms.²¹

If relatedness and technology speciality makes for a more attractive merger, then mergers between relatively unrelated firms might be attractive for other unobservable reasons. The Heckman selection allows accounting for the dependence between TR and PR and ΔV due to some unobservable components in the choice of targets. The inverse Mills ratio computed from the probit estimates in column 2 of Table IV is added to the specification (2) in order to control for the part of the error term that might be correlated with technology and product relatedness.

The results using these two approaches are reported in column 5 and 6 of Table V, respectively. The figures confirms that PR and TR have a positive and a negative effect on postmerger performances, respectively. The point estimates are similar to those reported in the previous columns and are significant at the 1 % level.

Ideally, one could explore the relevance of human capital dissipation by analyzing the relationship between technological relatedness and changes in the number of scientists and researchers. Unfortunately, the information on R&D employees is scattered and incomplete, so this paper uses the available data on total employment (Emp) and R&D expenditure ($R\&D$) instead. As changes in the number of R&D employees determine parallel changes in R&D costs, the correlation between ΔEmp and $\Delta R\&D$ must be higher when the reduction in total

21. It must be remembered that the probit model of Table IV not only includes the measures of similarities among merging firms but also controls for the technology position and product speciality of these firms. The use of probit estimates to select a control sample when agents differ in several characteristics was introduced by Rosenbaum and Rubin in their 1983 seminal paper.

TABLE VI.
HUMAN CAPITAL DEPRECIATION

Dependent Variable Independent Variable	$\Delta R\&D$ (1)	ΔEmp First-Step (2)	$\Delta R\&D$ Second-Step* (3)
ΔEmp	0.178 [0.23]		0.744 [<0.01]
<i>Cit</i>		0.636 [0.09]	
<i>Spill</i>		-2.810 [0.04]	
<i>GD</i>		-0.008 [0.11]	
Time dummies	Included	Included	Included
R^2	0.26	0.32	0.30
No. of observations	95	95	95

Notes: p -values computed using robust standard errors in square brackets. In bold, estimated coefficients that are significant at 5% or more. Diagnostic tests for the presence of outliers have been performed.

*Fitted values of ΔEmp from the "first-step" regression reported in column 2 are used as regressors (instead of the actual values of ΔEmp).

employment (typically observed during the postmerger restructuring) involves a large number of researchers. If the number of scientists leaving the company is actually larger when merging parties have higher levels of technology relatedness, we should find a stronger correlation between the two variables by first regressing ΔEmp on TR and then using the fitted values $\widehat{\Delta Emp}$ to explain changes in $\Delta R\&D$.

The results in Table VI seem to support this approach. Column 1 shows that there is a positive but not significant relationship between ΔEmp and $\Delta R\&D$: this confirms that only a fraction of the changes in total employment affect R&D activities. The coefficients reported in column 2 show that higher levels of technology relatedness imply a larger reduction in employment.²² Fitted values of $\widehat{\Delta Emp}$ from this "first-step" estimation are found to have a positive and statistically significant effect on $\Delta R\&D$, as shown in column 3.

5. CONCLUSIONS

This paper finds strong evidences in support of the "positive assortive merging" hypothesis: mergers are more likely to be signed among

22. The variables *Cit* and *Spill* are meant to measure direct links between merging firms: one for the knowledge flow from targets to acquirers and the other for the opposite flow. Higher values of these two variables suggest that scientists of the two firms have very similar expertise, thus increasing the probability of job reductions.

firms with similar technology, products, and culture. Empirical findings confirm the anticipated positive effect of product relatedness on postmerger performances. The data used in this study do not allow discerning whether this positive effect is due to market power or efficiency gains. It is interesting to notice that these two effects seem to assume a particular meaning in the pharmaceutical industry. In most countries, prices of drugs are agreed with health authorities and cannot be unilaterally changed by pharmaceutical companies. In this sense, mergers are unlikely to increase the market power of consolidated companies. But, competition among drug companies is through advertising, more than prices. Higher efficiencies in the advertising (measured, for instance, as the number of prescriptions signed by physicians divided by the number of visits by sale representatives) are somehow synonymous with a higher degree of market power.

Higher levels of technology relatedness are found to deliver worse postmerger performances, possibly because a large overlapping of research activities implies a more drastic dissipation of human capital. Mergers of alike can raise serious anticompetitive concerns, given that consolidated companies might reinforce their market power in some technology area through patent thicket and litigation.²³ At the same time, the empirical findings neglect that this negative effect might be compensated by the fact that mergers among companies with similar high level of technologies can deliver large knowledge synergies and efficiency gains in innovation.

Our analysis of the choice of targets and postmerger performance seems to support the “managerial hubris” hypothesis. Managers seem to favor mergers among similar companies as they might be (over)optimistic about the synergy gains in innovation, production, and advertising that can be achieved. At the same time, they may not foresee postmerger integration problems and large human capital depreciation. In a recent article, Brown and Sarma (2007) confirm the importance of CEOs overconfidence in the decisions to acquire other firms. At the same time, the findings in Capron (1999) show the importance of an adequate postacquisition integration strategy on the long-term performances of consolidated companies. In an experimental study, Weber and Camerer (2003) find that the conflicting culture of two merged laboratory firms leads to performance decreases.

Given the paucity of empirical work in this area, future research should study whether the findings of this study concerning the effect

23. In January 2008, several newspapers have reported the news that inspectors from the European Commission have raided some of the world’s largest pharmaceutical groups in a probe over whether they had abused their patent rights to delay the entry of rival medicines (see, i.e., the *New York Times* of January 17, 2008).

of technology and product relatedness on postmerger outcomes are confirmed in other industries. More importantly, we need to understand what are the causes that drive these effects. Is the positive relationship between product relatedness and market value due to large synergies or, more worryingly, due to increases in market power? Is the hypothesis of a more drastic dissipation of human capital when firms have higher technology relatedness confirmed or rejected using other data? Data at the firm level are not useful to address most of these questions. A proper analysis would require the use of information at the level of single products and individual research programs.

APPENDIX

Table AI in this Appendix checks the robustness of the relationship between technology and product relatedness and postmerger performances. The first three columns refers to a specification in which ΔV is computed as yearly changes over different horizons so that multiple observations are used for each merger (see notes for further details). Standard errors for specifications in these three columns are clustered by merger. Columns 4 and 5 use only one observation per merger over two different horizons. Note that the specifications in columns 2, 4, and

TABLE AI.
TECHNOLOGICAL/PRODUCT RELATEDNESS AND MARKET VALUE

Dependent Variable	ΔV	ΔV	ΔV	ΔV	ΔV
Independent Variable	(1)	(2)	(3)	(4)	(5)
<i>Over</i>	-1.648 [<0.01]	-1.494 [0.02]	-1.027 [<0.01]	-2.359 [0.24]	-2.935 [0.31]
<i>ATC3Cr</i>	0.546 [<0.01]	0.352 [0.03]	0.384 [<0.01]	0.852 [0.07]	1.723 [0.02]
<i>CD</i>	-0.023 [0.36]	-0.010 [0.68]	-0.034 [0.13]		
<i>GD</i>	-0.014 [0.24]	-0.019 [0.07]	-0.008 [0.42]		
Time dummies	Included	Included	Included	Included	Included
R^2	0.70	0.73	0.63	0.84	0.91
No. of observations	77	64	105	25	17

Notes: p -values computed using robust standard errors in square brackets. In bold, estimated coefficients that are significant at 5% or more. Column 1 is the same as column 2 in Table V. For a merger signed in period τ , the time window used in the above five specifications is: (1) annual growth from $\tau - 1$ to $\tau + 3$, (2) annual growth from τ to $\tau + 3$, (3) annual growth from $\tau - 1$ to $\tau + 5$, (4) "unique" growth from τ to $\tau + 3$, and (4) "unique" growth from τ to $\tau + 5$.

5 do not include the year of the merger in order to minimize the effect of divestiture. Although some of the coefficients are not precisely estimated because of the small number of observations, overall, the results in Table AI confirm the findings discussed in Section 4.

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