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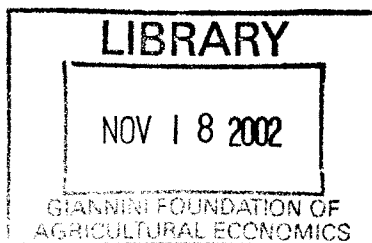
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**COMPLEMENTARITIES AND SPILL-OVERS IN MERGERS:  
AN EMPIRICAL INVESTIGATION USING PATENT DATA**

by

**Alan C. Marco and Gordon C. Rausser**



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Complementarities and Spill-overs  
in Mergers:  
An Empirical Investigation Using Patent Data

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## **Abstract**

Many recent empirical studies have examined the effect of the patent system on R&D, innovation and patenting behavior. However, few micro-level empirical papers have addressed the impact of the patent system on industry structure. In this paper we build on our previous work to investigate merger activity of firms in light of their patent holdings. We use agricultural biotechnology as an example. Three innovations are introduced: firm-level patent data is investigated as a predictor of merger activity; second, we develop a measure of patent enforceability based on patent litigation data; third, we combine both duration models and logit models in order to investigate both the timing of mergers and the matching of merger partners. The empirical results demonstrate that patent statistics are a useful predictor of merger activity; mergers in agricultural biotechnology appear to be partially motivated by difficulties in enforcing patent rights when firms have overlapping technologies; and some of the merger activity may be explained by attempts to reduce spillovers.

## 1 Introduction

In recent years, much empirical work has been done using patent data. However, most of this work focuses on estimating the value of patents. In this paper we seek to address the lack of empirical work on the impact of patent law, patent holdings, and spillovers on incentives for consolidation. We develop a methodology with which to incorporate firm-level patent data in merger analysis, explicitly accounting for the role of patent holdings in firms' decisions to merge. Our methodology contains three main innovations. First, we combine both static and dynamic methods in investigating mergers. Second, we use patent data as explanatory variables for mergers. And, third, we develop a measure of patent enforceability. The results of our study have implications for both patent policy and competition policy.

The empirical study focuses on the US agricultural biotechnology (ag-biotech) industry; however, the methodology is more general. This sector is a useful case study because of the recent consolidation activity. Through dozens of mergers, acquisitions and strategic alliances, there has been a rapid and dramatic change in control over intellectual assets. At the time that many of these acquisitions and mergers took place, the recorded control premia were surprising. Our concern is with developing a methodology with which to examine the role that intellectual property plays in merger activity.

Figures 1 and 2 tell the story of consolidation in the ag-biotech sector. The frequency of acquisitions is presented in Figure 1, over the period from January 1984 through April 2000. Each data point indicates an acquisition, and the solid line represents the density of those acquisitions. As shown in Figure 2, the concentration of agricultural patent holding fell from the mid-1980s. Each data point is the measurement of the Herfindahl-Hirschman Index of the ownership of agricultural patents in our sample at the time of an acquisition. There is a trough in the mid-1990s, and since that time concentration of patent holdings has risen.

In August of 1996, the announced purchase of Plant Genetic Systems (PGS) for \$730

million was made when PGS's prior market capitalization was \$30 million. According to AgrEvo, \$700 million of the purchase price was assigned to the valuation of the patent-protected trait technologies owned by PGS. The acquisition of Holden's Foundation Seeds by Monsanto may have been even more surprising. Here, a privately owned company, Holden's, with gross revenues of only \$40 million, was acquired for a purchase price of \$1.1 billion. A principal regulatory issue in this merger was the potential effect that might arise for germplasm access by Monsanto's competing trait developers. Holden's germplasm is widely disbursed throughout the industry and at least one of its elite lines is present in most commercial corn pedigrees. In the case of Monsanto's acquisition of DeKalb Genetics, Monsanto paid not only a control premium of 122% for the 60% of DeKalb that they did not already own, but also indemnified DeKalb against any disapproving regulatory action. DuPont acquired 80% of Pioneer for \$7.7 billion that it did not already own. In this instance the control premium was only 14% while the initial premium paid for 20% of Pioneer (purchase price of \$1.7 billion) was significantly higher.

Changing and uncertain intellectual property rights affect ag-biotech in much the same way that they affect biotechnology in general. First, many layers of patented technology are necessary for production and those layers may be owned by different firms. Second, new technologies embodied by biotechnology patents are frequently ill-defined, which leads to uncertainty over patent scope and validity.

Additionally, until the landmark Supreme Court ruling in the matter of *Diamond v. Chakrabarty* (447 U.S. 303, 1980), plant-related inventions based in genes or cells from nature or applied to living organisms were viewed as natural phenomena and were thus deemed unpatentable. In this case, however, the court re-affirmed that "anything under the sun that is made by man" is patentable subject matter (447 U.S. 309). Specifically, the court found that "the patentee has produced a new bacterium with markedly different characteristics from any found in nature and one having the potential for significant utility. His discovery is not nature's handiwork, but his own; accordingly it is patentable subject

matter under the section 101” (447 U.S. 310). This decision broadened the reach of utility patent laws to encompass living organisms. Accordingly, utility patents are now granted in the U.S. for genetically engineered organisms, for processes that transform cells and express proteins, and for the genes themselves. At the same time as this decision, there was a broader pro-patent movement in the U.S. (Hall and Ziedonis 2001, Kortum and Lerner 1998).

The uncertain and overlapping patent rights suggests an interesting link between patent policy and competition policy. It may be that uncertainty in patent rights causes a breakdown in contracting which provides incentives for consolidation. However, to date, there is no hard evidence to support this hypothesis. Our results show that patent statistics are a useful predictor of merger activity; mergers in agricultural biotechnology appear to be partially motivated by difficulties in enforcing patent rights when firms have overlapping technologies; and some of the merger activity may be explained by attempts to reduce spillovers. Anti-trust authorities need to be aware of these incentives when evaluating mergers.

After a literature review (Section 2), our methodology is presented in Section 3. Three empirical models are advanced to investigate the influence of patent holdings on merger decisions: two duration studies, and a matching model. In Section 4, we describe the merger and patent data used in the study, and we present our patent enforceability measure, as well as variables designed to capture the similarity of patent portfolios. In Section 5, we estimate a duration model measuring the rate at which firms pursue acquisitions in agricultural biotechnology. Next, we estimate a second duration model—this one on the rate of being acquired. Last, we use a fixed effects model to investigate the probability that a given acquirer will match with a potential target, conditional on the firm having decided to pursue an acquisition. In Section 6, we present our concluding remarks.



## 2 Literature Review

Much of the theoretical patent literature has focused on patents as an incentive for R&D. The debate has centered on the two most obvious patent tools: length and breadth (Gilbert and Shapiro 1990, Klemperer 1990, Cornelli and Schankerman 1999), though some have included discussions of the ways in which anti-trust law may prevent certain welfare improving agreements, especially when innovations are cumulative (Meurer 1989, Scotchmer 1991, Green and Scotchmer 1995).

Much empirical work on the patent system attempts to estimate the value of patent rights, and to determine the factors that influence value. Geroski, Machin and VanReenen (1993) show that innovating firms are highly valued by the market; but, it is unclear how much of this value is created by patents rights. Renewal models attempt to explicitly value patent rights; generally, they show that the distribution of patent valuations is highly skew (Pakes 1986, Schankerman and Pakes 1986, Schankerman 1998). Other empirical work has shown that while patents may stimulate R&D, they are dwarfed by R&D in explaining the value of a firm (Schankerman and Pakes 1986, Cockburn and Griliches 1988, Schankerman 1998, Lanjouw 1998). Patents are a very noisy signal about the value of a firm (Pakes 1985); though, weighting schemes may improve the precision of estimates (Lanjouw, Pakes and Putnam 1998). Lerner (1994) investigates the impact of a broader patent scope, and finds that average scope is a significant contributor to firm value.

Despite evidence that patent rights stimulate some aggregate R&D expenditures, the results from marginal changes in patent law are ambiguous. For instance, simulation estimates from Germany show that changes in patent law can significantly change the value of patent protection (Lanjouw 1994). However, recent empirical studies that examined actual changes in patent law (Kortum and Lerner 1998, Sakakibara and Branstetter 2001, Hall and Ziedonis 2001) conclude that it is unclear whether reforms that supposedly “strengthen” patent rights have any noticeable impact on innovative output.

Some empirical papers have addressed the impact of patent rights on strategic behavior, including patenting (Lerner 1995, Kortum and Lerner 1998, Hall and Ziedonis 2001) and litigation (Waldfogel 1995, Lanjouw and Lerner 1998, Lanjouw and Schankerman 2001).<sup>1</sup> Firms may patent “strategically,” when there are concerns about hold-up (Grindley and Teece 1997, Hall and Ziedonis 2001), and bargaining may break down when broad patents are enforced in technology areas that require many actors (Merges and Nelson 1994).

It is important to point out that industry organization can affect patenting behavior; in particular, concentrated industries may be better able to bargain or to contain spillovers. However, few empirical papers have sought to examine the impact of patent rights on industry structure and integration, although there is a developed theoretical literature on licensing and entry (Meurer 1989, Reinganum 1989, Scotchmer 1991, Choi 1998), and empirical work on local spillovers (Jaffe, Trajtenberg and Henderson 1993).

Hall and Ziedonis (2001) touch on entry in the semiconductor industry following the 1980s strengthening of US IP rights. They note that “stronger patent rights may have facilitated entry by specialized firms and contributed to vertical disintegration in this industry.” This disintegration is interesting in the present case, because—as we discuss below—we find that poorly defined patent rights in ag-biotech may have led to incentives for integration.

Scotchmer (1991) points out that most of the literature has focused on innovations in isolation. She discusses spillovers that occur through sequential innovation. This has implications on the “research exemption.” A “prior agreement” merges the interests of first- and second-generation inventors, but it might be limited by anti-trust authorities. Scotchmer offers no empirical evidence. (Green and Scotchmer 1995) find that patent protection should be broadened when subsequent innovations are likely to be made by several firms, and when prior agreements are legal.

Turning to the empirical firm consolidation literature, a variety of tools exist to examine the causes and consequences of mergers and other types of restructuring. Hall (1990) and Sinay (1998) investigate the consequences of mergers by comparing merged firms to

non-merged firms. Hall examines the R&D behavior of firms under different types of restructuring (including mergers and leveraged buyouts). Sinay investigates the effects of mergers on hospital costs by examining pre- and post-merger cost function estimates.

Qualitative choice models have also been used to examine the determinants of mergers (see Werden, Froeb and Tardiff (1996) for a survey). Hall (1988) contains an excellent description of the econometric issues that arise in applying qualitative choice models to the market for corporate control. The paper discusses the problems of a market where the buyers and sellers are *ex ante* indistinguishable, and the problems involved in defining the choice set. In the merger market, the set of choices is equal to the number of possible participants in the market (all firms). In some cases, this calls for some simplification in order to feasibly analyze a given sample. Since Hall uses a large inter-industry sample, she uses sampling in order to reduce the choice set for each firm (see also McFadden (1973) for a discussion of the cost of sampling in the context of qualitative choice). Werden et al. (1996) describe the uses of simulation methods with qualitative choice models, which they argue is preferred to traditional approaches. Sorenson (2000) uses factor analysis and logit regression on a large sample to investigate the motives for mergers in the 1990s. Since he focuses on 1996, the static nature of a logit analysis is not problematic.

Some researchers have analyzed industries in isolation (Tremblay and Tremblay 1988, Bacon, Shin and Murphy 1994). Bacon et.al. use a logit analysis to predict whether firms belong to the merged or non-merged groups in the rural electricity market. Tremblay and Tremblay estimate the probability that beer manufacturers will be involved in mergers. The benefits of focusing on a particular industry are that the choice set becomes feasible, and also that the results do not suffer from potentially contaminating differences among industries. Of course, to then apply the results to other industries becomes problematic.<sup>2</sup>

In merger analysis, qualitative choice methods suffer from the problem that they are inherently static. When the analyzed period of time is small, this may not be a problem. However, when the study ranges over many years, static analysis does not seem appropriate.

Tremblay and Tremblay (1988) study the beer industry from 1950-1983. They account for the problem by estimating the probability of merger year by year. However, because of the dynamic nature of merger decisions, and the fact that they occur at different times within a sample, duration analysis is a useful alternative.

Several studies have applied duration models to mergers and the evolution of corporate structure. Wheelock and Wilson (2000) estimate a competing-risks hazard model with time-varying covariates to examine the failure and acquisition of U.S. banks. Dickerson, Gibson and Tsakalotos (1998) examine the impact of a (UK) companies' dividend strategies and their risk of takeover. They find that the hazard of takeover is lower when dividends are high. Jaggia and Thosar (1995) use a duration model to study tender offers. Since they are interested explicitly in the timing of the resolution of tender offers, hazard analysis is useful.

For other forms of changing corporate structure, Van de Gucht and Moore (1998) use a duration model to estimate the factors that influence the survival of leveraged buyouts. Many LBOs revert to public forms of ownership, while some do not. Since these events happen over a length of time, and since some observations are truncated, duration analysis is appropriate. Additionally, Ravenscraft and Scherer (1991) investigate the probability that firms will sell-off divisions (the flip side of the merger market). They point out three benefits of using duration analysis: (1) when events occur at different times, (2) when the probability of events may be changing over time, and (3) when observations are censored. The intuition is that duration analysis uses valuable information about the timing of events that logit analysis is not able to capture. However, they also point out two problems with the approach: (1) it requires specification of a particular hazard function (at least for parametric approaches), and (2) it is difficult to deal with time varying covariates. They state that while theoretically time varying covariates can be incorporated, "[i]n practice, this step is plagued with computational complexities and collinearity."

### **3 Methodology**

Previous merger papers have considered one empirical approach in isolation. In this paper, we combine duration and logit models. Specifically, three models are constructed to identify the factors that increase the likelihood of consolidation in ag-biotech. First, we estimate a duration model measuring the probability with which firms will pursue acquisitions. Next we estimate the hazard rate of being acquired. Last, conditional on a firm deciding to pursue an acquisition, we use a fixed effects logit model (or conditional logit) to investigate the probability that a given acquirer will match with a potential target.

Duration analysis is employed to investigate the timing and factors influencing the merger decision. However, once that decision is made, we employ a conditional logit model to estimate the probability of “matching.” The conditional logit model is appropriate for the matching decision since—by conditioning on the acquisition decision—we reduce the decision to a static one. Additionally, censoring does not arise in the matching model. By using both dynamic and static models, more insight into the factors that influence merger decisions is possible.

#### **3.1 Duration models**

Our duration analyses examine the probability that a firm will make an acquisition, or be acquired, in the ag-biotech sector. In both the acquirer estimation, and the target estimation, we model this probability as a hazard function that depends upon individual firms’ patent portfolio characteristics and overall industry environmental variables, as well as the duration of the spell. The two models are similar, so we will outline the theory using the probability of acquisition.

We begin by specifying a reduced form model for the probability of acquisition. The firm will choose to make an acquisition in the next small interval of time when the value of doing so exceeds the reservation value (the status quo). Of course, the value of an acquisition to

any particular firm is dependent upon the choice set of possible targets.

However, in this formulation the choice of target is irrelevant. Our interest is in only whether a firm chooses to make an acquisition at all. Since the choice set is (almost) the same for all firms, the only distinguishing characteristics are the characteristics of the potential acquirer. The choice set is almost the same, because for any firm  $j$ , the set of choices does not include  $j$ . Or alternatively, the set includes  $j$ , but acquiring oneself is equivalent to making no acquisition. Because of this, the probability that firm  $j$  will make an acquisition is dependent only on its own characteristics. If this is an industry typified by a highly attractive acquisition set, then this will show up in the intercept term. Accordingly, we model the probability of a firm making an acquisition at time  $t$  as a function only of the firm's characteristics and the characteristics of the market (the HHI). The hazard function,  $\lambda(t)$ , gives the probability that the firm will undertake an acquisition given that it has not made an acquisition for  $t$  years. The hazard function is defined as  $\lambda(t) = \frac{f(t)}{1-F(t)}$ , where  $f(t)$  and  $F(t)$  are the usual density and cumulative probability functions.

The exponential specification assumes a constant hazard:  $\lambda(t) = \lambda$ , so that the hazard function does not vary with time. That is, there is no duration dependence; the length of time a firm has gone without a merger does not, *ceteris paribus*, affect the likelihood of merger in the next interval of time. The hazard rate is constant in  $t$  if  $1 - F(t)$  is distributed according to the exponential distribution. The Weibull distribution leads to a hazard function of the form  $\lambda(t) = \lambda p(\lambda t)^{p-1}$ . This hazard function includes the exponential as a special case where  $p = 1$ , therefore it is useful to include it as a comparison. For values of  $p < 1$ , the hazard function will be decreasing in time (it will exhibit negative duration dependence). For  $p > 1$ , the hazard function will exhibit positive duration dependence. For both the exponential and Weibull models, the parameter  $\lambda$  is modeled as

$$\lambda = e^{X\beta + \varepsilon} \tag{1}$$

where  $X$  is a matrix of firm and market characteristics (given in Table 1).

The Cox proportional hazards model specifies a hazard function of

$$\lambda(t_i) = \exp(-\beta'x_i)\lambda_0(t_i)$$

for each firm  $i$ .  $\lambda_0$  is a baseline hazard function common to all firms and is adjusted by the exponential coefficient. The Cox representation is semi-parametric because only the  $\beta_k$ 's are estimated:  $\lambda_0$  is left unspecified.

Estimation involves maximum likelihood estimation where the censored observations are incorporated much like the Tobit model (Greene 1993):

$$\ln L = \sum_{uncensored} \lambda(t|\theta) + \sum_{all} \ln(1 - F(t|\theta)) \quad (2)$$

Estimating the equation for the probability of becoming a target is similar: we assume that firms voluntarily become targets. Since the choice of acquirer is (almost) the same for all firms, the only distinguishing characteristics are those of the potential target. So, we model the probability of becoming a target at time  $t$  as a function of the firm's characteristics and the characteristics of the market (the HHI).

### 3.2 Matching

The duration models do not address who merges with whom, but only the timing of mergers conditional on the choice set. To determine the factors that will make one choice of target more attractive than another choice of target, we employ a matching model and condition on the fact that an acquisition has been made.

We estimate the matching model using a conditional, or fixed-effects, logistic regression following Greene (1993). Let  $A_t$  be the acquirer at time  $t$ , and let  $T_t = \{T_{t1}...T_{tN_t}\}$  be the set of potential targets at time  $t$ .  $y_{ti}$  is an event variable describing whether  $T_{ti}$  was acquired by  $A_t$  ( $y_{ti} = 1$ ) or not ( $y_{ti} = 0$ ). Importantly, the acquirer is restricted to making one and only one acquisition at time  $t$ . So, we want to measure the probability that  $y_{ti} = 1$ , conditional on  $\sum_1^{N_t} y_{ti} = 1$ .

For  $A_t$  to find it worthwhile to acquire  $T_{ti}$ , it must be that the value ( $V$ ) of making the acquisition is greater than that for the other potential targets.<sup>3</sup> Let the value of an acquisition be

$$V_{ti} = \alpha_t + \beta' \mathbf{x}_{ti} + \varepsilon_{ti}$$

where  $\mathbf{x}_{ti}$  is a vector of characteristics of the pair  $(A_t, T_{ti})$  and  $\alpha_t$  is a scalar representing characteristics specific to  $A_t$  (the fixed effect). If  $A_t$  chooses target  $T_{tj}$ , then it must be that  $V_{tj} \geq V_{ti} \forall i \neq j$ . If  $\varepsilon_{ti}$  is distributed with the Weibull distribution, we can write the probability of this as

$$\Pr \left( y_{ti} = 1 \mid \sum_1^{N_t} y_{ti} = 1 \right) = \frac{e^{\alpha_t + \beta' \mathbf{x}_{ti}}}{\sum_1^{N_t} e^{\alpha_t + \beta' \mathbf{x}_{ti}}} \quad (3)$$

Since  $\alpha_t$  enters all the terms, it drops out of the probability. That is, acquirer specific effects do not alter the probability that a particular target is chosen, *conditional on the fact that the acquirer has already chosen to make an acquisition*. On the other hand, the joint characteristics (which involve characteristics of  $A_t$ , but which vary with the target) remain in the equation. These characteristics include the overlap variables, described below.

## 4 Data

In order to estimate Equation 2 for acquirers and targets, we require a set of firms in the market, actual acquisition dates, and patent portfolio data for each firm over time. To estimate the matching model in Equation 3, a set of all potential targets for each actual acquisition date, and joint acquirer-target patent data is needed. Below, we describe the data sources and the variables used in each model.

### 4.1 Merger data

Following Graff, Rausser and Small (forthcoming), a sample of ag-biotech firms is tracked for control changes over the post-1994 period. From this sample, we obtained merger dates by



searching Lexis' Mergers and Acquisitions file. The sample was augmented with additional agricultural mergers found in Lexis from January 1984 to April 2000.

In total we researched agricultural merger histories for 111 firms (see Appendix B). Note that we include agricultural mergers only. So, while Dow is involved in agricultural chemicals, if it purchases an electronics firm, that merger and target were not included in the sample. We obtained data on the patent portfolios of these firms from Micropatent.

In the merger context, the duration—or “spell”—refers to the length of time without making an acquisition. With regard to tracking mergers, several assumptions about who was buying whom are required. These assumptions are:

- The sample consists only of patent-holders. Since we are interested in the consolidation among technology companies, we do not examine mergers among non-patent-holders.
- Parent firms are always the acquirers; i.e., if a subsidiary makes an acquisition, we classify that as an acquisition by the parent.
- Parents are assumed to have a patent portfolio consisting of the current patents of all their subsidiaries.
- Companies formed by the merger of equals are considered to be new entities, e.g., Novartis was formed by the merger of Ciba Geigy and Sandoz. This makes a difference only in classifying the merger history of the firm. However, a name change is not considered to be a new entity, e.g., ELM becomes Savia. So, Savia retains the merger history of ELM.
- The beginning of a firm's spell is assumed to be the month in which it applies for its first patent, or 1/1/1984, whichever is later. When a firm makes an acquisition, its spell has ended, and the following month it begins a new spell with its history augmented by one.

- A firm remains in the sample until the earliest of (1) the date it is acquired, (2) ten years after the issuance of its last patent, or (3) the end of the sample period (April 2000).

## 4.2 Patent characteristics

Measuring time varying covariates in duration models necessitates some simplification. Using discrete measurement times is a necessary limitation of using time-varying covariates in duration analysis (Ravenscraft and Scherer 1991). In the data, time-varying explanatory variables for a given firm are measured at the end of the spell (at the event date,  $t_1$ ) for “short” spells. For longer spells, we measured the explanatory variables at discrete intervals. In particular, we measure covariates at December 1 of each year if the current spell is more than 180 days old and if the spell does not end for at least another 180 days. Each measurement corresponds to a new record for that firm in that spell.<sup>4</sup> The probability that a firm will make an acquisition at any time  $t < t_m$  is a function of the firm’s characteristics at time  $t_m$ , where  $t_m$  is a measurement date. We chose to use a default measurement date of December 1 because it reduces the complexity of the resulting dataset, and therefore reduces the computation time of measuring patent portfolio statistics over time.

Patent data were obtained from Micropatent by searching on company name, and variations of company name. The data consist of 94,976 US patents issued by the 111 firms in the sample between the years of 1975 and 1998. For each firm, and for each measurement date (the date of a merger between any two firms in the sample, or December 1) we calculated the variables found in Table 1.

All of the explanatory variables are calculated using firms’ “live” patent portfolios as of time  $t$ . In the analysis, a patent is alive from the application date until 17 years after the issue date. Because we use the application date, the portfolio includes patents that are “in the pipeline,” i.e., those whose applications have been filed, but have not yet been issued.

This is appropriate since firms will base their decisions on in-process technology as well as developed technology.

Once a firm acquires a target, the target's portfolio is absorbed by the parent. Since HHI data needed to be calculated at all measurement dates, it was necessary to calculate each firm's patent market share at all measurement dates. We tracked the portfolios of each firm at each event date, accounting for all consolidations of portfolios through mergers, and using only live patents.

### 4.3 Patent enforceability

One of the explanatory variables (*priv.ag*) measures the average "enforceability" of a firm's agricultural patent portfolio. This variable is derived from patent litigation data used in Marco (2000). These data represent the outcomes of patent litigation suits. Here we calculate the probability of winning in court on validity and infringement using a probit approach. We use the results to predict the probability of winning on validity and infringement in the merger sample.

We estimate the probability that a patent will be found valid and infringed if it is brought to court:

$$\Pr(V = 1) = f(X\beta_1) + \varepsilon$$

$$\Pr(I = 1) = g(X\beta_2) + u$$

where  $X$  is a matrix of patent characteristics, including:

- *age1*: The age of the patent at the time of litigation.
- *age2*: The age of the patent at the time of adjudication.
- Dummy variables for the year in which the patent was issued (1982 or before, 1983-1989, and 1990 or after).

- *forlif*: Average annual forward citations to the patent.
- *selfor*: The proportion of forward citations that are self-citations.
- *numback*: The number of backward citations.
- *numicd*: The number of unique 4-digit international patent classes to which the patent has been assigned.
- Dummies for the technology field of the patent (agriculture, medicine, chemicals, electronics, mechanical)
- *patdelay*: The delay of the patent between application and issuance.

For validity and for infringement, we estimate a probit model and obtain the parameter estimates found in Table 2. Using these parameters, we predict the probability that each patent in the sample would be found valid if litigated, and infringed if litigated.

To create the enforceability measure, an interaction term equal to the product of the predicted probability that a patent is valid and the predicted probability that it would be found infringed is specified. That is,

$$prvi = \Pr(\text{patent is valid and infringed}) = \Pr(\text{valid}) \cdot \Pr(\text{infringed}).$$

The calculation implicitly assumes that the probabilities of validity and infringement are independent. An alternative specification would have been to directly estimate a probit model of the joint probability of validity and infringement findings. However, some court decisions do not rule on both matters, so we are able to increase the sample size by estimating them separately.<sup>5</sup>

Firms in ag-biotech claim that one of the reasons that they engage in mergers is because of the difficulty in enforcing their property rights and the difficulty in producing where other firms are enforcing theirs. A patent is only enforceable if a court will find it both valid and

infringed. Therefore, we interpret the predicted probability of validity and infringement (conditional upon being litigated) as a measure of “enforceability.” The variable *prvi* is the average predicted enforceability for a firm’s patent portfolio, based on the estimates of Table 2.

#### 4.4 Matching data

The matching data consist of acquirer-target pairs for each acquirer at the date of each actual acquisition. At a date  $t$  one acquirer-target pair is the consummated transaction. The other acquirer-target pairs at date  $t$  consist of the actual acquirer matched with all possible targets. A possible target is any independent firm as of the date of acquisition.

The sample contains 34 acquisitions of independent firms. The acquisition events can be described by a particular acquirer at date  $t$ :  $A_t$ . An acquirer may enter more than once, so that  $A_t = A_{t+1}$ , but acquirer-date combinations are unique.

Each acquirer-date combination contains one observation for each potential target. In our sample, there are—on average—68 available targets, yielding 2315 observations. At any given date there may be more or fewer available targets, due to entry and exit. An event is set equal to one if the acquirer actually purchased the target, zero otherwise.

The explanatory variables for the matching data are similar to those of the duration models. We use the target’s values for *share.pat*, *pct.ag*, *pct.yng*, and *prvi*. Additionally, we create two new sets of variables. The first—overlap—is developed following Podolny, Stuart and Hannan (1996).

Let  $B_A$  be the set of patents that are cited by the acquirer’s patent portfolio (backwards citations); the time subscript is omitted. Similarly, let  $B_T$  be the set of patents that are cited by a potential target’s portfolio. Then the overlap between the acquirer and target is  $over.at = \frac{(\text{number of patents in } B_A \cap B_T)}{(\text{number of patents in } B_A)}$  and the overlap between the target and acquirer is  $over.ta = \frac{(\text{number of patents in } B_A \cap B_T)}{(\text{number of patents in } B_T)}$ . Note that the measures are not symmetric; if  $B_T \subset B_A$ ,

then  $over.ta = 1$ , and  $over.at < 1$ .

The overlap variables are intended to measure the similarity between the research programs of a pair of firms. If backward citations can be thought to define a technology space, then the overlap variables measure whether the firms' research programs lie in the same space. There is no need to define that technology precisely. For our purposes, it is only necessary that we be able to observe whether the firms lie in the same space or not. The overlap variables help to determine whether overlapping property rights are at the heart of the matches between firms.

We define another variable measuring the affiliation between acquirers and targets, by using the amount of cross-citation between the firms. The variable  $xcite.ij$  is the proportion of  $i$ 's patents that cite  $j$ . Cross-citation measures direct linkages between firms rather than placing firms in a technology space.

#### 4.5 Descriptive Statistics

The duration data yield 133 spells: 48 acquisitions, 31 observations are censored on the right because they are acquired, and 54 observations are censored because the firms do not acquire anyone before they exit the sample. For long spells, we obtain multiple records per spell by measuring covariates at discrete intervals during the spell. Measuring the data this way yields 1124 observations. The means of the variables for the acquisition analysis are given in Table 3. The means for *duration* and *history* are measured using the 133 spells, and the other variables are given for all the observations.

Note that the maximum *history* is seven. This firm is Monsanto, who acquires seven firms in the sample before it is acquired. After its seventh acquisition, its *history* is seven, at which point it exits the sample by being acquired. Also, the maximum duration is 16 years, which reflects firms that are in the sample for the entire sample period, but never acquire. All the Japanese firms belong in this category. For these firms, it is especially

important to measure covariates at discrete intervals over the spell.<sup>6</sup>

Table 4 summarizes the overlap and cross-citation variables. The results are reported in percentages, so that the theoretical maximums are 100. The distributions of all the variables are skewed, though not highly correlated.<sup>7</sup> For both sets of variables, the target to acquirer variables tend to be higher than the acquirer to target variables. This is due mostly to the fact that acquirers' portfolios tend to be larger than those of targets, so their portfolios tend to be more diverse.

The matching data contain information for 23 acquirers purchasing 34 distinct targets. For each acquisition there were on average 68 potential targets, so that each acquisition accounts for approximately 68 observations, for a total of 2315 observations. The sample is narrow enough that we can feasibly include all possible targets in the industry.<sup>8</sup>

## 5 Estimation

The results of estimating Equation 2 for three distributional assumptions are given in Table 5.<sup>9</sup> We present the coefficients in the proportional hazards representation; i.e., the estimates for Equation 1 are presented as  $\exp(\beta_i)$ . Since the coefficients are multiplicative, parameter estimates greater than one imply a positive effect on the hazard rate and those less than one imply a negative effect. The specific interpretation can be more easily seen by examining the particular parameter estimates.

From Table 5 there are several factors that appear to be important in determining the rate at which firms acquire. For all three specifications, *history*, *hhi*, *share.pat*, and *prvi* enter significantly at the ten percent level. In fact, the parameter estimates are remarkably stable among the specifications, and the scaling parameter  $p$  on the Weibull model is very near one ( $\ln p \approx 0$ ), meaning that it replicates the exponential model. As a result, we limit our discussion to the exponential model.<sup>10</sup> For the constant hazard model, the mean predicted hazard rate of acquisition is 4.7% per year, meaning that in a given year a firm

is 4.7% likely to make an acquisition, on average.

For the parameter estimate on history, a one-unit increase in the number of previous mergers increases the hazard rate by about 60%.<sup>11</sup> Firms that have a history of acquiring are much more likely to acquire again. This is not surprising, as some firms seem to have a “taste” for acquiring.

A one-unit increase in HHI of patents in the sample (measured from 1 to 10,000) decreases the hazard rate by about 1.5%. A more significant change of 50 points in the HHI would decrease the hazard of acquisition by 47% (.985<sup>50</sup>). So, we can see that even as individual firms may accelerate their likelihood of merger by previous mergers, higher merger activity in the industry decreases the likelihood of mergers. Seen another way, a merger by firm *A* will increase firm *A*'s likelihood to merge again, but the merger also has an externality: it decreases other firms' likelihood to merge. The HHI effect is counter-cyclical so that low concentration will increase the hazard of acquisition, which will raise the HHI and then lower the hazard rate.

Not surprisingly, large firms are more likely to acquire: a one-unit increase in the market share of patents held by a firm (measured from 1 to 100) increases the hazard rate of acquisition by 10%. However, recall that a one percentage-point increase in market share is very large in this industry: the maximum share in the sample is 14.9% and the mean is 1.5%.

Importantly, *prvi* enters significantly in a negative direction. A one percentage-point increase in the average enforceability of a firm's patents leads to an 11% drop in the hazard rate. This means that firms are more likely to pursue acquisitions if their portfolios are less enforceable. This finding suggests that firms who find themselves weakly protected in their intellectual property may attempt to remedy this position through consolidation. However, in order to draw more inferences about firm strategy, we must move to a duration model that measures the hazard rate of being acquired.

The parallel analysis for acquirer duration is target duration. This model estimates the



probability that a firm will be acquired, conditional upon its characteristics and the industry environment. As previously noted, we use only the target's characteristics—as opposed to the acquirer's.

The sample for the target duration analysis (the rate of being acquired) is similar to that in the acquirer duration analysis, with one additional restriction: that independent firms are the only candidates for acquisition. That is, a firm can only be acquired once. Once it is a subsidiary, it is “off the market.”

Clearly there is another market for the acquisition of assets, including wholly owned subsidiaries. We do not include these assets in the sample. Had we, it would have involved tracking the patenting behavior of all subsidiaries, and entering them independently as potential targets at the same time as they contribute to the parents patent portfolio. Unfortunately, different firms handle post merger patenting differently. While some maintain independent patenting by the subsidiary, some absorb the R&D activities of the new subsidiary into those of the parent, making the entities inseparable. Since we cannot always observe the difference from available information, we exclude sales of subsidiaries from the analysis.

The 31 observations that are censored in the acquirer analysis by being bought are now the non-censored data. Aside from redefining the event variable the data are identical to those presented for the acquirer's model. We again estimate an exponential model for the target analysis. The results are summarized in Table 6.

The target duration results are quite different from those of the acquirer duration model, with two exceptions: the percent of young patents continues to be insignificant; and, *history* remains significant in all three models. The parameter estimate is greater than one, just as it was in Table 5, which means that a positive merger history will increase both the probability of making an acquisition and the probability of becoming a target. Put another way, a previous merger market participant is likely to be involved in a merger again—on either side of the table.

In all three models, the percent of agricultural patents—*pct.ag*—becomes significant. A one percentage-point increase in the percent of agricultural patents will increase the likelihood of being acquired by 2% to 3%. Size (the market share of patents given by *share.pat*) is significant only in the Cox specification, and HHI becomes insignificant.

Enforceability (*prvi*) is insignificant in the exponential model, but significant in the Weibull and Cox models. It is clear why when one examines the scale parameter on the Weibull model. Recall that the Weibull model assumes a hazard function of  $\lambda(t) = \lambda p(\lambda t)^{p-1}$ , where  $p = 1$  implies the exponential model. We obtain an estimate of  $p \approx 2$  ( $\ln p = .652$ ), which suggests that the exponential model is inappropriate. Based on the significance of the estimate of  $p$  and also based on the Akaike criterion (at 150.8, the Weibull has the lowest Akaike criterion, meaning it is preferred according to this criterion), we find support for the Weibull model. The mean predicted hazard rate of being acquired implied by the Weibull model is 3.6% per year. With  $p = 2$ , the hazard function exhibits positive duration dependence, meaning that the longer a firm has gone without being acquired, the more likely it is to be acquired. In particular, the hazard function is nearly linear. At the beginning of a spell ( $t = 0$ ), the hazard rate of being acquired is about .04% evaluated at the means of the independent variables. At  $t = 16$  years, the hazard rate rises to 5.6% at the means of the independent variables.

If the Weibull estimates are to be believed, then increasing enforceability by one percentage-point will increase the hazard rate by almost 8% to 3.9% per year. Importantly, the variable works in the opposite direction than it did for the probability of making an acquisition. Firms with high enforceability are less likely to make acquisitions and more likely to be acquired. At this point we can infer that the strategies of acquirers and targets differ with regard to enforceability: on average strong property rights will be purchased by weak property right holders.

In an industry where intellectual property is important, firms with low enforceability face a disadvantage. Since their portfolios are not as easily protected, their intellectual

property may spill-over into common property. One defense mechanism is to buy up those with strong property rights. We can infer from the two duration models that this may indeed be occurring. However, another explanation is that firms may also be consolidating with those who will benefit from the spill-overs.

Whether acquirers target those who may benefit from their specific spill-overs cannot be determined without investigating acquirers and targets simultaneously. Thus, we turn now to a model of acquirer and target matching in order to ascertain which characteristics made the realized target the best choice for the acquirer. Our methodology is to use a conditional—or fixed effects—logit, conditioning on the acquirer having made a decision to acquire at date  $t$ . The results are in Table 7.<sup>12</sup> The independent variables listed are for the target, except for the overlap and cross-citation variables which are defined for acquirer-target pairs.

Table 7 shows the results of sequentially adding the measures designed to capture the linkages between acquirers and targets. The coefficients are presented as “odds ratios,” so the interpretation is much the same as in the duration models: a one unit increase in the independent variable will increase the likelihood of the acquirer picking that particular target by  $1 - \beta$  percent, where  $\beta$  is the coefficient for the independent variable.

The first model uses only the target’s observable characteristics, and the second, third, and fourth models show the results of adding the overlap and cross-citation variables. The share of a target’s portfolio that is agriculturally related appears to increase the likelihood of a match; a one percentage-point increase in *pct.ag* will lead to a 2-3% increase in the likelihood of being chosen.

Enforceability enters significantly in three of the four models. Just as in the target duration model, the effect is positive; a one percentage-point increase in *prvi* leads to a 6.5-8.5% increase in the likelihood of being acquired relative to other targets.

The interesting variables in these models are those that are unique to a particular acquirer-target pair. Of those, the overlap of the target with the acquirer (*over.ta*) has

some explanatory power. Cross-citation does not appear to be a good predictor of matching. However *xcite.at* and *xcite.ta* do appear to marginally improve the fit of the regression, as measured by the likelihood ratio. The overlap between the acquirer and target (*over.at*) does not enter significantly; but, again, since acquirers tend to be larger and more diverse, the relationship is more likely to show up in *over.ta*.

The economic interpretation of *over.ta* is important. First, a high value for *over.ta* may indicate complementarities in intellectual property. Second, a high value may also indicate blocking technologies. We cannot determine from the results which is the larger effect. However, we can make some general statements about matching. From Table 7, we can infer that acquirers in this industry prefer targets that lie in the same technology space, have enforceable patent portfolios, and whose portfolios are agriculture intensive.

## 6 Conclusion

Integrating the results of the duration analyses and the matching model allows some conclusions to be drawn about the recent consolidation in ag-biotech. From the acquirer's model, we found that firms with less enforceable patent portfolios will be more likely to make acquisitions. The target's model tells us that the firms being targeted tend to have more enforceable patent portfolios. Hence, strategies of acquirers and targets differ with regard to enforceability: on average strong property rights will be purchased by weak property right holders.

Without the matching model, it was unclear whether the acquisitions were designed to increase the overall enforceability of acquirers' portfolios, or whether acquirers were targeting those particular firms that may be gaining from the spill-overs resulting from the lack of enforceability. However, the results from the matching model show that matches are more likely to occur when a target's portfolio lies in the technology space of the acquirer. Since spill-overs are more likely to occur within that technology space, acquirers will reduce the

spillage by purchasing those who benefit. This interpretation does not exclude the possibility that other complementarities may drive the importance of overlap in the matching model. To be sure, complementarities alone do not explain the importance of enforceability in the duration models. This explanation is consistent with industry anecdotal evidence that suggests that many of the mergers were rooted in conflicts about overlapping patents. In fact, a handful of mergers, including Monsanto/Calgene and Monsanto/DeKalb, were completed in the midst of patent infringement suits.

## Notes

<sup>1</sup>Theoretical papers have also addressed the litigation issue (Meurer 1989, Choi 1998, Schankerman and Scotchmer 2001), and some papers have studied general litigation empirically (Eisenberg and Farber 1997), and theoretically (Priest and Klein 1984, Schweizer 1989).

<sup>2</sup>Also, see Hall (1988) for problems that arise from assuming too narrow a choice set.

<sup>3</sup>We assume that the acquirer makes a unilateral choice. It is possible that for the target there may be a more suitable acquirer, where the complementarities are greater. However, had this been the case, the target should already have merged with the more suitable acquirer. Hence, at time  $t$ , all potential targets should be willing to merge with the acquirer, assuming that they are able to bargain for a share of the surplus. Another caveat is our implicit assumption that the most profitable acquisition actually makes the acquirer better off. This assumption is subsumed in our condition that the acquirer has already decided to make an acquisition, implying that it must be made better off by doing so.

<sup>4</sup>Based on our measurement algorithm the longest possible spell for which we obtain only one measurement on the covariates is almost two years. For example, if a spell begins on 6/5/1990, we would not measure the covariates on 12/1/1990 because the spell is only 179 days old. If the spell ends on 5/28/1992, then we also would not measure the covariates on 12/1/1991, because the spell is “about” to end in 179 days. The length of the spell would be almost two years, and we would measure the covariates at the end of the spell.

In our data, the longest spell for which we obtain only one measurement is one year and nine months.

<sup>5</sup>In an unreported regression we estimate the probability that a patent is found both valid and infringed for those cases that report a decision in both categories. The correlation

between the fitted values with the independence assumption and without is .82, so that the predictions are very similar. Since the specifications have similar results, we chose to use the specification with the independence assumption in order to use a larger sample.

<sup>6</sup>Also note that percentages and probabilities are measured from 1 to 100, and the HHI is measured from 1 to 10,000. These scales will make the interpretation of the parameter estimates more transparent.

<sup>7</sup>The correlation coefficient between *over.at* and *xcite.at* is .087 and between *over.ta* and *xcite.ta* is .032.

<sup>8</sup>Hall (1988) examines a sample of over 2000 mergers of publicly traded companies. Including all possible targets (all publicly traded firms) is not feasible in a sample of that size, so she relies on sampling. 2000 mergers by 2000 acquirers would imply at least 4,000,000 observations. While this may in itself be feasible, calculating the dependent variables for our study would require calculating the overlap variables for each observation - a task involving hundreds of millions of backward patent citations.

<sup>9</sup>Estimation was performed with Stata, using a Newton-Raphson method.

<sup>10</sup>The Akaike criterion also confirms this choice, though in this case it hardly matters.

<sup>11</sup>Since  $\lambda$  is parameterized as  $\lambda = \exp(X\beta)$  a one unit increase in  $X_1$  will increase  $\lambda$  multiplicatively by  $\beta_1$ , or will increase  $\lambda$  by  $\beta_1 - 1$  percent.

<sup>12</sup>The estimation was performed using Stata.

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## A Figures and tables

Figure 1: Empirical density of mergers in agricultural biotechnology, 1984-2000

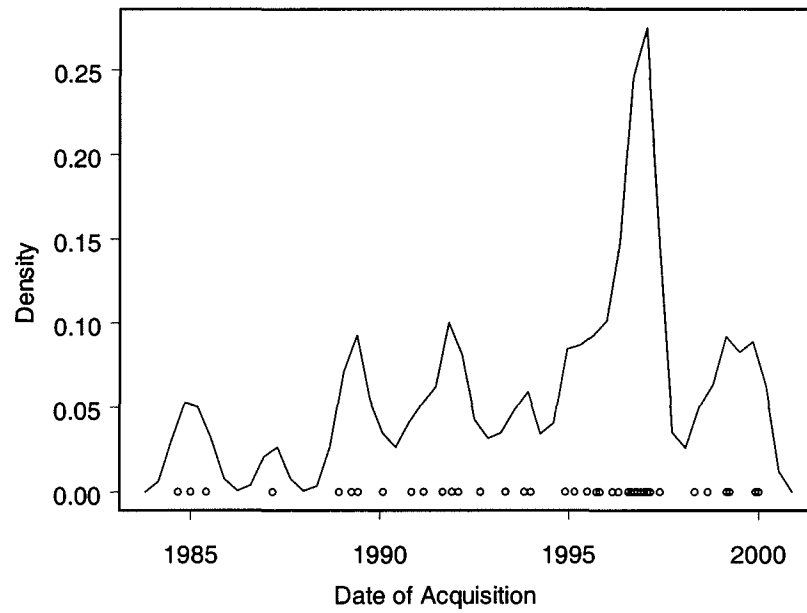


Figure 2: HHI of agricultural patents owned by firms in sample, 1984-2000

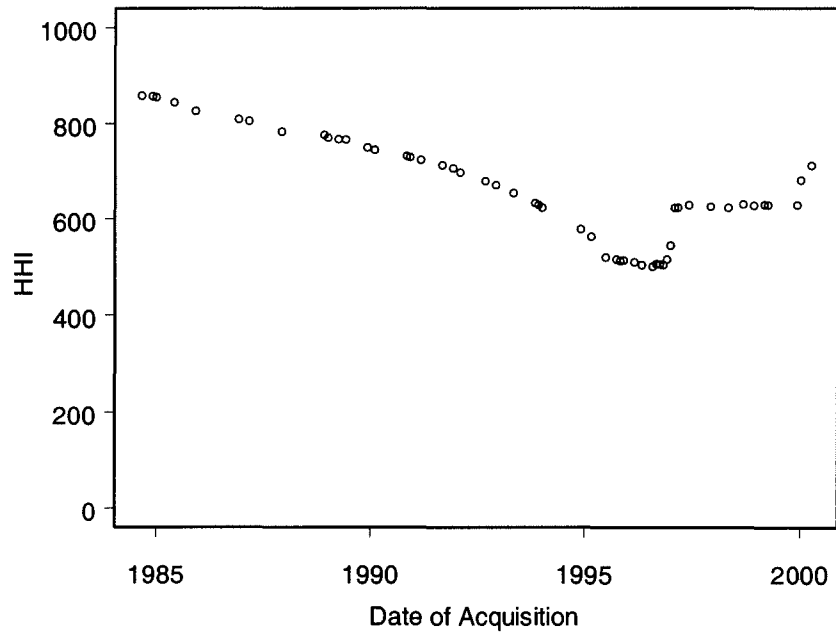


Table 1: Variables used in the acquirer duration analysis

$event_{jt}$	1 = firm j made an acquisition at time t. 0 = firm j exited the sample or did not make an acquisition.
$dur_{jt}$	duration of the spell up to date t. This is either the entire spell or the sub-spell up to a measurement date.
$history_{jt}$	number of previous agricultural mergers by firm j prior to the current spell.
$share.pat_{jt}$	firm j's share of all patents issued by firms in the sample at time t. This variable is a proxy for firm size.
$pct.ag_{jt}$	The proportion of firm j's patents that are agriculture related at time t. This variable measures agriculture intensity. Agricultural patents are defined as those assigned to international patent classes A01, C07H, C07K, C12M, C12N, or C12Q.
$pct.yng_{jt}$	The proportion of firm j's patents that are less than four years old at time t. This variable measures whether a firm is an active patenter or not.
$prvi_{jt}$	The estimated enforceability of firm j's patent portfolio. This is a derived covariate, which is described below.
$hhi_t$	HHI of all patents in the sample at time t.

Table 2: Estimation of the probability that a patent will be found valid or infringed

Variable	Description	Validity		Infringement			
		Coef.	S.E.	Coef.	S.E.		
<i>Constant</i>	-	-1.19	0.542	**	-0.0210	0.564	
<i>age1</i>	Age at case filing	-0.0332	0.0429		-0.153	0.0537	**
<i>age2</i>	Age at adjudication	0.0963	0.0488	**	0.0757	0.0600	
<i>iss8389</i>	Issued 1983-1989	0.705	0.227	**	-0.373	0.215	*
<i>iss9098</i>	Issued 1990-1998	-0.0440	0.432		-1.16	0.356	**
<i>forlif</i>	Avg. Forward cites	0.0329	0.0520		0.0275	0.0362	
<i>selfor</i>	Self-citation intensity	-0.246	0.445		-0.265	0.441	
<i>numback</i>	Backward cites	0.00297	0.00792		0.00685	0.00780	
<i>numicd4</i>	Number of ICDs	0.326	0.166	*	0.0944	0.178	
<i>tekag</i>	Agricultural tech.	-0.754	0.482		-0.677	0.537	
<i>tekmed</i>	Medical tech.	-0.0843	0.354		0.446	0.321	
<i>tekchem</i>	Chemical tech.	-0.480	0.364		0.255	0.353	
<i>tekelec</i>	Electronics tech.	0.0873	0.298		0.558	0.273	**
<i>tekmech</i>	Mechanical tech.	-0.203	0.295		0.529	0.293	*
<i>patdelay</i>	Patent issuance delay	-0.00235	0.0587		0.0412	0.0608	
Observations		272			273		

\* = p-value < .10. \*\* = p-value < .05.



Table 3: Summaries of variables used in acquirer duration analysis

Variable	Min.	1st Q.	Median	Mean	3rd Q.	Max.
<i>duration</i> (years)	0	3	7	8	14	16
<i>history</i> (count)	0.0	0.0	0.0	0.6	1.0	7.0
<i>share.pat</i> (%)	0.0	0.0	0.2	1.5	2.1	14.9
<i>pct.ag</i> (%)	0.0	4.4	10.0	27.2	50.0	100.0
<i>pct.yng</i> (%)	0.0	33.3	49.6	55.6	83.3	100.0
<i>prvi</i> (probability, 1-100)	0.3	6.0	12.6	12.6	17.9	48.0
<i>hhi</i> (index, 1-10,000)	609	617	621	631	629	747

1124 obs. 133 spells and 48 acquisitions, from Jan. 1984 to Apr. 2000.

Table 4: Overlap and Cross-citing variables

Variable	Min.	1st Q.	Median	Mean	2nd Q.	Max.
Overlap of acquirer with target ( <i>over.at</i> )	0.00	0.00	0.01	0.86	0.55	26.81
Overlap of target with acquirer ( <i>over.ta</i> )	0.00	0.00	0.12	1.73	1.99	66.67
% acquirer patents that cite target ( <i>xcite.at</i> )	0.00	0.00	0.00	3.79	0.21	100.00
% target patents that cite acquirer ( <i>xcite.ta</i> )	0.00	0.00	0.00	7.06	1.83	100.00

2315 obs. 34 acquisitions by 23 acquirers, from Jan. 1984 to Apr. 2000.

Table 5: Results of the acquirer duration analysis

	Exponential		Weibull		Cox	
	Haz. Ratio	Z-stat	Haz. Ratio	Z-stat	Haz. Ratio	Z-stat
<i>history</i>	1.586	4.00 **	1.586	3.94 **	1.610	3.58 **
<i>hhi</i>	0.984	-2.20 **	0.984	-2.20 **	0.983	-1.79 *
<i>share.pat</i>	1.100	1.99 **	1.100	1.98 **	1.094	1.84 *
<i>pct.ag</i>	0.996	-0.60	0.996	-0.58	0.995	-0.64
<i>pct.yng</i>	0.995	-0.75	0.995	-0.69	0.994	-0.74
<i>prvi</i>	0.889	-2.67 **	0.889	-2.50 **	0.887	-2.38 **
ln(p) (scale)	-	-	0.001	0.01	-	-
Log likelihood	-87.9		-87.9		-174.4	
Likelihood Ratio	39.0		35.8		34.5	
Akaike criterion	189.76		191.76		362.8	

1124 obs. 133 spells and 48 acquisitions, from Jan. 1984 to Apr. 2000.

\* = p-value < .10. \*\* = p-value < .05.

Table 6: Results of the target duration analysis

	Exponential		Weibull		Cox	
	Haz. Ratio	Z-stat	Haz. Ratio	Z-stat	Haz. Ratio	Z-stat
<i>history</i>	1.897	4.20 **	1.747	3.58 **	1.639	2.58 **
<i>hhi</i>	0.994	-0.92	0.994	-0.96	0.945	-3.37 **
<i>share.pat</i>	0.838	-1.32	0.871	-1.05	0.764	-1.75 *
<i>pct.ag</i>	1.017	1.96 **	1.026	2.75 **	1.031	3.11 **
<i>pct.yng</i>	0.999	-0.11	1.009	1.11	1.009	0.99
<i>prvi</i>	1.012	0.30	1.078	1.75 *	1.101	2.25 **
ln(p) (scale)	-	-	0.652	3.48	-	-
Log likelihood	-72.1	-	-67.4	-	-113.9	-
Likelihood Ratio	26.6	-	30.4	-	52.6	-
Akaike criterion	158.3	-	150.8	-	241.9	-

1124 obs. 133 spells and 34 acquisitions, from Jan. 1984 to Apr. 2000.

\* = p-value < .10. \*\* = p-value < .05.

Table 7: Matching model: probability that an acquirer purchases a particular target

	Odds		Odds		Odds		Odds	
	Ratio	Z-stat.	Ratio	Z-stat.	Ratio	Z-stat.	Ratio	Z-stat.
<i>share.pat</i>	0.952	-0.447	0.913	-0.776	0.948	-0.474	0.922	-0.691
<i>pct.ag</i>	1.024	2.677 **	1.021	2.277 **	1.027	2.773 **	1.024	2.469 **
<i>pct.yng</i>	1.003	0.406	1.003	0.495	1.005	0.637	1.006	0.790
<i>prvi</i>	1.069	1.688 *	1.064	1.579	1.087	1.851 *	1.087	1.823 *
<i>over.at</i>	-	-	1.071	1.199	-	-	1.082	1.151
<i>over.ta</i>	-	-	1.053	2.431 **	-	-	1.059	2.608 **
<i>xcite.at</i>	-	-	-	-	1.029	0.605	0.984	-0.270
<i>xcite.ta</i>	-	-	-	-	0.992	-0.925	0.991	-1.060
Log likelihood	-136.4	-	-133.2	-	-135.8	-	-132.5	-
Likelihood Rat.	14.0	-	20.3	-	15.2	-	21.8	-

Independent variables are target's values, except overlap and cross-citing variables.

\* = p-value < .10. \*\* = p-value < .05.

2315 obs.; 34 acquisitions by 23 acquirers, from Jan. 1984 to Apr. 2000.

## B Company list

Advanced Genetic Sciences  
Advanced Polymer Systems  
AgriBio Technology  
Agridyne/Native Plants Inc.  
Agrigenetics  
Agritope  
Allelix Biopharmaceuticals  
American Cyanamid  
American Maize  
Amoco  
Astra  
AstraZeneca  
Aventis  
Bayer  
Biosource  
Biosys  
Biotechnica  
Boswell  
Calgene  
Cargill  
Celanese  
Chevron  
Ciba Geigy  
Continental Grain  
Copley Pharmaceuticals

Corn States International  
Crop Genetics  
Dekalb  
Delta and Pine Lands  
DNA Plant Technology  
Dow Chemical  
DuPont Chemical  
Ecogen  
EcoScience  
Empressa La Moderna (ELM)/Savia  
Epitope  
Escagenetics  
Espro  
FMC  
Genencor  
Helena Chemical  
Hoechst AG  
Imperial Chemical Industries (ICI)  
International Paper  
Japan Tobacco  
Jinro  
Kirin  
Limagrain  
Lubrizol  
Mallinckrodt  
Merck  
MGI Pharmaceuticals/Molecular Genetics

Mitsubishi Chemical	Sungene
Mogen	Syntro
Monsanto	Systemix
Morganseeds	Takara Shuzo
Mycogen	Thermo Ecotek/Thermo Trilogy
Nordisk	Tosco
Northrup King	Transgene
Novartis	Unilever/Lever Bros.
Novo	Union Camp
Novo Nordisk	Union Carbide
NPS Pharmaceuticals	Upjohn
Nunhems	Westvaco
Pfizer	Weyerhaeuser
Pharmacia	Wilbur-Ellis
Pharmacia & Upjohn	W.R. Grace
Pioneer Hi-Bred	Yissum Research Development Co
Plant Genetics Inc. (PGI)	Zeneca
Plant Genetic Systems (PGS)	
Prodigene	
Rhone-Poulenc	
Rorer	
Royal Dutch Shell	
Sandoz	
Sapporo	
Scotts	
Sepracor	
Sumitomo Chemical	