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Alan C. Marco and Gordon C. Rausser

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Alan C. Marco[2] Gordon C. Rausser[3]

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[2]Corresponding author. Department of Economics, Vassar College, Poughkeepsie, NY, 12604. marco@vassar.edu. TEL: 845-437-7669, FAX: 845-437-7576.

[3]Robert Gordon Sproul Distinguished Professor, Department of Agricultural & Resource Economics, U.C. Berkeley, Berkeley, CA 94720-3310. rausser@are.berkeley.edu. TEL: 510-642-3345, FAX: 510-643-8911.

Abstract

Few micro-level empirical papers have addressed the impact of the patent system on industry structure. Using firm-level patent data for public and private firms in plant biotechnology, we develop a measure of patent enforceability. Duration models show that patent statistics are a useful predictor of the timing of merger activity. We find that patent enforceability is an important factor influencing the likelihood of mergers. Mergers in plant biotechnology may be partially motivated by the enforcement of patent rights when firms have overlapping technologies; some of the merger activity may be explained by attempts to avoid mutually blocking technology, as exemplified in the case of Roundup Ready corn.

Keywords: Mergers, duration models, hazard estimation, patents, plant biotechnology.

JEL: L22, L65, O34

1 Introduction

In complex knowledge markets, new products are often the result of cumulative innovation, or depend on a system of complementary technologies (Scotchmer 1991). More generally Mowery (1983) has shown that it is impossible for firms to fully internalize R&D spillovers. In the case of plant biotechnology, the range of technologies necessary to market a new product are rarely controlled by a single firm (Rausser 1999). As a case in point, the production of Roundup Ready corn relies on nine patented technologies, controlled at one point by five independent firms. Consolidations in the 1990s reduced that control to two firms, but also generated costly litigation—some of which is still pending.

In a market with zero transaction costs, one would expect the control of valuable complementary assets to agglomerate either through direct control or via costless arms-length transactions. But, in reality overlapping patent rights and fragmented control of mutually blocking technologies can beget an anti-commons, in which resources are under-utilized and innovation is inhibited (Heller 1998, Heller and Eisenberg 1998). Over the last two decades, the plant biotechnology sector as undergone continual restructuring in the form of mergers and acquisitions. Many purchased entities have later been spun off as separate firms, or sold to other firms. Industry insiders have claimed that an important motivation behind this restructuring is the control of the patent rights necessary for producing various products, such as Roundup Ready corn (Rausser 1999).

In this paper we attempt to assess the role that patent rights have played in the consolidation of the plant biotechnology industry in the 1980s and 1990s. We find that firms with more enforceable patent portfolios are more likely to engage in consolidation, whether as acquirers or as targets; however, enforceability increases the likelihood of spinoffs rather than complete acquisitions of targets.

One obstacle in the assessing the quantitative impact of fragmented patent control on the behavior of firms has been the difficulty in developing appropriate ways to characterize the patent holdings of firms, including their legal enforceability. A second obstacle arises from the different forms of the agglomeration of control: cross-licensing, patent pooling, acquisition of corporate assets, or wholesale merger. In light of this, our empirical study makes two main contributions: we use patent data as explanatory variables for mergers; and, we apply a measure of patent enforceability to firms' patent portfolios. These explanatory variables are used to estimate hazard rates for consolidation in plant biotech. We consider both wholesale mergers and partial acquisitions.

It is well recognized in the literature that patent rights have consequences for the firm beyond simple R&D incentives. 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). Firms may also change the areas in which they do research and patent in order to avoid the threat of litigation (Lerner 1995). Litigation behavior itself has been studied in several papers (Waldfogel 1995, Lanjouw and Lerner 1998, Lanjouw and Schankerman 2001, Marco 2005).

However, few empirical papers have sought to examine the impact of patent rights on industry structure, 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). Additionally, anti-trust consequences of licensing are explicitly recognized by the US Department of Justice and Federal Trade Commission in their Antitrust Guidelines for the Licensing of Intellectual Property (1995).

Branstetter and Sakakibara (2002) examine the relationship between R&D spillovers and the incentives to participate in research consortia in Japan. They find that the level of R&D spillovers

is positively correlated with the rate of consortia patenting. This result is consistent with our claim that higher technological overlap creates incentives for integration. They also find that the productivity of research consortia are weakly negatively correlated with the degree of competition among members. That is, research productivity is higher if firms are complementary.

Danzon, Epstein, and Nicholson (2004) study mergers in the pharmaceutical and biotech industries. They find that imminent patent expirations are a motivation for acquisition. Hall and Ziedonis (2001) touch on entry in the semiconductor industry following the 1980s' strengthening of U.S. patent rights. They note that because of stronger patent rights, specialized research firms may have been able to enter more easily. In contrast, industries with poorly defined property rights may find contracting over patent rights less desirable. Under such circumstances they may turn to various forms of less-than-arms-length transactions, including patent pools, cross-licenses, joint ventures, or consolidation.

2 Plant biotechnology

The plant biotech sector is a useful case study because of the history of consolidation activity (Oehmke, Wolf, and Raper 2005, Brennan, Pray, Naseem, and Oehmke 2005). Through dozens of mergers, acquisitions and strategic alliances, there has been a 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. Kalaitzandonakes (1998) has offered a number of explanations for the large difference between prior market capitalizations and acquisition prices, illustrating the potential value of intellectual property (IP).

The process of consolidation of IP began in earnest in August of 1996 with the announced purchase of Plant Genetic Systems (PGS) for $730 million, made when PGS's prior market capital-

ization 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. 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 the 80% of Pioneer that it did not already control for $7.7 billion. 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. These examples of consolidation allow premiums paid to be readily estimated because the companies in question were publicly traded.

Figures 1 and 2 tell the story of consolidation in the plant biotech sector. The frequency of acquisitions is presented in figure 1 as a histogram (with corresponding kernel density) over the period January 1984 to April 2000. The merger "wave" is readily visible. As shown in figure 2, the concentration of agricultural patent holdings actually fell for the firms in our sample through most of the period, even during a period of significant consolidation. Each data point is a monthly measurement of the Herfindahl-Hirschman Index (HHI) of the ownership of patents in our sample (based on simple counts).[1] There is a trough in the mid-1990's, and since that time concentration of patent holdings has risen. The concentration of patent holdings is important to antitrust authorities, especially in the context of a consolidating industry. The fact that concentration continued to fall even during the beginning part of the merger wave indicates that new patents were being issued

disproportionately to smaller and/or non-merging firms.

Changing and uncertain intellectual property rights affect plant biotech in much the same way as biotechnology in general. First, many layers of patented technology are necessary for production and those layers may be owned by different firms (King and Schimmelpfennig 2005). Second, new technologies embodied by biotechnology patents are frequently ill-defined, which leads to uncertainty over patent scope and validity. To be sure, following the landmark Supreme Court ruling in the matter of *Diamond v. Chakrabarty* (447 U.S. 303, 1980), utility patents for plant-related invention are now more secure (Lesser 2005) but nevertheless numerous patent interferences and expensive intellectual property alleged infringements and disputes have arisen over the last decade.

Uncertain and overlapping patent rights in the midst of significant merger activity suggest an interesting link between industry concentration and the control of patent rights (U.S. Department of Justice 1995). It may be that uncertainty in patent rights causes a breakdown in arms-length contracting that provides incentives for consolidation. For example, Lerner, Tirole, and Strojwas (2003) find that some patent pools are formed to settle bargaining problems created by overlapping patent rights. Further, the competitive consequences of patent rights consolidation depends upon the characteristics of the merged portfolios.

Beard and Kaserman (2002) discuss the trade-off between antitrust policy and incentives for innovation in the context of cross-licensing. They note that encouraging innovation is now an explicit policy goal of antitrust enforcement (U.S. Department of Justice 1995). Further, they argue that the use of cross-licensing to concentrate ownership (or use) of intellectual property may be necessary to foster innovation, in much the same way that the monopoly patent right is necessary to foster innovation. Antitrust authorities need to assess these same incentives when evaluating

mergers.

Utilizing patent data affords us three main benefits. First, we are able to investigate explicitly the role of intellectual property holdings in mergers. Second, we are able to include private (patent-holding) firms in the sample. And last, we are able to make use of patent indices, like generality, originality, and enforceability, in investigating the role such factors play in consolidation.

Section 3 presents the empirical models used to investigate the influence of patent holdings on merger decisions. We utilize hazard estimation in order to investigate the timing of when a firm becomes a target or an acquirer. In Section 4, we describe the merger and patent data used in the study. 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 plant biotechnology. We also estimate a parallel duration model—this one on the rate of being acquired. In Section 6, we present our concluding remarks.

Our results show that patent statistics are a useful predictor of merger activity; mergers in plant biotechnology appear to consolidate the more enforceable patent portfolios. However, some of the merger activity may be explained by attempts to reduce spillovers by firms who can credibly threaten to enforce property rights, suggesting a Coasian explanation.

3 Methodology

Qualitative choice models are commonly used to examine the determinants of mergers (see Werden, Froeb, and Tardiff (1996) for a survey). Hall (1988) describes the econometric issues that arise in applying qualitative choice models to the market for corporate control. Two critical issues are that the market for corporate control has buyers and sellers who are *ex ante* indistinguishable, and the empirical obstacles of defining the choice set. In the merger market, the set of choices is equal

to the number of possible participants in the market (i.e., all firms). Because Hall uses a large inter-industry sample, she uses sampling in order to reduce the choice set for each firm.[2]

Danzon, Epstein, and Nicholson (2004) study mergers in the pharmaceutical and biotech industries from 1988-2001 using a multinomial logit approach. They rely primarily on financial measures as merger determinants, but they also consider "excess capacity" based on patent expirations. Qualitative choice methods suffer from the problem that they are inherently static. Tremblay and Tremblay (1988), in their analysis of the beer industry, account for this problem by estimating the probability of merger year by year.

Previous studies have applied duration models to mergers (Wheelock and Wilson 2000, Dickerson, Gibson, and Tsakalotos 1998, Jaggia and Thosar 1995), leveraged buyouts (Van de Gucht and Moore 1998), and divisional spin-offs (Ravenscraft and Scherer 1991). Ravenscraft and Scherer (1991) note that duration analysis is appropriate when: (1) events occur at different times, (2) the probability of events may be changing over time, and (3) observations are censored. Duration analysis uses valuable information about the timing of events that logit analysis is not able to capture. In our empirical analysis, a duration model is employed to investigate the timing and factors influencing the merger decision.

We employ patent data because the anecdotal evidence in the plant biotech industry is that patent rights are important considerations in mergers (Rausser 1999). Thus, an essential element of any analysis of plant biotech mergers is direct measurement of IP holdings. An additional benefit of this approach is that patent data are publicly available for all firms, regardless of whether they are publicly or privately held. Most merger analysis restricts itself to publicly held firms due to data constraints. By including private firms we are unable to employ financial data that is only available for publicly held firms.[3] Regardless, the inclusion of private firms is rare in merger studies (and

most other firm-level studies), and the use of patent data relaxes this constraint to some degree.

Our duration analyses examine the probability that a firm will make an acquisition, or be acquired, in the plant biotech sector. In both the acquirer estimation and the target estimations, 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 fundamentally similar, so we will outline the methodology using the probability of acquisition. In essence, a 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.

In this formulation, the choice of target is irrelevant. Our interest is only in whether a firm chooses to make an acquisition at all. Because the choice set is (almost) the same for all firms, the only distinguishing characteristics for the timing of a merger are the characteristics of the potential acquirer. The choice set varies slightly among firms because for any firm j, the set of choices does not include j. Accordingly, the probability that firm j will make an acquisition is dependent only on its own characteristics and the characteristics of the market (represented, for example, by the concentration of patent ownership). If an industry is typified by a highly attractive acquisition set, then this will show up in the intercept term.

Following the accelerated failure time metric for survival analysis, we assume that the time to failure (acquisition) can be written as

$$\ln t_j = \mathbf{x}_j \beta + z_j, \tag{1}$$

where t_j is the time until failure for subject j, $\mathbf{x}_j$ is a vector of covariates, β is a vector of coefficients, and z_j is a disturbance term with probability density function $f(\cdot)$ and cumulative distribution function $F(\cdot)$.

The survival function, $S(t)$, gives the probability that the firm will have survived t periods without an acquisition, or $1-F(t)$. The hazard function is defined as $h\left(t\right)=\frac{f(t)}{S(t)}$. For our analysis, we utilize the lognormal distribution.[4] The implied survival function is

$$S(t_j) = 1 - \Phi\left(\frac{\ln(t_j) - \mathbf{x}_j\beta}{\sigma}\right), \tag{2}$$

where Φ is the cumulative distribution function for the standard normal, and z_j is distributed normally with mean zero and standard deviation σ. The ancillary parameter σ is estimated alongside β. The lognormal distribution generates a hump-shaped hazard function, so that there is positive duration dependence for small t and decreasing duration dependence for large t.

Estimation involves an application of maximum likelihood methods where the censored observations are incorporated (Cleves, Gould, and Gutierrez 2004), viz.:

$$\ln L = \sum_{uncensored} \ln f(t_j) + \sum_{censored} \ln S(t_j) - \sum_{all} \ln S(t_{0j}) \tag{3}$$

where t_{0j} is the time that the subject enters the sample.

Estimating the equation for the survival of targets is similar, where we assume that firms voluntarily become targets. Since the choice of acquirer is (almost) the same for all firms at a given time, the only distinguishing characteristics are those of the potential target. Thus, 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.

4 Data

In order to estimate Equation 3 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. In this section, we

describe the data sources and the variables used in each model. Table 1 gives a brief description of the variables used for all the estimations.

4.1 Sample

Following Graff, Rausser, and Small (2003) and Marco and Rausser (2002), we track a sample of non-Japanese[5] plant biotech firms for control changes over the 1984-2000 period. Beginning with their sample of firms, we obtained merger dates by searching Lexis/Nexis' Mergers and Acquisitions file. Firms remain in the sample if and only if they are patenters. Thus mergers are tracked only between patent-holding firms.

The sample was augmented with additional plant biotechnology mergers found in Lexis/Nexis from January 1984 to April 2000 involving one of the sample firms. If the sample firm is purchased by a non sample, or "outside," firm, then the merger is included and the outside firm is added to the sample. This is necessary in order to track the parent patent portfolio. On the other hand, if the sample firm purchases an outside firm, then that merger and target are added only if the target is deemed to be an plant biotechnology firm. For example, while Dow Chemical is involved in agricultural chemicals, if it purchases an electronics firm, that merger and target are not included in the sample. The purpose in defining the sample this way is to remove as much subjectivity as possible from the process. Unfortunately, some discretion is necessary to separate the sample set from its complement, while simultaneously keeping the sample a feasible size.

In total we researched plant biotechnology merger histories for 98 parent firms.[6] Joint ventures are considered to be subsidiaries of a single parent when the equity stake of the parent exceeds 50%. For instance, Agrevo began as a joint venture between Hoechst (60%) and Schering (40%). The Agrevo patents are assigned to Hoechst. Using this methodology, our sample identifies over 70%

of the top plant biotech companies as defined by the U.S. Department of Agriculture's Economic Research Service.[7]

The sample consists only of patent-holders. Because we are interested in the consolidation of technology companies, we do not examine mergers among non-patent-holders. The sample includes 98 parent firms engaged in 44 transactions, including 33 "mergers" (acquisitions of independent firms) and 11 "spinoffs" (acquisitions of subsidiaries).

4.2 Merger spells

Firms are included in the sample as long as they have an active patent portfolio. Thus, a firm remains in the sample until the earliest of: (1) the date it is acquired, (2) seventeen years after the issuance of its last patent, or (3) the end of the sample period (April 2000).

The beginning of a firm's spell is assumed to be the month in which it applies for its first patent, or January, 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 merger history augmented by one. The ensuing duration analysis is one where subjects (firms) are subject to "multiple failures."[8] Multiple failures generate econometric issues similar to those that arise in panel data. We account for dependence across spells by clustering errors at the parent firm level, across spells. We account for potential "occurence dependence" (Cameron and Trivedi 2005) by including the merger history as a regressor.

Acquisitions are defined to be performed by parent firms; 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. This assumption is necessary because it is impossible *ex ante* to distinguish fully integrated subsidiaries from stand alone subsidiaries.

Companies formed by a "merger of equals" are considered to be new entities, e.g., Novartis was

formed by the merger of Ciba Geigy and Sandoz. Distinguishing mergers of equals from acquisitions necessitates some subjectivity. When the management and control of the new company appears to be a combination of the merging partners, and the partners are of roughly equal size, then the merger is of equals. The distinction makes a difference only in classifying the merger history of the firm and in clustering error terms. A merger of equals becomes a new parent firm with a merger history of zero. Clustering of error terms in the estimation is done on the basis of the parent firm. Because the structure and patent portfolio in the merged firm is radically different from the unmerged partners, it is reasonable to assume that the new firm's behavior is independent from the two former firms. Additionally, in these cases it is impossible to distinguish one of the merging partners as the "parent."

Finally, 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 duration data yield 137 spells for 98 parent firms.

4.3 Patent characteristics

We obtained data on the patent portfolios of sample firms and identifiable subsidiaries from Micropatent using company name searches.[9] The data consist of 94,976 US patents issued by the 98 firms in the sample between the years of 1975 and 1998. For each firm, and for each measurement date we calculated the variables found in table 1, with descriptive statistics presented in table 2.

Using discrete measurement times is a necessary limitation of using time-varying covariates in duration analysis (Ravenscraft and Scherer 1991). In our sample, time-varying explanatory variables are measured monthly, and merger dates are recorded monthly. Each measurement corresponds to a new record for that firm in that spell. The probability that a firm will make an

acquisition at any time between t_{n-1} and t_n is a function of the firm's characteristics at time t_{n-1}, where t_{n-1} is a measurement date.

Some patent statistics, including some patent citation data, as well as the originality and generality indices were taken from the NBER Patent Citations Data File (Hall, Jaffe, and Trajtenberg 2001). The generality index was first proposed by Trajtenberg, Jaffe, and Henderson (1997), and is defined by Hall, Jaffe, and Trajtenberg (2001) as

$$Generality_i = 1 - \sum_{j}^{n_i} s_{ij}^2$$

where s_{ij} is the proportion of citations from class j received by patent i (out of n_i patent classes). The higher the generality index, the broader the impact of the particular patent has been, as measured by patent classification. Originality is defined similarly using backward citations rather than forward citations, and is a measure of the technological breadth of patents cited.

All of the explanatory variables are calculated using firms' "live" patent portfolios as of the measurement date. 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. Note, however, that we are not tracking patent applications but only granted patents; the application date is used only for the purposes of dating the technology. Applications that do not lead to granted patents are not included. Once a firm acquires a target, the target's portfolio is absorbed by the parent.

4.4 Patent enforceability

One important explanatory variable measures the average "enforceability" of a firm's patents. For an individual patent, enforceability is defined as the predicted probability that a court would rule the patent valid and infringed. Our metric of enforceability is based on the average enforceability for a firm's current patent portfolio.

Patent enforceability is related to the ability of firms to appropriate patent value, or to threaten to block use of a technology. If patents are not enforceable, then competitors can infringe with impunity. Firms in plant biotech claim that one of the reasons that they engage in mergers is because of overlapping or mutually blocking property rights (Rausser 1999).

One should note that it is not necessarily optimal for the patenting authority to issue only perfectly enforceable patents. As the patenting area matures, uncertainty will be resolved and patents will become either more enforceable or less enforceable based on court precedents. For firms, poor enforceability not only reduces patent value, but also reduces the ability to transact at arms length.

The calculation of the enforceability measure is based largely on Marco (2004). The initial sample of patents used in that paper comes from a dataset of over 400,000 corporately owned patents, issued between 1965 and 1995 collected by Case Western Reserve University and the NBER. Adjudication data are from the US Patents Quarterly (USPQ) (Allison and Lemley 1998, Henry and Turner 2006). It is important to note that adjudicated patents are a subset of all litigated patents, since most filed cases will be settled prior to a court decision. Thus, the selection equation accounts for selection into *verdicts* and not selection into *lawsuits.* The adjudication data include published decisions on validity or infringement from 1970-1997. In contrast to Marco (2004), we include only patents issued since 1975 because that range aligns with the patent sample for plant

biotech firms.

Our final sample of adjudicated patents includes 212 patents facing a validity decision, and 232 facing an infringement decision. These patents were matched with unlitigated patents in order to estimate the selection equations. Matching was done on the basis of corporate ownership and the date of grant (the grant week).

Patent characteristics are from Micropatent and the NBER Patent Citations Data Files. The variables used are defined in table 1, and summary statistics for adjudicated patents and matched patents are available in table 3.

The estimation strategy involves a selection-corrected probit estimated via maximum likelihood (Marco 2004, Van de Van and Van Pragg 1981). For patent i the probability of winning in court (whether on validity or infringement) is based on the latent "strength" of the case,

$$w_i^* = \mathbf{x}_i\beta + \varepsilon_i \tag{4}$$

where ε_i is distributed normally and $\mathbf{x}_i$ is a vector of observable characteristics. Only the dichotomous outcome w is observed, so that

$$\begin{aligned} w_i &= 1 \text{ if } w_i^* > 0, \\ w_i &= 0 \text{ if } w_i^* \leq 0, \end{aligned}$$

where $w = 1$ is a win.

A win or loss is only observed if a particular patent is litigated through trial on that issue. We assume that patents are adjudicated based on a latent "contentiousness," given by

$$y_i^* = \mathbf{z}_i\gamma + u_i \tag{5}$$

where u_i is distributed normally and $\mathbf{z}_i$ is a vector of observable characteristics. The observed

selection mechanism is

$$\begin{aligned} y_i &= 1 \text{ if } y_i^* > 0, \\ y_i &= 0 \text{ if } y_i^* \leq 0, \end{aligned}$$

where $y = 1$ indicates that an adjudication is observed.

If there is no correlation between ε_i and u_i, then equation 4 can be estimated using a standard probit. However, if ε_i and u_i are correlated (as in the present case), such that $\rho = corr(\varepsilon_i, u_i) \neq 0$, then the probit estimate of β will be biased.

The log-likelihood function of the probit estimator with sample selection is given by

$$L = \sum_{\text{wins}} \ln \left[\Phi_2 \left(x_i\beta, z_i\gamma, \rho\right)\right] + \sum_{\text{losses}} \ln \left[\Phi_2 \left(-x_i\beta, z_i\gamma, -\rho\right)\right] + \sum_{\substack{\text{not} \\ \text{selected}}} \ln \left[1 - \Phi \left(z_i\gamma\right)\right] \tag{6}$$

where Φ_2 is the bivariate cumulative normal distribution function and Φ is the cumulative standard normal distribution function (Stata 2003). Estimation is implemented via maximum likelihood.

The specification follows the reduced form approach of Lanjouw and Schankerman. The win rate equation is modeled as

$$P(win) = f(court, citation, scope, technology, other)$$

for both validity and infringement, where the independent variables are given in Table (1). Since a potential selection bias exists, the selection equation is modeled as

$$P(selection) = g(citation, scope, technology, other).$$

Because the court variables describe the court setting, they cannot be used as explanatory variables for selection *into* adjudications. Additionally, because the explanatory variables for the selection equation are a subset of those in the win rate equation, there are no exclusion restrictions.

Ideally, one would use variables in the selection equation that do not influence the win rate. Eliminating patent characteristics from the win rate equation is not possible on theoretical grounds; so, the model is identified on the basis of the non-linearity in the probit (Puhani 2000). Citation and scope variables are associated with patent value, uncertainty, and the likelihood of encountering a dispute. These factors are important determinants of win rates and the probability of litigation in the theoretical literature (Lanjouw and Schankerman 2001, Waldfogel 1995). Technology dummies account for fixed effects in different technology areas.

We treat validity decisions and infringement decisions as independent for the purposes of estimation; Marco (2004) finds evidence that estimating validity and infringement separately is preferred to aggregation. The results of the estimation are given in table 4. We refer the reader to Marco (2004) for a detailed description of the individual parameter estimates. Note that while the signs are similar across types of rulings (validity v. infringement), the magnitudes of the coefficients are significantly different (as confirmed by a Wald test).

The fitted probabilities of validity and infringement in table 5 provide evidence on the credibility of the results. For both validity and infringement rulings, the predicted probability of selection is much higher for adjudicated patents (approximately two to one). For adjudicated patents, the predicted win rate for winners is higher than the predicted win rate for losers. This is true whether the predictions are conditional on selection or not.

The conditional and unconditional predicted probabilities of winning demonstrate the Priest-Klein hypothesis (Priest and Klein 1984) viz., that in common circumstances, observed win rates will be biased towards 50% relative to the population win rate. This effect is seen in two ways. First, conditional probabilities tend to be closer to 50% than unconditional probabilities. Second, adjudicated patents tend to have win rates closer to 50% than matched patents on average. The

exception is patents that are adjudicated on infringement and found "not infringed." The predicted unconditional win rates for these patents is about 50%, slightly lower for the conditional win rates.

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 as a measure of "enforceability:"

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

The calculation implicitly assumes that the probabilities of validity and infringement are independent. An alternative specification would be 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. Additionally, it is inappropriate to aggregate the two types of adjudications because selection into validity decisions is significantly different from selection into infringement decisions; so, the selection equations should be disaggregated.

Using the above methodology, we calculate enforceability for each patent within the plant biotech sample. The estimates correct for self-selection, so they are not conditional on litigation. Because we are predicting outside the original sample of adjudicated patents, we do not assert that this measure of enforceability is a precise estimate that the patent would win in court if it were to be adjudicated. Our concern is that we find a measure that is associated with the ability of the firms to protect their intellectual property when aggregated across the entire portfolio. So long as our enforceability measure is correlated with the ability to protect intellectual assets, then it is appropriate to use it as a regressor.

4.5 Data summary

The duration data yield 137 spells for 98 parent firms: 44 acquisitions, of which 33 are full acquisitions, and 11 are partial acquisitions, or acquisitions of spinoffs. The remaining spells reflect exits from the sample due to inactive patenting or truncation at the end of the sample period. Because independent variables are measured at monthly intervals, the dataset comprises 11,778 monthly observations for the 137 spells (indicating an average spell length of 86 months). The descriptive statistics for the variables for the duration models are presented in table 2. Note that the maximum number of previous transactions is six. This firm is Monsanto, which acquires six firms in the sample before it is acquired.[10] Also, the maximum duration is 16 years, which reflects firms that are not engaged in a transaction during the entire sample period.

5 Estimation

The estimates are presented in table 6.[11] The table presents the estimation of equation 3 for the lognormal distributional assumption. The hazard of making an acquisition is presented in column 1, and columns 2 to 4 present the hazard of being a target, based on different ways of defining target transactions.

For each estimation, we present the coefficients in two ways, first as time ratios, and then as incremental effects. Time ratios give the proportional change in the time until failure from a one unit change in the covariate. A time ratio of 1.10 implies that the time until failure increases by 10% as the covariate increases by one unit (the impact on the hazard rate would be in the opposite direction). The incremental effect is presented for significant coefficients for the purposes of comparing the relative impacts across different covariates. We examine a one interquartile increase in the covariate, from the 25th percentile to the 75th percentile. Because many of the

covariates exhibit skewed distributions, the interquartile range provides a better comparison than the standard deviation.

5.1 Acquirers

Three independent variables have statistically significant coefficients in the acquirer model: market share of patents, the agricultural intensity (percentage agricultural patents), and enforceability.[12] These explanatory variables show that firms with, large, enforceable, and ag-intensive patent portfolios tend to be more likely to acquire. The incremental effects show that ag-intensity and enforceability have similar effects on the time to acquisition: an interquartile increase lowers the time until acquisition by about half (ag-intensity) to two-thirds (enforceability). The effect of portfolio size is larger with an interquartile increase leading to a 90% reduction in the time until acquisition.

An interesting negative result is that of portfolio age. It is widely established in the merger literature that diverse, established firms tend to buy young specialized firms. In our sample the age of the patent portfolio does not appear to affect the hazard of acquisition. However, it is important to distinguish between the age of the firm and the age of the patent portfolio. While the two are likely to be correlated, there are exceptions. First, an old firm can pursue a new research program that would reduce its portfolio age. Second, through merger a firm can reduce (or increase) its portfolio age. Nonetheless, new entrants in any high tech industry are bound to have young portfolios.

5.2 Targets

The parallel analysis for acquirer duration is the hazard of becoming a target, which is also reported in table 6. The classification of mergers is slightly different for the target analysis because it is necessary to distinguish between spinoffs and whole firm acquisitions. Once a firm is wholly

acquired, its patents are absorbed into the patent portfolio of the parent, and the firm is off the market as a separate entity. Because of this, a firm is subject to acquisition by merger only once, making the hazard estimation one of single failure. In contrast, firms can engage in spinning off assets multiple times, making the hazard estimation for spinoffs one of multiple failures, as in the acquirer model. One can imagine that the market for the control of assets, including wholly owned subsidiaries, is different from the market for entire firms.

Unfortunately, different firms handle post merger patenting in multiple fashions. 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. It is impossible to delineate *ex ante* between the two approaches from observable data. Thus, we assume that all patents are owned and controlled by the parent alone, and the parent's characteristics make it attractive as a target of whole acquistion or as a target of partial acquisition. We accomodate for this by estimating three target models. The first target model (column 2) treats all merger events identically. The other two models (columns 3 and 4) distinguish mergers of independent firms from spinoffs.

For the aggregated target model, merger history, market share, and self-citations have statistically significant coefficients. An increase in acquisition history tends to shorten the spell duration and increase the hazard rate of becoming a target. This effect arises primarily from the target/merger estimation (column 3), where one additional prior acquisition decreases spell duration by 40%.

The impact of market share on target survival time is predictable. The size of the patent portfolio, as measured by the share of patents, has opposite effects for mergers and spinoffs. The effect is to lengthen survival time for mergers and to shorten survival time for spinoffs. This result is quite intuitive because large firms are more likely to be the targets of spinoffs rather than whole

acquisitions, relative to small firms. These effects cancel out when observing the aggregate target model.

For targets overall, the effect is opposite that of acquirer survival time, so larger firms are *less* likely to be targets. However, market share affects mergers and spinoffs differently. A one interquartile increase in market share increases merger survival by three-fold. In contrast, larger firms are *more* likely to engage in spinoffs as targets: a one interquartile increase in logged market share decreases spinoff survival by 95%.

The average self-citation intensity enters negatively on survival time, for aggregate targets. Self-citations are an indication of cumulative research. Those firms with a high propensity for cumulative research show a shorter surival time, or a larger hazard of being acquired. An interquartile increase in self-citations leads to a 40% decrease in survival time. This effect is not measured with precision for mergers or spinoffs separately.

The effect of HHI appears to be important for spinoffs only, and the magnitude of the incremental effects is very large. Part of the reason for this magnitude is the fact that spinoffs were not observed until after 1990, when the HHI for agricultural patents had already fallen from its peak. The positive correlation of HHI with survival time indicates that spinoffs become less likely as the concentration of agricultural patents increases. This result is not surprising when one considers the fragmentation in the control of patent rights. More spinoffs represent a reshuffling of assets, so that the control of certain technologies can agglomerate. The incentives for agglomeration will naturally be higher when fragmentation is higher.

The coefficient for ag-intensity is statistically significant only for spinoffs, although the direction of the effect is consistent across target specifications. As in the acquirer model, the effect is to shorten the survival time (by 40% for an interquartile increase in ag-intensity). Recall that the

covariates for spinoffs are the values of the parent firm, so that ag-intensity is important for the target parent, and not necessarily for the subsidiary that changed hands. Thus, the result shows that large, ag-intensive firms were more engaged in the reorganizing of assets than smaller, less ag-intensive firms.

The coefficient for enforceability is statistically significant for target spinoffs, but it is not significant in the target merger estimation or in the target aggregate model. The effect of higher enforceability is to lower survival time, or to increase the hazard of engaging in a spinoff. A Wald test verifies that the enforceability coefficient is significantly lower for spinoffs than it is for mergers.

5.3 Comparison of acquirers and targets

Figure 3 graphs the observed and predicted cumulative number of transactions over the sample period. The predicted number of transactions is calculated using the fitted cumulative hazard. The first panel shows the aggregate acquirer estimation, and the second and third panel graph the target merger and spinoff estimations, respectively. A very close fit is found for all models. The spinoff model shows the greatest divergence from the observed number of transactions only because the discrete number of spinoffs from year to year is very small, whereas the predicted number of transactions is continuous. Similar results can be found from goodness of fit tests (Marco and Rausser 2007).

Wald tests show that the coefficient for enforceability for target spinoffs is smaller than the time ratio for acquirers, which is in turn smaller than the time ratio for target mergers; all differences are statistically different from zero at the five percent confidence level. The interpretation is that a more enforceable patent portfolio increases the hazard of engaging in a target spinoff relative to (a) an acquisition, and (b) a target merger. Similarly, higher enforceability increases the hazard

of making an acquisition relative to being a target of a merger. Consequently, a more enforceable patent portfolio makes a firm more likely to be the target of a spinoff relative to being the target of a merger.

6 Conclusion

In an industry where intellectual property is a critical part of enterprise value, firms with low enforceability face a serious challenge. Since their portfolios are not as easily protected, their intellectual property may spill-over into the commons. Other firms may "borrow" this technology in their own research and development or commercialized products. Firms with high enforceability posess a greater threat to exclude other firms from using their intellectual assets. However, high enforceability may exacerbate the anti-commons. One logical consequence is that firms with mutually blocking technologies may consolidate in some way, reducing fragmentation.

Anecdotal evidence in the plant biotechnology industry 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. We can infer from the survival models that consolidation of patent rights is correlated with consolidation activity, at least in terms of acquisitions and spinoffs. We find that firms with more enforceable patent portfolios are more likely to engage in corporate control transactions, on both the buy-side and the sell-side. On the buy-side, enforceability increases the likelihood of all types of acquisitions, and on the sell-side enforceability makes firms more likely to spin-off subsidiaries.

With respect to mergers, we find that large, ag-intensive, enforceable firms tend to be buy small diversified firms. So, the evidence is that enforceability is more likely to consolidate IPRs in spinoffs than in mergers. The difference between spinoffs and mergers suggests a Coasian interpretation,

in which less drastic forms of consolidation (spinoffs versus mergers) are a consequence of easier contracting over property rights.

Our analysis demonstrates that there is a strong association between measureable characteristics of patent rights and the consolidation behavior of plant biotechnology firms. The results are broadly consistent with the theoretical literature about property rights as well as the anecdotal evidence in the plant biotechnology sector. But, much of the theory was previously untested, in part due to the obstacles involved in accurately measuring the strength of patent rights and the fragmentation of control. We show that the effects of enforceability are statistically significant, and also that they are quantitatively as important as other measured factors in explaining consolidation choice in the sample.

Notes

[1]The HHI for patents is the sum of the squares of firms' market shares of sample patents, so that the index can vary between 10,000 (all patents owned by a single firm) and close to zero (patents are diffusely held by many firms). Brennan, et al. (2005) present a similar computation in terms of pre and post merger HHI for USDA field trials instead of for patents.

[2]See McFadden (1973) for a discussion of the cost of sampling in the context of qualitative choice.

[3]Further research is necessary to determine whether the exclusion of private firms or the exclusion of certain financial data (or patent data) is the more onerous restriction. Nonetheless, throughout the paper we attempt to proxy for some traditional explanatory variables using patent data; e.g., firm size is replace by patent portfolio size.

[4]Across all acquirer and target specifications, no distribution dominated according to the Akaike Information Criterion (AIC). The Bayesian Information Criterion (BIC) weakly preferred the exponential distribution. However, semi-parametric Cox estimates showed a hump-shaped hazard function, consistent with a lognormal or log-logistic distribution. Estimates using other distributional assumptions, and graphs of the Cox hazards are provided in a technical appendix available on *AgEcon Search* (Marco and Rausser 2007). The marginal effects of the regressors—especially those of enforceability—are broadly consistent across different distributional specifications.

[5]Japanese firms do not engage in mergers during the sample period. In general, they are unlikely to engage in mergers for reasons that are particular to their corporate structure. Our results—especially those of enforceability—are robust to whether or not they are included in the sample.

[6]For the complete list of firms, please see the technical appendix (Marco and Rausser 2007).

[7]See http://www.ers.usda.gov/data/AgBiotechIP, table 11, "Top 100 patent holders, U.S. and non-U.S., companies only (excluding subsidiaries)." Despite the title, the ERS list includes some universities and government agencies. For instance, the top two patentees listed are the U.S. Department of Agriculture, and the University of California at Berkeley. We exclude from this list non-firms as well as Japanese firms. Our sample identifies 70% of the residual firms.

[8]See Cleves, Gould, and Gutierrez (2004), chapter 6 and Cameron and Trivedi (2005), chapter 19 for discussions of multiple failures, or multiple spells, in hazard estimation. Marco (2007) provides an application to patent citations, where an individual patent is subject to multiple citations by other patents. Other examples in the literature include unemployment spells, births, heart attacks.

[9]Company name searches are bound to introduce some error, for at least two reasons. First, unknown subsidiary patenters will not be observed. Second, typographical errors at the patent office will make some patents unobservable. So, our data are likely to be a subset of the true population of patents owned by our sample firms.

[10]Interestingly, Monsanto was later spun out; but, this transaction is outside our sample period.

[11]Estimation was performed with Stata, using the Newton-Raphson method.

[12]Previous merger history and the HHI are significant in the exponential and Weibull specifications. See the technical appendix (Marco and Rausser 2007).

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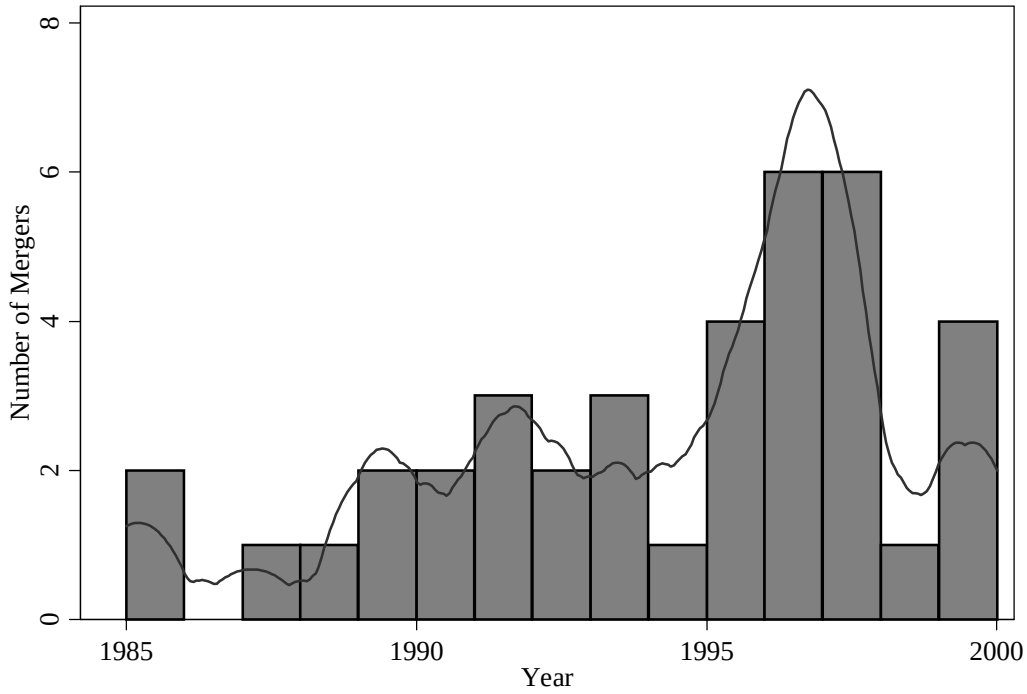
Figure 1: Frequency of Plant Biotechnology Mergers



Epanechnikov kernel, 0.5 kernel bandwidth.

Figure 2: Concentration of Patents in Sample

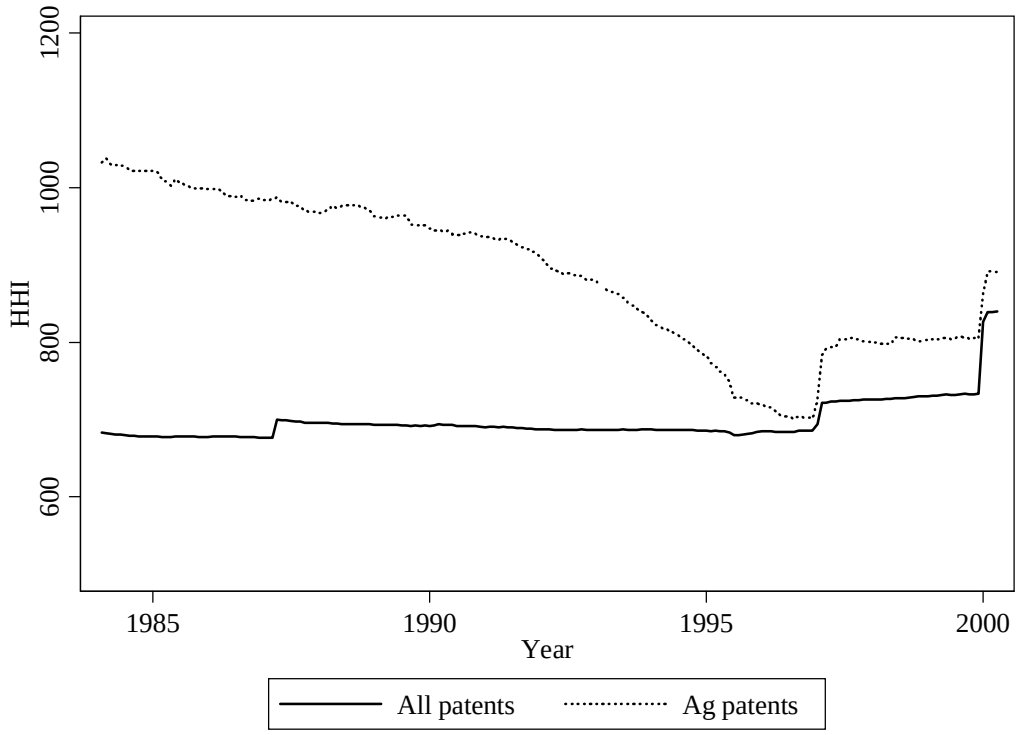
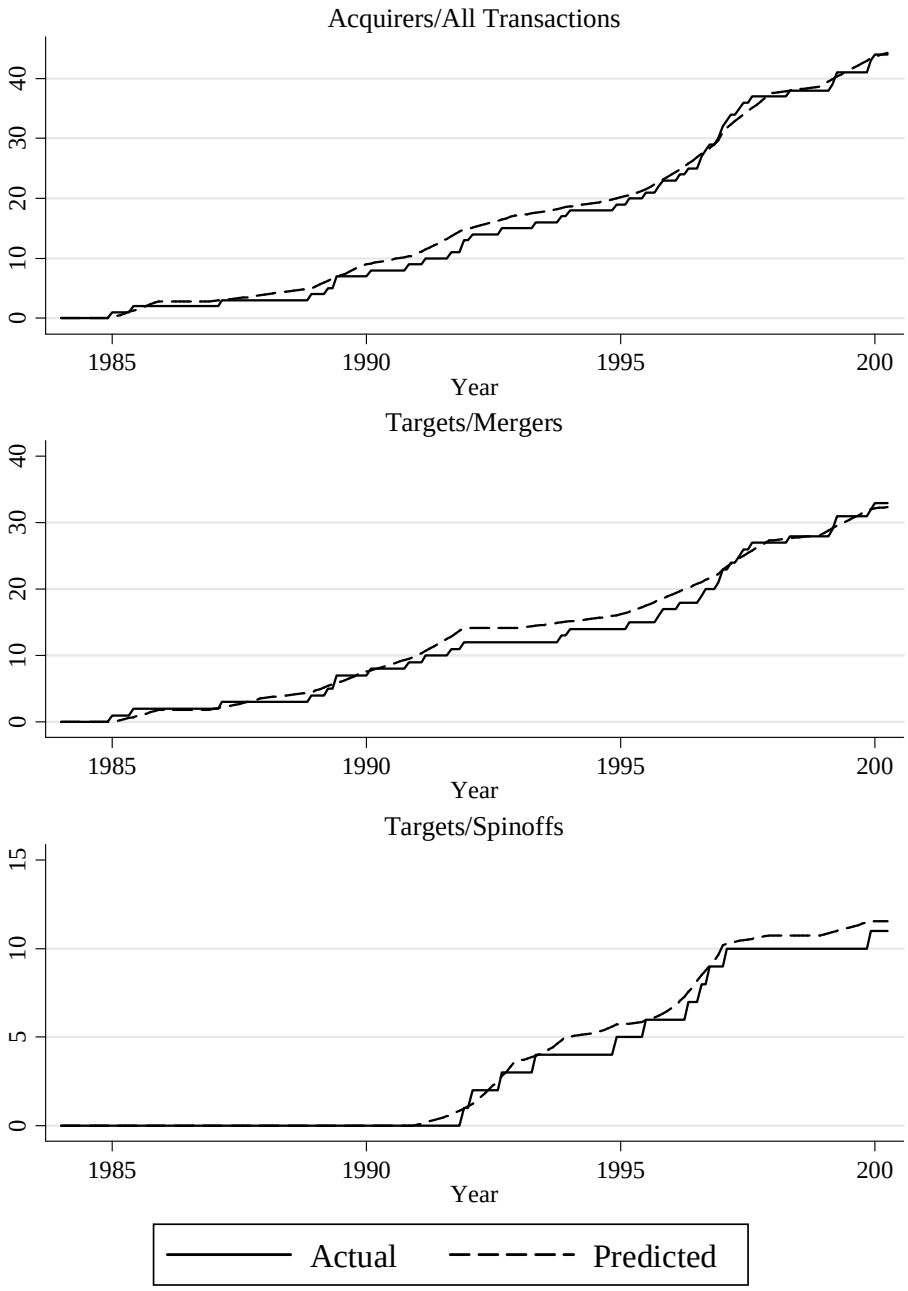


Figure 3: Cumulative number of transactions, predicted v. observed



Fitted values estimated using the lognormal distribution.

Table 1: Variables used in estimations

Enforceability estimation	
Prior Positive	Indicates there was a prior positive legal decision
Prior Negative	Indicates there was a prior negative legal decision
Appeal	Decision was made in an appellate court.
Defensive	The case was "defensive," i.e., the patent holder was the defendant.
Pre-1983 decision	Decision was made prior to 1983.
Age	Age at the time of decision, from application date.
Number of IPCs	The number of four digit international patent classes to which the patent was assigned.
Number of Claims	Number of claims in the patent.
Backward	Number of previous patents cited (citations made).
Forward	Number of citations received by subsequent patents, normalized by year of observed life.
Self citations	Proportion of backward citations made to patents owned by the same entity.
Patent delay	Delay (in years) between patent application and patent grant.
Originality	Originality index as described by Hall, Jaffe, and Trajtenberg.
Generality	Generality index as described by Hall, Jaffe, and Trajtenberg.
Pre-1983 application	Patent application was made prior to 1983.
1983-1989 application	Patent application was made from 1983-1989.
Technology dummies	Technology classifications, as described by Hall, Jaffe, Trachtenberg.

Duration estimation	
History	Number of previous transactions within the sample by firm prior to the current spell (on either the buy or sell side).
HHI Ag.	HHI at time *t* calculated based on the market share of agricultural patents held within the sample.
Share	Firm's share of all patents issued by firms in the sample at time *t.*
Pct. Ag.	The proportion of firms' patents that are agricultural at time *t* . Agricultural patents are defined as those assigned to international patent classes A01, C07H, C07K, C12M, C12N, or C12Q.
Age	Firm's average patent age (from application date) at time *t* .
Forward	Firm's average forward citations at time *t.*
Self citations	Firm's average backward citations at time *t.*
Originality	Firm's average originality at time *t.*
Generality	Firm's average generality at time *t.*
Enforceability	The average across a firm's portfolio at time *t* of the estimated probability of validity and infringement.

Table 2: Summary statistics: duration models

Variable	Obs.	Mean	Std. Dev.	IQR	Min	Max
All spells	137					
Previous mergers		0.7	1.1	1.0	0.0	6.0
Duration (years)		7.3	5.6	9.3	0.1	16.2
All spells ending in mergers	88					
Previous mergers		0.8	1.3	1.0	0.0	6.0
Duration (years)		5.4	4.3	6.3	0.1	15.2
Monthly observations	195					
HHI (all patents)		697	26	11	676	840
HHI (ag patents)		888	97	172	701	1038
All observations	11778					
Share		1.7	3.0	2.3	0.0	16.1
Ag intensity		16.7	23.8	15.8	0.0	100.0
Age		6.4	3.3	5.1	0.0	15.5
Forward citations/year		0.6	0.5	0.3	0.0	9.7
Self citation		10.0	9.0	13.9	0.0	50.0
Originality		29.8	13.4	15.3	0.0	82.0
Generality		29.3	13.9	15.6	0.0	75.0
Enforceability		61.6	14.5	22.0	16.8	96.4

137 spells. 11778 monthly observations.
Indices and proportions reported on a 1-100 scale.
HHI reported on a 1-10,000 scale.
IQR = Interquartile range

Table 3: Summary statistics: enforceability estimation

Variable	Obs.	Mean	Std. Dev.	IQR	Min	Max
All spells	137					
Previous mergers		0.7	1.1	1.0	0.0	6.0
Duration (years)		7.3	5.6	9.3	0.1	16.2
All spells ending in mergers	88					
Previous mergers		0.8	1.3	1.0	0.0	6.0
Duration (years)		5.4	4.3	6.3	0.1	15.2
Monthly observations	195					
HHI (all patents)		697	26	11	676	840
HHI (ag patents)		888	97	172	701	1038
All observations	11778					
Share		1.7	3.0	2.3	0.0	16.1
Ag intensity		16.7	23.8	15.8	0.0	100.0
Age		6.4	3.3	5.1	0.0	15.5
Forward citations/year		0.6	0.5	0.3	0.0	9.7
Self citation		10.0	9.0	13.9	0.0	50.0
Originality		29.8	13.4	15.3	0.0	82.0
Generality		29.3	13.9	15.6	0.0	75.0
Enforceability		61.6	14.5	22.0	16.8	96.4

137 spells. 11778 monthly observations.
Indices and proportions reported on a 1-100 scale.
HHI reported on a 1-10,000 scale.
IQR = Interquartile range

Table 4: Estimation of the probability that a patent will be found valid or infringed

		Validity		Infringement	
		Pr(win)	Pr(selection)	Pr(win)	Pr(selection)
COURT	Prior positive	.741 ***		.965 ***	
		(.286)		(.231)	
	Prior negative	- .735 **		- .384	
		(.319)		(.274)	
	Appeal	- .126		- .248	
		(.197)		(.195)	
	Defensive	- .691 **		- .457	
		(.334)		(.317)	
	Pre-1982 decision	- .612		- .408	
		(.410)		(.438)	
	Age at decision	.030		- .117 ***	
		(.034)		(.031)	
SCOPE	Number of IPCs	.384 *	- .080	.221	- .318 **
		(.232)	(.142)	(.224)	(.149)
	Number of claims	.080	.195 **	.295 *	.252 ***
		(.183)	(.088)	(.150)	(.091)
CITATIONS	Backward	- .085 **	.049	- .072	.030
		(.037)	(.036)	(.045)	(.036)
	Backward squared	.001 *	- .000	.002	.000
		(.001)	(.001)	(.001)	(.001)
	Forward	- .088	.763 ***	- .141	.928 ***
		(.208)	(.130)	(.192)	(.119)
	Forward squared	.003	- .042 ***	.010	- .057 ***
		(.014)	(.010)	(.015)	(.009)
	Generality	-1.102 **	.256	- .712	.408
		(.544)	(.303)	(.563)	(.313)
	Originality	.992 **	- .771 **	.704	- .412
		(.483)	(.321)	(.463)	(.299)
	Self citations	- .372	.368	- .525	.092
		(.452)	(.303)	(.513)	(.350)
OTHER	Patent Delay	- .059	- .005	.131 **	.032
		(.056)	(.035)	(.058)	(.055)
	Pre-1983 application	.494	1.031 **	1.643 ***	.917 ***
		(.817)	(.437)	(.584)	(.348)
	1983-1989 application	1.149	.229	1.022 **	.068
		(.720)	(.432)	(.505)	(.338)
	Chemical	- .207	- .201	.121	- .085
		(.328)	(.214)	(.333)	(.231)
	Computers	.186	- .204	- .228	.194
		(.441)	(.304)	(.362)	(.265)
	Drugs/Medical	- .315	.131	- .075	.225
		(.349)	(.280)	(.358)	(.322)
	Electronics	- .248	.015	.315	.087
		(.317)	(.224)	(.349)	(.238)
	Mechanical	- .057	- .342	- .534	- .201
		(.402)	(.237)	(.344)	(.232)
	Constant	.460	-1.880 ***	- .335	-1.982 ***
		(1.445)	(.571)	(1.126)	(.523)
	Log-likelihood	-336.0		-337.1	
	Wald statistic	46		60	
	p-value	.0027		.0000	
	LR test (independence)	.42		0.12	
	p-value	.5181		.7298	
	Obs.	424		464	

Standard errors in parantheses. * p<.1; ** p<.05; *** p<.01.

Table 5: Predicted probabilities of validity and infringement

Type of decision	Obs.	Pr(Win) Conditional	Pr(Win) Unconditional	Pr(Selection)
Validity				
Adjudicated Patents	212	.623	.710	.636
		(.017)	(.015)	(.017)
Valid	132	.723	.794	.650
		(.017)	(.014)	(.021)
Not Valid	80	.457	.571	.612
		(.027)	(.024)	(.029)
Matched Patents	212	.701	.830	.359
		(.013)	(.010)	(.013)
Infringement				
Adjudicated Patents	232	.590	.614	.687
		(.017)	(.017)	(.018)
Infringed	137	.710	.732	.686
		(.018)	(.018)	(.022)
Not infringed	95	.417	.444	.687
		(.024)	(.024)	(.029)
Matched Patents	232	.599	.660	.309
		(.014)	(.014)	(.014)

Standard errors in parantheses.

Table 6: Hazard of engaging in a transaction

	Acquirer			Target			Target---Merger			Target---Spinoff		
	TR		FX	TR		FX	TR		FX	TR		FX
History	.85			.66	***	.66	.59	*	.59	.99		
	(-1.02)			(-2.61)			(-1.90)			(- .04)		
HHI Ag.	1.02			1.02			1.01			1.03	***	288
	(1.45)			(1.19)			(.75)			(3.66)		
Share (log)	.62	***	.09	1.19	*	2.3	1.26	**	3.2	.51	***	.04
	(-3.63)			(1.75)			(2.37)			(-2.79)		
Pct. Ag.	.96	***	.50	.99			1.00			.97	**	.59
	(-5.09)			(-1.34)			(- .99)			(-2.26)		
Enforceability	.95	***	.33	.99			1.01			.86	***	.03
	(-2.72)			(- .63)			(.45)			(-3.32)		
Age	.99			.93			1.01			.88		
	(- .15)			(- .96)			(.20)			(-1.42)		
Generality	.99			1.00			1.01			1.00		
	(- .45)			(.23)			(.86)			(- .08)		
Originality	.99			1.00			1.00			.98		
	(- .76)			(- .04)			(- .10)			(- .65)		
Forward	1.06			.91			1.01			.33		
	(.13)			(- .43)			(.07)			(-1.30)		
Self citations	1.00			.96	*	.60	.98			1.00		
	(- .16)			(-1.73)			(-1.11)			(- .13)		
Constant	.00			.00			.07			.00	*	
	(- .97)			(- .78)			(- .34)			(-1.85)		
Year dummies	YES			YES			YES			YES		
Dist. Parameter	1.45	***		1.12			.89			.98		
	(3.54)			(.85)			(- .52)			(- .09)		
AIC	245			208			170			92		
BIC	452			415			376			298		
Log-likelihood	-95			-76			-57			-18		
Chi-squared	591			157			780			35480		
p-value	.00			.00			.00			.00		
Obs.	11732			11760			11771			11760		
Subjects	86			86			86			86		
Spells	125			97			86			97		
Failures	44			44			33			11		

Z-statistics in parantheses. * p<.1; ** p<.05; *** p<.01.
Incremental effect ("FX") indicates the proportional impact on the time to failure from an interquartile increase in the independent variable (from 25th percentile to 75th percentile).
All results assume the lognormal distribution, and are presented in the accelerated failure time metric as time ratios.
Robust standard errors are clustered by firms.

AJAE Appendix:

The Role of Patent Rights in Mergers:

Consolidation in Plant Biotechnology[1]

Alan C. Marco[2] Gordon C. Rausser[3]

April 18, 2007

[1]Note: The material contained herein is supplementary to the article named in the title and published in the American Journal of Agricultural Economics (AJAE).

[2]Corresponding author. Department of Economics, Vassar College, Poughkeepsie, NY, 12604. marco@vassar.edu. TEL: 845-437-7669, FAX: 845-437-7576.

[3]Robert Gordon Sproul Distinguished Professor, Department of Agricultural & Resource Economics, U.C. Berkeley, Berkeley, CA 94720-3310. rausser@are.berkeley.edu. TEL: 510-642-3345, FAX: 510-643-8911.

The four distributions chosen for the survival estimates are intended to cover a range of parametric survival estimation, since they cover constant (exponential), monotonic increasing or decreasing (Weibull), and hump-shaped (lognormal and log-logistic) hazard functions. Figure 1 graphs the hazard function from semi-parametric Cox proportional hazards estimation. The baseline hazard estimates indicate a hump-shaped hazard function, which supports the lognormal or log-logistic parameterizations. The AIC results do not strongly support any single parameterization across all the models, and the BIC generally supports the exponential distribution. It can be seen in tables 3 to 6 that the time ratios across distributional assumptions are broadly similar.

Figure 2 shows a standard goodness of fit test for survival analysis, as described in Box-Steffensmeier and Jones (2004). The test is based on the cumulative Cox-Snell residuals from the regression using the lognormal distribution. Using the residuals as the analysis time, the integrated hazard rate is estimated from the non-parametric Kaplan-Meier survival function. The integrated hazard is plotted against the cumulative Cox-Snell residuals. A perfect fit would lie along the 45 degree line. Although the fit is not perfect, there is not serious cause for concern. The fit is best for the target/merger model. The target/spinoff model has larger error due to the infrequency of events, and the acquirer model has more error toward the right hand side of the distribution. All four distributions yield similar graphs, so there is little evidence to support one distribution over another.

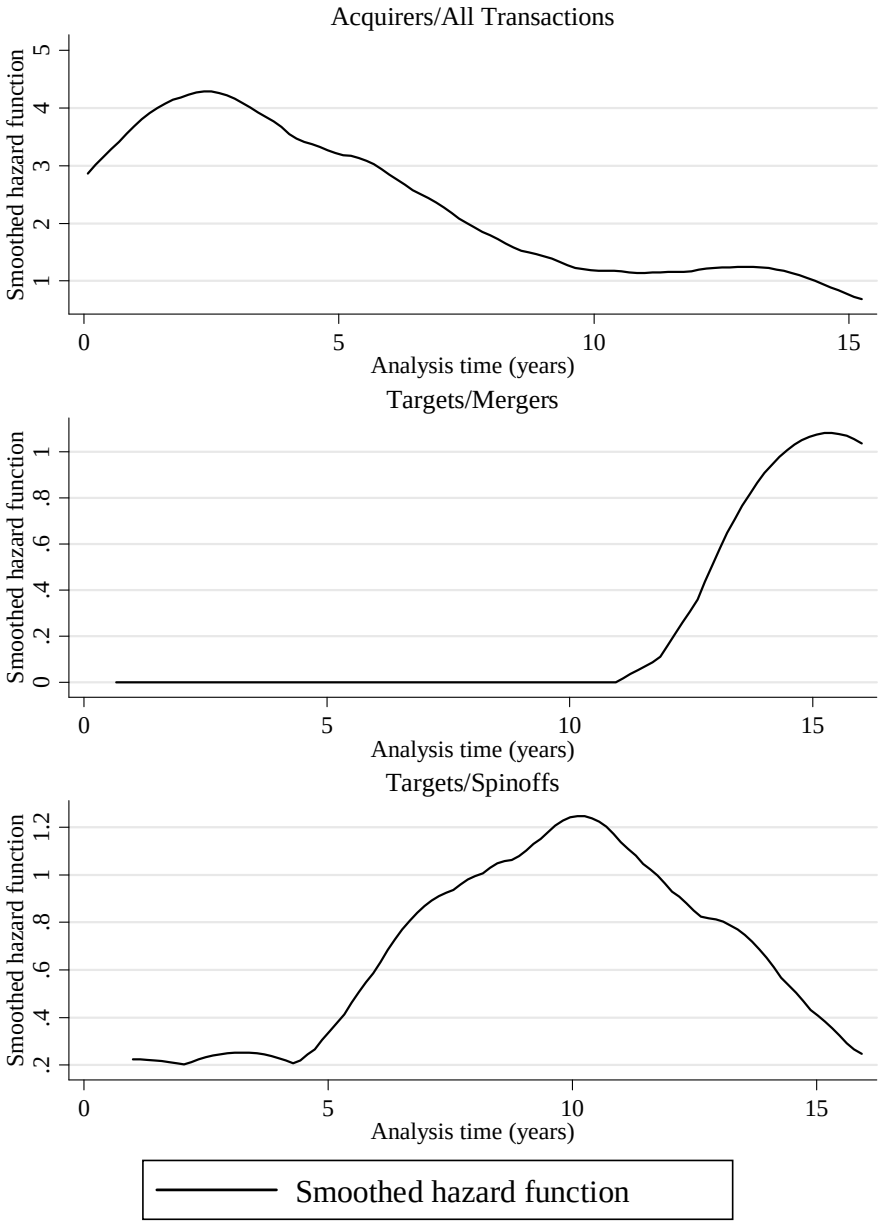
Table 1 lists the sample of firms used in the analysis. Table 2 replicates the primary analysis excluding Monsanto. The results remain essentially unchanged, except that the coefficient on acquisition history for is sensitive to Monsanto's inclusion in the Acquirer model. Tables 3 to 6 compare the original distributional specification (lognormal) to three other distributions: exponential, Weibull, and log-logistic. The time ratios—especially for enforceability—are very consistent

across specifications. No one specification is preferred by the Bayesian information criterion (BIC) and Akaike information criterion (AIC) jointly, although the exponential is preferred by the BIC alone.

References

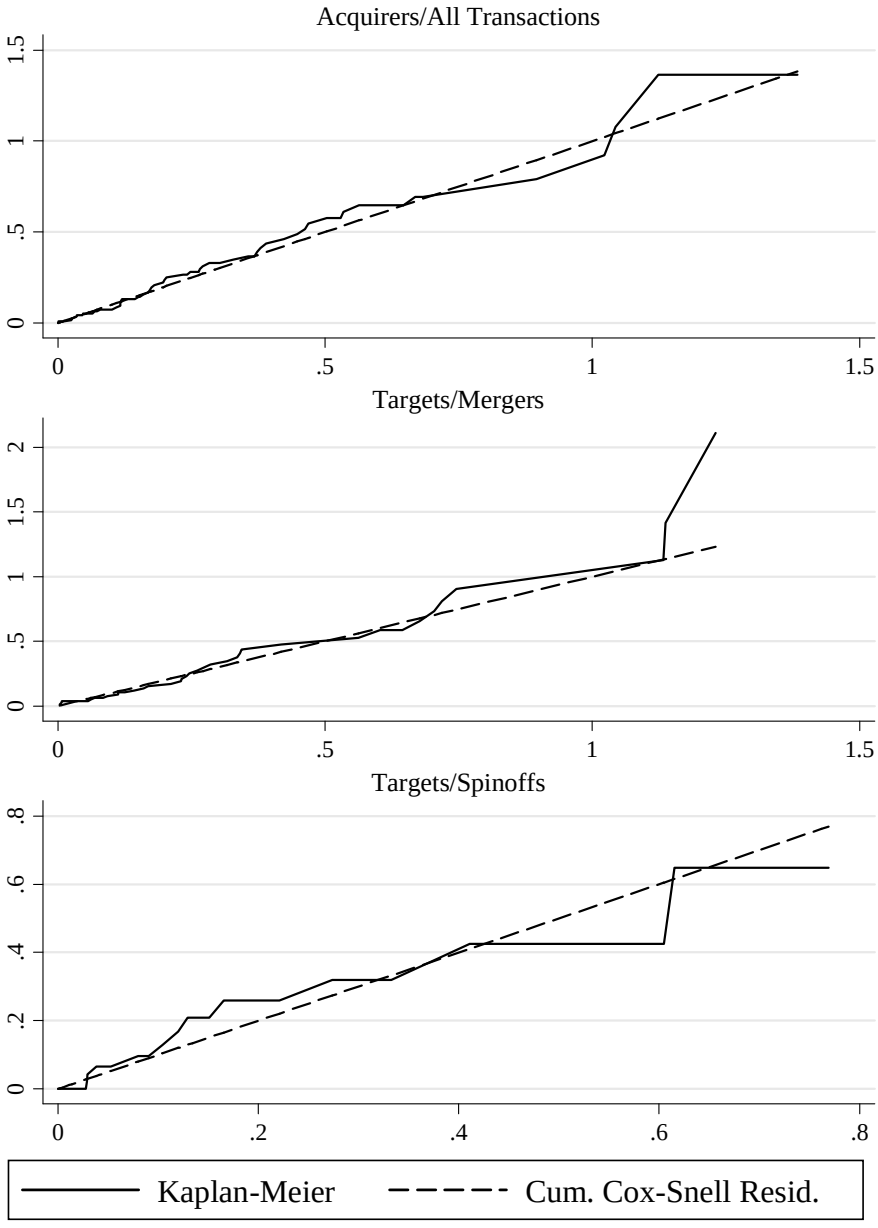
Box-Steffensmeier, J. M., and B. S. Jones (2004): *Event History Modeling: A Guide for Social Scientists*. Cambridge University Press, New York, NY.

Figure 1: Semi-parametric Hazard Estimation



Baseline hazards estimated with Cox proportional hazards model, smoothed with kernel width 1.5.

Figure 2: Goodness of fit



Kaplan-Meier cumulative hazard estimates based on cumulative Cox-Snell residuals (lognormal distribution) as the time variable.

Table 1: Firms used in sample

Advanced Genetic Sciences	Lubrizol Corp
Advanced Polymer Systems	Mallinckrodt Group Inc
Agracetus Corp	Marion Merrell/Merrell Pharmaceuticals
AgrEvo/AgrEvo USA Co	Merck & Co
Agribiotech Inc	MGI Pharma Inc
Agri-Diagnostics Associates	Mogen International NV
AgriDyne Technologies Inc	Monsanto Co
Agrigenetics, LP	Mycogen Corp
Agritope Inc	Nordisk Gentofte
Allelix Inc/Allelix Biopharmaceuticals	Northrup King Co
American Cyanamid Co	Novartis AG
American Maize Products	Novo Corp
Amoco Co	Novo-Nordisk A/S
Asgrow Seed Company	NPS Pharmaceuticals Inc
Astra AB	Nunhems Seeds
AstraZeneca PLC	Ortho Pharmaceutical Corp
Aventis, Inc/Aventis CropScience	Pasteur Merieux
Bayer Corporation	Pfizer Inc
Biosource International Inc	Pharmacia & Upjohn Inc
Biosys Inc	Pharmacia Inc
Biotechnica International Inc	Pioneer Hi-Bred International
Calgene Inc	Plant Genetics Inc
Cargill, Inc	Plant Genetics Systems
Celanese Corp	Plant Science Institute
Chevron Corp	ProdiGene Inc
Ciba-Geigy, Ltd	Rhone-Poulenc SA
Continental Grain Co	Rorer Group, Inc
Copley Pharmaceutical Inc	Savia, SA de CV
Corn States Hybrid	Sandoz AG
Crop Genetics International Corp	Scotts Company
DeKalb Genetics Corp	Sepracor Inc
Delta & Pine Land Co	Shell Oil Company
DNA Plant Technology/Bionova	Sungene Technologies Corp
Dow Chemical (Dow Agrosciences)	Syntro Corp
Du Pont (E I) De Nemours	Systemix Inc
Ecogen Inc	Thermo Ecotek Corp
Ecoscience Corp	Tosco Corp
Empresas La Moderna/ELM	Transgene SA
Epitope Inc	Unilever PLC
Escagenetics Corp	Union Camp Corp
Espro Inc	Union Carbide Corp
FMC Corp	United AgriSeeds, Inc
Genencor International	Upjohn Company
Harris Moran Seed Company	W R Grace & Company
Helena Chemical Co	Westvaco Corp
Hoechst AG	Weyerhaeuser Company
Imperial Chemical Industries	Wilbur-Ellis Company
International Paper Co	Yissum Research Development Co
Limagrain Group/Limagrain Genetics	Zeneca PLC

Table 2: Hazard of engaging in a transaction (excluding Monsanto)

	Acquirer			Target			Target---Merger			Target---Spinoff		
	TR		FX	TR		FX	TR		FX	TR		FX
History	1.24			.71	**	.71	.63			.93		
	(.74)			(-2.11)			(-1.56)			(- .26)		
HHI Ag.	1.03	*	155	1.01			1.01			1.03	***	214
	(1.77)			(1.09)			(.66)			(3.72)		
Share (log)	.56	***	.06	1.19	*	2.3	1.26	**	3.2	.52	***	.04
	(-3.28)			(1.70)			(2.32)			(-2.85)		
Pct. Ag.	.95	***	.48	.99			1.00			.97	**	.58
	(-4.32)			(-1.39)			(-1.03)			(-2.37)		
Enforceability	.94	**	.27	.99			1.01			.86	***	.04
	(-2.46)			(- .69)			(.38)			(-3.35)		
Age	1.03			.93			1.01			.87	*	.49
	(.33)			(-1.07)			(.10)			(-1.68)		
Generality	.99			1.00			1.01			1.00		
	(- .74)			(.20)			(.84)			(.08)		
Originality	1.00			1.00			1.00			.98		
	(- .26)			(- .08)			(- .11)			(- .89)		
Forward	1.07			.90			1.01			.33		
	(.15)			(- .46)			(.04)			(-1.32)		
Self citations	1.01			.96	*	.58	.98			.99		
	(.40)			(-1.77)			(-1.16)			(- .26)		
Constant	.00			.00			.14			.00	*	
	(-1.41)			(- .68)			(- .24)			(-1.73)		
Year dummies	YES			YES			YES			YES		
Dist. Parameter	1.51	***		1.14			.90			.94		
	(3.02)			(.98)			(- .46)			(- .35)		
AIC	217			207			169			90		
BIC	423			413			375			296		
Log-likelihood	-80			-75			-57			-17		
Chi-squared	649			370			951			47230		
p-value	.00			.00			.00			.00		
Obs.	11546			11568			11579			11568		
Subjects	85			85			85			85		
Spells	118			96			85			96		
Failures	38			43			32			11		

Z-statistics in parantheses. * p<.1; ** p<.05; *** p<.01.
Incremental effect ("FX") indicates the proportional impact on the time to failure from an interquartile increase in the independent variable (from 25th percentile to 75th percentile).
All results assume the lognormal distribution, and are presented in the accelerated failure time metric as time ratios.
Robust standard errors are clustered by firms.

Table 3: Hazard of becoming an acquirer

	Exponential			Weibull			Lognormal			Log-logistic		
	TR		FX	TR		FX	TR		FX	TR		FX
History	.76	**	.76	.82	*	.82	.85			.89		
	(-2.57)			(-1.69)			(-1.02)			(- .43)		
HHI Ag.	1.02	**	40	1.03	**	112	1.02			1.02		
	(2.09)			(2.35)			(1.45)			(1.46)		
Share (log)	.66	***	.13	.61	***	.09	.62	***	.09	.60	***	.08
	(-3.31)			(-3.20)			(-3.63)			(-2.89)		
Pct. Ag.	.96	***	.54	.96	***	.49	.96	***	.50	.95	***	.47
	(-5.59)			(-4.62)			(-5.09)			(-4.26)		
Enforceability	.96	*	.44	.95	*	.36	.95	***	.33	.95	**	.29
	(-1.76)			(-1.85)			(-2.72)			(-2.52)		
Age	1.03			1.02			.99			.97		
	(.36)			(.17)			(- .15)			(- .34)		
Generality	1.00			1.00			.99			.99		
	(.06)			(.10)			(- .45)			(- .60)		
Originality	.99			.99			.99			.99		
	(- .81)			(- .95)			(- .76)			(- .59)		
Forward	1.00			.92			1.06			1.15		
	(- .01)			(- .20)			(.13)			(.29)		
Self citations	1.01			1.01			1.00			1.00		
	(.48)			(.40)			(- .16)			(- .07)		
Constant	.00			.00			.00			.00		
	(-1.33)			(-1.58)			(- .97)			(-1.00)		
Year dummies	YES			YES			YES			YES		
Dist. Parameter				.81	*		1.45	***		.86		
				(-1.91)			(3.54)			(-1.32)		
AIC	250			249			245			247		
BIC	449			456			452			453		
Log-likelihood	-98			-97			-95			-95		
Chi-squared	15754			595			591			671		
p-value	.00			.00			.00			.00		
Obs.	11732			11732			11732			11732		
Subjects	86			86			86			86		
Spells	125			125			125			125		
Failures	44			44			44			44		

Z-statistics in parantheses. * p<.1; ** p<.05; *** p<.01.
Incremental effect ("FX") indicates the proportional impact on the time to failure from an interquartile increase in the independent variable (from 25th percentile to 75th percentile).
All results are presented in the accelerated failure time metric as time ratios.
Robust standard errors are clustered by firms.

Table 4: Hazard of becoming a target

	Exponential			Weibull			Lognormal			Log-logistic		
	TR		FX	TR		FX	TR		FX	TR		FX
History	.69	***	.69	.72	***	.72	.66	***	.66	.73	**	.73
	(-3.48)			(-3.35)			(-2.61)			(-2.08)		
HHI Ag.	1.02	**	41.3	1.02	*	20.1	1.02			1.01		
	(2.30)			(1.84)			(1.19)			(.69)		
Share (log)	1.12			1.09			1.19	*	2.3	1.16		
	(1.34)			(1.17)			(1.75)			(1.42)		
Pct. Ag.	.99			.99			.99			.99		
	(-1.07)			(-1.01)			(-1.34)			(-1.13)		
Enforceability	.98			.99			.99			.98		
	(- .75)			(- .73)			(- .63)			(- .83)		
Age	.95			.97			.93			.92		
	(- .74)			(- .49)			(- .96)			(- .86)		
Generality	1.00			1.00			1.00			1.00		
	(.09)			(.01)			(.23)			(.32)		
Originality	1.01			1.01			1.00			1.00		
	(.67)			(.72)			(- .04)			(- .03)		
Forward	.90			.94			.91			.79		
	(- .33)			(- .19)			(- .43)			(- .80)		
Self citations	.97	**	.63	.98			.96	*	.60	.97		
	(-2.18)			(-1.50)			(-1.73)			(-1.19)		
Constant	.00	*		.00			.00			.04		
	(-1.65)			(-1.29)			(- .78)			(- .27)		
Year dummies	YES			YES			YES			YES		
Dist. Parameter				1.21			1.12			.61	***	
				(.96)			(.85)			(-2.73)		
AIC	198			199			208			210		
BIC	397			405			415			417		
Log-likelihood	-72			-71			-76			-77		
Chi-squared	11481			530			157			232		
p-value	.00			.00			.00			.00		
Obs.	11760			11760			11760			11760		
Subjects	86			86			86			86		
Spells	97			97			97			97		
Failures	44			44			44			44		

Z-statistics in parantheses. * p<.1; ** p<.05; *** p<.01.
Incremental effect ("FX") indicates the proportional impact on the time to failure from an interquartile increase in the independent variable (from 25th percentile to 75th percentile).
All results are presented in the accelerated failure time metric as time ratios.
Robust standard errors are clustered by firms.

Table 5: Hazard of becoming a target (mergers)

	Exponential			Weibull			Lognormal			Log-logistic		
	TR		FX	TR		FX	TR		FX	TR		FX
History	.61	***	.61	.74	**	.74	.59	*	.59	.70		
	(-3.61)			(-2.11)			(-1.90)			(-1.64)		
HHI Ag.	1.02	*	28.5	1.01			1.01			1.01		
	(1.70)			(1.42)			(.75)			(.61)		
Share (log)	1.31	***	3.7	1.19	**	2.3	1.26	**	3.2	1.22	*	2.6
	(3.18)			(2.17)			(2.37)			(1.86)		
Pct. Ag.	.99			1.00			1.00			1.00		
	(- .86)			(- .72)			(- .99)			(- .82)		
Enforceability	1.00			1.00			1.01			1.00		
	(- .12)			(- .03)			(.45)			(.03)		
Age	.98			1.02			1.01			1.01		
	(- .25)			(.42)			(.20)			(.21)		
Generality	1.01			1.00			1.01			1.01		
	(.56)			(.35)			(.86)			(.76)		
Originality	1.01			1.01			1.00			1.00		
	(.55)			(.88)			(- .10)			(.13)		
Forward	.88			.96			1.01			.96		
	(- .49)			(- .17)			(.07)			(- .20)		
Self citations	.96	**	.60	.98			.98			.99		
	(-2.38)			(-1.40)			(-1.11)			(- .74)		
Constant	.00			.01			.07			.64		
	(-1.17)			(- .81)			(- .34)			(- .07)		
Year dummies	YES			YES			YES			YES		
Dist. Parameter				1.67			.89			.44	***	
				(1.58)			(- .52)			(-2.96)		
AIC	165			164			170			169		
BIC	364			371			376			375		
Log-likelihood	-55			-54			-57			-56		
Chi-squared	8471			1419			780			2119		
p-value	.01			.00			.00			.00		
Obs.	11771			11771			11771			11771		
Subjects	86			86			86			86		
Spells	86			86			86			86		
Failures	33			33			33			33		

Z-statistics in parantheses. * p<.1; ** p<.05; *** p<.01.
Incremental effect ("FX") indicates the proportional impact on the time to failure from an interquartile increase in the independent variable (from 25th percentile to 75th percentile).
All results are presented in the accelerated failure time metric as time ratios.
Robust standard errors are clustered by firms.

Table 6: Hazard of becoming a target (spinoffs)

	Exponential			Weibull			Lognormal			Log-logistic		
	TR		FX	TR		FX	TR		FX	TR		FX
History	.98			.96			.99			1.24		
	(- .08)			(- .15)			(- .04)			(.59)		
HHI Ag.	1.03	*	172	1.03			1.03	***	288	1.05	***	2100
	(1.84)			(1.55)			(3.66)			(4.58)		
Share (log)	.52	**	.04	.57			.51	***	.04	.41	***	.01
	(-2.13)			(-1.60)			(-2.79)			(-2.77)		
Pct. Ag.	.97			.97			.97	**	.59	.95	**	.47
	(-1.33)			(-1.12)			(-2.26)			(-2.43)		
Enforceability	.87	**	.04	.88	*	.06	.86	***	.03	.82	***	.01
	(-2.20)			(-1.71)			(-3.32)			(-4.27)		
Age	.89			.91			.88			.86		
	(- .87)			(- .83)			(-1.42)			(-1.38)		
Generality	1.00			1.00			1.00			1.01		
	(- .08)			(- .06)			(- .08)			(.22)		
Originality	.98			.98			.98			.98		
	(- .41)			(- .43)			(- .65)			(- .65)		
Forward	.32			.37			.33			.21		
	(-1.19)			(- .99)			(-1.30)			(-1.26)		
Self citations	1.00			1.00			1.00			.98		
	(.04)			(.04)			(- .13)			(- .45)		
Constant	.00			.00			.00	*		.00	**	
	(- .82)			(- .70)			(-1.85)			(-2.47)		
Year dummies	YES			YES			YES			YES		
Dist. Parameter				1.16			.98			.58	**	
				(.64)			(- .09)			(-2.16)		
AIC	94			96			92			91		
BIC	293			303			298			297		
Log-likelihood	-20			-20			-18			-17		
Chi-squared	5558			1274			35480			2072		
p-value	.12			.00			.00			.00		
Obs.	11760			11760			11760			11760		
Subjects	86			86			86			86		
Spells	97			97			97			97		
Failures	11			11			11			11		

Z-statistics in parantheses. * p<.1; ** p<.05; *** p<.01.
Incremental effect ("FX") indicates the proportional impact on the time to failure from an interquartile increase in the independent variable (from 25th percentile to 75th percentile).
All results are presented in the accelerated failure time metric as time ratios.
Robust standard errors are clustered by firms.