INSTITUTE FOR SOCIAL AND ECONOMIC RESEARCH AND POLICY
COLUMBIA UNIVERSITY
WORKING PAPERS

AGRICULTURAL BIOTECHNOLOGY'S COMPLEMENTARY INTELLECTUAL ASSETS

Gregory D. Graff
Agricultural and Resource Economics
University of California at Berkeley

Gordon C. Rausser
Agricultural and Resource Economics
University of California at Berkeley

Arthur A. Small
School of International and Public Affairs / Earth Institute
Columbia University

August 2001

ISERP WORKING PAPER 01-08

ISERP
Institute for Social and Economic Research and Policy

Gregory Graff is Graduate Researcher in the Department of Agricultural and Resource Economics, University of California, Berkeley. Gordon Rausser is Robert Gordon Sproul Distinguished Professor and Member of the Giannini Foundation of Agricultural Economics at the University of California, Berkeley. Arthur Small is Assistant Professor in the School of International and Public Affairs and the Columbia Earth Institute at Columbia University. The authors acknowledge generous financial support from the University of California Systemwide Biotechnology Research and Education Program. Helpful comments were provided by Marianne de Laet, Bronwyn Hall, David Mowery, Brian Wright, Rosemarie Ham Ziedonis, and participants in the Innovation Seminar at the Haas School of Business, University of California, Berkeley. The authors acknowledge particularly the thoughtful comments of two anonymous referees, while accepting responsibility for all remaining omissions and errors. Correspondence to: Gregory Graff, Dept. of Agricultural and Resource Economics, University of California, Berkeley, CA, 94720, USA, ggraff@are.berkeley.edu.

Abstract: We formulate and test a hypothesis for the dramatic restructuring that the plant breeding and seed industry has recently undergone: the reorganization can be explained in part by the desire to exploit complementarities between intellectual assets needed to create genetically modified organisms. This hypothesis is tested using data on agricultural biotechnology patents, notices for field tests of genetically modified organisms, and firm characteristics. The presence of complementarities is identified with a positive covariance in the unexplained variation of asset holdings. Results indicate that coordination of complementary assets have increased under the consolidation of the industry.

JEL Classifications: O32 - Management of Technological Innovation and R&D; Q16 - Agricultural R&D, Technology; L22 – Firm Organization and Market Structure: Markets vs. Hierarchies; Vertical Integration

I. Introduction

One of the central problems in the economics of innovation concerns how industries change as they absorb fundamental research breakthroughs. Rarely has change been more pronounced than in agriculture following the introduction of recombinant DNA technology and affiliated techniques of genetic engineering. By offering breeders the ability to alter plant traits by directly manipulating sequences of genetic code, tools of agricultural biotechnology change the possibilities for crop improvement profoundly. The new techniques enhance the speed and precision of agricultural R&D, while expanding the space of potential new products. Seed firms now offer farmers crop varieties embodying new approaches for controlling pests, managing physical stresses on plants, increasing crop yields, and growing differentiated, quality-enhanced crops.

Concurrent with these technical changes in the R&D process, the agricultural inputs industry has over the past two decades witnessed a comprehensive restructuring. Several large chemical firms including Monsanto, Dow, and DuPont moved aggressively into plant biotechnology, making huge investments in the life sciences. As newly minted “agronomic systems” companies, these firms acquired all of the large, national seed firms in North America, including Pioneer, DeKalb, Asgrow, Garst, and many others. Meanwhile, the research-intensive agricultural biotechnology sector, from its appearance in the 1980s as a large set of small start-up firms, had by the end of the 1990s already reached a second stage, with most of the start-ups either folded or acquired by the new agronomic systems giants. The industry’s consolidation was surprising not only for its rapid pace and comprehensive scope, but also for the extremely high valuations at which some predecessor firms were acquired. In 1997, for example, Monsanto acquired Holdens’ Foundation Seeds of Williamsburg, Iowa, together with two marketing subsidiaries, for $1.02 billion—twenty-five times the annual sales of the mature, privately held firm whose revenues derived entirely from the breeding and distribution of corn seed.

The emergent industry structure—with a relatively small number of tightly woven alliances, each organized around a major life sciences firm, each vertically integrated from basic R&D through to marketing—stands in contrast to the more diffuse structure of twenty years ago. This structure is likewise noteworthy when one considers trends in other research-intensive fields. The pharmaceutical biotechnology industry, for example, maintains a large number of freestanding firms specializing in R&D and earning revenues through various licensing agreements (Majewski, 1998). Hall and Ziedonis (2001) observe that the U.S. semiconductor industry has over the past two decades witnessed a substantial vertical *dis*integration, featuring the appearance of new firms specializing in the intellectual work of chip design while out-sourcing manufacturing tasks. Merges (1998) and Arora (1995) argue that factors increasing the strength of patents in the U.S. during the 1980s have generally enhanced firms’ ability to manage technologies through contractual arrangements, inducing an increase in vertical specialization.

This change in the agricultural-inputs industry structure can be explained as a response to the emergence of new technological opportunities for directly tailoring the genetic makeup of crops. To take advantage of these opportunities firms need to develop or acquire an array of specialized capacities in plant genetics, including tools for plant genetic transformation, genes, and, elite crop germplasm, all of three of which have been patentable in the U.S. and other major markets since the mid 1980s. Furthermore, these three types of intellectual assets are mutually complementary within any given crop system: more of one type of asset yields an increase in the marginal value derived from the other two. These complementarities generate incentives for firms to gain access to all three. However, for a variety of reasons, firms confront serious difficulties or transaction costs in accessing these assets from external sources via licensing agreements. The response of firms is thus to aggregate the intellectual assets in-house.

While the general trend toward consolidation in the agricultural inputs industry is consistent with this complementarities *cum* transaction-costs hypothesis, it is consistent with alternative theories as well. Some economists have argued that the restructuring can be explained by firms' desire to leverage control over key intellectual property to erect barriers to entry and exert market power (Lesser, 1998; Phillips and Stovin, 2000). Others in the industry see firms accumulating patents to use as 'bargaining chips' in negotiations with other firms (Jondle, 1992; Shimoda, 1995), or pursuing acquisitions in an opportunistic response to a transient shift in share prices (Ghodsian, 1995). These and perhaps other explanations can each in principle provide a valid alternative—another element of motivation—for the gross pattern of consolidation and integration. To evaluate a claim that technological complementarities played a key role, additional evidence is required.

Fortunately, the complementarities *cum* transaction-costs model generates distinctive and testable implications about the details of firms' intellectual property (IP) management strategies, which bare upon both their R&D and patenting choices and their merger and acquisition (M&A) strategies. If each of the key types of intellectual property is more valuable in combination with the others, and if combinations through external contracts are inhibited, then we should expect firms to invest in R&D that produces patent portfolios that are not merely larger, but also more *diversified*—following a strategy of "IP diversification through R&D." Likewise, we should expect firms to be especially interested in pursuing mergers and acquisitions that combine dissimilar IP portfolios—following a strategy of "IP diversification through M&A." We would, conversely, not expect to see firms maintaining specialized R&D programs in just one or two of the three patent classes. Nor would we expect to find many mergers that combine similar specialized IP portfolios; opposites should attract.

To test these hypothesis, data are gathered on agricultural biotechnology patents awarded to firms by the U.S. Patent and Trademark Office from 1975 and to 1998, and on characteristics of the firms to which these patents were assigned.[1] Patents are sorted into three classes corresponding to the key categories of plant biotechnology: genetic transformation tools; genetic characteristics; and elite plant germplasm. Using a version of the patent production function pioneered by Griliches (1979) and Hausman, Hall, and Griliches (1984), patent counts in each of the three classes are estimated as functions of firm R&D spending and other characteristics. The presence of complementarities is identified with a positive covariance in the unexplained variation in patent counts. To examine the relationship between patent holdings and M&A activity during the 1990s, the test is performed on data configured two ways: with patents assigned to firms according to the industry's organization in 1994, and again with patents assigned to firms according to the consolidated structure that had emerged by 1999. The procedure allows an examination of whether complementarities—as indicated by positive covariance in the residuals—had increased due to the industry's consolidation.

Results indicate that the patent portfolios of agricultural biotechnology firms exhibit on average a significantly greater dispersion across the three technology classes than can be explained by firm characteristics alone. That is, the evidence supports the hypothesis that firms "diversify through R&D." Moreover, mergers and acquisitions over the five years between 1994 and 1999 served to increase the measured degree of dispersion in patent portfolios. This evidence in support of the "diversification through M&A" hypothesis is further borne out by a case-by-case analysis of individual mergers. We interpret both empirical findings as providing support for a model of endogenous industry restructuring that emphasizes complementarities and transaction costs in the coordination of intellectual assets.

The balance of the paper proceeds as follows. Section 2 develops the conceptual model that explains R&D strategy and M&A strategy as joint responses to a problem of coordinating complementary intellectual assets in the face of high transaction costs. Section 3 describes the data and statistical model used to test our IP management hypothesis that firms "diversify through R&D" and "diversify through M&A." Empirical findings are presented in section 4. Section 5 extends these results with an analysis of how the complementarities-with-transaction-costs framework clarifies the logic behind a number of individual mergers. Section 6 concludes with a discussion of how our empirical findings relate to alternative theories of market restructuring. An appendix details the rules employed to structure patent data into intellectual classes.

II. Coordinating complementary intellectual assets

The theory of asset complementarities provides an explanation of the potential benefits of deliberately coordinating intellectual assets (Teece, 1986). When research processes or assets exhibit complementarities, the decentralization results of welfare economics are no longer assured. It is possible for agents acting independently to become stuck in a strategic dilemma, in which production of knowledge occurs at one of the (privately and socially) less desirable of multiple equilibria. When the owners of different assets adjust their own research outputs independently of one another, without taking into account the positive effect that their production has on the holders of other complementary assets, the total potential (private and social) value of the assets may not be realized. During times of rapid technological or environmental change, and in complex systems industries, effective coordination can be particularly valuable, yet is made even more difficult by additional uncertainty or complexity (Milgrom and Roberts, 1990).

If coordination between complementary assets is required for their full value to be realized, how is it to be achieved? In theory, any of a number of different channels could suffice, ranging from the (external) market exchange of specific assets to the (internal) integration of assets within a firm. (A spectrum of possibilities is illustrated in Figure 1.) The most drastic response to an asset coordination challenge is the complete internalization of assets within a single firm through integration. In such an event, the assets are placed under a unified managerial authority that can dictate a move to a level of utilization corresponding to a (privately) preferred equilibrium. Integration is not, however, always the best solution to a coordination problem: as a firm grows in size, it must coordinate transactions between its internal assets through increasingly bureaucratic procedures of command and control. The advantages of exploiting complementarities internally must be balanced against increases in the cost of governance that accompany coordination of assets within a firm's boundaries. Indeed, the cost-of-governance argument implies that, *ceteris paribus*, complementary assets should be coordinated through arms-length market contracts.

On the other hand, external transactions for knowledge are also inherently problematic and costly. The economic literature on problems of contracting for knowledge (Arora, Fosfuri, and Gambardella, 1999; Pisano, 1990; Rausser, 1999; Somaya and Teece, 2000; Zeckhauser, 1996) describe several general classes of problems that cause technology licensing markets to fail: (1) *diffuse entitlement problems* result from the fragmentation of technology space by the assignment of mutually blocking property rights often compounded by problems of poorly defined boundaries between separately assigned rights; (2) *value allocation problems* result from both rational and biased asset valuation differences between buying (in-licensing) and selling (out-licensing) parties; (3) *monitoring and metering problems* involve difficulties in writing and enforcing contracts over technological and commercial contingencies that can arise in dynamic, uncertain environments; and (4) *strategic problems* arise from the rent dissipating effects of licensing to other firms and thereby creating new competitors in final product markets or result from the inevitable existence of market power and small-numbers bargaining problems in thin markets for individual, idiosyncratic, and highly specific intellectual assets.

The choice of coordination channel is based on an *ex ante* assessment of the difference between the likely future benefits and costs of each option. When the *ex ante* distribution of expected returns under an internalized solution (appropriable rents from a full set of complementary assets minus the cost of internal governance of those assets) dominates the *ex ante* distribution of expected returns under an externalized solution (share of appropriable rents from a specialized subset of complementary assets minus the transaction costs of coordinating with external assets), internalization is the rational choice. The greater the degree of failure in markets for licensing knowledge and contracting R&D, the greater the transaction costs and thus the more likely will decisions be made to internalize complementary intellectual assets.

Agricultural biotechnology, indeed, suffers from many of the ailments common to technology markets. Patenting authorities have apparently had a difficult time defining patent boundaries appropriately and reliably. The early history of patent awards clearly show patent examiners struggling to navigate unsteady terrain. Two early patents originally assigned to W.R. Grace & Co. would as written have given the company control over *all* genetically engineered varieties of cotton. The scope of these patents was eventually narrowed, following appeals and protests. Such reversals, even if not usually so dramatic, have been relatively common in the agricultural biotechnology field. At times patent litigation has seemed rampant in the industry. At one point in the mid 90s, while the six major companies developing Bt insect resistance traits for crops were simultaneously pursuing no less than seven cooperative R&D agreements among themselves, the same six companies were simultaneously fighting eight separate patent infringement lawsuits against one another other (Krattiger, 1997). More subtle licensing problems have arisen as well, such as *'anti-stacking provisions'* where one company contracting to insert its genetic traits into a collaborating company's germplasm prohibits any third-party genetic material into the same germplasm to be marketed together. While this could be understood as a blanket contract policy to avoid unforeseeable technological problems, it may also be a strategy to avoid rent dissipation effects or simply a refusal to confront value allocation problems. In general, the costs and risks associated with transacting IPRs over cutting-edge biotechnologies in agriculture have been high enough to inhibit those transactions (Barton, 1998; Wright, 1999).

Given such an environment of high transaction costs, this theory of agricultural firms coordinating complementary intellectual assets is reduced to the two following testable hypotheses, the first predicting the pattern of firm diversification through R&D and the second predicting the pattern of firm diversification through M&A:

Hypothesis 1.a: We hypothesize that the following pairs of broadly defined intellectual asset are complementary: (1) plant genetic transformation technologies are complementary to trait-specific plant gene technologies; (2) plant genetic transformation technologies are complementary to germplasm of high-yielding commercial plant varieties; and (3) trait-specific plant gene technologies are complementary to germplasm of high-yielding commercial plant varieties. These combinations are summarized in Table 1, where a plus (+) indicates an individual pair of intellectual asset types is hypothesized to be complementary.

Hypothesis 1.b: As a direct result of hypothesis 1.a, we hypothesize that firms' portfolios will be biased towards a balance across all three mutually complementary technologies and away from specialization in a single technology. Specifically, *we would expect firms to hold more balanced, diversified patent portfolios than would be explained solely by the firms' observed characteristics*.

Hypothesis 2: Firms have an incentive to execute mergers and acquisitions that combine disparate intellectual asset portfolios. Accordingly, we expect to see the degree of specialization decline over time as a result of mergers. Thus, we expect to observe that *changes in market structure brought about by mergers and acquisitions over the course of several years increase the aggregate degree of portfolio diversification*. If complementarities were not present, or were balanced by incentives toward technological specialization, we would not expect to see a systematic increase in diversification over time.

III. Data and methodology

The first task is to identify the particular intellectual assets or knowledge that contribute to the value of agronomic or seed product lines. Fortunately, the historical configuration of the agricultural inputs industry makes identification of the key types of knowledge assets rather convenient, given the roughly separate seed sector, the chemicals sector, and, more recently, the startup biotechnology R&D sector. The actual measurement of knowledge assets is, however, not as straightforward. While we are fundamentally interested in the intangible knowledge assets of a firm, no reliable direct measures exist from secondary sources that quantify such intangible assets. We follow the literature reviewed by Griliches (1990) and look to patent counts as an indirect measure of a firm's economically significant knowledge. Our model assumes that a firm's key intellectual assets in plant biotechnology are reasonably represented by the count of US utility patents assigned to that firm in three distinct technological categories: technologies for plant transformation; gene sequences and genetically identified traits; and elite germplasm.[2]

Technologies for plant transformation. Utility patents cover an array of techniques for transferring DNA into plant cells and for regenerating from these cells mature plants that have the new genetic trait stably integrated and properly expressed. Patents have been issued for genetic transformation methods including agrobacterium, microprojectiles, electoporation, and virus vectors. Plant tissue culture patents cover culture media and methods, somatic embryogenesis, plant regeneration, micropropagation, and *in vitro* selection techniques. Other patented technologies necessary for successful genetic transformation include selectable genetic markers, gene promotors, and other non-specific molecular mechanisms for the regulation of an inserted gene's expression. The variable "TRANS" counts the number of patents granted to a firm from 1975 through the end of 1998 for plant transformation technologies.

Gene sequences and genetically coded traits and enhancements. Utility patents are likewise granted for genes and genetic sequences, "the software" that codes for specific physical or behavioral traits of an organism. Patents have been issued for genes that improve crop yield, resist disease or pests, allow host plants to tolerate applied herbicides or environmental stress, improve nutrient content, delay the ripening of fruits, or cause the production of biological molecules in the tissues of the host plant. The variable "GENE" counts a firm's gene patents granted from 1975 through 1998.

Elite germplasm. Utility patents are also granted for plant varieties, "the hardware" or "the rest of the plant" which are genetically transformed to create genetically enhanced crop varieties. These patents are typically issued for hybrid crop lines, such as maize, and for major crop varieties that reproduce sexually, such as soybean. This class also includes a few patents on processes of plant breeding, hybridization, and selection. A firm's germplasm utility patents granted from 1975 through 1998 are counted in the variable "GERM".

The test we develop to detect the presence of complementarities among these classes of intellectual property is fashioned after a test formulated by Arora and Gambardella (1990). According to a review by Athey and Stern (1999), most recent empirical studies of complementarity use such a revealed preferences-type approach. After controlling for all observable, exogenous characteristics, the unobservable complementarity can be detected as it drives positive correlation or clustering between observed actions that are assumed to be optimizing solutions of the firm. In agricultural biotechnology, the unobserved asset valuation of firm *i*, $V(\mathbf{y}_i;\ \boldsymbol{\theta}_i)$, is a function of the observed numbers of patents held by firm *i* in the three classes, $\mathbf{y}_i = [y_{i1}, y_{i2}, y_{i3}]^T$ where $y_{i1}=\text{TRANS}_i$, $y_{i2}=\text{GENE}_i$, and $y_{i3}=\text{GERM}_i$, conditional on $\boldsymbol{\theta}_i$, a set of conditioning firm characteristics that includes a firm's share of the entire set of agbiotechnology patents, a firm's holdings of other biotechnology patents, total firm sales, firm R&D expenditures, and a count of field tests conducted by that firm of genetically modified crops. These variables reflect, respectively, the following characteristics: a firm's degree of monopolization of the total intellectual assets in the agricultural biotechnology industry, a firm's internal stock of other related biotechnological knowledge, a firm's overall size, the amount of resources a firm dedicates to developing its total stock of knowledge, and R&D activities undertaken by a firm specifically to develop its stock of knowledge in plant biology.

A firm's share of all plant biotechnology patents is simply what percentage the firm holds of the industry's total agbiotech patents: the sum of the firm's agbiotech patents divided by the sum of the industry's. It is intended to serve as a proxy for the degree of market power that a firm exercises over the source of new product innovations in the agricultural biotechnology industry through concentration of proprietary technologies. By employing this variable in the complementarity test, we seek to separate out the market power hypothesis from the complementary intellectual assets and transaction costs hypotheses.

The count of other biotechnology patents was made at the same time as the count of agricultural biotechnology patents. It includes all of a firm's patents in US patent classifications 435 (molecular biology and microbiology), 436 (analytical and immunological testing), 530 (peptides, proteins, and lignins), and 930 (peptides and protein sequences), except for those patents already counted in TRANS, GENE, and GERM. By including this variable we encompass the entire set of biotechnology patents granted to a firm by the end of 1998.

Total sales revenues in 1994 represent the overall size of a firm. It is expected that the size of a firm partially explains the propensity of a firm to develop and patent innovations. Sales figures for 1994 were obtained from CompuStat, various analyst reports in Lexis-Nexis, a US biotechnology industry survey by Dibner (1995), and direct firm disclosures.

Research and development intensity is the most significant available measure of a firm's capacity to develop patented technologies relative to its size (Griliches, 1990; Hausman, Hall, and Griliches, 1984). R&D intensity is the ratio of a firm's total R&D expenditures to a firm's total sales. Figures for 1994 R&D expenditures are taken from the same sources as those for sales.

The number of transgenic regulatory notices filed with USDA-APHIS by commercial agricultural biotechnology researchers can be considered a measure of R&D activities undertaken specifically to develop agricultural biotechnology knowledge assets (Huttner, Miller, and Lemaux, 1995). The USDA Animal and Plant Health Inspection Service (APHIS) regulates the release and field-testing of genetically modified organisms. Effective since April 1993, firms and other research organizations are required to file a 'notice' with APHIS whenever they intend to make a shipment or an outdoor field test of one of the major types of genetically modified plant or microorganism (as specified on a predefined list.) Our variable 'NOTICES' counts the cumulative number of such notices that a firm had made to APHIS between 1993 and the end of 1998. [3]

Data were collected for a total of 76 separately named firms and business units, many of which are now commonly owned or merged. An individual firm or business unit was included in the sample if it met one or more of the three following criteria: (1) if patents in any of the three agricultural biotechnology classes were assigned to it, (2) if any APHIS notices had been submitted in its name, or (3) if it was otherwise known to play a significant role in the US agricultural biotechnology industry.[4]

A. Constructing unconsolidated and consolidated industry samples

Significant changes have occurred in the industry's structure in recent years, with a major round of consolidation occurring specifically between 1994 and 1999.[5] In order to explore with limited data the relationship between changes in industry structure and intellectual asset complementarities, the data were tabulated into two separate samples. The first sample aggregates our data on 76 separate business units and firms into 60 individual observations by adding together the data of merged firms, owners and subsidiaries, and alliances partners, in 60 distinct 'businesses or business groups'[6] (See Table 4.a). This list of 60 reflects the relatively *un*consolidated structure of the industry observed in 1994, just before the surge of agbiotech mergers and acquisitions commenced in earnest. The second sample tabulates the same data from the 76 separate firms and business units into 46 combined 'businesses or business groups' (Table 4.b), reflecting the more consolidated industry's structure observed in 1999 resulting from five years of intense merger and acquisition activities.[7] The same underlying data—the counts of patents and APHIS notices at the beginning of 1999 and the figures for sales and R&D from 1994—were used in both samples, so they do not constitute true, separate data panels from different points in time; the only difference between the two samples rests in how the observations are tallied up.

In essence, the first sample presents a counterfactual scenario: what *would* the allocation of patents (granted by 1999) *have* looked like *if* no mergers or acquisitions had occurred since 1994. Because of the lag of several years between (the unobservable) patent application and (the observable) patent grant, the first sample may also be interpreted as presenting the private information held by firm managers about intellectual assets in the pipeline pending as patent applications in 1994, when they began making decisions to consolidate. The second sample presents the actual scenario: what *did* the allocation of those same patents look like in 1999, *after* those decisions had been made by managers and the mergers and acquisitions had occurred, holding all other factors constant.

B. The statistical model

By definition, two classes of patents are complementary if an increase in the stock one raises the marginal value of the other. Formally, two classes of patents *k, l, k≠l*, are complementary if $V_{kl} \equiv \partial^2 V/\partial y_k \partial y_l > 0$, where, as above, y_k and y_l denote a firm's patent counts in the respective classes. Arora & Gambardella (1990) posit a testable criterion for the presence of complementarities: for a pair of patent classes, the covariance between counts y_k and y_j, conditional upon firm characteristics $\boldsymbol{\theta}$, must be positive:

$$E[(y_k - E(y_k\,|\boldsymbol{\theta}))\cdot(y_l - E(y_l\,|\boldsymbol{\theta}))\,|\boldsymbol{\theta}] > 0$$

or

$$\text{Cov}\,(y_k,y_l\,|\boldsymbol{\theta}) > 0. \tag{1}$$

Expected counts of the size of patent portfolios are generated, conditioned on other firm characteristics, $E(y_{ik}\,|\theta_i)$, for firms $i = 1\ldots I$ and patent classes k = TRANS, GENE, GERM. This is accomplished by estimating equations for TRANS(θ), GENE(θ), and GERM(θ) using observed patent counts— y_{ik} = [TRANS_i, GENE_i, GERM_i] on the left hand side—and conditioning variables, θ_i, on the right hand side, for each of the *i* firms. Given the particular nature of these patent count data, we follow Hausman, Hall, and Griliches (1984) and specify a negative binomial model, a generalization of the Poisson model that allows for overdispersion of the dependent count variable.[8]

The negative binomial, with Poisson parameter λ_{ik}, represents the average count of events (patents) in class *k* which occur "randomly and independently" over a period of time for firm *i* when the observed number of events (patents) has been y_{ik}. A useful specification of the Poisson parameter is

$$\lambda_{ik} = \exp(\beta_k \theta_i). \tag{2}$$

The expected value of the negative binomial is

$$E[y_{ik}(\theta_i)|\theta] = \lambda_{ik}/\delta_k = \exp(\beta_k \theta_i) / \delta_k \tag{3}$$

where the β_k are vectors of coefficients to be estimated along with the negative binomial distribution's variance parameter, δ_k, and the left-hand-side expected count parameter, λ_{ik}. The conditioning set, $\boldsymbol{\theta}$ = [CONST, SHARE, (0.001×BIOTECH_i), (0.00001×SALES_i), RANDINT_i, (0.001×NOTICES_i)], is the same for all three patent class estimations.[9] From the estimation results, residuals are obtained

$$u_{ik} = y_{ik} - E[y_{ik}(\theta_{ik})|\boldsymbol{\theta}] = y_{ik} - \lambda_{ik}/\delta_k \tag{4}$$

from which standardized residuals can be calculated for each patent class *k*,

$$\varepsilon_{ik} = u_{ik} / \sigma_{ik} \tag{5}$$

where $\sigma^2_{ik} = \exp(\beta\theta_{ik}) / \delta_k^2$ is the estimated variance of the negative binomial process. Finally, the pairwise correlation of the standardized residuals of the three classes of patents can be calculated as

$$\rho_{k,l} = \text{Cov}(\varepsilon_k, \varepsilon_l \mid \boldsymbol{\theta}) / (\sigma_k \sigma_l), \tag{6}$$

where σ_k is the standard deviation of the standardized residuals for patent class $k \neq l$. Complementarity between the knowledge stocks of two technology classes would be indicated, in accordance with equation (1), by a positive correlation coefficient. We test for this condition in all three pairings of agricultural biotechnology patents classes in both the actual (consolidated) 1999-structure sample and the counterfactual (unconsolidated) 1994-structure sample.

Two important limitations of this residuals based complementarity test should be noted. First, the model necessarily assumes that the variables in the conditioning set, **θ,** fully explain the systematic variation among firms in the numbers of patents held in each of the three plant biotechnology classes; in other words, the test is good only to the extent that there are no significant omitted variables. (Or, more accurately, it is claiming that just one significant explanatory variable has been necessarily omitted because it cannot be measured, that is the effect of the complementarity.) Second, in any such method for measuring revealed complementarity among multiple pairs of variables, each of the individual pair-wise tests is, in theory, sensitive to interaction effects with the others. In particular, strong complementarity between two pairs—say between A and B and between B and C—could drive a positive correlation between the third possible pairing—between A and C—even if A and C were in fact weak substitutes. Thus, the test has full explanatory power only to the extent that all three variables are mutually complementary.

IV. Results

Results from the negative binomial maximum likelihood estimations are presented in Table 2.a. for the unconsolidated industry sample (reflecting the industry structure in 1994 with 60 observations) and in Table 2.b. for the consolidated industry sample (reflecting the industry structure in 1999 with the same firm data combined or consolidated into 46 observations). A number of insights can be gleaned from the coefficient estimates in the regressions since the estimated independent variable coefficients of the negative binomial model have a semi-elasticity interpretation (Cameron and Trivedi, 1996),

$$\beta_{\theta k} = \frac{\partial E[y_{ik}(\theta_i) | \theta]}{\partial \theta_i} \cdot \frac{1}{E[y_{ik}(\theta_i) | \theta]} \ . \tag{7}$$

In the unconsolidated 1994 industry (Table 2.a), the measure of a firms' share of total patents in the agbiotech industry (SHARE) is, as would be expected, a significant and positive predictor of the firm's patent count in all three classes of technology. For the consolidated 1999 industry (Table 2.b), where the significance of all the independent variables is lower, across the board, the effect of SHARE on germplasm patents (GERM) is still significant. This reflects the fact that the strongest players in the industry, those with the largest shares of total agbiotech patents had moved aggressively during this time period to obtain access to germplasm. Most importantly, the significance of SHARE in these regressions assures us that the generated estimates of firm patent holdings—the E[TRANS(θ)|$\boldsymbol{\theta}$], E[GENE(θ)|$\boldsymbol{\theta}$], and E[GERM(θ)|$\boldsymbol{\theta}$]—do take into account each firms' degree of monopolization over the industry's total intellectual capital stock, and it is thus not omitted from the model nor does it end up in the estimate residuals.

The conditioning variable that counts APHIS field-test filings (NOTICES) is, under both regimes, strongest for plant transformation and plant gene patents. In the unconsolidated 1994 industry sample, APHIS filings positively and significantly predict transformation and gene patent counts, but not germplasm patent counts. This is understandable: transformation and gene patents were already strongly correlated with one another in 1994 (Figure 1.a), and firms rich in these two technologies were generally able to generate more field tests of genetically modified organisms. Meanwhile most of the independent seed firms, while rich in germplasm patents, lacked access to transformation methods and genes except through costly, risky, and strategically unstable external licensing channels. In fact, the point estimate for the NOTICES coefficient is negative (albeit not significantly so) for germplasm patents in the consolidated 1999 industry. This seems curious since in the 1999-structured industry the independent seed firms had been folded into the larger corporate groups who are indeed filing many notices with APHIS. However, this result is driven by the simple fact that, while NOTICES are rather spread out across firms, germplasm patents are concentrated into effectively just four firms: a large proportion of firms in the sample have a positive measure of NOTICES but do not have any germplasm patents.

The negative relationships obtained between R&D intensity (R&DINT) and patent outputs contradict conventional wisdom from empirical R&D-patenting studies (Griliches, 1990) [10], although it is indistinguishably close to zero in the TRANS and GENE equations in both years. On closer examination, however, this seemingly counterintuitive result does make sense. Most of the seed firms rich in germplasm and independent in 1994 invested less intensively in R&D than did the chemical, pharmaceutical, and biotech R&D firms that make up the bulk of the industry. Since our R&D expenditure data are not field-specific, the variable captures a general-to-specific 'total-R&D'-to-'agbiotech-patents' relationship. The relationship is negative because enough of the firms with small agbiotech patent portfolios (such as Upjohn, Pfizer, Mitsubishi, Sumitomo, etc.) have greater R&D intensity than the major agbiotech patent holders.

Finally, the size of the firm, as represented by the SALES variable, shows a significant positive relationship with gene patents in the unconsolidated 1994 industry sample, indicating simply that the larger corporations dominated in plant gene development before consolidation. In the consolidated 1999 industry sample, size matters only weakly in all three technologies.

A. Estimated correlation between deviations in patent counts: hypothesis testing

The results of the pair wise complementarity tests among the three classes of patents—the correlation coefficients of the standardized Poisson residuals—are displayed in Tables 3.a. and 3.b. Particularly in the consolidated 1999 industry results (Table 3.b), the correlation coefficients are close in magnitude to estimates generated by a similar procedure in Gambardella (1995), which he claims as evidence of complementarity among strategic research linkages of pharmaceutical firms.

The hypothesis that a correlation coefficient is greater than zero (H_1: $\rho_{k,l} > 0$)—the criterion revealing complementarity (Eq. 1 and 6)—is tested with a bootstrapped distribution of the estimate. The standardized residuals in two technologies are sampled with replacement, and the correlation coefficient between the drawn samples is calculated; iterated 1000 times. This process generates bootstrapped distributions of the correlation coefficient estimates from which a *p* value can be calculated for the null hypothesis that the correlation coefficient is less than or equal to zero (H_0: $\rho_{k,l} \leq 0$). When $p < 0.010$ the null is rejected with 99% confidence; when $p < 0.050$, with 95% confidence; when $p < 0.100$, with 90% confidence.

In order to display the correlation coefficient estimates, histograms of the bootstrapped distribution for each of the three technology-type pairings (TRANS-GENE, TRANS-GERM, and GENE-GERM) from the two different industry structure samples are smoothed by a kernel density estimator and plotted together (Figure 2). A quantile-quantile plot of each pairing demonstrates whether the two distributions are significantly different (Figure 3), particularly whether or which one stochastically dominates the other.

Tests of Hypothesis 1.a: In the unconsolidated industry (as represented by the sample organized according to the 1994 industry structure), the estimated correlation between standardized residuals of the TRANS patent equation and the GENE patent equation is 0.562. (See Table 3.a.) The *p* value derived from the bootstrapped distribution of the correlation coefficient estimate is 0.001; only a single value resulting from the 1000 bootstrap calculations is less than zero, and thus the null hypothesis that the correlation coefficient is less than or equal to zero is rejected with 99.9% confidence. In the consolidated industry (as represented by the sample organized according to the 1999 industry structure), the point estimate of the correlation between the TRANS and GENE equations' standardized residuals is slightly larger, at 0.572, with a *p* value of 0.015. (See Table 3.b.) The correlation between standardized residuals of the TRANS patent equation and the GERM patent equation in the 1994 unconsolidated industry sample, at a point estimate of -0.003 and less than zero over 49 percent of its bootstrapped distribution (*p* value = 0.486), appears very nearly centered on zero, and the null hypothesis fails to be rejected. (See Table 3.a. and Figure 2.) Yet, in the consolidated 1999 industry sample the point estimate is 0.230 with a *p* value of 0.100 (Table 3.b.), and the null is rejected with precisely 90 percent confidence. The correlation between GENE and GERM residuals in the unconsolidated 1994 industry sample is -0.142 and is less than zero over 87 percent of its bootstrapped distribution (*p* value = 0.869) and again the null hypothesis that the correlation coefficient is less than zero clearly fails to be rejected. (Table 3.a.; Figure 2.) In the consolidated industry sample the correlation is 0.321 with a *p* value of 0.135 (Table 3.b and Figure 2.); thus, the confidence with which the null is rejected is slightly weaker, at 86 percent.

The complementarity criterion is clearly met for transformation technology patents (TRANS) and plant gene patents (GENE) under both the 1994 and the 1999 industry structures, and thus we do not hesitate to conclude that these two are indeed complementary technologies. Likewise, the unexplained deviations in transformation patents (TRANS) and germplasm patents (GERM) move together at least within the consolidated structure of the 1999 industry, revealing the complementarity of these two technologies. Finally, unexplained deviation in plant gene patents (GENE) and germplasm patents (GERM) in the consolidated 1999 industry are similarly correlated, revealing a degree of complementarity of these two technologies as well.

Tests of Hypothesis 1.b: Taken together, the results from the 1999-structured sample directly imply that firms' patent portfolios are biased towards balance of this full set of mutually complementary agricultural biotechnologies and away from specialization in any one of the three. It should be noted that firm portfolios across the industry are more balanced *than can be* *explained solely by the firms' conditioning characteristics*, including their individual shares of total patent holdings. In other words, a randomized lottery generated by a negative binomial process to give away the industry's intellectual assets in lots identical in size to observed firm shares would tend to assign lots of patents that are more clustered into one or two of the technologies than is actually observed. This hypothetical lottery would not spread the three types of intellectual assets as smoothly among firms as the actual industry has in fact done.

Tests of Hypothesis 2: Moving from the unconsolidated to the consolidated industry samples we detect a shift in the degree to which the three categories of plant biotechnology patents occur together. This suggests that, again on an industry wide basis, the internalization of asset ownership has been realized or "unlocked" a greater degree of complementarity in these intellectual assets. While the distribution of the TRANS-GENE correlation coefficient remains relatively unchanged by the restructuring of the sample from the 1994 industry's structural regime to the 1999 industry's structural regime, the point estimate does increase slightly. A distinct shift is observed in the distribution for TRANS and GERM holdings from roughly zero to a significantly positive estimated correlation. Distributions of the estimates are shown to be significantly different by the corresponding TRANS-GERM q-q plot in Figure 3. Likewise, change in industry structure causes a distinct shift from the 1994 distribution to the 1999 distribution of estimated correlation between the unexplained portions of GENE and GERM holdings, as shown in the GENE-GERM q-q plot in Figure 3.

The direction of mergers and acquisitions between 1994 and 1999 has combined disparate intellectual asset portfolios, and the aggregate degree of technological specialization has decreased as a result. Conversely, *the aggregate degree of portfolio diversification has increased over time*. If complementarities were not present, or were balanced by incentives toward technological specialization, we would not have seen a systematic increase in diversification.

V. Individual acquisitions and mergers

These results suggest the IP management logic behind many of the particular merger and acquisition events observed in the agricultural biotechnology industry during the five years from 1994 to 1999. The small sample size of firms and the simplicity of the procedures in this analysis make it convenient to display the patent count data, which illustrate firm-by-firm patterns in patent holdings in these three technologies. Tables 6.a and 6.b display the agbiotech patent portfolios of the individual firms or corporate groups, listing the actual count of patents alongside the model's estimation of how many patents 'should' be held by each firm in each technology. The tables also show the standardized residuals; correlation between these columns is the test we have just used to reveal complementarity between the respective technology classes at the industry level. Qualitatively, at the firm level the standardized residual in a technology category indicates the direction and relative magnitude by which a firm's actual holdings in that technology class deviate from predicted holdings. The following observations and commentary on individual merger and acquisition deals suggest a may suggest more systematic ways to seek or to predict acquisitions using this kind of individual firm data.

Several interesting observations emerge from comparisons of firms' portfolios in the industry before and after consolidation (Tables 6.a and 6.b respectively.) Consider the patent position of Monsanto in the 1994 industry: the firm held fewer patents than the model leads us to expect in all three categories, based on its strength in other biotechnologies, its size, its R&D intensity, and its proclivity to file APHIS notices. The addition of ten cotton and soybean transformation (TRANS) patents through the purchase of Agracetus from W. R. Grace[11] helps to explain that acquisition by Monsanto in 1996 even though it had been licensing Agracetus' technology since 1991. Other gaps in Monsanto's portfolio were helped by the stepwise acquisition of Calgene between 1995 and 1997, which was rich in TRANS and GENE patents, and by the purchases of Holden's Foundation Seed and Asgrow Agronomics in 1997, rich in corn and soybean GERM patents respectively. Interestingly, the acquisition of DeKalb by Monsanto in 1998 appears to have been more favorable for its transformation technologies than for its stock of corn germplasm. The planned addition of Delta & Pine Land clearly brought with it little in the way of patented technologies, which may in part explain why that acquisition was recently called off. With its numerous acquisitions, the assembled Monsanto group almost exactly fits the model's expectations for its intellectual property portfolio in Table 4.b. The fact that it does not exceed expectations may in part explain Monsanto's recent acquisition by a more diversified corporation, Pharmacia-UpJohn.

The 1996 marriage of Ciba-Geigy and Sandoz in the formation of Novartis made good sense in light of the differences in their 1994 agricultural biotechnology portfolios. While Ciba clearly entered the deal as the stronger partner in all three technologies, the addition of Sandoz technologies allowed the combined Novartis to emerge in 1999 as a strong industry leader, exceeding portfolio expectations across the board and clearly ahead of the positions of both Ciba and Sandoz measured in the context of the 1994 industry structure.

The Zeneca group strengthened its IP portfolio through its acquisition of Mogen in 1997. Mogen's positions in the TRANS and GENE categories bolstered the portfolio of the existing Zeneca group (ICI, Zeneca, and Garst) already solid in these areas, while complementing the latter's strong GERM presence. This acquisition put the Zeneca group well ahead of the model's estimates in all three categories in the 1999 industry.

Another good IP decision was the acquisition of Mycogen by Dow, which took place in sequential stages between 1996 and 1998. In the unconsolidated 1994 industry Dow was relatively weak in all three technologies while Mycogen was the star of the industry in generating GENE patents and held a solid advantage in TRANS patents. In the consolidated industry the combined Dow group is one of the strongest in TRANS and GENE technologies, yet is still lagging in germplasm.

The purchase of Plant Genetic Systems (PGS) by Hoechst's AgrEvo subsidiary in 1996 and Hoechst's merger with Rhone-Poulenc in 1999 to create Aventis results in a combined agricultural biotechnology patent portfolio that still fails to achieve the model's expectations for the firm in TRANS and GERM. Before the purchase and the merger, both Hoechst and Rhone-Poulenc held small relative advantages in GENE patents and both lagged in TRANS and GERM patents. PGS added strength in TRANS and GENE patents, particularly in *Bt* insect resistance technologies; however, the end result in the Aventis portfolio, ahead of expectations only moderately in GENE patents, seems to combine the constituents' weaknesses and to dilute some of their strengths.

The industry dark horse is Savia (formerly Empresas La Moderna). In the 1994 industry ELM had no US patents and thus lagged in all three technology-asset categories. After the acquisition of PetoSeed in 1995, the piecewise acquisition of DNA Plant Technologies in 1996, and the formation of Seminis in 1997, the new Savia group in 1999 emerged ahead of model expectations in all three technologies and came to dominate in the vegetable seed sector.

The top seven firms in terms of intellectual-asset holdings clearly came to dominate in the consolidated 1999 industry. (See Table 5.) Together these seven firms controlled three quarters of the TRANS and GENE patents and nearly all of the GERM patents in the industry. Given the higher industry-wide correlation that has emerged in patent holdings, many of the opportunities for combining disparate complementary portfolios in these technologies appear to have already been exploited.

VI. Conclusions

This work uses the complementarity between different types of genetic engineering technologies to explain firm boundaries and industry consolidation of agricultural biotechnology. As a result R&D and M&A strategies are examined as joint, coordinated activities. We test the hypothesis that the reorganization of the industry can be explained in part by the desire to exploit these complementarities, using data on agricultural biotechnology patents, government permits to release genetically modified organisms, and firm characteristics from seventy-six companies engaged in agricultural biotechnology research. Statistically significant complementarity is measured by a positive covariance in the unexplained variation in the intellectual asset holdings of the firms across the industry. We find that firms build intellectual asset portfolios that are more evenly balanced than would be otherwise expected, and that the industry's reorganization over the past five years has strengthened this effect.

These findings support the hypothesis that the industry's recent restructuring is causally driven by the attempt of firms to achieve coordination between complementary intellectual assets in the face of transaction costs on the external exchange of those assets. The findings, of course, do not rule out other considerations; however, they do raise questions about models that explain the industry's recent restructuring in terms of economy-wide influences. The incentive to erect barriers to entry and enhance market power; the strengthening of the U.S. patent system; technical changes that increase the productivity of the IP management process—all of these factors operate across all technology sectors, so it is not clear why the differential outcomes we observe in these three agricultural biotechnology classes should obtain.

As an example, if R&D and M&A strategies were jointly oriented toward a goal of achieving market power, then there would be no obvious reason to find in firms' patent portfolios any systematic dispersion across the three patent classes. If anything, one might expect the reverse: incentives to develop narrowly specialized IP portfolios. Economies of scale in the R&D process might give firms an incentive to specialize their patent production activities more narrowly. Mergers and acquisitions would seek to internalize technological substitutes, not complements. By controlling as many patents as possible in one class, a firm might then be able to extract rents by controlling the market for an essential input to the product development process. Once established in a technology, a firm would be more likely to undertake arms length contracts to coordinate with complementary technologies given its stronger negotiating position and would thus be less likely to internalize complementary assets.

In combination with complementarities and transaction costs, economy-wide forces could well have played an important role in the restructuring: a firm with a substantial portfolio of important intellectual property, for example, might indeed attempt to exert market power. The claim, rather, is that none of these other factors *by themselves* would have generated the dispersed pattern or the direction of change in IP holdings that we see in the data.

The case of the agricultural inputs industry provides a clear example of firms coordinating R&D strategy with M&A strategy, both in service to an overarching goal: assembly of the large and diverse arrays of intellectual property needed to pursue biotechnology-based approaches to complex agricultural product development, with greater reliability and lower cost than licensing the numerous component technologies.

REFERENCES

Arora, Ashish, "Licensing tacit knowledge: intellectual property rights and the market for know-how," *Economics of Innovation and New Technologies* 4 (1995), 41-59.

________, and Alfonso Gambardella, "Complementarity and external linkages: the strategies of the large firms in biotechnology," *Journal of Industrial Economics* XXXVIII:4 (June 1990), 361-379.

________, Andrea Fosfuri, and Alfonso Gambardella, "Markets for technology (why do we see them, why don't we see more of them, and why we should care)," Heinz School of Public Policy and Management working paper, Carnegie Mellon University (1999).

Athey, Susan, and Scott Stern, "An Empirical Framework for Testing Theories About Complimentarity in Organizational Design," NBER working paper no. 6600 (June 1998).

Barton, John, "The Impact of Contemporary Patent Law on Plant Biotechnology Research," in S.A. Eberhart, H.L. Shands, W. Collins, and R.L. Lower (Eds.), *Global Genetic Resources: Access and Property Rights*, (Madison, WI: Crop Science Society of America, 1998)

Cameron, A. Colin and Pravin K.Trivedi, "Count Data Models for Financial Data," in G. S.Maddala and C. R. Rao (Eds.), *Statistical Methods of Finance*, Handbook of Statistics series, Vol. 14, (Amsterdam, New York, and Oxford: Elsevier, North-Holland, 1996), 363-391.

Dibner, Mark, *Biotechnology Guide U.S.A.*, 3rd ed., (Research Triangle Park, NC: Institute for Biotechnology Information, 1995).

Gambardella, Alfonso, *Science and Innovation: The US Pharmaceutical Industry During the 80s,* (Cambridge: Cambridge University Press, 1995).

Ghodsian, Fariba F., "Acquisition as a best-case scenario," *Bio/Technology* 13 (May 1995), 426-427.

Goss, Peter J., "Guiding the hand that feeds: toward socially optimal appropriability in agricultural biotechnology innovation," *California Law Review* 84 (1996), 1395-1436.

Griliches, Zvi, "Issues in assessing the contribution of research and development to productivity growth," *Bell Journal of Economics* 10 (Spring 1979), 92-116.

________, "Patent statistics as economic indicators," *Journal of Economic Literature* XXVIII (December 1990), 1661-1707.

Hall, Bronwyn H. and Rosemarie Ham Ziedonis, "The patent paradox revisited: an empirical study of patenting in the U.S. semiconductor industry, 1979-1995," *RAND Journal of Economics* 32:1 (Spring 2001), 101-128.

Hausman, Jerry, Bronwyn H. Hall, and Zvi Griliches, "Econometric models for count data with an application to the patents-R&D relationship," *Econometrica* 52:4 (July 1984), 909-938.

Huttner, Susanne L., Henry I. Miller, and Peggy G. Lemaux, "U.S. Agricultural Biotechnology: Status and Prospects," *Technological Forecasting and Social Change* 50 (1995), 25-39.

Jondle, R., "The Licensing Game: Without Patents, You Don't Get to Play," *AgBiotechnology News* (December 1992), 1-5.

Krattiger, Anatole F., "Insect Resistance in Crops: A Case Study of *Bacillus thuringiensis (Bt)* and its Transfer to Developing Countries," International Service for the Acquisition of Agri-biotech Applications (ISAAA) Brief no. 2 (Ithaca, NY: ISAAA, 1997).

Lesser, William, "Assessing the Implications of Intellectual Property Rights in Plant and Animal Agriculture," *American Journal of Agricultural Economics* 79:5 (1997), 1584-1591.

________, "Intellectual property rights and concentration in agricultural biotechnology," *AgBioForum* 1:2 (Fall 1998), 56-61.

Macher, Jeffrey, David C. Mowery, and D. Hodges, "Reversal of Fortune? The Recovery of the U.S. Semiconductor Industry," *California Management Review* 41 (1998), 107-136.

Majewski, Suzanne E., *Causes and Consequences of Strategic Alliance Formation: The Case of Biotechnology*, University of California-Berkeley Ph.D. dissertation (1998).

Merges, Robert, "Property Rights, Transactions, and the Value of Intangible Assets," Boalt School of Law manuscript, University of California-Berkeley (1998).

Milgrom, Paul and John Roberts, "The Economics of Modern Manufacturing: Technology, Strategy, and Organization," *American Economic Review* 80:3 (June 1990), 511-528.

Phillips, Peter W.B., and Derek Stovin, "The Economics of Intellectual Property Rights in the Agricultural Biotechnology Sector," in M. Qaim, A. F. Krattiger, and J. von Braun (Eds.), *Agricultural Biotechnology in Developing Countries: Toward Optimizing the Benefits for the Poor*, (Dordrecht: Kluwer Academic Publishers, 2000).

Pisano, Gary, "The R&D Boundaries of the Firm: An Empirical Analysis," *Administrative Sciences Quarterly* 35 (1990), 153-176.

Rausser, Gordon C., "Private/Public Research: Knowledge Assets and Future Scenarios," *American Journal of Agricultural Economics* 81:5 (1999), 1011-1027.

Shimoda, Sano, "Putting Together the Patent Puzzle: the Key to Competitive Position and Profits," BioScience Securities, Inc. report (May 1995).

Somaya, Deepak, and David Teece, "Combining Inventions in Multi-invention Products: Organizational Choices, Patents, and Public Policy," Haas School of Business manuscript, University of California-Berkeley (2000).

Teece, David, "Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy," *Research Policy* 15 (1986), 285-305.

Wright, Brian D., "Challenges for Public Agricultural Research and Extension in a World of Proprietary Science and Technology," Department of Agricultural and Resource Economics manuscript, University of California-Berkeley (1999).

Zeckhauser, Richard, "The challenge of contracting for technological information," *Proceedings of the National Academy of Science* 93 (November 1996), 12743-12748.

FIGURE 1. SPECTRUM OF CHANNELS OF COMPLEMENTARY INTELLECTUAL ASSET COORDINATION

Acquisition and integration of other innovating firm	**Partial acquisition of other innovating firm**	**Strategic research partnership with other innovating firm**	**Ongoing R&D contract**	**Purchase or exclusive license of patent**	**Non-exclusive license of patent; purchase of input technology component**

Most internalized ⟷ **Most externalized or "arms-length"**

TABLE 1. HYPOTHESIZED ASSET COMPLEMENTARITIES UNDER THE NEW TECHNOLOGICAL REGIME OF AGRICULTURAL BIOTECHNOLOGY

Having more of one asset has what effect on the marginal value of the others?	Process Technologies (TRANS)	Genetic Traits: (GENE)	Elite Germplasm Lines: (GERM)
Process Technologies (TRANS)	*		
Genetic Traits: (GENE)	+	*	
Elite Germplasm Lines: (GERM)	+	+	*

*On the diagonal, the self-effect is the economies of scale of that asset.

TABLE 2.A. REGRESSION RESULTS FOR THE UNCONSOLIDATED INDUSTRY (1994 STRUCTURE)

Independent variables:	Dependent variables: TRANS	GENE	GERM
CONST	**-1.186***	**-1.063***	**-2.38***
	(.314)	**(.282)**	**(.358)**
SHARE	**.103***	**.117***	**.242***
	(.026)	**(.020)**	**(.020)**
BIOTECH	**.157**	**0.042**	**.055**
	(.101)	**(.159)**	**(.165)**
SALES	**.125**	**.206***	**.161**
	(.084)	**(.057)**	**(.112)**
R&DINT	**-.118**	**0.092**	**-1.912***
	(.234)	**(.198)**	**(.820)**
NOTICES	**.720***	**.853***	**.135**
	(.211)	**(.250)**	**(.261)**
$\boldsymbol{\delta}_k$ (variance parameter)	**.147***	**0.076***	**0.049***
	(.042)	**(.027)**	**(.022)**
Log Likelihood Function	**218.9**	**1187.3**	**1106.0**
R^2	**.202**	**.358**	**.828**

Heteroskedastic-consistent standard errors computed from analytic first and second derivatives (Eicker-White) in parentheses.

* Indicates significant t statistic.

TABLE 2.B. REGRESSION RESULTS FOR THE CONSOLIDATED INDUSTRY (1999 STRUCTURE)

Independent variables:	Dependent variables: TRANS	GENE	GERM
CONST	**-1.132***	**-0.783***	**-1.808***
	(.359)	**(.294)**	**(.448)**
SHARES	**.062**	**.074**	**.210***
	(.042)	**(.065)**	**(.031)**
BIOTECH	**.157**	**.135**	**-.121**
	(.140)	**(.255)**	**(.173)**
SALES	**.083**	**.155**	**.132**
	(.094)	**(.103)**	**(.127)**
R&DINT	**-.298**	**-.123**	**-2.416**
	(.311)	**(.231)**	**(1.330)**
NOTICES	**.620**	**.298**	**-.032**
	(.471)	**(.657)**	**(.320)**
$\boldsymbol{\delta}_k$ (variance parameter)	**0.152***	**0.086***	**0.159***
	(.053)	**(.038)**	**(.075)**
Log Likelihood Function	**378.8**	**1483.0**	**1299.5**
R^2	**.755**	**.618**	**.984**

Heteroskedastic-consistent standard errors computed from analytic first and second derivatives (Eicker-White) in parentheses.

* Indicates significant t statistic.

TABLE 3.A. PAIR WISE CORRELATION AMONG THE STANDARDIZED RESIDUALS FROM THE REGRESSIONS FOR THE UNCONSOLIDATED INDUSTRY (1994 STRUCTURE)

Correlation coefficients	TRANS	GENE	GERM
TRANS	1.000		
GENE	.562	1.000	
	(.001)		
GERM	-.003	-.142	1.000
	(.486)	(.869)	

In parenthesis: *p* value of test that coefficient is less than or equal to zero.

TABLE 3.B. PAIR WISE CORRELATION AMONG THE STANDARDIZED RESIDUALS FROM THE REGRESSIONS FOR THE CONSOLIDATED INDUSTRY (1999 STRUCTURE)

Correlation coefficients	TRANS	GENE	GERM
TRANS	1.000		
GENE	.572	1.000	
	(.015)		
GERM	.230	.321	1.000
	(.100)	(.135)	

In parenthesis: *p* value of test that coefficient is less than or equal to zero.

FIGURE 2. BOOTSTAPPED DISTRIBUTIONS OF ESTIMATED CORRELATION COEFFICIENTS.

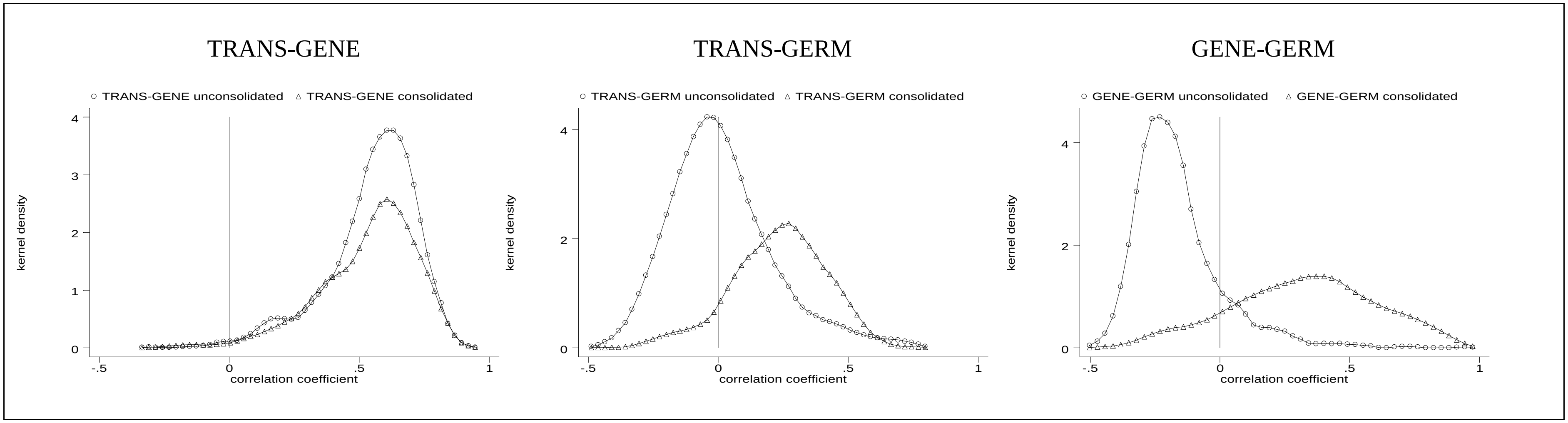

FIGURE 3. QUANTILE-QUANTILE PLOTS COMPARING DISTRIBUTIONS OF THE CORRELATION COEFFICIENT ESTIMATES BETWEEN CONSOLIDATED AND UNCONSOLIDATED INDUSTRY SAMPLES.

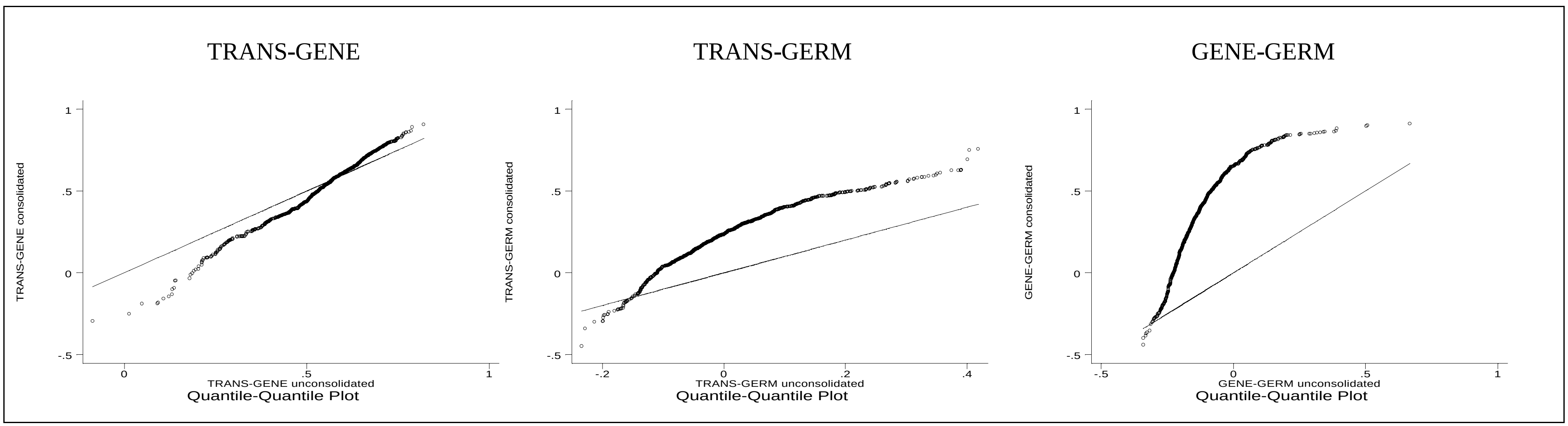

TABLE 4.A. ACTUAL VERSUS ESTIMATED PATENT PORTFOLIOS—WITH STANDARDIZED RESIDUALS—FOR THE UNCONSOLIDATED INDUSTRY (1994 STRUCTURE)

Patent counts: **TRANS**		Patent counts: **GENE**		Patent counts: **GERM**		Standardized residuals:			
Actual	Estimate	**Actual**	Estimate	**Actual**	Estimate	ε_{TRANS}	ε_{GENE}	ε_{GERM}	**FIRM(S)**
0	1.75	**1**	5.26	**0**	0.11	-0.51	-0.51	-0.07	**AgriDyne**
2	2.09	**3**	5.27	**0**	0.63	-0.02	-0.27	-0.18	**Agritope**
2	2.90	**6**	5.81	**0**	1.99	-0.20	0.02	-0.31	**American Cyanamid**
0	2.25	**8**	4.98	**0**	2.24	-0.58	0.37	-0.33	**American Maize**
1	4.76	**10**	14.77	**0**	5.53	-0.66	-0.34	-0.52	**Amoco**
2	4.15	**11**	9.86	**0**	3.68	-0.40	0.10	-0.42	**Bayer**
4	2.01	**0**	5.10	**0**	0.50	0.54	-0.62	-0.16	**Biosource**
0	2.00	**1**	4.77	**0**	0.86	-0.54	-0.48	-0.21	**biosys/ Crop Genetics**
0	2.11	**0**	4.57	**0**	1.77	-0.56	-0.59	-0.29	**Biotechnica**
5	2.18	**0**	4.84	**0**	1.95	0.73	-0.61	-0.31	**Boswell/ Phytogen**
25	4.10	**41**	10.66	**0**	3.92	3.95	2.56	-0.44	**Calgene**
0	2.25	**0**	5.10	**3**	2.07	-0.57	-0.62	0.14	**Campbell Soup**
0	4.23	**4**	13.74	**1**	4.48	-0.79	-0.73	-0.36	**Cargill**
13	6.84	**37**	15.98	**16**	8.90	0.90	1.45	0.53	**Ciba-Geigy/ (Novartis**)**
9	3.37	**5**	8.17	**19**	3.00	1.18	-0.31	2.04	**DeKalb**
1	2.15	**0**	4.86	**0**	1.56	-0.30	-0.61	-0.28	**Delta & Pine Land**
20	2.95	**14**	7.25	**4**	2.18	3.80	0.69	0.27	**DNA Plant Technology**
5	6.77	**0**	11.11	**0**	3.91	-0.26	-0.92	-0.44	**Dow/ Lilly/ DowElanco**
11	10.75	**28**	29.34	**5**	11.83	0.03	-0.07	-0.44	**Du Pont/ (Optimum Quality Grains**)**
0	2.24	**10**	5.09	**0**	1.68	-0.57	0.60	-0.29	**Ecogen**
0	1.23	**0**	6.83	**0**	0.00	-0.43	-0.72	0.00	**EcoScience**
0	2.08	**0**	4.59	**0**	1.78	-0.55	-0.59	-0.29	**Empresas La Moderna (ELM) (now Savia)**
1	1.71	**4**	5.73	**0**	0.05	-0.21	-0.20	-0.05	**ESCAGenetics**
1	2.27	**2**	5.10	**0**	2.00	-0.32	-0.38	-0.31	**FMC**
0	2.32	**0**	4.77	**0**	1.48	-0.58	-0.60	-0.27	**Genencor**
4	10.86	**26**	22.59	**1**	6.89	-0.80	0.20	-0.50	**Hoechst/ Schering/ AgrEvo**
0	3.24	**0**	7.60	**47**	4.64	-0.69	-0.76	4.34	**Holden's Foundation Seeds**
6	2.71	**0**	6.83	**0**	2.80	0.76	-0.72	-0.37	**International Paper**
6	3.59	**4**	10.44	**1**	4.13	0.49	-0.55	-0.34	**Japan Tobacco**
0	2.19	**5**	4.82	**0**	2.11	-0.57	0.02	-0.32	**Jinro**
4	2.62	**3**	5.98	**0**	2.51	0.33	-0.34	-0.35	**Kirin**
0	2.14	**0**	4.79	**0**	1.73	-0.56	-0.60	-0.29	**Limagrain**
7	2.48	**6**	5.49	**2**	2.33	1.10	0.06	-0.05	**Lubrizol**
0	1.97	**7**	5.36	**0**	0.30	-0.54	0.20	-0.12	**MGI Pharma (Molecular Genetics Inc.)**
0	3.17	**5**	6.65	**0**	2.58	-0.68	-0.18	-0.35	**Mitsubishi Chemical**
4	2.06	**11**	5.86	**0**	0.27	0.52	0.59	-0.12	**Mogen International**
17	17.44	**44**	46.88	**2**	9.40	-0.04	-0.12	-0.53	**Monsanto**
21	5.93	**88**	14.93	**3**	16.87	2.37	5.22	-0.75	**Mycogen/ Agrigenetics**
0	2.97	**6**	5.52	**0**	1.90	-0.66	0.06	-0.30	**Novo Nordisk**
0	1.99	**10**	5.57	**0**	0.26	-0.54	0.52	-0.11	**NPS Pharmaceuticals**
0	2.25	**0**	5.05	**0**	1.74	-0.57	-0.62	-0.29	**PetoSeed/ (Seminis**)**
0	2.70	**2**	5.79	**6**	1.66	-0.63	-0.43	0.74	**Pfizer**
11	26.58	**52**	86.33	**172**	198.92	-1.16	-1.02	-0.42	**Pioneer Hi-Bred International**
6	2.35	**27**	7.83	**0**	0.12	0.91	1.89	-0.08	**Plant Genetic Systems**
0	1.67	**1**	5.56	**0**	0.04	-0.50	-0.53	-0.05	**ProdiGene**
1	3.69	**18**	8.26	**0**	3.27	-0.54	0.93	-0.40	**Rhone-Poulenc/ Harris Moran**
5	3.38	**10**	8.17	**5**	3.01	0.34	0.18	0.25	**Sandoz/ Northrup King/ (Novartis**)**
1	2.41	**4**	5.48	**0**	2.34	-0.35	-0.17	-0.34	**Sapporo**
0	2.09	**0**	4.62	**0**	1.74	-0.55	-0.59	-0.29	**Scotts**
0	2.45	**4**	5.15	**1**	2.07	-0.60	-0.14	-0.16	**Sumitomo Chemical**
0	2.09	**5**	5.01	**0**	0.83	-0.55	0.00	-0.20	**Syntro**
0	2.46	**3**	5.13	**3**	2.24	-0.60	-0.26	0.11	**Takara Shuzo**
0	2.70	**0**	6.34	**0**	6.13	-0.58	-0.59	-0.31	**Thermo Trilogy*/ Thermo Ecotek***
1	4.75	**6**	14.63	**2**	11.02	-0.60	-0.53	-0.34	**Unilever (Conopco/ Van den Bergh)**
0	2.89	**2**	6.82	**0**	6.32	-0.60	-0.43	-0.32	**Union Camp**
5	3.76	**0**	8.13	**62**	5.30	0.23	-0.67	3.09	**Upjohn/ Asgrow**
10	3.28	**10**	7.54	**0**	6.43	1.30	0.21	-0.32	**W R Grace/ Agracetus**
6	3.02	**0**	6.96	**0**	6.43	0.60	-0.62	-0.32	**Westvaco**
6	3.15	**0**	7.90	**0**	7.20	0.56	-0.66	-0.34	**Weyerhaeuser**
6	4.25	**38**	10.20	**22**	7.62	0.30	2.04	0.65	**Zeneca/ ICI/ Garst**

* Independent startups after 1994 were treated as independent observations in the unconsolidated industry.
** Patents assigned to firms created after 1994 by merger or joint venture were attributed in the unconsolidated industry to the parent firm at which the lead inventor of the patent had worked prior to the creation of the combined firm.

TABLE 4.B. ACTUAL VERSUS ESTIMATED PATENT PORTFOLIOS—WITH STANDARDIZED RESIDUALS—FOR THE CONSOLIDATED INDUSTRY (1999 STRUCTURE)

Patent counts: TRANS Actual	TRANS Estimate	Patent counts: GENE Actual	GENE Estimate	Patent counts: GERM Actual	GERM Estimate	Standardized residuals: ε_{TRANS}	ε_{GENE}	ε_{GERM}	FIRM(S)
2	1.86	**3**	5.17	**0**	0.24	0.04	-0.28	-0.20	**Agritope**
2	2.76	**6**	7.13	**0**	0.76	-0.18	-0.12	-0.35	**American Cyanamid**
0	2.23	**8**	5.68	**0**	1.18	-0.58	0.29	-0.43	**American Maize**
1	3.78	**10**	13.61	**0**	2.25	-0.56	-0.29	-0.60	**Amoco**
11	11.83	**67**	34.07	**1**	3.96	-0.09	1.65	-0.59	**Aventis (Hoechst/ Rhone-Poulenc/ PGS)**
2	3.55	**11**	10.83	**0**	1.32	-0.32	0.02	-0.46	**Bayer**
4	1.77	**0**	5.06	**0**	0.18	0.65	-0.66	-0.17	**Biosource**
2	2.13	**0**	5.41	**0**	0.98	-0.04	-0.68	-0.39	**Boswell**
0	2.23	**0**	5.77	**3**	1.09	-0.58	-0.70	0.73	**Campbell Soup**
0	3.44	**4**	11.80	**1**	2.04	-0.72	-0.66	-0.29	**Cargill**
26	5.81	**88**	18.56	**3**	8.60	3.26	4.72	-0.76	**Dow/ Mycogen/ Agrigenetics/ Phytogen**
22	39.03	**80**	124.83	**177**	185.51	-1.06	-1.17	-0.25	**Du Pont/ OQG/ Pioneer**
0	2.14	**10**	5.59	**0**	0.81	-0.57	0.55	-0.36	**Ecogen**
0	0.56	**0**	3.08	**0**	0.00	-0.29	-0.51	0.00	**EcoScience**
3	4.10	**0**	10.18	**0**	0.55	-0.21	-0.93	-0.29	**Eli Lilly**
1	1.20	**4**	4.30	**0**	0.01	-0.07	-0.04	-0.04	**ESCAGenetics**
1	2.24	**2**	5.83	**0**	1.02	-0.32	-0.46	-0.40	**FMC**
0	2.33	**1**	5.90	**0**	0.65	-0.59	-0.59	-0.32	**Genencor/ Prodigene**
6	2.52	**0**	7.20	**0**	1.42	0.85	-0.79	-0.47	**International Paper**
6	3.05	**4**	9.92	**1**	1.93	0.66	-0.55	-0.27	**Japan Tobacco**
0	2.19	**5**	5.55	**0**	1.13	-0.58	-0.07	-0.42	**Jinro**
4	2.51	**3**	6.74	**0**	1.21	0.37	-0.42	-0.44	**Kirin**
0	2.24	**1**	5.58	**0**	0.91	-0.58	-0.57	-0.38	**Limagrain/ Biotechnica/ Harris Moran**
7	2.36	**6**	6.11	**2**	1.12	1.18	-0.01	0.33	**Lubrizol**
0	1.63	**7**	4.94	**0**	0.09	-0.50	0.27	-0.12	**MGI Pharma (Molecular Genetics Inc.)**
0	2.99	**5**	8.10	**0**	1.02	-0.67	-0.32	-0.40	**Mitsubishi Chemical**
64	63.06	**100**	98.76	**130**	132.71	0.05	0.04	-0.09	**Monsanto/ Agracetus/ Asgrow/ Calgene/ DeKalb/ Delta&Pine[#]/ Holden's**
18	7.15	**47**	20.94	**21**	4.11	1.58	1.67	3.32	**Novartis (Ciba/ Sandoz)/ Northrup King**
0	2.87	**6**	7.24	**0**	0.68	-0.66	-0.14	-0.33	**Novo Nordisk**
0	1.59	**10**	4.94	**0**	0.08	-0.49	0.67	-0.11	**NPS Pharmaceuticals**
0	2.52	**2**	6.73	**6**	0.65	-0.62	-0.53	2.64	**Pfizer**
1	2.35	**4**	6.20	**0**	1.20	-0.34	-0.26	-0.44	**Sapporo**
20	2.90	**14**	7.23	**4**	1.78	3.91	0.74	0.66	**Savia (formerly ELM)/ DNAP/ PetoSeed/ Seminis**
0	2.60	**3**	6.72	**0**	0.59	-0.63	-0.42	-0.30	**Schering**
0	2.11	**0**	5.34	**0**	0.92	-0.57	-0.68	-0.38	**Scotts**
0	2.42	**4**	6.17	**1**	0.96	-0.61	-0.26	0.01	**Sumitomo Chemical**
0	1.92	**5**	5.27	**0**	0.34	-0.54	-0.03	-0.23	**Syntro**
0	2.43	**3**	6.16	**3**	1.07	-0.61	-0.37	0.75	**Takara Shuzo**
0	2.11	**2**	5.39	**0**	0.88	-0.57	-0.43	-0.37	**Thermo Trilogy/ Thermo Ecotek/ AgriDyne/ biosys/ Crop Genetics**
1	3.46	**6**	12.06	**2**	2.00	-0.52	-0.51	0.00	**Unilever (Conopco/ Van den Bergh)**
0	2.29	**2**	5.87	**0**	1.05	-0.59	-0.47	-0.41	**Union Camp**
3	2.69	**0**	6.89	**0**	0.61	0.07	-0.77	-0.31	**Upjohn**
0	2.35	**0**	6.01	**0**	0.91	-0.60	-0.72	-0.38	**W R Grace**
6	2.47	**0**	6.41	**0**	1.14	0.87	-0.74	-0.42	**Westvaco**
6	2.48	**0**	6.82	**0**	1.31	0.87	-0.76	-0.46	**Weyerhaeuser**
10	4.75	**49**	13.92	**22**	4.04	0.94	2.75	3.56	**Zeneca/ ICI/ Garst/ Mogen**

[#] Monsanto holdings in Delta & Pine were later divested. This occurred however after the time scope of this study. See discussion of Monsanto's acquisitions in Section 5.

Table 5. ***Agricultural biotechnology patent holdings of top seven corporate groups as of January 1999***

FIRM(S)	TRANS patents	GENE patents	GERM patents
Monsanto/ Agracetus/ Asgrow/ Calgene/ DeKalb/ Delta & Pine/ Holden's Foundation Seed	64	100	130
Du Pont/ Optimum Quality Grains/ Pioneer	22	80	177
Zeneca/ ICI/ Garst/ Mogen	10	49	22
Novartis (Ciba/ Sandoz)/ Northrup King	18	47	21
Dow/ Mycogen/ Agrigenetics/ Phytogen	26	88	3
Savia (ELM)/ DNA Plant Technology/ PetoSeed/ Savia	20	14	4
Aventis (Hoechst/ Rhone-Poulenc) Plant Genetic Systems	11	67	1
TOP SEVEN'S TOTAL PATENT HOLDINGS:	171	445	358
INDUSTRY'S TOTAL PATENT HOLDINGS:	229	582	377
TOP SEVEN'S HOLDINGS AS PERCENT OF INDUSTRY TOTAL:	74.5	75.5	95.0

ENDNOTES

[1] The USPTO did not award utility patents on plants or plant parts before 1985. Thus, most of these patents accrued in the latter years.

[2] For detailed specifications of the following technology categories, an appendix is available from the corresponding author.

[3] In practice firms often file APHIS notices while they are in the application process for patents on a given technology. While this raises the concern of possibly simultaneity between NOTICES and the patent counts, all of the key results are found to be robust to the exclusion of the NOTICES variable.

[4] A handful of smaller private seed firms filed APHIS notices but had no patents. These firms are left out of this sample because their financial data are proprietary and thus unavailable.

[5] Four major corporations merged into two. (Ciba-Geigy and Sandoz merged to form Novartis; Rhone-Poulenc and Hoechst merged to form Aventis). Most of the leading independent plant biotech firms were acquired by larger corporations (Calgene by Monsanto, DNA Plant Technology by Savia, Mycogen by Dow, Mogen by Zeneca, and Plant Genetic Systems by Aventis). Likewise, most of the top US crop seed companies were acquired by those same corporations (Pioneer by DuPont and Asgrow, DeKalb, Delta & Pine Land, and Holden's all by Monsanto; however, Monsanto later divested Delta & Pine Land in 2000).

[6] The resulting individual observations are constructed as the smallest group of business units or firms among whom the coordination of assets could be considered an internal decision. A single independent firm's data is counted alone as in individual observation, while a parent and subsidiary firms' data is summed and the sum is treated as a single observation. Partial equity acquisitions and 'strong' alliances (meaning ones that soon led to equity acquisitions) are treated as internalizing solutions.

[7] For example, Monsanto, Holdens, DeKalb, Delta & Pine Land, Agracetus and Calgene are treated as six separate observations in the 1994 sample. Their data are summed into one observation in the 1999 sample, reflecting Monsanto's alliance with or effective acquisition of the other five firms.

[8] Since the first two moments of the Poisson distribution are E(y) = λ and Var(y) = λ, the model imposes the restriction E(y) = Var(y). For all three the patent count variables the sample variance is significantly greater than the sample mean; these data exhibit over-dispersion.

[9] The independent variables are transformed by a constant before being entered into the log-likelihood function in order to yield conveniently scaled parameter estimates.

[10] R&D expenditures, considered as inputs in the innovation process, typically have a positive, quantifiable effect on the number of patents produced as outputs.

[11] This transaction included the infamously broad cotton transformation patents mentioned above.