Transitions in Agbiotech: Economics of Strategy and Policy

EDITED BY
William H. Lesser

Proceedings of NE-165 Conference
June 24-25, 1999
Washington, D.C.

Including papers presented at the:

International Consortium on Agricultural Biotechnology Research Conference
June 17-19, 1999
Rome Tor Vergata, Italy

PART SIX: Public/Private Sector Relationships

33. Universities and Agricultural Biotechnology Patent Production

Jeremy Foltz, Bradford Barham, and Kwansoo Kim

Food Marketing Policy Center
Department of Agricultural and Resource Economics
University of Connecticut
and
Department of Resource Economics
University of Massachusetts, Amherst

Universities and Agricultural Biotechnology Patent Production

Jeremy Foltz, Bradford Barham, and Kwansoo Kim

Department of Agricultural and Resource Economics
University of Connecticut

Chapter 33

Universities and Agricultural Biotechnology Patent Production

Jeremy Foltz, Bradford Barham, and Kwansoo Kim[1]

I. Introduction

In recent years new innovations in biotechnology[2] have started to change the agricultural economy in ways similar to the growth of the semiconductor industry. As Zilberman et al. (1997) suggest, the unique features of these innovations will reshape agriculture as profoundly as any other past paradigm change. Such rapid changes in agriculture will require new types of research if society is to formulate appropriate policies to manage this new economy. Many land grant institutions are in the process of investing heavily in research and education efforts in agricultural biotechnology (ag-biotech) as part of an effort with state and local support to assist in developing a vibrant and proximate biotechnology sector.

Like the nascent agricultural biotechnology industry, the literature in agricultural economics is mostly in a beginning stage characterized by thought pieces (Zilberman et al. 1997; Ollinger and Pope, 1995) and theoretical models (Just and Hueth, 1993; Moschini and Lapan 1997). This study seeks to go beyond that work by providing an initial empirical examination of the importance of university research in the agricultural biotechnology industry. One of the key differences in agricultural biotechnology from previous agricultural technology is that innovations have intellectual property rights that produce private value that can potentially accrue to the university. We focus on university agricultural biotechnology patent production as a measure of such economically valuable research that can be appropriated by public and private actors.

Using data for the last five years from patent databases, the Association of University Technology Managers (Massing, 1996), and supplemental sources, we estimate econometric count data models of university-owned agricultural biotechnology patents on a series of explanatory variables. This methodology builds on recent empirical work that explores the broader patterns of university patents and licenses (Jaffe, 1989; Audretsch and Feldman, 1996). These studies have effectively demonstrated the importance of universities in overall rates of technical innovation. This work extends that research to include agricultural biotechnology.

The next section reviews the relevant literature on biotechnology, patent production, and agricultural biotechnology. The second section develops a general model of patent production and describes the process of agricultural biotechnology patenting highlighting differences from other agricultural technologies and other types of biotechnology. Section III provides a brief discussion of the data sources and data issues underlying empirical analyses of patent production. This is followed by the estimation of a count data econometric model of the probability of a university producing ag-biotech patents as a function of university and regional characteristics. Among the issues to be addressed by the econometric models are (i) Do universities with more overall resources for research and development produce more ag-biotech patents? (ii) Do universities with more technology transfer employees produce more ag-biotech patents? (iii) What is the relationship between the emphasis of the university on agriculture and ag-biotech patent production?

II. Literature Review

The economics of research and development has received an increase in interest in part because of the arrival of endogenous growth theory. Recent thinking in the economic growth literature has pointed to the importance of R&D to overall economic growth (see for example: Aghion and Howitt, 1998). Many studies (most recently Jones and Williams, 1998) have found that the social return to research and development exceeds the private return, implying under-investment by the private sector. Whether in explicit response to this situation or not, the US has had a long-standing tradition of public investment in R&D, much of it channeled through the university system.

Universities have over the years produced a great deal of commercially important R&D, from milking machines to nuclear resonance scanners. Most studies have shown the value of this university research to local industries to be significant. The classic work on university research, Jaffe (1989), finds an association between industry R&D and university research. Jaffe also finds suggestive evidence that university research promotes industry R&D rather than vice-versa. More recently, Henderson, Jaffe and Trajtenberg (1998) investigate the effects of university research by measuring the citation of university patents by private firms in their own patents. They find that recent rules making it possible for universities to patent products derived from federally funded research, the Bayh-Dole act of 1980, has increased the quantity and lowered the quality of university patents.[3] They, however, find no evidence to suggest that the recent increase in university commercialization efforts has been accompanied by an increase in the generation of commercially important innovations by universities.

Parallel to the literature on overall university research has been one focused specifically on the biotechnology industry. The clustering of the biotech industry in proximity to major research universities led a number of researchers including Audretsch and Stephan (1996) to investigate the locational linkages between biotech companies and university scientists. They find that geographic spillovers are most common when knowledge spillovers are informal. In cases where knowledge spillovers take place in a formal setting geographic proximity is less important. Zucker, Darby and Brewer (1998) believe that in the first 10-15 years of the biotech revolution biotech innovations were characterized by naturally excludable knowledge in the hands of only a few "star" scientists. They find that the generation of biotech knowledge in a specific location was the principle determinant of the growth of the biotech industry in that area. They find that research universities and their star scientists are central to the formation of an industrial sector based on scientific breakthroughs.

What is Different about Ag-Biotech?

The literature on agricultural biotechnology has pointed out that differences in property rights and industry market structure imply that ag-biotech deviates from the standard models of innovation in agriculture. In some quarters this has called into question the validity of public research in what is seen as a private domain. Moschini and Lapan (1997) show that conventional measures of welfare will over estimate the impacts of agricultural R&D when intellectual property rights are established over those innovations. Zilberman et al. (1997) see public research and extension as essential to assuring competition in the ag-biotech industry and access to genetic materials and techniques. Also they forsee an increase in new commodities, branded agricultural products, and production contracting. Hayenga (1998) sees the potential for too much market power in the seed and chemical industries by the five top ag-biotech companies who have been buying up smaller companies. He, however, suggests that the pace of innovation may in the long-run favor the new companies with new technologies.

While the agricultural biotechnology industry is still in its infancy, one can learn from its more mature cousin, pharmaceutical biotechnologies. The literature on innovation has demonstrated that a key variable that will determine the spread of innovation will be the degree to which there exist strong enforceable property rights. von Hippel (1988) shows that relative to other industries, pharmaceuticals have very strong, enforceable patent rights. While this probably also applies to pharmaceutical biotechnology, agricultural biotechnology may have less enforceable property rights. Recent court cases involving patents on biotech seed varieties have suggested that many of the patents are unenforceable. Agricultural biotechnology may also be more easily "invented around" than the chemical compounds of the pharmaceutical industry.

If intellectual property rights over agricultural biotechnology are indeed weaker, the value of the innovation will be closely tied to: (i) access to the techniques, (ii) first mover advantages, (iii) access to the personnel. Also agricultural biotechnology may continually need to be reinvented, as insects and weeds develop resistance. This implies that the social returns to continual research and innovation will keep accruing, but that the private value of single discoveries may be reduced. This possibility for greater social than private benefits from agricultural biotechnology research provides another rationale why university research in this area may need to play a major role.

III. Agricultural Biotechnology Patent Production

A General Model of Patent Production:

Measuring the value of research output presents many problems because most of the effects are ill defined in monetary terms. Clearly the value to society of your average research article in most university disciplines is hard to measure. Typically patents are used as a proxy for the economic value of research even though most research is not patentable. Arguably much university research is not patentable, but instead creates publicly appropriable knowledge.

Even if research is patentable, not all such research is patented. Let a university's decision rule for patenting a piece of research be as follows: an innovation will be patented if the value of research output as a patent is greater than the transaction cost of obtaining patent[4]. Let the index function of patent production be:

$$p_h = \begin{Bmatrix} 1 & if\, V(r_h, \boldsymbol{D}) - TC \geq 0 \\ 0 & if\, V(r_h, \boldsymbol{D}) - TC < 0 \end{Bmatrix}, \tag{1}$$

where p_h is an index variable denoting the existence of a patent on that research (indexed by h), V(r_h , $\boldsymbol{D}$) is a value function describing the economic value of the individual piece of research, r_h, with university level inputs $\boldsymbol{D}$, and transaction costs associated with the patenting process, TC.

The key to understanding the patenting process will be the inputs and parameters of the value function V(r_h , $\boldsymbol{D}$). The first input into the value function will be research output, r_h, which can be thought of as a classic production process using labor, capital, and structures (labs, etc.) in the following fashion:

$$r_h = f(L, K, T). \tag{2}$$

Note that while the research and the patent are individualized, the inputs in its production are general to the whole university. In this equation labor, L, will include the number of scientists, the quality of scientists, and the quality of the research neighborhood. The research neighborhood accounts for knowledge spillovers and potential agglomeration effects. Capital, K, includes research funds from federal, state, industry, and university sources. Structure, T, includes research facilities, labs, libraries, etc.

Other factors in the value function, $\boldsymbol{D}$, include inputs that increase the value of research by making the commercialization process easier. Among these will be the technology transfer infrastructure at the university, the research neighborhood, and the state economic structure. Better technology transfer offices would likely be more able to create value out of research through their contacts. Similarly a vibrant research neighborhood provides contacts and networks for turning ideas into commercial applications.

Adding up all of the research at the university, and their associated patents, gives us a count of the total number of patents. The equation describing the count of patents at an individual university (indexed by i) is as follows: $P_i = \sum_{h=1}^{H} (p_h \,|\, V(r_h, \boldsymbol{D}) - TC \geq 0)$, where H is the total number of research projects at the university. This equation gives a count of the number of patents as a function of variables affecting research output, the value of patenting, and the transaction costs of patenting.

What Is Distinctive About Ag-biotech?

Having developed a general theory of university research and patent production, we now turn to the distinctive aspects of agricultural biotechnology. First, in contrast to much university research, most of the output of ag-biotech research has value as patents. In fact much of the driving force in ag-biotech is the creation and utilization of property rights by universities in order to shore-up ever shrinking agricultural research budgets.[5] This implies that in the case of ag-biotech, patents are the relevant unit of analysis for measuring research output.

A number of unique features of ag-biotech stand out as opposed to pharmaceutical biotechnology. First, because the technology is in its infancy one will see fewer patents and potentially more clustering of patents in a small number of places. The second unique feature is the legacy of agricultural research at land grant universities in every US State. These universities have received funding from the federal and state level for more than a century to promote the production of useful knowledge for the farmers of their respective states and regions. Historically, the land grant mission has explicitly acknowledged and encouraged geographically localized spillover effects. Both state and federal governments have funded research infrastructure in agricultural colleges as well as outreach programs directly tied to the types of technologies produced at the university. Clearly ag-biotech research due to its appropriable property rights structure will be a different sort of technology with different diffusion patterns and clientele (life science businesses rather than farmers themselves). But much of the infrastructure and tradition of agricultural colleges will be applicable. Note that because of the potential synergy between ag-biotech and pharmaceutical biotech, one would also expect to see some universities with strong biological sciences producing ag-biotech patents, even though they might lack the infrastructure of an agricultural college.

IV. Data

A. Output Data

Our data divides into research output (patents) and on the inputs to the research process. With the research output we needed to develop a consistent definition of agricultural biotechnology which defines it separately from other types of agricultural inventions and from other non-agricultural biotechnology.

Source

The ag-biotech patent data comes from the complete U.S. patent office database.[6] In order to get a consistent measure of ag-biotech patents we designed a search strategy that gathers only biotechnology patents specifically related to agriculture. Note that there may be a large number of biotechnology patents that are useful for the production of agricultural biotechnology but not specific to agriculture. Thus, the measure we used will capture primarily patents on final products related to agriculture and not any intermediate patents. Table 1 lists the relevant patent classifications and definitions used to determine whether a patent was agricultural biotechnology. All of the patents in classes 47, 71, 119, 426 are agricultural but only a small number of those patents are biotechnology. All patents in classes 435, 800, 930, and 935 are biotechnology, but only those in class 800 are clearly agriculturally related. We chose all the patents in class 800, except those on laboratory rats and mice. Since a patent can be listed in more than one category, we then took patents in classes 435, 930, and 935 if they were also cross-listed in one of the agricultural product categories. The remaining patents were primarily on agricultural final products, rather then intermediate inputs in the research process. Note that plant patents are a specific separate category of patent without any of the cross listings necessary for determining whether they are biotechnology. Since they also have different patenting requirements and less stringent property rights associated with them, plant patents are not included and remain an issue for future research.

TABLE 1 Patent Class Definitions

Class Number	Definition
47	Plant Husbandry
71	Chemical Fertilizers
119	Animal Husbandry
426	Food or Edible Material: Processes, Compositions, and Products
435	Chemistry: Molecular Biology and Microbiology
800	Multicellular Living Organisms and Unmodified Parts Thereof
930	Peptide or Protein Sequence
935	Genetic Engineering: Recombinant DNA, Hybrid or fused cell technology, and related manipulations of nucleic acid

Since most patents take 2-3 years before they are approved, we chose patents by application dates. This gives the date closest to the actual date of the research discovery. We chose all patents with applications after Jan. 1, 1991 and through the end of 1998. This provided the best match for the other university expense data we were able to obtain.

We used every university we included in the data available to us (n=142). There were 53 universities identified as having ag-biotech patents. Table 2 presents the top 10 universities in producing agricultural biotechnology patents. With only a few exceptions they represent top state universities from major agricultural states.

TABLE 2 Top 10 Universities Ranked by the Number of Patents

University	Number of Patents
Iowa State Univ.	23
Univ. of California-Davis	14
Cornell Univ.	13
Michigan State Univ.	12
Louisiana State Univ.	10
Univ. of Wisconsin-Madison	10
Univ. of Pennsylvania	9
North Carolina State Univ.	8
Rutgers	7
Texas A & M Univ.	7
Univ. of California-Berkeley	7

B. Input Data Sources

As described in the theory section, the inputs to the patent production process consist of variables determining research output: labor (L), capital (K), and structures (T) and university input variables in the patent value function (***D***).

Labor

Labor inputs include the number and quality of scientists and the quality of the research neighborhood. In the model we present in the next section, we employ several measures of the rank of university as proxies for the number and quality of scientists and the quality of the research neighborhood. Using Gourman's Guide (1993), we developed measures of the overall university graduate school ranking (URANK) and biology and related departments ranking (BIORANK).

Capital

Capital inputs include research funds from federal, state, industry, and university sources. In order to obtain this information, we use the data from the National Science Foundation, NSF, on research and development, R&D, funding at U.S. academic institutions. In order to match the other data we have, we use an average of R&D expenditures for the years 1991-1997. The variables are as follows: FED_STA denotes the sum of R&D expenditures from federal and state & local government sources; IND denotes R&D given to universities from industry sources; and INS_OTH denotes the sum of own institutional and all other sources. As expected, Table 3 shows that the majority of the R&D money comes from federal government followed by institution (and others) and industry.

TABLE 3 Input Data

Variable	Mean	Std. Dev.	Minimum	Maximum
OTT	2.56	2.81	0	19.00
TOTALPAT	11.12	12.75	0	100.25
FED_STA	79.605	72.380	0.462	287.498
INS_OTH	30.563	27.888	0	139.571
IND	8.078	8.604	0	54.829
AGD915	6.54	11.84	0	57.20
AGRATIO	0.025	0.022	0	0.135
EXPFUND	1116.46	1870.01	0	6688.92
URANK	3.61	0.91	0	4.95
INIPAT	8.6	11.96	0	92
INIOTT	2.0	2.88	0	19
AGRANK	1.03	1.65	0	4.91
BIORANK	1.34	1.79	0	4.96

Note: Number of observations=142.

The zeros account for 62.5%, 68.3%, 65.5%, 58.5% of AGD915, EXPFUND, AGRANK and BIORANK, respectively. FED_STA, INS_OTH, IND, and EXPFUND are measured in $1,000,000.

Structure

Research structures include, among others: laboratories, buildings, and experimental farms. Preliminary investigations of the data showed high correlations between available measures of structures for research and the people (faculty and students) who work in them or the research monies that pay for them. Since we had higher quality measures of research funding and researchers themselves than the structures they worked in, we used these as proxies for the infrastructure. A variable AGD915, the average agricultural science doctorate degrees awarded over 1991-1995 period, is included to reflect the importance of agricultural graduate programs in producing ag-biotech research output. AGD915 had near perfect correlation (over 0.8) with other measures we developed on experiment station funding. Agricultural degrees provided a more complete and cleaner measure that included more universities and better described how research money in agriculture was spread to different campuses in each state.

Other Variables in the Value Function

As mentioned in the theoretical model a number of variables will shift the value of all patents to a university. We expect that better technology transfer infrastructure (reflected as a lager number of employees) would create more value out of research ideas by better knowledge of the patent process. The average number of employees (measured in full-time equivalents) in technology transfer offices over the 1992-1996 period (OTT) is included as a measure of this technology transfer infrastructure (AUTM, 1992-1996). To capture the impact of state economic structure on patent values, we include a variable, AGRATIO, which measures the ratio of gross state product in agriculture (farms, forestry, and fisheries) to total state gross product[7]. The average value of this ratio equals 0.025 with the maximum value 0.135 in North Dakota and minimum of 0.006 in the misnamed "Garden State" of New Jersey.

V. Empirics

The empirics undertaken below involve three steps. The first is to estimate a reduced-form count data regression model on patent production including various factors that might influence the securing of ag-biotech patents by research universities. Next, the patent data base is used to further explore the potential value of individual patents to the university and the local economy by tracking the number of citations of each patent, including all local, in-state, citations (excluding those made by the same university). The third step is to identify whether there are some “star-scientists” who may be responsible for a large proportion of patents in some locales.

Among these steps, only the econometric models need some further elaboration. Standard procedure with count data is to use a poisson regression framework (Hausman et al., 1984). Our data exhibit two distinct problems that require some modification. Our data exhibit overdispersion relative to the poison distribution—the sample variance of the patent variable is not equal to the sample mean. This implies that the correct procedure estimates the model assuming a negative binomial distribution.

The second econometric problem comes from the censoring of our dependent variable. In contrast to most patent studies, we use all potential patent producers within a definable universe, research universities. By using all universities in our data, we can determine the factors promoting ag-biotech patenting. On the other hand, our ag-biotech count data feature the partial observability associated with zero outcomes since most universities without an explicit agricultural focus would not be expected to produce ag-biotech patents. Moreover, some universities with agricultural research capacity might not be able to produce patents due to various impediments including the transaction costs associated with the application process. Thus our dependent variable, P_i, may equal zero for one of two reasons:

> $P_i = 0$*, because there is no ag-biotech related research on campus, or no patent office.*

$P_i = 0$*: because the ag-biotech research on campus did not yield a patent.*

In the former case the dependent variable will always be zero, in the latter case the dependent variable is zero because of factors we have specified as independent variables.

Following Mullahey (1986), Hausman et al. (1984), and the discussion in Greene (1997) we specify a Zero-Inflated Negative Binomial (ZINB) regression model to analyze our university ag-biotech patent count data. This specification allows for partial observability of zero outcomes as well as over-dispersion of the count data. Let z denote a binary indicator of regime 1 (z = 0) or regime 2 (z = 1), and let P^* denote the outcome of the generalized Poisson (negative binomial) process in regime 2. Note that the observed number of patents, P, is z × P^*. This splitting model is extended to allow z to be explained by a set of covariates. A ZINB model then becomes

$$\Pr(\mathrm{z}_\mathrm{i} = 0) = F(\mathbf{w}_\mathrm{i}, \mathbf{g}), \tag{3}$$

$$\Pr(P_i = j \mid z_i = 1) = \frac{e^{-m_i} m_i^j}{j!}, \tag{4}$$

where F is a cumulative pdf assumed to have a logistic distribution[8], μ_i is a generalized Poisson parameter formulated by the log-linear model ($\ln \mu_\mathrm{i} = \mathbf{b}'\mathbf{x}_\mathrm{i} + \varepsilon_\mathrm{i} = \ln \lambda_\mathrm{i} + \ln u_\mathrm{i}$), $\mathbf{b}$ and $\mathbf{g}$ are parameter vectors to be estimated, and $\mathbf{w}$ and $\mathbf{x}$ are covariates. We assume the exponential of the disturbance ε_i (i.e., u_i), which reflects cross-sectional heterogeneity, to have gamma distribution.[9] Then the probability density function for the observed random variable (P_i) becomes

$$\Pr(P_i = j) = \Pr(z_i = 0) + (1 - \Pr(z_i = 0)) \cdot f(P_i = j), \tag{5}$$

where the distribution of P_i conditional on $\mathbf{x}_\mathrm{i}$ and u_i, $f(P_i = j \mid \mathbf{x}_i, u_i) = \dfrac{e^{-l_i u_i}(l_i u_i)^j}{j!}$.[10]

Therefore, the log-likelihood is simply

$$\ln L = \sum_i \ln\left(\Pr(P_i = j)\right). \tag{6}$$

Our main model of interest estimates a ZINB model of the production of ag-biotech patents. We run two versions of this model: the first is a constrained model that ignores the agricultural college infrastructure variables, while the second includes two potentially relevant measures of agricultural college importance. Before running these ag-biotech models we explore a benchmark model for comparison purposes that estimates a negative binomial model of all university patents.

The benchmark model, with total university patents (from AUTM) as a dependent variable, has the following regressors: (1) number of employees working in the office of technology transfer (OTT); (2) research money from government (FED_STA), industry (IND), and institutional and other sources (INS_OTH), and, (3) academic rank of the university's graduate school (URANK). Respectively, these regressors are meant to represent the resource commitment of the university to pursuing patents from research, the capital resources available for the pursuit of research, and the quality of the faculty involved in research.

Of the two ag-biotech patent models, the constrained model basically replicates the structure of the benchmark model with the addition of a variable AGRATIO to measure the relative importance of agriculture in the state economy and three variables to describe the censoring at zero. In order to describe universities that would not be expected to have any ag-biotech patents, we use three variables: INIOTT, INIPAT, and LAND. The first two are the number of technology transfer personnel and the total number of patents the university held at the beginning of the period our data cover. The variable LAND is a dummy variable for land grant institutions.

The second ag-biotech patent model adds two additional variables which may be more specific to the production of ag-biotech research: (1) the total number of agricultural department Ph.Ds awarded at the university over the 1991-1995 period (AGD915); and (2) the ranking of the universities graduate biology programs (BIORANK). Other variables, such as ranking of top agricultural degree programs, USDA funding, or number of experimental station scientists, which could also provide measures of the specific resources committed to agricultural research are omitted because of their very high correlation with the number of agricultural Ph.Ds awarded (they are also not as comprehensive in their coverage of universities across the sample as the measure we used).

VI. Results

The benchmark negative binomial patent model results are reported in Table 4. The results of this model are consistent with our underlying theoretical model. Two of the estimated coefficients, the number of office of technology transfer employees and university academic rank, have positive values that are statistically significant. Thus, an increase in any of these variables is likely to increase the number of patents secured by a research university. Interestingly, the coefficient of the square of the number of offices of technology transfer employees (OTT2) is negative and statistically significant. This and the positive coefficient of OTT identify a quadratic relationship between patent production and the number of office of technology transfer employees, i.e., decreasing returns to scale in the technology transfer bureaucracy. The coefficient on Federal funding is positive and statistically significant at a 10% confidence level. The coefficients on research funds from both industry and institutional and other sources are not significant. Having controlled for university quality and investments in technology transfer personnel, actual levels of funding are less important.

TABLE 4 The Benchmark Patent Model Dependent Variable: All University Patents

Parameters	Coefficients	Standard Errors
Constant	1.07	0.309***
OTT	0.2924	0.0725***
OTT2	-0.0159435	.0039303***
FED_STA	0.00378	0.00202*
INS_OTH	0.00366	0.0033
IND	0.0182	0.0112
URANK	.3099	0.0928***
Ln Alpha	-0.627	0.141***
Log likelihood	-599.5722	

Likelihood ratio test of epsilon (generalized poison parameter) = 0:
χ^2 (1) = 1492.29 Prob > χ^2 = 0.0000

The two ag-biotech patent regressions are reported in Table 5. In both cases likelihood ratio tests of the zero inflated negative binomial model specification are significant at greater than a 1% level. The specification is robust with respect to both the distributional assumptions (negative binomial rather than poison) and censoring at zero. Although the zero inflation specification is correct, only the initial number of office of technology transfer personnel is at all significant (10%). The negative sign on its coefficient, though barely significant, is consistent with our operational hypothesis. The insignificant coefficient on LAND confirms what University of Pennsylvania's presence in Table 2 suggests: that ag-biotech patenting is also done outside the land grant system.

The ag-biotech estimations follow the same pattern as the benchmark patent model, although the agricultural variables suggest that, as hypothesized, ag-biotech patents are related to agricultural infrastructure. In the constrained model, as in the benchmark model, the coefficients on technology transfer office employees (OTT and OTT2) are statistically significant (at a 10 and 5% level respectively) and have the expected signs. Only one coefficient among R&D expenditure variables, institutional and other sources (INS_OTH), is statistically significant and positively related to ag-biotech patent production. The percent of agriculture in the state's economy (AGRATIO) is also positively related to ag-biotech patent production, although it is only significant at a 10% level. Since the constrained estimation does not account for agricultural college infrastructure, AGRATIO becomes a proxy for having an agricultural research agenda.

TABLE 5 Simple Ag-Biotech Patent Regression Model Zero-Inflated Negative Binomial Regression Dependent Variable: Ag-Biotech Patents

Parameters	Coefficients	Standard Errors
Constant	-1.874	1.053*
OTT	0.317	.1666*
OTT2	-0.0263	0.012**
FED_STA	0.00019	0.00392
INS_OTH	0.0133	0.00608**
IND	-0.0013	0.0212
URANK	0.314	0.3007
AGRATIO	13.81	7.13*
Inflate Variables		
Constant	1.184	0.539**
INIOTT	-0.322	0.1697*
INIPAT	-0.0132	.0424
LAND	-15.98	775.86
Log Likelihood	Number of obs = 142	
-180.87	Non-zero obs = 56	

Likelihood ratio test of inflate=0: $\chi^2(4) = 26.01$ Prob > $\chi^2 = 0.0000$
Likelihood ratio test vs. poison: $\chi^2(5) = 179.97$ Prob > $\chi^2 = 0.0000$

The unconstrained ag-biotech patent model in Table 6 explores the potential importance of university orientation to agriculture in predicting ag-biotech patent production. The regression coefficient of the number of agricultural degrees issued in 1991-1995 is positive and statistically significant. This measure seems to capture the empirical regularity that most of the universities with larger numbers of ag-biotech patents are indeed ones with a strong agricultural emphasis. Our measure of university quality, URANK, is significant and positively related to ag-biotech patent production. Counter to one of our working hypotheses, the negative and significant coefficient on BIORANK suggests that there is little or no synergy between strong biology programs and ag-biotech patent production. Perhaps just as interesting is the fact that none of the research fund variables are statistically significant in the regression. This suggests that having controlled for the financing of the agricultural college and university quality, overall financing levels are not as important.

TABLE 6 Full Ag-Biotech Patent Regression Model Zero-Inflated Negative Binomial Regression Dependent Variable: Ag-Biotech Patents

Parameters	Coefficients	Standard Errors
Constant	-3.569	1.248***
OTT	0.4596	0.170***
OTT2	-0.030	0.0129**
FED_STA	0.00000088	0.0000034
INS_OTH	0.0000038	0.0000057
IND	-0.000012	0.000018
AGRATIO	7.56	6.45
AGD915	0.034	0.0098***
URANK	0.844	0.368**
BIORANK	-0.287	0.144**
Inflate Variables		
Constant	1.184	0.539**
INIOTT	-0.3109	0.184*
INIPAT	-0.0248	0.0543
LAND	-15.61	1144.89
Log Likelihood	Number of obs 142	
-172.27	Non-zero obs 56	

Likelihood ratio test of inflate=0: χ^2 (4) = 17.46 Prob > chi2 = 0.0016
Likelihood ratio test vs. poison: χ^2 (5) = 90.56 Prob > chi2 = 0.0000

Note: Number of observations=142. The symbol *, ** and *** denote significance at 10, 5, 1%, respectively.

Another way of looking at the patent data is to identify the top 10 patent producers, i.e., the research scientists who have produced the most ag-biotech patents. Table 7 presents these results. Iowa State is at the top, with one scientist who has produced 20 patents. Overall, this table captures the potential importance of “star scientists” in the production of ag-biotech patents, and supports a fairly focused event analysis to understand what factors may contribute to their success and to explore whether this success translates into university and local gains.

TABLE 7 Top 10 Patent Producers (Numbers for Scientists)

Star	No. of Patents
Iowa State Univ. #1	20
U. of Idaho #1	5
UC-Davis #1	4
Louisiana State U. #1	4
Cal. Inst. of Technology #1	4
North Carolina State U. #1	3
New York U. #1	3
U. of Pennsylvania #1	3
U. of Wisconsin-Madison #1	3
Louisiana State U. #2	3
Rutgers U. #1	3
Clemson U. #1	3

VII. Conclusions

Agricultural biotechnology is still in its infancy as a technological revolution. This work has provided the starting point for future empirical research on the production of ag-biotech innovations in US universities. The data used here are the first to measure comprehensively ag-biotech patent production at the university level. We develop a consistent theoretical model and an econometric methodology for understanding the university patent production process. In contrast to many patent studies, the zero-inflated negative binomial estimation procedure we employ can describe a specific type of patent production from a census of all universities.

The empirical investigations have demonstrated the importance of the land grant system in ag-biotech innovation. Ag-biotech patent production does seem to respond to the infrastructure of agricultural colleges as well as (in one of our regressions) the importance of agriculture in the local economy. We also demonstrate the importance of having a technology transfer office to the production of patents in general as well as ag-biotech patents. We do however, find that there are decreasing returns to scale in the technology transfer bureaucracy.

Along with agricultural college infrastructure, own institutional support proved to be potentially important. If this own institutional funding comes from patent revenues, there is the potential for a virtuous cycle with better patent producing universities able to produce more patents. Among the surprising results is that industry financing does not promote more privately capturable research (patents). While the emerging debate on ag-biotech has been preoccupied by a “commercial frenzy” invading the sanctity of universities, the data here provide little or no support for the effectiveness of this as a path to patent production. Again, there may be too little time for such arrangements to show results in this data set in terms of patent production. However, we think that industry brokered funding agreements may lead to company owned patents rather than to university owned ones that would show up in our data set. Future research could delve in depth into the relationship between university/industry agreements using case studies.

Much research remains into the production of ag-biotech patents. Better data can help refine the empirical methods used here by disaggregating the years and improving the measurement of what constitutes agricultural biotechnology by including process patents. Future research on ag-biotech licensing at the key universities identified here can shed some light on the issues of spillover effects and the different values created by individual ag-biotech patents. Finally, the research presented here suggests the importance of star scientists. Future research should develop the data to delve deeper into their importance.

Endnotes

[1] We wish to thank participants at the "Transitions in Agricultural Biotechnology" conference and the Northeast Ag. and Resource Economics Association meetings, William Lesser, and Boris Bravo-Ureta for helpful suggestions as well as Charles Goodwin for help in data access. The authors are respectively Assistant Professor, Dept. of Ag. and Resource Economics, University of Connecticut; and Associate Professor and Post-Doctoral Researcher, Dept. of Ag. and Applied Economics, University of Wisconsin-Madison. Correspondence to: Jeremy Foltz, Dept. of Ag. and Resource Economics, U-4021, 1376 Storrs Rd. Storrs CT, 06269. Email: Jeremy.Foltz@Uconn.edu

[2] The authors define biotechnology as the application of the tools of molecular biology, primarily recombinant DNA and related techniques, to modify organisms in order to increase productivity, improve quality, or introduce novel characteristics.

[3] They measure the quality of a patent by the number of references to that patent by other patents.

[4] Note that we are abstracting from the process. Universities in fact make applications for patents, but final decisions on them are made by government patent inspectors.

[5] To date, the empirical evidence has shown that patents of all types are only a small source of revenue at most universities.

[6] Since the US has the strongest rules on biotechnology patents, US patents represent the important patents relative to European or World patents. A number of services abstract agricultural biotechnology patents, but proved difficult to use for total

measures of patent production because of often subjective search criteria used. They also tended to have a large time lag for inclusion in the database.

[7] Source: U.S. Bureau of Economic Analysis, *Survey of Current Business*, May 1995.

[8] This is sometimes specified as a normal distribution, leading to the equivalent of a "probit" model on the censoring rather than the "logit" style model specified here. Changing these distributional assumptions did not qualitatively change the results.

[9] Overdispersion can be caused by the type of zero outcomes we correct for using the zero-inflated model. However, correctly specifying the censoring problem under the assumption of a poisson distribution did not eliminate the overdispersion problem, suggesting that the ZINB model is the correct one.

[10] The unconditional distribution $f(P_i = j \mid \mathbf{x}_i)$ is the expected value (over u_i) of $f(P_i = j \mid \mathbf{x}_i, u_i)$,

$$f(P_i = j \mid \mathbf{x}_i) = \int_0^\infty \frac{e^{-l_i u_i}(l_i u_i)^j}{j!} g(u_i)\,du_i \ ,$$

where $g(u_i)$ is assumed to have a gamma distribution.

References

Aghion, Phillippe and Peter Howitt. 1998. *Endogenous Growth Theory*. Cambridge: MIT Press.

Audretsch, David B. and Maryann P. Feldman. 1996. "R&D Spillovers and the Geography of Innovation and Production." *American Economic Review* 86(3):630-640.

Audretsch, David B. and Paula Stephan. 1996. "Company Scientist Locational Links: The Case of Biotechnology." *American Economic Review* 86(3):641-652.

Gourman, Jack. 1993. *The Gourman Report: A Rating of Graduate and Professional Programs in American and International Universities*. Sixth Edition, National Education Standards.

Greene, William. 1997. *Econometric Analysis,* 3rd Edition. Upper Saddle River, New Jersey: Prentice-Hall Publishers.

Hausman, J., B. Hall, and Z. Griliches. 1984. "Economic Models for Count Data with an Application to the Patents-R&D Relationship." *Econometrica* 52:909-938.

Hayenga, Marvin. 1998. "Structural Change in the Biotech Seed and Chemical Industrial Complex." *Agbioforum*.1(2):43-55

Henderson, Rebecca, Adam Jaffe, and Manuel Trajtenberg. 1998. "Universities as a Source of Commercial Technology: A Detailed Analysis of University Patenting, 1965-1988." *Review of Economics and Statistics*, pp. 119-127.

von Hippel, Eric. 1988. *The Sources of Innovation*. Oxford: Oxford University Press.

Jaffe, Adam. 1989. "Real Effects of Academic Research." *American Economic Review* 79(5):957-970.

Jaffe, Adam, Manuel Tratjenberg, and Rebecca Henderson. 1993. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." *Quarterly Journal of Economics*, pp. 577-598.

Jones, Charles and John C. Williams. 1998. "Measuring the Social Return to R&D." *Quarterly Journal of Economics*, pp. 1119-1135.

Just, Richard E. and Darrell L. Hueth. 1993. "Multimarket Exploitation: The Case of Biotechnology and Chemicals." *American Journal of Agricultural Economics* 75:936-945.

Massing, Daniel. Ed. 1996. *AUTM Licensing Survey: FY 1991-FY 1995*. Association of University Technology Managers. Norwalk, CT.

Moschini, Giancarlo and Harvey Lapan. 1997. "Intellectual Property Rights and the Welfare Effects of Agricultural R&D." *American Journal of Agricultural Economics* 79:1229-1242.

Mullahey, J. 1986. "Specification and Testing of Some Modified Count Data Models." *Journal of Econometrics* 33:341-365

National Science Foundation. 1999. "NSF Webcaspar: Your Virtual Bookshelf of Statistics on Academic Science and Engineering." http://caspar.nsf.gov/

Ollinger, Michael and Leslie Pope. 1995. "Strategic Research Interests, Organizational Behavior, and the Emerging Market for the Products of Plant Biotechnology." *Technological Forecasting and Social Change* 50:55-68.

U.S. Bureau of Economic Analysis. 1995. *Survey of Current Business*. Washington DC, May.

USDA. 1996. "Inventory of Agricultural Research Fiscal Year 1996." Washington DC.

U.S. Patent Office. 1999. "Patent Bibliographic and Abstract Database." http://www.uspto.gov/patft/index.html

Zilberman, David, Cherisa Yarkin, and Amir Heiman. 1997. "Agricultural Biotechnology: Economic and International Implications." Dept. of Agricultural and Resource Economics, University of California-Berkeley.

Zucker, Lynne, Michael Darby, and Marilynn Brewer. 1998. "Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises." *American Economic Review* 88(1):290-306.