A Dynamic Analysis of University Agricultural Biotechnology Patent Production

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This article examines the factors that account for agricultural biotechnology patenting success among universities using a dynamic count data model. It builds a theoretical and econometric model to capture the inherently dynamic and nonlinear process of technological innovation, wherein a feedback mechanism from previous success partially determines current patent counts. The econometric estimates reveal the importance to agricultural biotechnology patent production of land grant infrastructure, quality faculty, patent-oriented technology transfer offices, as well as dynamic feedback effects.

Key words: agricultural biotechnology, count data, dynamics, patents, technology transfer.

The advent of exclusive property rights for university research (specifically the Bayh-Dole act) has created the potential for major changes in the missions of U.S. universities, especially among land grant universities (LGUs), as well as in the overall system of technology creation and distribution in agriculture. At the same time, new genetic and cloning technologies, along with the recently created ability to patent plants and living organisms, are profoundly changing the range of agricultural technologies that are likely to be available in the United States and internationally. Indeed, as Zilberman, Yarkin, and Heiman argue, these new agricultural biotechnologies (ag-biotech), and their associated intellectual property rights, appear to be creating a new paradigm, a veritable revolution, in the organization and interaction of university research and the agricultural sector. Under this new paradigm, universities emphasize patenting innovations, and then granting (at times exclusive) licenses to individual companies, or in some cases investing directly in the development of new products and processes through start-ups or other joint ventures.

As part of this change, many universities, especially LGUs, are investing heavily in establishing biotechnology centers, building new laboratory and research infrastructure, and hiring faculty, all with the intent of advancing their biotech research capabilities, including ag-biotech.[1] Beyond the inherent promise of the research itself, payoffs are possible in the classic form of public and private research funds in this growth area, but also in revenues from patents. Not surprisingly, perhaps, the annual number of ag-biotech patents issued to universities grew from twenty-five to thirty per year in the late 1980s, to over 150 per year in the mid to late 1990s, and appears likely to continue growing at a very rapid rate.

The tremendous pace of growth in university research and patenting of ag-biotech so far has dramatically outpaced economic analyses of the degree and effects of ag-biotech patenting at the university level. The seminal studies of the social returns to agricultural research and development (Alston and Pardey, Just and Huffman) essentially predated the mid 1990s take-off in ag-biotech patenting, and as such do not explicitly incorporate either the

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[1] At the University of Wisconsin, for example, a joint state-university-private effort, the Biostar initiative, will invest over $350 million in strengthening the university's research in biotechnology.

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potential positive or normative effects of ag-biotech patenting on agricultural productivity or the broader economy. A recent flurry of research (see, e.g., papers in the conference volume: Santaniello et al.) has started the process of evaluating public and private incentives of agricultural research with intellectual property rights. While a number of articles have developed the theory of public/private interactions (e.g., Moschini and Lapan; Rausser, Simon, and Ameden) and the economics of intellectual property rights in agriculture in general (e.g., Evenson), no study has effectively quantified and analyzed the dynamic process of ag-biotech patenting at the university level.

This article analyzes the factors that account for ag-biotech patenting success among universities, seeking to fill a void in the literature and provide the necessary empirical basis for future theory. The approach developed here builds on the study of Blundell, Griffiths, and Van Reenen (1995) who capture the inherently dynamic and nonlinear process of technological innovation using a dynamic count model, wherein a feedback mechanism between previous success in innovation (patent production) is incorporated explicitly into the modeling structure. Moreover, by using the panel structure of the model, both observed and unobserved components that might explain heterogeneity across universities in patent production can be examined. As such, this work provides a more realistic analysis than Foltz, Barham, and Kim, which used a static model to estimate university ag-biotech patenting.

This research focuses on patents as a measure of intellectual property rights production in ag-biotech. The analysis implicitly assumes that patent production itself is an output objective of university administrators, but it also provides a first-cut measure of the values generated from intellectual property rights in ag-biotech. Whereas broader studies of patenting (e.g., Pakes, Trajtenberg) have shown that the distribution of returns to patents is highly skewed, with the vast majority having little or no value, a few patents are spectacularly lucrative.[2] Given that those values will be hard to predict *ex ante* and the high cost of patent applications, most university patents have a low probability of ever producing more in licensing revenues than they cost to produce. If, however, each patent is viewed as a random draw on a distribution, then a university with more patents will clearly have a greater chance of revenue generation than one with less, especially if the probabilities of success grow with patenting experience. Thus, while empirical tests of the payoffs to ag-biotech patents are left for future research, some correlation between the patent counts used here and university revenue generation can be expected.

The econometric model of patent production developed below combines a negative binomial count model with a random-effects panel data model. The panel nature of this data set, with repeat observations on each university, allows not only for a different statistical process to describe whether universities have patents at all from the number of patents obtained, but also tests for the presence of a dynamic feedback structure in the research process.

Specifically, the empirical modeling effort tests five hypotheses regarding university ag-biotech patent production. They are:

(H1) *The presence of correlated dynamic effects*, wherein the knowledge accumulation inherent in the process of generating ag-biotech patents influences a university's future ability to produce ag-biotech patents (i.e., path dependence). This dynamic effects hypothesis also suggests the potential for there to be barriers to entry over time in ag-biotech patent production;

(H2) *Land grant effect*, (e.g., Alston and Pardey) wherein the funding provided historically by federal and state sources to land grant institutions is a major determinant of agricultural research output, in this case ag-biotech patents;

(H3) *Biological science spillover effect*: wherein having strong biological research contributes to the production of ag-biotech patents. Because the technology of genetic transformation allows research in biological fields to produce agricultural patents, ag-biotech patents can occur at universities with strong biological research even if they lack a tradition of agricultural research;

(H4) *The presence of industry effects*, (e.g., Harvey) wherein industry funding will play a critical role in shaping the production of ag-biotech patents from university research;

(H5) *The presence of patenting culture effects*, (e.g. Foltz, Barham, and Kim)

[2] In Pakes' classic study of the value of patents held by companies, the top 15% of patents represented between 60 and 80% of the overall distribution of values, depending on the country in question.

wherein universities with a higher proclivity toward patenting overall will also have more ag-biotech patents.

The empirical basis for this study is a unique panel data set, covering the years 1994 to 1999, constructed from various sources, including the U.S. Patent Office, the National Science Foundation, and the Association of University Technology Managers (Massing, 1996, 1997, 1998). As in Foltz, Barham, and Kim, the data set includes all major universities, many of which (e.g., non-LGUs) might not be expected to have ag-biotech patents. Since not all LGUs have ag-biotech patents, and many non-LGUs conduct agricultural research, having data from all universities allows us to test hypotheses *H2* and *H3*.

Following the elaboration of the theoretical and econometric models of patent production in the next two sections, the sources and basic characteristics of the data set are detailed. In the next to last section, the results of the econometric estimation are presented. In the last section we summarize the key findings of this article and point to directions for future research.

A Theoretical Framework for Modeling University Patent Production

The primary focus of this article is to estimate a reduced form model of the determinants of ag-biotech patent production. The standard departure point in the literature (e.g. Hausman, Hall, and Griliches; Blundell, Griffiths, and Van Reenen, 1999) is a patent production equation of the form

$$(1) \qquad Y_{it} = f(\mathbf{X}_{it}, u_{it}) \quad \text{for } i = 1, \ldots N \text{ and } t = 1, \ldots T$$

where Y_{it} is a count of patents produced and $\mathbf{X}_{it}$ is a vector of the characteristics of university i and general conditions outside the university that influence the process, for example, government policy. The term u_{it} represents unobservable university differences.

Let the relationship between the patents produced, Y_{it}, and university characteristics, $\mathbf{X}_{it}$, be thought of as the outcome of both a research and a patenting process. The research process involves inputs into the production of knowledge, often independent of economic considerations, while the patenting process depends on the technology transfer infrastructure, university patenting experience, and university patenting proclivity.

Let the overall research produced by a university at time t, R_{it}, be described by a classic production function using labor and capital allocated at time $t-\tau$, where τ represents the gestation period of research. Formally, one can specify the equation in the following fashion:

$$(2) \qquad R_{it} = r(L_{it-\tau}, K_{it-\tau}).$$

In this equation labor, L, includes both the quantity and quality of scientists. Capital, K, includes research funds from federal, state, industry, and university sources.

Re-specifying equation (1) to capture the research process R_{it} and a patenting process driven by technology transfer infrastructure and patenting experience, one can model the dynamics of university ag-biotech patents. The model will be as follows:

$$(3) \qquad Y_{it} = f(\mathbf{X}_{it}, u_{it}) = f(R_{it}, D_{it}, G_{it-1}, u_{it})$$

where R_{it} is research output produced from resources allocated at time $t-\tau$, D_{it} describes contemporaneous labor and capital inputs in the technology transfer office, and G_{it-1} represents a dynamic feedback effect, the culture and knowledge the university has developed in producing patents up to the previous period.

Note that the determinant of the patent process, D_{it}, is contemporaneous to patent production, whereas R_{it} is produced with lagged inputs to reflect the fact that the research leading up to a patent would take time. The determination of this lag, that is, the value of τ, is discussed in the data description. Whereas the lag in the research process is driven by the time spent on research, the dynamic feedback effect of accumulated patent knowledge, G_{i-1}, operates directly in the next period. In the next section the econometric approach and specification used to investigate the role of innovation dynamics is further developed.

Econometric Approaches to Capture the Dynamics of Patent Production

Models of patent production typically use the count data framework (Hausman, Hall, and Griliches; Blundell, Griffiths, and Van Reenen, 1995). These models assume either a Poisson or negative binomial distribution on the dispersion term (Cameron and Trivedi). The first moment condition for these models is

$$(4) \qquad E(Y_{it}) = e^{X'_{it}\beta}$$

where Y_{it} represents the patents produced. Accordingly, the patent model presented above can be parameterized by the following linear equation:

$$X_{it}'\boldsymbol{\beta} = \theta_0 + \theta_1 L_{it-\tau} + \theta_2 K_{it-\tau} + \theta_3 D_{it} + \theta_4 G_{it-1} + \eta_i + \nu_t \quad (5)$$

where the first two variables represent parameterizations of the research process and the next two denote the patent application process and experience. The variables η_i and ν_t denote the university and time-specific unobservables, respectively.

The proposed estimation procedure uses a random effects formulation to control for the unobserved university specific effect, η_i, thereby assuming that the unobserved heterogeneity is randomly distributed across universities. The main advantage of the random effects model is that it can utilize the panel structure of our data set in a more efficient way. Because a substantial proportion of the sample has zero values for all years of the dependent variable, a fixed effects model, which focuses on year-by-year variation, would not produce the desired information. Also, fixed effects models can produce noisy results when the explanatory variables are slow moving, as, for example, would be the case of faculty numbers and salaries.

In terms of the distribution on the disturbance terms, a negative binomial approach is chosen here over a Poisson model, because it allows more flexibility by not requiring that the mean and the variance of the estimated disturbance term be equal. The negative binomial approach, instead, allows the dispersion parameters to vary across individuals (i.e., universities).

Formally, the dependent count variable, Y_{it}, is assumed to be i.i.d. negative binomial with parameters α_i, λ_{it}, and ϕ_i, where we have set $\lambda_{it} = \exp\,(X_{it}'\boldsymbol{\beta})$. This gives Y_{it} mean $\alpha_i\lambda_{it}/\phi_i$ and variance $(\alpha_i\lambda_{it}/\phi_i)*(1+\alpha_i/\phi_i)$. In the random effects model, it is commonly assumed that the dispersion parameter, $(1+\alpha_i/\phi_i)^{-1}$ will vary between groups according to a beta distribution with parameters (a, b).[3] Following Hausman, Hall, and Griliches these assumptions produce a model with the joint density for the *i*th group as follows:

(6)

$$\Pr\{y_{i1}, \ldots y_{it}\} = \left(\prod_t \frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})!\Gamma(y_{it}+1)} \times \frac{\Gamma(a+b)\Gamma\left(a+\sum_t \lambda_{it}\right)\Gamma\left(b+\sum_t y_{it}\right)}{\Gamma(a)\Gamma(b)\Gamma\left(a+b+\sum_t \lambda_{it} \sum_t y_{it}\right)}\right).$$

This formulation provides the basis for the log-likelihood function estimated below.

Although the random effects model takes into account unobserved heterogeneity, it does not help to explain the origins of this heterogeneity. Blundell, Griffiths, and Van Reenen (1995) propose two methods to parameterize a part of the unobservable heterogeneity. One parameterizes the level of search activities in a pre-sample period, whereas the other measures the accumulated knowledge in patent production throughout the sample period.

The search activity measure, whose derivation appears in appendix A, is based on the idea that the average patent search level will be proportional to the unobservable university specific effect, η_i. Over a long enough time span, the number of actual patents received should be a reasonable proxy for average search activities, allowing us to proxy the individual unobservable heterogeneity by a pre-sample measure of patenting. The empirical implementation incorporates a count variable ($BEFORE_i$) to capture the number of pre-sample patents as a proxy for past search activities. This variable can be used to test for evidence of persistence or barriers to entry into patenting across the pre-sample and sample time periods.

A second measure uses a within-sample continuous measure of past patent production to proxy for the accumulation of patenting knowledge and its importance in patent production within the sample time period. We use the assumption that previous patents provide knowledge about the patenting process, but that the quality of this knowledge depreciates over time. More specifically G_{it-1} is defined as follows:

$$G_{it-1} = y_{it-1} + (1-\delta)G_{it-2} \quad (7)$$

where δ is the rate at which patenting experience depreciates. G_{it-1} provides a continuous

[3] See Cameron and Trivedi for a description of Gaussian random effects models which make the alternate assumption of a normal distribution on the dispersion parameter. Unfortunately, these models do not have clean analytics, making estimation less certain. Cameron and Trivedi also develop moment-based methods that could be used with the negative binomial model.

Table 1. Data Summary

Variable	Definition	Mean	Std. Dev.	Min	Max
Y_{it}	Number of Ag-biotech patents	0.653025	1.606216	0	14
FED_{it-2}	University-wide federal funding	55260.72	75452.05	64.755	638119.3
$NFED_{it-2}$	University-wide non-federal funding	28594.25	25166.37	0	120620.4
$ASFED_{it-2}$	Agricultural science federal funding	2524.068	4869.191	0	37601.64
$ASNFED_{it-2}$	Agricultural science non-federal funding	6571.749	12496.9	0	67018.58
$BSFED_{it-2}$	Biological science federal funding	12808.06	14082.48	0	74904.93
$BSNFED_{it-2}$	Biological science non-federal funding	5734.304	5948.349	0	32594.1
$PCIND_{it-2}$	Percent of all university funding from industry sources	0.075181	0.058555	0	0.373409
AF_{t-2}	Average faculty salary	50.48602	10.44497	29.028	107.75
$FUNFAC_{t-2}$	Funding per faculty member, university wide	228.8102	676.0911	0.514266	8923.343
AS_{t-2}	Agricultural science graduate students	36.86833	67.21811	0	280
BS_{t-2}	Biological science graduate students	189.7954	156.9694	1	741
$PROPENS_t$	Ratio of patent applications to invention disclosures	0.349196	0.203732	0	1
OTT_t	Number of FTE's in the office of technology transfer	5.244369	5.635075	0	32.8095
LGU	Land grant status	0.290036	0.454183	0	1

Note: $N = 562$, Number of universities = 128.
FED, NFED, ASFED, ASNFED, BSFED, BSNFED, and *AF* are measured in $1,000.

representation of patenting dynamics with a more realistic discounting structure than the pre-sample measure, which is constant over time.

Data

All of the descriptive variables used in the econometric analysis are summarized in table 1. They were constructed as follows:

Patent Data Source

The patent data identify all ag-biotech utility patents owned by U.S. universities from a search of the complete U.S. patent office data base.[4] Among European and world patents, it is well known that U.S. patents represent the more innovative patents because of stronger property rights protection.[5] Appendix B describes the process used to determine which patents are ag-biotech.

The patent search algorithm chose all ag-biotech patents with application dates after 1 January 1971 and through the end of 1999. So as not to confound the effects of different lengths between application and acceptance, this work uses the date of application as the date of a patent. Measuring the dependent variable, ag-biotech patents, from the time the application was submitted rather than from the date of award, matches more closely the timing of the discovery process of the research and the observed patent.

During this time period, a total of 107 universities received 795 ag-biotech patents.[6] The vast majority of the patenting happened between 1991 and 1999, during which time 580 ag-biotech patents were granted to ninety-nine universities. Because of complementary data limitations, the actual data set used for the model estimation has information from 1994 to 1999 on 127 universities of whom 65 received at least one ag-biotech patent. Also, a dummy variable, *YrDum*, is included to control for the patent drop after 1997, because most patent applications filed in the period 1997–99 are still under review. Thus, patent data from those years offer incomplete information on acceptances.

The top twenty universities, ranked by accepted agricultural biotechnology patents during the post 1990 time period (1991–99) are,

[4] The data base includes only utility patents and not plant patents, which provide plant variety protection. Plant patents have lower novelty standards and provide lower levels of intellectual property rights than utility patents. For this reason, most genetically altered plants are submitted for utility patent protection and very few plant patents involve genetic alterations.

[5] In particular, recent reticence by European governments to patent life forms has made U.S. patents the intellectual property right of choice for protecting ag-biotech innovations.

[6] The patent-culling technique of reading through patent abstracts improves on the methods of previous research, and more than doubles the number of ag-biotech patents identified.

Table 2. University Rankings of Ag-Biotech Patent Production 1971–99

University	Rank 91–99	Patents 91–99	Pre-Sample Rank 71–90	Pre-Sample Patents 71–90
Michigan State	1	43	44	1
Iowa State University	2	40	8	17
Cornell	3	36	2	16
UW-Madison	4	34	1	19
UC-Davis	5	26	12	6
Louisiana State University	6	21	21	3
University of Minnesota	6	21	16	5
University of Florida	8	19	4	10
Rutgers	9	15	23	3
Texas A&M	9	15	17	4
Purdue	11	14	3	12
University of Pennsylvania	12	13	NA	0
NC State University	13	12	5	9
Penn State University	14	11	NA	0
Washington State	14	11	NA	0
University of Georgia	16	10	10	7
University of Kentucky	16	10	35	2
UC-Berkeley	16	10	7	9
Washington University	19	9	NA	0
University of Maryland–College Park	20	8	15	5
Total		580		215

with two exceptions, public land-grant institutions, with agricultural colleges (table 2). Because these two exceptions are private universities with traditionally strong biological research, they are suggestive of some spillovers from biological science to ag-biotech, that is, hypothesis *H3*. Overall, ag-biotech patent holdings among U.S. universities are moderately concentrated with the top five holders having 31% of the total number of patents, the top ten having 47%, and the top twenty having 65%. Ag-biotech patent holdings among U.S. universities are, however, almost completely dominated by public land grant institutions, which hold 84% of the total issued in the past thirty years.

The data show some persistence between the two time periods, with twelve of the top twenty producers before 1990 still in the top twenty for the decade of the 1990s and the entire top five still in the top fifteen. Barham, Foltz, and Kim use the same data to provide a more thorough examination of persistence and concentration in university ag-biotech patenting. Ag-biotech patent production in the pre-sample period has a simple correlation of (0.48) with production in the 1990s. Michigan State, however, presents a striking contrast having vaulted from having only one patent in the pre-sample period to being the leader in patent production in the 1990s.

The pattern of persistence in ag-biotech patent production over the two time periods helps to motivate the use of lagged measures of ag-biotech patent production in the subsequent estimation. As discussed in the previous section, two different variables $BEFORE_i$ and G_{it-1} were constructed in order to measure search levels and knowledge stocks. The variable $BEFORE_i$ the number of patents produced by university i before 1990 is created to capture university heterogeneity in ag-biotech patent search levels before ag-biotech patent production exploded in the 1990s. G_{it-1} is defined as the sum of the current patents and discounted previous knowledge stock ($G_{it-1} = Y_{it-1} + (1 - \delta)\ G_{it-2}$, where Y_{it-1} is university i's number of patents obtained at time $t1$ and δ is a depreciation rate of 30%).[7] It captures the dynamics of innovation histories and continuous knowledge acquisition and hence the potential for persistence over time in ag-biotech patent production.

[7] Because the measure of patent production uses the patent application date, for successful applications, as the date of a patent, this formulation of G_{it-1} allows the use of actual patents received in the year as a measure of patent process knowledge. The typical lag between application and acceptance is about three years. During those three years a patent office may learn more about the patent process and thus improve the next patent application, giving rise to dynamics in the patent process. While G_{it-1} was generated using a 30% depreciation rate, changing that to either 10 or 20% did not measurably influence the results.

Input Data Sources

As stated earlier, input data for the study come from the National Science Foundation (NSF) and the Association of University Technology Managers (Massing, 1996, 1997, 1998) data bases. Inputs to the research process include labor (L), capital (K), and university input variables in the patent production process (D).[8] The appropriate lag for the inputs into the research process, labor and capital, is one that represents a reasonable duration of a research project. We choose a two-year lag as representative of the time a successful research project would take from receiving funding and labor allocations to the moment of patent application.

Labor

The ideal labor input data would measure the quantity and quality of scientists in each laboratory conducting ag-biotech research. Since such detail is unavailable, several alternative measures of labor input are developed to proxy for the number and quality of scientists. To measure quantities of labor in ag-biotech-related research we use: the number of full-time graduate students in Agricultural Sciences (AS_{it}) and the number of full-time graduate students in Biological Sciences (BS_{it}). Preliminary investigations of the data showed graduate student numbers were highly correlated with both funding and faculty numbers in agricultural colleges. The variables used to proxy labor quality are measured at the university level: the average faculty salary (AF_{it}) and average funding per faculty member ($FUNFAC_{it}$). The former indicates an ability on the part of the university to pay for higher quality labor,[9] whereas the latter is often used in national university ratings.

Capital

Capital inputs, from NSF, include research funds from two sources: federal and non-federal (state, industry, and own university funds). Federal and non-federal sources are divided into three categories: (*a*) overall university funding not related to agriculture or biological science (FED_{it} and $NFED_{it}$), (*b*) agricultural science funding ($ASFED_{it}$ and $ASNFED_{it}$), and, (*c*) biological science funding ($BSFED_{it}$ and $BSNFED_{it}$). Whereas the overall funding measures capture university quality, the latter two allow us to examine hypotheses *H2* and *H3* that high-quality agricultural and biological research are important to ag-biotech patenting. In addition, to probe hypothesis *H4*, we include a variable that measures, at the university level, the percent of total funding that comes from industry sources ($PCIND_{it}$).

Land Grant Effect

We include a dummy variable to capture the LGU effect put forth in hypothesis *H2*. Although it may be collinear with such variables as federal funding in agriculture, it is expected to have a positive effect on the number of ag-biotech patents.

Patent Production Variables

Two variables are used to describe the process of turning research into patents. One measures quantity of inputs. The other measures the patenting propensity of the university. We include the number of employees (measured in full-time equivalents in both staff and professional technology transfer people) in technology transfer offices (OTT_{it}) as a measure of the available stock of technology transfer capacity (Massing, 1996, 1997, 1998). We expect that a larger number of technology transfer employees would create more patents out of research ideas by providing some combination of better specialization and more effort in the patent production process.

To proxy these differences between universities in propensities toward patenting we use a variable measuring the ratio of total university patent applications to invention disclosures ($PROPENS_{it}$).[10] To avoid spurious correlations, ag-biotech patent applications were subtracted out of the total patent application numbers and the invention disclosure figures were adjusted proportionately. This measure, expected to be positive, captures the effect of overall university patenting proclivity on ag-biotech patents.

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[8] All monetary values have been deflated using 1996 as the base year.

[9] For any single individual, salary might be a poor proxy for quality, as it is just as likely a function of the individual's field and longevity. Averaging across the university, however, it should provide a reasonable proxy measure for overall university quality.

[10] An invention disclosure, the first step in the patent application process, is produced when a researcher finishes a project and wants to claim the rights to the ideas. Many invention disclosures never turn into patent applications in part because they are licensed without the stronger intellectual property of a patent.

Table 3. Random Effects Negative Binomial Estimate of Ag-Biotech Patent Production

Variable	Definition	Comparison Model	Pre-Sample Dynamic Effects	Continuous Dynamic Effects
FED_{it-2}	University-wide federal funding	2.13E-07	2.34E-07	1.32E-07
		(1.77E-06)	(1.76E-06)	(1.66E-06)
$NFED_{it-2}$	University-wide non-federal funding	4.86E-06	5.11E-06	3.04E-06
		(5.64E-06)	(5.70E-06)	(5.52E-06)
$ASFED_{it-2}$	Agricultural science federal funding	2.88E-05	2.85E-05	1.28E-05
		(2.E-05)	(2.00E-05)	(2.20E-05)
$ASNFED_{it-2}$	Agricultural science non-federal funding	−6.57E-07	−7.30E-07	−9.82E-07
		(9.84E-06)	(9.82E-06)	(9.64E-06)
$BSFED_{it-2}$	Biological science federal funding	6.56E-06	6.00E-06	5.12E-06
		(1.1E-05)	(1.10E-05)	(1.0E-05)
$BSNFED_{it-2}$	Biological science non-federal funding	4.12E-05	4.29E-05**	3.66E-05**
		(1.8E-05)	(1.9E-05)	(1.8E-05)
$PCIND_{it-2}$	Percent of all university funding from industry sources	−1.9711	−1.92218	−2.138
		(2.35697)	(2.35938)	(2.272)
AF_{t-2}	Average faculty salary	0.026343	0.026333**	0.0235**
		(0.01141)	(0.01139)	(0.0112)
$FUNFAC_{t-2}$	Funding per faculty member, university wide	9.65E-05	9.35E-05	8.94E-05
		(7.9E-05)	(7.9E-05)	(7.5E-05)
AS_{t-2}	Agricultural science graduate students	0.0032	0.0033	0.00357*
		(0.0021)	(0.0021)	(0.00196)
BS_{t-2}	Biological science graduate students	−3.8E-05	9.51E-07	0.000103
		(0.0012)	(0.0012)	(0.0011)
$PROPENS_t$	Ratio of patent applications to invention disclosures	1.579***	1.591***	1.521***
		(0.361)	(0.363)	(0.358)
OTT_t	Number of FTE's in the office of technology transfer	0.0162	0.0166	0.0197
		(0.0202)	(0.0201)	(0.0196)
LGU	Land grant status	1.0134***	1.0331***	0.992***
		(0.372)	(0.378)	(0.355)
$YrDum$	1997–98	−0.723***	−0.724***	−0.778***
		(0.186)	(0.186)	(0.190)
$BEFORE_i$	Number of ag-biotech patents (1971–90)		−0.010	
			(0.036)	
G_{t-1}	Dynamic patenting knowledge accumulation			0.034*
				(0.0206)
Constant		−2.108***	−2.132***	−1.990***
		(0.768)	(0.774)	(0.744)
Log likelihood		−453.49	−453.45	−452.20

$N = 562$, $i = 128$, standard errors in parentheses, ***, **, * significant at greater than a 1%, 5%, 10% level.

Results

The results of maximum likelihood estimations using a random effects negative binomial model are shown in table 3. Three models were estimated: (*a*) a base model with no dynamic effects, (*b*) a dynamic model with pre-sample measurements of heterogeneity, $BEFORE_i$, and (*c*) a model with continuous dynamic patent effects, G_{it-1}. All models pass a likelihood ratio test of the random effects versus a pooled data model at greater than 99% level. Also, all models produce estimates of dispersion, the parameters of the beta distribution (a,b), which are significantly different from zero.

The signs on the coefficients on all models are generally as expected, with the possible exception of a nonsignificant negative sign on the percent industry financing.[11] As expected, the time dummy (*YrDum*) captures significantly lower levels of patent acceptances for applications made in 1997 and 1998, due to

[11] In a negative binomial model the coefficients are proportional to the marginal effects so that relative values of importance can be read directly from table 3.

the truncation inherent in this time period. The variables having a positive and significant effect on ag-biotech patent production are: non-federal biological funding, average faculty salaries, agricultural graduate students, patenting propensity, LGU status, and dynamic knowledge accumulation. In general, the results suggest that the quality of the inputs matter more than the absolute quantity.

Regarding hypothesis *H1*, the results provide little evidence of barriers to entry related to the pre-sample search level. The static measure of search levels, $BEFORE_i$, is not significant, which suggests that ag-biotech patent production levels prior to the take off in the 1990s were not important in explaining patent production in the sample period. However, the dynamic effects formulation, G_{it-1}, in model 3 shows, at a 10% significance level, the importance of knowledge accumulation in the patenting process. Consistent with the results for industrial innovation reported by Blundell, Griffiths, and Van Reenen, the results here show evidence of path dependence in innovation activities. Therefore, whereas we do not find evidence of barriers to entry before and after the 1990s explosion in ag biotech patent production, we do find evidence of persistence in ag-biotech patent production.

The estimation results on LGU status show strong evidence of a land grant effect (hypothesis *H2*). In addition, model 3 suggests the importance of the agricultural college infrastructure as proxied by the number of graduate students. While federal funding in agriculture is not significant in the results presented, further investigations suggested that this is due to multicollinearity with the LGU dummy variable rather than the ineffectiveness of federal funding. It seems that absolute funding levels in agriculture are less important for ag-biotech patenting than whether that money translates into more people doing research.

Non-federal funding for biological science research is also a significant determinant of ag-biotech patent production. This result suggests that even after controlling for the amount of agricultural research, biological sciences are important for ag-biotech patent production (hypothesis *H3*), apparently having the effect of spilling into ag-biotech related research.

The non-federal biological funding estimate also has weak implications for hypothesis *H4* related to the role of industry financing, because non-federal funds come primarily from state and/or industry sources. On the other hand, the estimation result on overall university reliance on industry financing is negative and not significant. Combined, these results make it hard to draw an inference on whether industry financing matters to university ag-biotech patenting.

The estimations also provide evidence of the importance of patenting culture (hypothesis *H5*), even after controlling for patenting knowledge accumulation effects and the number of technology transfer personnel. The patenting propensity estimate is similar in magnitude to the estimated effect of being a land grant university. The similarity of these effects underscores the potential value of the overall culture of a university's technology transfer system to its ag-biotech patent production.

Conclusions

The remarkable increase in the numbers of ag-biotech patents awarded to U.S. universities in the last decade demonstrates that universities in and out of the land grant system take patenting ag-biotech innovations seriously. This work has examined a panel count data model of university ag-biotech patent production and introduced an econometric method focused on understanding unobserved university heterogeneity through a dynamic feedback effect. Applying this method to university ag-biotech patenting data we find strong evidence of a correlated dynamic effect in which patenting experience helps to produce more patents (*H1*). We also find that ag-biotech patent production is enhanced by the overall university propensity to patent (*H5*), a strong land grant effect (*H2*), and a biological science research funding effect (*H3*). We do not find convincing evidence that university reliance on industry financing increases patent production (*H4*).

If the goal of policy makers is to increase university production of ag-biotech patents, the results presented here suggest some possible directions. Pursuing links between biological and agricultural research would seem to have a payoff, even for universities without an agricultural research tradition. The results also suggest that administrators should look to invest in quality rather than quantity and to generate a campus culture that promotes patenting. Administrators at "lagging" universities should be heartened that while there is evidence of persistence in the production of ag-biotech patents we did not find strong evidence of barriers to entry into ag-biotech patent production prior to the recent takeoff in patent activity.

Some compelling questions deserve further study. First, while this work has found that ag-biotech patent production is positively influenced by knowledge acquisition dynamics, it does not identify at which levels of the university these effects operate. For example, does the dynamic effect of knowledge acquisition occur among technology transfer employees, across the whole university, or among a few individual scientists who learn more about the research and patenting process? Any or all three could be at work in varying combinations. Second, this work does not examine the more normative question of whether it is desirable for universities to patent ag-biotech innovations. To address this question comprehensively, future research will need to examine empirical evidence on the values of patents to universities in terms of licenses and other revenue sources, the spillovers from university research to private industry research, and the possible market distortions induced by university patenting. Contributions in these areas will move economists closer to making meaningful empirical contributions to normative debates about the enormous changes taking place in agricultural research and development.

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References

Alston, J.M. and P.G. Pardey. *Making Science Pay: The Economics of Agricultural R&D Policy*. Washington DC: AEI Press, 1996.

Barham, B., J.D. Foltz and K. Kim. "Trends in University Ag-Biotech Patent Production." Q1 *Review of Agricultural Economic*. In press.

Blundell, R., R. Griffith and J. Van Reenen. "Dynamic Count Data Models of Technological Innovation." *Economic Journal* 105(1995): 333–44.

——. "Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms." *Review of Economic Studies* 66(1999):529–54.

Cameron, A.C. and P. Trivedi. *Regression Analysis of Count Data*. Cambridge, UK: Cambridge University Press, 1998.

Evenson, R. "Economics of Intellectual Property Rights for Agricultural Technology." In V. Santaniello, R. Evenson, D. Zilberman, and G. Carlson, eds. *Agriculture and Intellectual Property Rights*. Oxon, UK: CABI Publishing, 2000.

Foltz, J.D., B. Barham and K. Kim. "Universities and Agricultural Biotechnology Patent Production." *Agribusiness* 16(2000):82–95.

Harvey, D. "University, Inc." *The Atlantic Monthly* 282(1998):112–16.

Hausman, J., B. Hall and Z. Griliches. "Economic Models for Count Data with an Application to the Patents-R&D Relationship." *Econometrica* 52(1984):909–38.

Just, R.E. and W.E. Huffman. "Economic Principles and Incentives: Structure, Management, and Funding of Agricultural Research in the United States." *American Journal of Agricultural Economics* 74(1992):1101–8.

Massing, D. *AUTM Licensing Survey: FY 1991–FY 1995*. Association of University Technology Managers. Norwalk, CT, 1996.

——. *AUTM Licensing Survey: FY 1996*. Association of University Technology Managers. Norwalk, CT, 1997.

——. *AUTM Licensing Survey: FY 1997*. Association of University Technology Managers. Norwalk, CT, 1998.

Moschini, G. and H. Lapan. "Intellectual Property Rights and the Welfare Effects of Agricultural R&D." *American Journal of Agricultural Economics* 79(1997):1229–42.

National Science Foundation. "NSF Webcaspar: Your Virtual Bookshelf of Statistics on Academic Science and Engineering." http://caspar.nsf.gov/ (accessed on 15 July 2000).

Pakes, A. "Patents as Options: Some Estimates of the Value of Holding European Patent Stocks." *Econometrica* 54(1986):755–84.

Rausser, G., L. Simon and H. Ameden. "Negotiating public/private Research Alliances." Working paper, Dept. of Agricultural and Resource Economics, University of California-Berkeley, 1999.

Santaniello, V., R. Evenson, D. Zilberman and G. Carlson eds. *Agriculture and Intellectual Property Rights*. Oxon, UK: CABI Publishing, 2000.

Trajtenberg, M. "A Penny for Your Quotes: Patent Citations and the Value of Innovations." *Rand Journal of Economics* 21(1990):172–87.

U.S. Patent Office. "Patent Bibliographic and Abstract Database." http://www.uspto.gov/patft/index.html (accessed on 15 July 2000).

Zilberman, D., C. Yarkin and A. Heiman. "Agricultural Biotechnology: Economic and International Implications." Working paper, Dept. of Agricultural and Resource Economics, University of California-Berkeley, 1997.

Appendix A

Search Activity Variable (Before) Derivation

Following Blundell, Griffiths, and Van Reenen (1995), let an observable latent variable, S_{it}, describe a university's patent searching activities. It will be a function of previous search activities, university characteristics, and unobservable variables (a university-specific effect η_i and a random shock variable ε_{it}) such that

$$\text{(A.1)} \quad S_{it} = w_1 S_{it-1} + w_2 x_{it-1} + \eta_i + \varepsilon_{it}$$

where w_1, w_2 are constants. Letting university characteristics, x_{it} , be related to previous levels of university characteristics and searching the dynamic feedback will be

$$\text{(A.2)} \quad x_{it} = \gamma_1 x_{it-1} + \gamma_2 S_{it-1} + \nu_{it}$$

where γ_1 and γ_2 are constants. Substituting this into equation (A.1), taking expectations over time, t, and assuming stationarity of S_{it} and that the stochastic terms have mean zero ($E(\varepsilon_{it}) = 0$ and $E(\nu_{it}) = 0$) yields the following equation in $\bar{S}_i$ and η_i

$$\text{(A.3)} \quad (1 - w_1)(1 - \gamma_1)\bar{S}_i = w_2\gamma_2\bar{S}_i + (1 - \gamma_1)\eta_i$$

where $\bar{S}_i$ is the expected value of S_{it}. This equation can then be solved for $\bar{S}_i$ so as to express it as a function of η_i and some constants

$$\text{(A.4)} \quad \bar{S}_i = \eta_i(1 - \gamma_1)[(1 - w_1)(1 - \gamma_1) - w_2\gamma_2]^{-1}.$$

Thus, for any university, the search activities will be proportional to the unobservable university-specific effect. If we are willing to assume that, over a long enough time span, the number of actual patents received is a reasonable proxy for search activities, then we can proxy some of the individual unobservable heterogeneity by a pre-sample measure of patenting.

Appendix B

Defining Ag-Biotech

To establish an appropriate ag-biotech patent data base we use a consistent definition that says that ag-biotech:

(1) genetically alters some product and/or is in U.S. patent class 800 or 435; and
(2) uses extensively a product produced on a farm; or
(3) modifies or improves a product produced on a farm; or
(4) modifies, improves, or produces a food, wood, or aqua-culture product.

Note that the above definition includes a large number of patents that might not be specific to agriculture. However, the search strategy also excludes from our definition of ag-biotech products or processes with no direct connection to agriculture. These excluded include:

(1) any animals or plants produced entirely for research purposes, for example, mice, rats, monkeys;
(2) any animal primarily designed as a pet, for example, dogs and cats;
(3) any product that merely uses animal or plant cells in minor quantities for a nonagricultural product; or
(4) any vaccine or vaccine technique or disease diagnostic technique that is intended primarily for use in humans, or on human diseases, or on diseases not currently treated in animals.

The data base does include patents on plants intended only for ornamentation so long as they fit the definition of being biotechnology.