Food Marketing Policy Center

A Dynamic Count Data Analysis of
University Ag-Biotech Patents

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Preface

This paper examines the factors that account for ag-biotech 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 ag-biotech patent production of land grant infrastructure, quality faculty, state and institutional funding, patent-oriented technology transfer offices, as well as dynamic feedback effects.

1. Introduction

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 in the Land Grant system, 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 U.S. 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 land grant institutions) are investing heavily in establishing ag-biotech centers, building new laboratory and research infrastructure, and hiring faculty, all with the intent of advancing their ag-biotech research capabilities.[1] Beyond the inherent promise of the research itself, pay-offs 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 25 to 30 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 potential positive or normative effects of ag-biotech patenting on agricultural productivity or the broader economy. A recent flurry of research (see for example papers in the conference volumes: Santaniello, et al.; and Evenson, et al.) has started the process of evaluating public and private incentives of agricultural research with intellectual property rights. While a number of papers 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 agricultural in general (e.g. Evenson), no study has effectively quantified and analyzed the dynamic process of ag-biotech patenting at the university level.

This paper 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 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. While 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 pay-offs to ag-biotech

[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 ag-biotech.

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

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. As in Foltz, Barham, and Kim, the data set used includes all major universities, many of whom (e.g. non-land grants) might not be expected to have ag-biotech patents. 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. In other words, this paper places special emphasis on understanding how previous patent experience (including none) affects current patent production and thus tests the extent to which feedback effects are important in shaping patenting success.

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

(H1) The presence of correlated dynamic effects, (e.g. Zilberman, Yarkin, and Heiman) wherein universities with initial success in obtaining ag-biotech patents receive more patents in the future, while those that do not have initial success find it difficult to participate in the process. This hypothesis about dynamic effects could be supported by a virtuous cycle of licensing and research dollars returning to successful patenting efforts, or by some significant barriers to entry that rise with time (learning costs for catch-up);

(H2) The presence of industry effects, (e.g. Harvey) wherein industry funding will play a critical role in shaping the direction and success of university research;

(H3) The 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 patent production; and,

(H4) The presence of university specific effects, (e.g. Foltz, Barham, and Kim) wherein certain universities will have a higher proclivity toward patenting than others because of more investment in technology transfer offices and other "patent" inducing infrastructure.

The empirical basis for this study is a unique panel data set, covering the years 1991 to 1999, constructed from various sources, including the U.S. Patent Office, the National Science Foundation, and the Association of University Technology Managers. 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. The next to last section provides the results of the econometric estimation. The last section summarizes the key findings of this paper.

2. A Theoretical Framework for Modeling University Patent Production

The primary focus of this paper 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

$$Y_{it} = f(x_{it}, u_{it}) \text{ for } i = 1,\dots N \text{ and } t = 1,\dots T, \qquad (1)$$

where Y_{it} is a count of patents produced and x_{it} is a vector of the characteristics of university i and general conditions outside the university that influence the process (e.g. government policy). The term u_{it} represents unobservable university differences. Let the relationship between patents produced, y_{it}, and university characteristics, x_{it}, be thought of as the outcome of both a research, R_{it}, and a patenting process, H_{it}. The research process involves inputs into the production of knowledge, often independent of economic considerations, while the patenting process will be an explicit function of the potential value of that research as intellectual property rights and university patenting experience.

Let the overall research produced by a university, R_{it}, be described by a classic production process using labor, capital, and structures (labs, etc.) to produce research in the following fashion:

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

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. For our purposes, one needs to note that the research process happens prior to the patent application. Typically the research leading up to a patent would take a couple of years, if not considerably longer.

By contrast, the variables influencing the patenting process, described in the equation H_{it}, will be contemporaneous to the patent application. The function describing patent development is as follows:

$$H_{it} = h(D_{it} , G_{it-1}), \tag{3}$$

where the variable D_{it} describes labor and capital inputs in the technology transfer office and G_{it-1} represents the culture and information that the university has developed in producing patents in the past, which feeds into the technology transfer process. Among the key elements of D_{it} 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.

Having divided out the university characteristics in x_{it} one can re-specify the model of patent production in a way that takes into account research dynamics. Here the model is

$$Y_{it} = f(x_{it} ,u_{it}) = f(R_{it-1} , H_{it} , u_{it}), \tag{4}$$

where H_{it} is contemporaneous to patent production while R_{it} has been lagged one period to account for the dynamics of the research process. Note that H_{it} also contains a dynamic element in the information feedback effects from past patents, G_{it-1}. The lagged structure of the research process and the dynamic feedback effects need to be taken into account in any estimates of the patenting process. The next section develops the econometric methods used to investigate the role of innovation dynamics.

3. 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:

$$E(Y_{it}) = e^{X_{it}'\beta} , \tag{5}$$

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

$$X_{it}'\beta = \theta_o + \theta_1 L_{it-1} + \theta_2 K_{it-1} + \theta_3 T_{it-1} + \theta_4 D_{it} + \theta_5 G_{it-1} + \eta_i + \nu_t, \tag{6}$$

where the first four 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. More specifically, L_{it-1} represents the labor inputs (both quantity and quality) in the research production process, K_{it-1} measures the financial capital in the research process, and T_{it-1} is the physical capital such as labs. For the moment, all variables in the research process are lagged one period. The first of the variables in the patent generation process D_{it} represents the degree of university interest and competence in patenting innovations. The last variable, G_{it-1}, represents the potential dynamic learning and perhaps financing effect from previous successful patents in the research area. The econometric justification for its inclusion is further explored below.

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. Since 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 the former allows more flexibility by not requiring that the mean and the variance of the estimated disturbance term be equal and instead allowing the dispersion parameters to vary across individuals (i.e. universities).

Formally, the dependent count variable, y_{it} , is assumed to be *iid* negative binomial with parameters α_i, λ_{it} and ϕ_i where we have set $\lambda_{it} = \exp(x_{it}\, \beta)$. 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 ith group as follows:

$$\Pr\{y_{i1},\ldots y_{iT}\} = \left(\prod_t \frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})!\Gamma(y_{it}+1)} \times \frac{\Gamma(a+b)\Gamma(a+\sum_t \lambda_{it})\Gamma(b+\sum_t y_{it})}{\Gamma(a)\Gamma(b)\Gamma(a+b+\sum_t \lambda_{it}\sum_t y_{it})} \right). \tag{7}$$

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. However, as suggested in the model and the opening of the paper, it seems reasonable to hypothesize that earlier patenting experience captures some of that heterogeneity. For example, as shown in Table 1, being among the leaders in ag-biotech patenting in the pre-sample period (1971-1990) appears to increase greatly the likelihood of producing patents in the sample period. Thus, one way of approaching this issue would be to use pre-sample information to parameterize η_i.

Blundell, Griffiths, and Van Reenen (1995) present a method for using pre-sample information to parameterize a part of the unobservable heterogeneity. Imagine there is an observable latent variable, S_{it} , that describes the state of 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}) in the following manner:

$$S_{it} = w_1 S_{it-1} + w_2 x_{it-1} + \eta_i + \varepsilon_{it}, \tag{8}$$

where w_1, w_2 are constants between zero and one. We presume that university characteristics, x_{it} , will in fact be related to previous levels of university characteristics as well as university patenting such that there will be dynamic feedback effects of the form

$$x_{it} = \gamma_1 x_{it-1} + \gamma_2 S_{it-1} + v_{it}, \tag{9}$$

[3] See Cameron and Trevedi (1998) 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 Trevedi also develop moment based methods possible with the negative binomial model.

where γ_1 and γ_2 are constants between zero and one. Substituting this definition of x_{it} into equation (8), taking expectations over time, t, and assuming stationarity of S_{it} and that the stochastic terms have mean zero (E(ε_{it}) = 0 and E(ν_{it}) =0) yields a simpler form. It gives the following equation in $\overline{S_i}$ and η_i:

$$(1-w_1)(1-\gamma_1)\overline{S_i} = w_2\gamma_2\overline{S_i} + (1-\gamma_1)\eta_i, \tag{10}$$

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

$$\overline{S_i} = \eta_i(1-\gamma_1)\left[(1-w_1)(1-\gamma_1) - w_2\gamma_2\right]^{-1}. \tag{11}$$

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. One approach used below incorporates a count variable (*BEFORE*$_i$) to capture the number of pre-sample patents as a proxy for search activities.

An alternative to using this pre-sample information to capture university search activity and quality is to use a within sample continuous proxy for this variable. Using the same assumption that actual patents received proxy for the search experience, one can create a variable G_{it} , which is the depreciated sum of previous patents. More specifically G_{it} is defined as follows:

$$G_{it} = y_{it} + (1-\delta)G_{it-1}, \tag{12}$$

where δ is the rate at which patenting experience depreciates. G_{it} provides a continuous representation with a more realistic discounting structure of $\overline{S_i}$ than in equation (11). This is the other approach used in the subsequent estimations to capture dynamic effects.

4. Data

All of the descriptive variables used in the econometric analysis are summarized below in Table 2. They were constructed as follows:

Patent Data Source

The patent data identifies all ag-biotech utility patents owned by US universities from a search of the complete

U.S. patent office database[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]. The appendix describes the process used to determine which patents are ag-biotech.

Using the definition of ag-biotech in the appendix, the search chose all ag-biotech patents with application dates after Jan 1, 1971 and through the end of 1999. During this time period, a total of 107 universities received 795 ag-biotech patents[6]. In the period used for our estimations, 1991-1998, there were 99 universities with ag-biotech patents. Due to complementary data limitations, the actual data set used for the model has information 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 patents filed in the period 1997-1999 are still under review. Thus, patent data from those years offer incomplete information on acceptances.

Table 1 shows that the top 20 universities, ranked by accepted agricultural biotechnology patents during this time period, are, with one exception, public land-grant institutions, with agricultural colleges. Overall, ag-biotech patent holdings among U.S. universities are moderately concentrated with the top five holders having 29% of the total number of patents, the top 10 having 45%, and the top 20 having 63%. Ag-biotech patent holdings among U.S. universities are almost completely dominated by public land-grant institutions, which hold 84% of the total issued in the past 30 years.

The rather strong pattern of persistence in ag-biotech patent production over the two time periods is particularly noteworthy given the dramatic growth of patents acquired by universities over the past few years. It 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} were constructed in order to measure knowledge stock. The variable $BEFORE_i$ – the number of patents produced by university i before the year of 1990 – is created to analyze the effects of patent production history in 70's and 80's. G_{it} is defined as the sum of the current patents and discounted previous knowledge stock ($G_{it} = Y_{it} + (1-\delta)\, G_{it-1}$, where Y_{it} is university *i*'s number of patents obtained at time t and δ is a discount rate of 30%)[7]. It captures the dynamics of innovation histories.

Input data sources

Input data for the study come from National Science Foundation (NSF) and the Association of University Technology Managers (AUTM) databases. The inputs to the research process include labor (*L*), capital (*K*), and university input variables in the patent production process (*D*)[8]. As described in the econometric model the relevant measures of research production should be lagged in order to reflect possible time lags between the start of research and the actual research discovery. Here, a two period lag is selected as most representative of the time a successful research project would take.

Labor

We developed several measures of labor input to proxy for the number and quality of scientists. Specifically, we use: the number of full-time graduate students in Agricultural Sciences (AS_{it}), the number of full-time graduate students in Biological Sciences (BS_{it}), and the number of faculty (NF_{it}) to capture the quantity of labor and the average faculty salary (AF_{it}) as a proxy for the quality of labor and the university.[9]

Capital

Capital inputs include research funds from federal, state, industry, and university sources. The following variables, from NSF (2000), are included: federally

[4] The database 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 have made US 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 our previous research in more than doubling the number of patents identified as being ag-biotech.

[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} 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 3 years. During those 3 years a patent office may learn much about the patent process which could improve the next patent application and thus give rise to dynamics in the patent process. G_{it} was generated using a 30% discount rate. Changing that discount rate to either 10% or 20% did not measurably influence the results. The larger discount rate was preferred as it assumed less structure.

[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.

financed R&D expenditures (FED_{it}), state & local government R&D expenditures (STA_{it}), industry R&D expenditures (IND_{it}), institutional R&D expenditures (INS_{it}), and other R&D expenditures (OTH_{it}). As expected, Table 2 shows that the majority of the R&D money comes from federal government followed by institutional sources, state government and industry.

Patent Production variables

As mentioned above, the productive potential of research as patents to a university could be affected by a number of variables. 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. Thus, 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 this technology transfer infrastructure (AUTM, 1991-1997). To capture the quality or efficiency of the office of technology transfer office, we include a variable, $EFFOTT_{it}$, which measures the percent of total invention disclosures for all classes of patents that result in actual patent applications.

5. Results

Table 3 shows the estimates of ag-biotech patent production from a maximum likelihood estimation of a random effects negative binomial model. The table presents three models, a base model with no dynamic effects, a dynamic model with pre-sample measurements of heterogeneity, $BEFORE_i$, and a model with continuous dynamic patent effects, G_{it}. All models pass a likelihood ratio test of the random effects versus a pooled data model at a greater than a 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 non-significant negative sign on industry financing. As expected, the time dummy captures significantly lower levels of patent acceptances for applications made in 1997 and 1998, due to the short time horizon in the data.

The base case demonstrates most of the effects found in the data. Among the funding variables, state and own institutional funding are the only ones to have a significant effect on ag-biotech patent production. The lack of a significant effect of industry funding on ag-biotech patent production, a consistent result across all models, suggests that industry funding is not the primary driving force in university ag-biotech patent production. The positive coefficient on own institutional funding gives some evidence of the presence of a virtuous circle in ag-biotech funding since some of the own institutional funding can come from patent revenues. The estimates also demonstrate evidence of the importance of the land grant infrastructure, since one measure of this feature, agricultural science graduate students, is positive and significant. The econometric estimates, surprisingly, do not support the idea of a strong complementarity between research programs in the biological sciences and ag-biotech patent production.[10] The labor variables demonstrate that average faculty salary is significantly related to university ag-biotech patent production perhaps capturing an effect of faculty quality. However, quantity of faculty fails to explain patent output.

The variables measuring university patent production efforts again find a similar relationship between university patent production and labor variables in the technology transfer process. The technology transfer office labor quantity variable is insignificant and very close to zero. On the other hand, the measure of technology transfer efficiency ($EFFOTT_{it}$) in turning invention disclosures into patent applications is significant and positive. The strength of this effect suggests that this efficiency in managing all invention disclosures may carry over into ag-biotech patent application management.

The second model, which includes the university specific variable, $BEFORE_i$, shows little difference in its coefficients from the base model. The pre-sample effect variable itself is not significantly different from zero. Thus, the model is unable to describe unobserved heterogeneity with an "entry stock" variable serving as an intercept shifter across universities. This non-result calls into question the hypothesis that those universities best poised in 1990 to produce ag-biotech patents, as evidenced by a positive ag-biotech track record in the 1970's and 1980's, are those producing the most in the 1990's. Although our funding variables suggest a possibility of a virtuous cycle for institutional funding and patent acceptances, this particular result on $BEFORE_i$ suggests that having had ag-biotech patents in the pre-sample period is not a necessary condition of later ag-biotech patent production.

The dynamic effects formulation with G_{it}, presented in the third column, provides a continuous and updated version of the pre-sample variable, $BEFORE_i$. It both parameterizes the pre-sample effect, since G_{it} for the first year of data contains information on patents in the years

[10] Further estimates of potential interaction effects between agricultural and biological sciences also did not produce any significant effects.

previous to the data set, and provides a variable with variations within years for universities. This model does give rise to a significant parameter estimate on $G_{it,}$ and suggests that a more continuous measure of the potential dynamic feedback provides a better method than that used in the second to capture the unobserved heterogeneity in university patent data. Consistent with the results for industrial innovation reported by Blundell, Griffiths, and Van Reenen, the results here show evidence of history dependence in innovation activities. Thus, this dynamic model suggests that there may, in fact, be a good deal of learning by doing in the university ag-biotech production process.

6. Conclusions

This work has examined a panel count data model of university ag-biotech patent production and introduced a method of understanding the underlying nonlinear and dynamic process of research and patent generation. Modeling this process has produced 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 produces more patents (H1) and a land grant effect (H3). We do not find any evidence that industry financing increases patent production (H2) and find that university proclivity toward patenting (H4) has more to do with the quality of investments rather than the size of the technology transfer infrastructure per se.

The results presented here provide some interesting points of departure for research administrators at both large and small land grant universities. Dominant universities, as measured by their previous patent production, tend to produce more ag-biotech patents, as the ongoing effect of producing more ag-biotech patents clearly spurs the process along. Thus, lagging universities can catch up, but the dynamic feedback effects of previous inexperience will slow the catch-up process. Funding variables at least partially within the choice set of university administrators, own institutional and state financing, are the most highly correlated with ag-biotech patent production, which is potentially good news for them. According to these estimations, the best method for investing in ag-biotech patent production is quality personnel.

This research leaves open the fundamental question of the value of patents to universities. This reduced form model implicitly assumes that ag-biotech patent production is of value to universities, but research has not yet demonstrated the degree to which or the scale at which this is in fact true. By explaining the dynamics of ag-biotech patenting, this paper provides a necessary first step in understanding the determinants of values created by university ag-biotech patents. Quantifying and estimating these values in a more comprehensive structural model of university research is left for future research.

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Table 1. University Rankings of Ag-Biotech Patent Production 1971-1999

University	Rank 71-99	Patents 71-99	Pre-Sample Rank 71-90	Patents 71-90
UW-Madison	1	53	1	19
Cornell	2	52	2	16
Iowa State Univ.	3	47	8	7
Michigan State Univ.	4	44	45	1
UC-Davis	5	32	12	6
Univ. of Florida	6	29	4	10
Purdue	7	26	3	12
Univ. of Minnesota	8	26	16	5
Louisiana State Univ.	9	24	21	3
NC State Univ.	10	21	5	9
Texas A&M	11	19	17	4
UC-Berkeley	12	19	7	9
Rutgers	13	18	23	3
Univ. of Georgia	14	17	10	7
Oregon State	15	14	6	9
Univ. of Maryland-College Park	16	13	15	5
Univ. of Pennsylvania	17	13	0	0
Univ. of Kentucky	18	12	35	2
Ohio State Univ.	19	11	9	7
Penn State Univ.	20	11	0	0

Table 2. Data Summary

Variable	Definition	Mean	Std. Dev.	Minimum	Maximum
Y_{it}	Number of Ag-biotech patents	0.65	1.61	0	14
FED_{t-2}	Federal funding	70665	83511	132	692704
STA_{t-2}	State funding	7996	12048	0	65600
IND_{t-2}	Industry funding	6768	7041	0	54573
INS_{t-2}	Own institutional funding	18219	18470	0	95653
OTH_{t-2}	Other funding	7950	9228	0	59587
AS_{t-2}	Agricultural science graduate students	36.84	67.27	0	280
BS_{t-2}	Biological Science graduate students	189.95	157.07	1	741
AF_{t-2}	Average faculty salary	50.49	10.45	29.03	107.76
NF_{t-2}	Number of faculty	819.62	470.45	37	3258
$EFFOTT_t$	Ratio of patent applications to invention disclosures	0.35	0.20	0	1
OTT_t	Number of FTE's in the office of technology transfer	5.26	5.63	0	33
$BEFORE_i$	Number of ag-biotech patents (1971-1990)	1.54	3.14	0	19
G_{t-1}	Dynamic patenting knowledge accumulation	1.33	2.83	0	23.23

Note: N = 561, Number of universities = 127
FED, STA, IND, INS, OTH, and *AF* are measured in $1,000.

Table 3. Random Effects Negative Binomial Estimation Results (Dependent variable Y_{it} , the count of ag-biotech patents)

Variable	Definition	Base Model	Pre-Sample Dynamic Effects	Continuous Dynamic Effects
FED_{t-2}	Federal funding	7.14e-07 (1.85e-06)	7.15e-07 (1.85e-06)	5.42e-07 (1.68e-06)
STA_{t-2}	State funding	0.000028 (9.12e-06)***	0.000028 (9.72e-06)***	0.000021 (9.36e-06)**
IND_{t-2}	Industry funding	-0.000017 (0.000018)	-0.000017 (0.000018)	-0.000016 (0.000017)
INS_{t-2}	Own institutional funding	9.90e-06 (5.28e-06)*	9.89e-06 (5.39e-06)*	9.58e-06 (5.14e-06)*
OTH_{t-2}	Other funding	0.0000175 (0.000015)	0.0000174 (0.000015)	0.000016 (0.000014)
AS_{t-2}	Agricultural science graduate students	0.0064 (0.0020)***	0.0064 (0.0020)***	0.0068 (0.0018)***
BS_{t-2}	Biological Science graduate students	0.00042 (0.0011)	0.00042 (0.0011)	0.00033 (0.0010)
AF_{t-2}	Average faculty salary	0.027 (0.011)**	0.027 (0.011)**	0.021 (0.011)*
NF_{t-2}	Number of faculty	0.00018 (0.00023)	0.00018 (0.00023)	0.00013 (0.00021)
$EFFOTT_t$	Ratio of patent applications to invention disclosures	1.58 (0.36)***	1.58 (0.36)***	1.54 (0.36)***
OTT_t	Number of FTE's in the office of technology transfer	0.0033 (0.022)	0.0033 (0.022)	0.012 (0.022)
YrDum	1997-1998	-0.66 (0.18)***	-0.66 (0.18)***	-0.77 (0.19)***
$BEFORE_i$	Number of ag-biotech patents (1971-1990)		0.00042 (0.041)	-0.012 (0.037)
G_{t-1}	Dynamic patenting knowledge accumulation			0.041 (0.020)**
Constant		-1.99 (0.73)***	-1.99 (0.73)***	-1.79 (0.68)***
Log-likelihood		-459.83	-459.83	-457.70

N = 561, Number of universities = 127, standard errors in parentheses,
***, **, * significant at greater than a 1%, 5%, 10% level respectively.

Appendix

Defining Ag-biotech

In order to establish an appropriate ag-biotech patent database we use a consistent definition that says that ag-biotech:

(1) genetically alters some product; 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. Those excluded include:

(1) any animals or plants produced entirely for research purposes (e.g., mice, rats, monkeys);
(2) any animal primarily designed as a pet: e.g. dogs and cats;
(3) any product that merely uses animal or plant cells in minor quantities for a non-agricultural 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 database does include patents on plants intended only for ornamentation so long as they fit the definition of being biotechnology.

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