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The Determinants of Research Productivity in the Agricultural Input Industry

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SHORT ABSTRACT
The ag-biotech industry underwent considerable consolidation in the last decade in part to take advantage of economies of scale and scope. The paper investigates the impact of such consolidation on inventive activity at the firm level. Careful attention is paid to the role of firm size, technology diversification and spillovers in the innovation process.

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1. Problem Statement

As a response to the emergence of new technological opportunities for directly tailoring the genetic makeup of crops, and new techniques that enhance the speed and precision of agricultural research and development, the global agricultural input industry has undergone a significant structural change. In particular large chemical firms moved aggressively into agricultural biotechnology and pharmaceuticals, transforming themselves into life science firms. In addition to this merger and acquisition (M&A) activity, many companies negotiated research joint ventures and strategic alliances with corporate partners.

A number of explanations as to the reasons behind the mergers have been hypothesized and tested. Graff, Rausser and Small and Johnson and Melkonyan argue that M&As in the plant biotechnology industry offers a least-cost way of combining and exploiting complementary intellectual assets. Kalaitanadonakes and Bjornson suggest that a vertically integrated firm in a concentrated industry is much more effective at appropriating rents from biotechnological innovations then if the industry were competitive. This Schumpeterian type conclusion would suggest that consolidation will continue until the firms are able to appropriate the rents from their inventive act ivies. At the same time, it has also been suggested that consolidation results in not only greater

market power both in the output market and the innovation market but also the concentration of enabling technologies in the hands of a few firms (Barton and Brennan, Pray and Courtmanche). Greater concentration under the market power hypothesis would imply that consolidated firms will have lower incentives to conduct research and may prevent other firms from accessing key technologies.

Although economists have a good understanding for the reasons behind the wave of mergers, its affect on innovation and competitiveness remains speculative and uncertain. Oehmke and Naseem provide a direct test between the number of M&As and inventive activity at the industry level and find opposing effects of concentration and consolidation. They find that inventive activity decreases with fewer firms in the market but increase with industry concentration, which suggests that inventive activity will be maximized when a few firms conduct the majority of the research but with a large number of firms in the periphery.

In this paper we address the issue of impacts of industry consolidation on innovation by examining firm level research and innovation data. More specifically we seek to understand the determinants of the innovation in ag-biotech by modeling a research production function. We hypothesize that as firms increase in size due to consolidation, their research output will increase proportionately. This economy of scale hypothesis would be consistent with Kalaitanadonakes and Bjornson view that agbiotech industry is Schumpeterian in that consolidation allows greater appropriation of rents and greater innovation. A failure to find such an increase would suggest that the direct relationship between consolidation and firm level R&D output is not strong, and perhaps the firms are exercising their market power and limiting innovation as suggested by

Brenna, Pray and Courtmanche. By modeling a knowledge production function, we are also able to test the hypothesis whether firms that have diversified research portfolio are more innovative than those that don't. That is, by maintaining diverse portfolios of research they exploit economies of scope in research activities, as they are better able to exploit research spillovers especially those that arise from basic research. If they indeed are more innovative due to diversification, this would lend credence to the argument that mergers occurred from a desire of firms to bring together and exploit complementary assets as suggested by Graff, Rausser and Small. Lastly, our modeling approach also allows us to understand external research spillovers, especially the impact of research activities done in the public research sector, such as universities and government labs.

The balance of the paper is organized as follows. The next section reviews some key papers in the literature on knowledge production functions. This provides us with the context to propose some testable hypothesis that follows in the conceptual framework section. A description of the data employed is in section four. Section five presents the regression results and section six concludes the paper.

2. Literature Review

What determines a firm's research output? Why are some firms more innovative than others? Does firm size matter? These questions have always intrigued economists and policy makers and have been a subject of much academic research. To better understand the process of innovation a number of researches have described and modeled the production of knowledge at the firm level. Typically this requires the measurement of

some research output, such as patents, and explaining the research output in terms of a variety of firm and industry specific variables. For example, a seminal paper in this literature is that of Griliches, Hausmann and Hall who use patent count as the output of research and R&D expenditure as the research input. They developed and adapted different statistical models of counts in the context of panel data and used them to analyze the relationship between patents and R&D expenditures. By examining firm-level cross sectional data, they find a strong relationship between the number of patents granted and R&D expenditures. This finding leads him to conclude that patent counts are a good indicator of differences of inventive activity.

The use of patents as a research output indicator is widely used to understand research output (see Griliches for a review of studies). With a large amount of biotechnological innovations being patented, they have also become a useful tool in understanding how structural changes in the agbiotech industry are affecting innovation. Graff, Rausser and Small, for example, look to patent counts as an indirect measure of a firm's economically significant knowledge, which is divided into three distinct technological categories: technologies for plant transformation; gene sequences and genetically identified traits; and elite germplasm. Another noticeable approach of theirs is the usage of R&D intensity—the ratio of a firm's total R&D expenditures to a firm's total sales as the measure of a firm's capacity to develop patented technologies relative to its size.

Although patent counts have proved to be a very good indicator of the research output of a firm's innovation activity, the nature of patenting does have its shortcoming and can't be totally ignored. One of them is the difference of importance between single

patents. “the unit of measurement does not adequately account for likely quality differences”(Pardey). Another concern is not all the innovations are patentable and not all patentable patents are patented.

Pardey studied the research process in the agricultural sector, using an alternative measurement of the knowledge generating process. He explored the nature of the relationship between agricultural research spending and research output. He used aggregate publication performance in scientific journals as a measurement of the knowledge increment for individual state agricultural experiment stations, instead of patents counts. By using quality- adjusted publication output variable instead of raw publication counts he finds a significant relationship between lagged research expenditures and (weighted) publication output, especially long-run differences in research expenditures between the states. His method will be used in building our time series and cross section model.

Henderson and Cockburn examine the issue of economies of scale and scope in pharmaceutical research. They find that there are significant returns to size in pharmaceutical research, but these return are derived more from economies of scope than from economies of scale. The major advantage of large firms is the ability to realize returns to economies of scope: “to sustain an adequately diverse portfolio of research projects, and to capture and utilize internal and external spillovers of knowledge.” They also explore the nature of spillovers between firms in the drug industry, which is also what we are interested in the agricultural input industry. The public-goods aspect of knowledge has played a central role in modern growth theory, which is also the source of externalities. They conclude that, at least in the pharmaceutical industry, larger firms

seem to have an advantage in the conduct of research. The second finding is both economies of scale and economies of scope have significant influence on the research output. They also find evidence of significant spillovers of knowledge between firms.

To our knowledge, Jaffe provides the best example of a careful attempt to account for problems in quantifying the effects on the productivity of firms R&D of exogenous variations in the state of technology and of the R&D of other firms. He suggests that spillovers have important effects on research productivity and he finds circumstantial evidence of spillovers of R&D from several indicators of technological success. That is, firms whose technological neighbors do a lot of R&D tend to get more research output (patents) per R&D dollar than firms whose technological neighbors do less R&D; though firms with much less R&D expenditure will have lower profits and market value if their neighbors are intensive in R&D.

Bernstein and Nadiri measure spillovers using a cost function and time-series data for the chemical industry. They measure the "spillovers pool" using the unweighted sum of the R&D of all other firms in the industry, which is, the summation of the R&D capital service flow of all firms other than the one who is the recipient of the spillovers. They developed and estimated a dynamic model of intra-industry R&D spillovers to investigate the cost-reducing and incentive effects of these spillovers, which can be adopted into our inter-industry R&D model. They obtained estimates for the spillover effects on the demands for R&D and physical capital, as well as on variable and average costs of production.

3. Conceptual framework

The above review of the literature gives us a basis to develop a research production functions appropriate for the agbiotech industry and suggest a number of testable hypothesis. In a nutshell, our hypothesis is that in the agricultural biotechnology industry, the research output is positively correlated with the size of the firm, R&D expenditure, labor inputs and spillover effects. That is, larger firms, firms that invest more in R&D, have more diversified research projects and firms that do more basic research are more effective in the conduct of industrial research.

Hypothesis 1: There exist economies of scope: a firm that has more diversified research activity which covers both basic and applied agbiothech produces more research output.

Hypothesis 2: There exist economies of scale: the larger a firm is, the greater its research output.

Hypothesis 3: There exist internal spillover: the basic research firm has done in the past is positively correlated with the output of the current research.

Hypothesis 4: There exist external spillover effects: the firm is operating in a "research space", which is composed of all the firms who are doing biotechnological research. Therefore, the firm's research will be more productive if the rest of the industry does more research.

Consider a simple knowledge production function of the form

$$Y_{i,t} = f\left(X_{i,t}, \beta\right);$$

where $Y_{i,t}$ is the number of innovations for firm *i* at time *t*, $X_{i,t}$ is a vector of firm specific variables that result in innovations and β is a vector of parameters to be tested.

Since the number of innovations we employ will be a non-negative integer, we assume that a Poisson process generates the innovation counts. But if we find that the distribution of innovation count data doesn't have equal variance and mean (i.e. over dispersion), then we shall use a Negative Binomial regression model instead (Wooldridge). The negative binomial model generalizes the Poisson model by allowing for an additional source of variance above that due to pure sampling error. (Hall, Griliches and Hausman,) Since it is a production function, we will apply a Cobb- Douglas production function. Our specification of the model is then

$$FTR_{i,t} = \beta_0 + \beta_1 FRD_{i,t} + \beta_2 Labor_{i,t} + \beta_3 KnowStock_{i,t} + \beta_4 IRD_{i,t} + \beta_5 Sale + \beta_6 Div_{i,t} + E_{i,t}$$

where subscripts *i*, *t*, are the firm and time index respectively, and

FTR is the number of field trials of GM crops. This is our research output measure and is discussed in the next section

FRD is the firm investment in the ag-biotech research and development sector;

Labor is the number of scientific personnel in the firm working on agbiotech activities

IRD is industry research, the externalities, Following Bernstein and Nadiri we use "external research pool" or "external knowledge pool", measured by the number of patents of the industry minus the patents awarded to the "receiver", and the R&D expenditure of the whole industry minus the R&D done by the "receiver".

KnowStock is the variable which measures the firm's knowledge and experience accumulated through former research, the "internal knowledge pool". We construct this variable by the patents owned by the firm as a measurement of formal research activity.

Sale is the annual sale in agbiotech of the firm.

DIV is a variable we constructed to measure the extent a firm diversifies its research and development activity.

E is the error term

Because we believe that different stages of the research process play different roles in contributing to the final research output—namely field trials—we categorize the patent counts into three sub-technological groups:

-- Gene (gene and genetically identified traits and enhancements, such as DNA sequences, nucleic or amino acid, protein, gene exhibition, etc. that improve yield, resist disease or pests, tolerate herbicides or environmental stress, improve nutrient content, delay ripening.)

-- Trans (Plant Transformation technology, such as agro bacterium, micro projectiles, electoporation, and virus vectors, and plant tissue culture patents cover culture media and methods, somatic embryogenesis, plant regeneration, micro propagation, and in vitro selection techniques, and genetic markers, gene promoters, other molecular mechanisms, etc.)

-- Variety ("elite germplasm" as in Graff's paper, such as cultivars, variety, hybrid, inbred, novel variety, GM variety, etc)

The sum of Gene and Trans patents will be used as the measurement of the basic research a firm has done, which will act as the knowledge stock variable in our model. The variety patents can be considered as a more downstream measure of output and will be used as another variable. Those patents that can't be put into these three categories will included in category labeled "other" which may be added into the construction of the knowledge stock variable as another component that reflects a firm's internal stock of other related biotechnological knowledge, or the internal "spillovers pool" (Jaffe).

The DIV variable is constructed using the three categories of patents. We used the Palepu entropy measures to get the research diversity measure:

$$DIV = \sum_{i=1}^{n} PiLn(1/Pi)$$

Pi = the share of patents in the ith category; we use the patents stock starting from 1984 when the patent data is available until year I, which gives a consecutive measure of a firm's research activity. *N* is the number of the categories, in our case, n=3. The value of this diversity measure ranges from 0 to 1.099. (When a firm has the same patent stock in each of the three categories, the firm has the most diversified research.)

In the future we may also add another firm specific dummy variable into our model whether the firm also does research in pharmaceutical. The knowledge production function depends on both the contemporaneous R&D spending and the accumulated stock of R&D. The R&D stocks will be constructed from the firm's formal patents. The error term represents the combined effects of all other omitted factors to firm i in year t; which is composed of three parts,

$$E_{it} = \varepsilon + \mu_i + \lambda_t$$

ε is the universal error term, which follows a independent normal distribution; μ_i is a firm specific (time invariant) variable, which represents firm-specific differences in research efficiency; λ_t is a time-specific (firm invariant) variable, which represents time-specific shifts in the productivity of the research process for the entire industry. (Pardey)

We measured the research output by the number of field trials a firm carried out in each year. There are multiple reasons why we use field trials as the measurement of the research output over patent counts. Field trial is the last stage of the inventive activity just prior to commercialization (Oehmke and Naseem), which is the ultimate goal of most R&D projects of private firms, so field trial is an adequate estimator of the overall research activity. On the other hand, although patent counts has been proven to be fairly good indicator of research output, and many prior researches have adopted it, several shortcomings of patent count data as an indicator of the research output have made us choose to use it as an input rather than output in the research process. Only a fraction of the knowledge production of a firm is patented or patentable (Jaffe, 1986), which makes patent count data not a very good indicator of the overall research activity of the firm. There is also evidence [Grabowski, Pakes , Schankerman and Pakes] that a larger fraction of patents granted are "worthless" or become worthless in a short period of time. The difference between the importance of patents, and the different economic value of patents, makes patent counts data not well-distributed. Also, there are differences across firms in the propensity to patent, that is, due to the cost occurred during the patent application process or due to others unknown reasons, a firm may not patent all their research output which are patentable.

In the context of research in agbiotech we argue that patent counts should be an

input to the R&D process rather than an output. The patent application occurs at an early point in the development process and most of the expenditures that would be associated with it occur after the application is made. But, with the weak evidence for this question of timing, at least in aggregate firm behavior, the strongest thing one can say is that R&D and patents appear to be dominated by a contemporaneous relationship, rather than leads or lags. (Hall, Griliches, Hausman)

We measured the size of a firm by its annual sales in agricultural biotechnology in 1985 dollars to compensate inflation effects. We measured the capital inputs by the firm's annual investment in its R&D sector, and the labor inputs by the number of scientists in the R&D sector. As for the internal spillover effect, we will create a firm specific variable as the measurement of the economy of scope, that is, the measurement of the diversity of the firm's research activity. In conducting new research, the overall former research done by a firm acts as a "knowledge pool", or "knowledge stock". We use patent counts of the same firm including patents for more basic research done by the firm as the component to construct the firm specific variable to measure the "economy of scope". For the external spillover effect, we will introduce the term "spillover pool", which is the total research done in a given year by the entire industry, minus the research done by the firm, which benefits from the public good aspect of the research down by others firms and public research institutions. For the measurement of the "external spillover pool" or "external knowledge pool", we will either use the count of patents of all the other firms, which is the measurement of the research output; or we can simply use the sum of the R&D expenditure of all the other firms, as quantified research done by other firms (Bernstein and Nadiri).

But, the impact of competing firms' efforts on a firm's research productivity can be ambiguous. In a race-like research competition for a particular goal, other firm's success imposes an "exhaustion externality" on a firm's research efforts, thus there will be a negative correlation with competitors' efforts. (Reinganum) On the other hand, a firm may benefit from competitors' research; the spillovers of knowledge between firms can increase the research productivity. Then the correlation between the research output of one firm and the research activities of other firms is the indicator of the research characteristic of the industry: a positive correlation indicates the presence of significant spillovers or research complementarities between firms; while a negative correlation indicates that rivals' research efforts are substitutes rather than complements, there are significant "exhaustion externality" but limited spillovers. (Henderson and Cockburn)

4. Data

We are using the field trial data to construct the dependent variable, $Y_{i,t}$ defined as the number of field trials carried out by firm *i* in year *t*. By law all such field trials must be registered with and accepted by the Department of Agriculture's Animal and Plant Health Inspection Service (APHIS), which provides information on these trials (environmental releases) in a publicly available data set. The information on each field trial includes the firm or organization conducting the trial, the date of application, the approval status, the commodity, the gene sequence(s), the expected phenotype, and other information less relevant. These data ranges between 1987 till 2002. (Oehmke and Naseem)

Although the field trial data provide information at only one stage of the continuum of inventive activity a firm carries out which runs from basic research to applied research to commercialization, as the stage just prior to the commercialization of new varieties, field trial is a satisfactory measure of the research output of a firm. While many previous empirical works on firm innovation often used ag-biotech patents as proxy measures of research output, we use patent count as the intellectual assets, or knowledge stock, which can be viewed as intermediate outputs which acts as research input. The patent data we are using are from Delphion, 4303 patents ranging from 1987 to 2002, from which we picked up the patents owned by the 14 firms as our sample. We categorized the patents data into 3 groups: patents on new genes, patents on transformation technology and patents on new varieties. We define the patents on new genes and transformation technology to be the indicator of basic research, the sum of which is going to be used as the internal knowledge stock.

The sample is composed of 14 major firms each of which has substantial interest and does extensive research and development in agricultural biotechnology. Our financial data of the 14 firms were readily obtained from the Compustat data base. Because the financial disclosures in the Compustat data base are generally available only for publicly held private firms, we had to exclude privately held private firms. Although this deprives our sample of several important firms with substantial ag-biotech interests, as well as smaller startup companies that are of interest in their own right, we are left with a representative sample of the major players in the ag-biotech industry. (Oehmke and Naseem)

The financial data includes several different variables. The *Sale* is a firm's annual sale in the ag-biotechnology sector, in millions of dollars. The *FRD* is the research and development expenditure in the ag-biotechnology sector. The *Labor* is the number of scientists currently employed in the ag-biotechnology R&D sector of a firm. The *IRD* is a variable which we construct to catch the external spillover effect of the industry's research and development in ag-biotechnology. We use the summation of the R&D expenditure of the 14 firms in our sample as the industry R&D[1]. Although this will exclude the R&D done by those smaller firms and the private owned firms and public institutions, but these 14 firms actually perform the most part of the research and development in agricultural biotechnology.

Our data basically includes 14 agricultural biotechnology companies, ranging from 1987 to 2002. Because of the data availability, mostly the financial data, most of the firms don't have all 16 years of time series data, which leaves us an unbalanced cross-section and time series data set.

5. Results

Because of the cross-section, time series and count nature of our data, we fitted the data with generalized linear model. Since the dependant variable (field trial counts) is nonnegative count data, we assume the distribution of field trial output follows the Poisson distribution. The limitation of Poisson distribution is that the mean and variance of the dependent variable need to be equal. Since there exist the possibility of over- or

[1] The 14 fims in our sample are Agritope, Astrazeneca, BASF, Calgene, Dekalb Genetics Delta & Pineland, Dow Chemicals, Du Pont (E.I.), Monsanto, Mycogen Corp, Novartis, Pioneer Hi-Bred, Seminis, and Syngenta

under- dispersion, which the highly restrictive Poisson distribution can't handle, we also test our hypotheses assuming negative binomial distribution, which generalizes the Poisson model by allowing for an additional source of variance above that due to pure sampling error.

The count data nature of our dependent variable and the cross-section and time series characteristic add some complexity to the regression. We utilized the Generalized Estimation Equations (GEE) procedure in our generalized linear model analysis procedure, which takes into account the effects of the correlation over time. GEE method of parameter estimation is more efficient for statistical hypothesis testing with correlated longitudinal data. (Ekuma and Lix)

From the comparison between the Poisson regression and the Negative Binomial regression, we can see that the Poisson model is not quite adequate to describe the counts of field trials. In assessing the Goodness of Fit, we see that value/df for both Pearson Chi-Square and Deviance statistics is much higher than one, suggesting over dispersion; while in the Negative Binomial model, Value /df for both Pearson Chi-Square and Deviance statistics is very close to one, that is the sign of a better fit: Deviance/DF = 148.24/125 = 1.1907, which shows almost no over-dispersion, compared with the Deviance/DF = 6025.00/125 = 48.20 of the ordinary Poisson model. (Pedan)

The estimation of the coefficients of the our Negative Binomial model shows that, all of the dependent variable are significant, except *FRD* and Sale are marginally significant at the 10% level. We ran the regression with each of them dropped and get satisfactory results with all the dependant variables are significant. Comparing the Goodness of Fit measure, Deviance, we can see that the two models with Sale or *FRD*

dropped have almost the same Goodness of Fit (150.2855 for Sale dropped and 150.2354 with **FRD** dropped). Also, compare the changes in Deviance between the original model and the models with Sale or *FRD* dropped, and we conclude that dropping Sale or *FRD* doesn't change the Goodness of Fit of the model significantly. (Chi-square test of the changes of Goodness of Fit shows the P-value of the test value is within 0.2 to 0.3, so we can't reject the null hypothesis that the Goodness of Fit doesn't change.)

However, for the three models, the estimates of the coefficient of *Labor* are all negative and significant, which is the opposite of our expectation. From this, we can draw the conclusion that, in the agricultural biotech industry, less research personnel produce more output; in other words, smaller firms are more productive in conducting research and development. A possible reason for this controversial result is that the "*Labor*" may not be a good measurement of the human capitol of the R&D. The "*Labor*" we are using is the total number of people hired in the R&D sector within a firm; ideally, it should be the number of scientists in the lab.

6. Conclusion

Then, for our four hypotheses, 3 of them, hypothesis1, 3 and 4 are accepted with statistical significance; that is,

Hypothesis 1 is accepted: There exist the economies of scope: a firm who has more diversified research activity produces more research output, because the *Div* variable is positive and statistically significant;

Hypothesis 3 is accepted: There exist the internal spillover effects: the research the firm has done in the past is positively correlated with the output of the current

research, since the coefficient of *Knowstock* is significant.

Hypothesis 4 is accepted: There exist external spillover effects, since the *IDR* is statistically significant.

However, hypothesis 2 has an ambiguous conclusion. For the coefficient of the size of the firm, measured by the sale in the agbiotech sector, and the size of the R&D sector of the firm, measured by R&D expenditure, are inconclusive; while the coefficients of *Labor*, another measurement the scale of the agbiotech research and development, showing a diminishing trend.

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Appendix1:

The empirical results from the regression analysis, with various distributional assumptions:

Dependent variable: Field trials	Distributional Assumption			
Coefficeient (standard deviation)	Poisson	Negative Binomial	Negative Binomial (FRD dropped)	Negative Binomial (Sale dropped)
Intercept	-1.1745	-13.4013*	-12.9812*	-12.8936*
	(4.04)	(2.4260)	(2.3599)	(2.6522)
Div	0.5568	2.6802*	2.6696*	2.5897*
	(1.3491)	(0.5915)	(0.6936)	(0.6007)
Knowstock	1.84	0.8959*	0.9892*	0.8163*
	(1.22)	(0.3649)	(0.3711)	(0.2536)
Labor	0.61	-0.7685*	1.0155*	-0.7396*
	(0.19)	(0.1243)	(0.1697)	(0.1539)
Sale	0.61	0.5554**	-0.6926*	
	(0.6362)	(0.2855)	(0.1240)	
FRD	0.5045	0.7777		1.4468*
	(0.9061)	(0.4694)		(0.2570)
IRD	-0.3655	3.2448*	3.1271*	1.6180*
	(1.5927)	(0.7629)	(0.7774)	(0.2098)
N	132	132	132	132
Chi-square	10061.56/125	115.34/125	131.58/126	123.29/127
Log Likelihood	17916.36	20672.40	20671.04	21166
Deviance	6025.00/125	148.84/125	150.24/126	150.29/127