Are Basic Science and Biotechnology Complementary Activities?

Yin Xia and Steven Buccola

Selected Paper delivered at the American Agricultural Economics Association

Annual Meetings, 5 – 8 August 2001, Chicago, Illinois.

Yin Xia is a Ph.D. student and Steven Buccola a professor in the Department of Agricultural and Resource Economics, Oregon State University, Corvallis, OR 97331.

The email addresses are: xiay@ucs.orst.edu and steven.t.buccola@orst.edu, respectively.

Are Basic Science and Biotechnology Complementary Activities?

A decade ago, most U.S. farmers thought genetically modified seed was in their distant future. Today, transgenic crops have substantial market share, including 50% of the corn, 45% of the cotton, and 60% of the soybeans grown in the United States. The cost and environmental advantages of the pest and herbicide resistance in transgenic plant and animal material is only the beginning of the picture. New generations of plant and animal tissue will embody novel product characteristics, enabling marketers to cater to specific demand profiles in ways unthinkable in the past. These opportunities will revolutionize agricultural research, extension, production, and marketing.

The revolution came about through a discrete jump in scientific knowledge. Discovery of recombinant DNA in the 1950s and 1960s led, after a substantial incubation period, to practical protocols for transferring potentially useful genes from one organism to another. The exploitation of these protocols soon led to patentable products, which found their way to market after years of field trials. Applied agricultural research in the biotechnological era has become increasingly science-based, less dependent on trial-and-error than in earlier years (Narin, Hamilton, and Olivastro 1997; Mansfield 1995). For example, a typical biotechnology patent document now cites an average of 15 to 20 scientific publications, an increase since even the mid-1990s and far higher than the one per patent document in non-biotech fields (CHI Research). As Arora and Gambardella (1993, 1994) point out, this has tended to universalize the categories with which applied technology operates, fostering greater communication between researchers in related fields.

Implications of the new science-based technology growth are profound. The enhanced research returns which recombinant DNA have made possible likely are responsible for much of the rise in R&D expenditures – and share of R&D in total investment – in the agricultural input industries since the 1970s. Just as importantly, the increasingly universal terms in which applied R&D can be conducted have enabled a greater division and specialization of research effort. Once, that is, science has mapped the broad features of the biophysical terrain, technologists can more easily partition this space for more detailed prospecting, coordinating their efforts through the language of molecular biology (Paul, Mowery, and Steinmueller 1992).

The emergence of a common technological paradigm, like the rise of standardized commodity grade standards sixty years ago, is in turn facilitating the growth of a market-based research system. Thus, the private sector's share of agricultural research is growing rapidly (Fuglie, et al. 1995) and patent protection is granted for an ever-widening array of product and process innovations (Jaffe 1999). The increasing ease of obtaining intellectual property protection, that is, can be viewed as an endogenous response to the increased ease of dividing innovation processes into sub-tasks, which stimulates the demand for transactions in intellectual property.

The Issues

Specialization of agricultural R&D functions poses a challenge to economic analysis. Studies of the returns to public agricultural R&D traditionally have employed university research and extension expenditures as shift terms in a production or cost function of a class of farm commodities (Fuglie, et al. 1998; Huffman and Evenson 1995; Khanna, Huffman, and Sandler 1994; Alston, Norton, and Pardey 1993; Pardey and Craig 1989). This approach exploited readily available data and permitted direct inferences about the social welfare effects of public expenditure decisions. Furthermore, the concentration of research in public institutions obviated the need for explicit models of public-private relationships or of intellectual property issues. With the science-based biotechnology revolution well underway, new approaches are needed. Now, a clear understanding of the returns to public investment in agriculture requires a detailed examination of the relationship between basic and applied research and between public and private R&D.

In the present study, we focus on the manner in which public research inputs interact with those in the private sector to produce agricultural biotechnology innovations. We are interested, that is, in the productivity of the public-private research enterprise, or in Arora and Gambardella's (1994) words, the "technology of technical change." Little explicit work has yet emerged on this subject in agricultural economics, although it was first broached forty years ago (Nelson 1959). Since the late 1980s, interest in the subject has intensified, especially in regard to pharmaceutical biotechnology. Some economists have focused on the conceptualization and measurement of research outputs, especially on the use of patent applications and awards as indicators of the quantity or value of research effort (Trajtenberg, Henderson, and Jaffe 1997; Zucker and Darby 1995). A few have investigated incentive schemes for rewarding scientists' efforts (Cockburn, Henderson, and Stern 1999; Stern 1999; Heller and Eisenberg 1998), while others have concentrated on knowledge accumulation as a dynamic process (Koo and Wright 1999; Aghion and Howitt 1992; Segerstrom, Anant, and Dinopoulos 1990).

Identifying Information Flows

The technology of technical change is the process through which information inputs are transformed into information outputs; it is the study of information transformation. Information variables cannot be traced as easily as physical inputs are. A researcher herself would have difficulty identifying every source of information or suggestion that led her to a particular insight. However, because ideas are fruitful only in combination with related ones, they are best bundled in some form, such as in patent documents, books, and journal articles. Bundling of this nature implies it is feasible to identify some of the principal sources of a researcher's inspiration and direction.

Document bundling has its limits. Scientists cannot put in writing everything they know about a genetic sequence on which they are working. Part of their knowledge remains "tacit" and local in the sense that they can provide practical information about it only through continuous and personal communication. As Zucker and Darby (1995), Jaffe, Trajtenberg, and Henderson (1993), and Stern (1999) have shown, this explains why start-up biotech companies tend to locate near universities. It explains also why firms engaged primarily in applied research, field trials, and marketing also employ basic scientists. Only by doing so can they develop the "absorptive" capacity" to evaluate and exploit prospective scientific breakthroughs (Nelson and Rosenberg 1994, Lim 1999, Rausser 1999). More generally, a research unit's human and physical capital influence the cost of exploiting the information sources available.

Intellectual property is patentable only if it has a direct, useful application. Most university bioscience research instead focuses on relatively abstract concepts, those which develop, refine, or test hypotheses that do not have *immediate* applications to goods or services. Thus, most university biological research has economic value, beyond its utility for teaching, only insofar as it affects the subsequent development of commercially viable intellectual property. In the absence of patent protection, university research typically is best disseminated through publicly accessible media. How these publications influence (spill over into) commercially valuable property rights, how subsequent commercial success spills back into basic science, and what university administrators can do to encourage a research that would best generate such complementarities, is therefore the frontier of work on the management of university biotechnology resources.

Complementarity Between Applied and Basic Research

An information complementarity especially relevant to both the research administrator and industrial organization analyst is that potentially found between basic bioscience and applied biotechnology. Just as science provides the technology lab with a general map of the biomolecular terrain, so do the successes and failures of a scientific insight to develop profitable products guide scientists in where next to look for fundamental insights. Thus, the practical success of the DNA paradigm in generating marketable products has stimulated more scientific research on DNA. For this reason, and as Rausser (1999) has discussed at some length, inputs allocated to applied research programs can enhance basic research, just as basic research insights facilitate technological development.

Cockburn, Henderson, and Stern (1999) provide an example of this complementarity in the design of research incentives at large biotech firms. They show that firms whose promotion systems weight an employee's published or basic research highly tend also to be those which offer high budgetary rewards to departments with significant patent successes. These firms tend to devolve decision-making power to departments, exploiting the complementarity between scientific and technological skill at the departmental level. Other firms specialize or centralize, treating basic and applied science inputs as though competitive for the same set of resources**.** Zucker, Darby, and Brewer (1998) demonstrate similarly that successful biotech start-up firms tend to concentrate in locales with the leading university bioscientists, since geographic proximity reduces the cost of exploiting the feedback between conceptual and patentable innovation. The intensive merger and co-venture activity we now are witnessing in agricultural biotechnology arises from attempts to seek and exploit such complementarities, a process which continually exhausts some complementary relations and thus provides niches for more specialized firms (Brennan, Pray, and Courtmanche 1999; Kalaitzandonakes and Hayenga 1999). Public universities face similar choices between pursuing a broad or focused research activity.

A model addressing these issues must distinguish between inputs and outputs of both applied and basic research, allow the feedback essential to complementary relationships, and more generally permit both complementarity and substitutability among research programs. Oehmke et al.(1999), Falck-Zepeda, Traxler, and Nelson (1999), Koo and Wright (1999), and Moschini and Lapan (1997), among others, have developed dual models of optimal R&D investment in generally imperfectly competitive market structures. Here, we focus instead on a primal model of knowledge production, stressing the relationship between applied and basic research.

Conceptual Framework

In a given time interval, let

I_b be the quality-weighted number of bioscience innovations at a given university;

I_a the quality-weighted number of agricultural biotechnological innovations linked to the bioscience innovations at the given university;

K_b, L_b the quantity of capital and bioscientist FTE, respectively, employed in bioscience research at the given university;

K_a, L_a the quantity of capital and biotechnologist FTE, respectively, employed in applied research at the university or institution producing the biotechnological innovations;

X_{univ} the vector of fixed factors (including overhead and qualitative characteristics) of the university producing the bioscience innovations; and

X_{firm} the vector of fixed factors of the firm or university achieving the biotechnological innovations.

The technology of biotechnological change might be specified as

(1) $$I_a = I_a(K_a, L_a, I_b, X_{firm})$$

(2) $$I_b = I_b(K_b, L_b, K_a, L_a, X_{univ})$$

where time subscripts and lag operators are, for notational simplicity, suppressed. Equation (1) says the number of applied innovations in a given time interval depends on the quantity of capital and technologist FTE devoted to producing applied innovations, on the number of basic innovations which the biotech firm has the capacity to absorb, and on the biotech firm's fixed factors and characteristics. Variable I_b in this equation reflects the scientific information guiding biotechnology development. Equation (2) says the number of basic innovations depends on the quantity of capital and labor allocated to producing basic innovations, on the quantity of inputs allocated to *applied* research in that field, and on the university's fixed factors and characteristics. Applied inputs K_a, L_a in equation (2) represent the feedback from applied to basic science, because it is applied research efforts – including failures as well as successes – rather than marketable outputs that arguably influence the direction and success of basic research.

Equations (1) and (2) form a schematic of the influence of university investments on commercial biotech outputs. The university allocates scientist and capital inputs to its basic and applied biological research programs. After the appropriate lags, these investments generate bioscience outputs I_b at a rate depending upon the university's fixed factors such as its location, history, and overhead structure. Biotech firms and universities exploit the science outputs by hiring capital, scientists, and technologists to develop them into patentable technological innovations. Their success in doing so depends on their location, market strategies, fixed investment, and other characteristics. In general, a society might wish to allocate public research inputs so as to maximize the long-run commercial value of patentable outputs. Of course, such decisions in the United States are not centrally directed. However, understanding the principal forces of agricultural biotechnological change can, under appropriate assumptions about private-sector market structure and behavior, provide useful guidance to public resource allocation.

To simplify the exposition, suppose equation (1) is weakly separable in the partition (K_a, L_a), (I_b, X_{firm}) and equation (2) in the partition (K_b, L_b), (K_a, L_a), X_{univ}. The technology then can be expressed in terms of expenditures $E_a = P_a^k K_a + P_a^l L_a$ and $E_b = P_b^k K_b + P_b^l L_b$ on applied and basic science, respectively, where the *P*'s are the associated prices. Holding prices fixed, we can write (1) and (2) as

$$(1') \qquad I_a = I_a\,(E_a\,,\; I_b\,,\, X_{firm})$$

$$(2') \qquad I_b = I_b\,(E_b\,,\; E_a\,,\; X_{univ})$$

The feedback from applied to basic, and from basic to applied science in the above equations form the essentials of a test of the hypothesis that the two enterprises are complementary with one another. In the weakly separable model, for example, substitute (2′) into (1′) to obtain the reduced form

$$(3') \qquad I_a = I_a\,[E_a\,,\; I_b(E_b\,, E_a\,, X_{univ})\,, X_{firm}] = I_a\,(E_a\,, E_b\,, X_{univ}\,, X_{firm})$$

This form is especially useful if consumer welfare is thought to depend only on applied innovations.

Complementarities and Spill-Ins

If X_{univ} , X_{firm} are held fixed, the total differential of (3′) is

$$(4) \qquad dI_a = \frac{\partial I_a}{\partial E_a} dE_a + \frac{\partial I_a}{\partial I_b}\frac{\partial I_b}{\partial E_b} dE_b + \frac{\partial I_a}{\partial I_b}\frac{\partial I_b}{\partial E_a} dE_a$$

Often, research administrators would operate under a budget restriction $B^o = E_a + E_b$, implying (3′) can be written as $I_a = I_a(S_b, X_{univ}, X_{firm})$, where $S_b = E_b / B^o$ is the budget share allocated to basic research. The restriction implies $dE_a = -\,dE_b$. Substituting the latter into (4) and dividing by dE_b gives total derivative

$$(5) \qquad \frac{dI_a}{dE_b} = -\frac{\partial I_a}{\partial E_a} + \frac{\partial I_a}{\partial I_b}\left(\frac{\partial I_b}{\partial E_b} - \frac{\partial I_b}{\partial E_a}\right)$$

Allocating another scarce dollar to basic bioscience reduces the money available for applied research. This has the direct effect – shown in the first right-hand term (5) – of reducing the output rate of applied biotech innovations. In addition, as reflected in $\partial I_b / \partial E_a$, it reduces the rate of bioscience innovation to the extent that applied research activity, which the budget cutback has retarded, stimulates successful basic science. Through $\partial I_a / \partial I_b$, this reduction feeds back into a lower rate of applied innovation. On the other hand, the extra dollar spent on bioscience research increases basic science output by amount $\partial I_b / \partial E_b$, *increasing* the rate of applied output by way of the positive influence ($\partial I_b / \partial I_a$) of basic research on applied innovations. Equation (5) is positive, that is shifting money from applied to basic science increases the rate of applied biotech innovations, if $(\partial I_a / \partial I_b)(\partial I_b / \partial E_b)$ exceeds $\partial I_a / \partial E_a + (\partial I_a / \partial I_b)(\partial I_b / \partial E_a)$ in absolute value. This will occur only if the impact $\partial I_b / \partial E_b$ of basic science expenditures on basic science outputs is especially large. Arguably, that has been the case in recent decades.

It is useful to distinguish between bioscience's partial and total effect on biotechnological innovations. The *partial* complementarity, $\partial I_a / \partial I_b$, of basic with applied research presumably is positive because scientific insight is a partial substitute for technological effort. But *total* complementarity dI_a / dI_b is positive only if (5) is, since only then do I_a and I_b both rise as science expenditures E_b do. That is, in the present formulation, basic and applied research outputs are complementary only if both rise as the research budget is exogenously reallocated toward basic science. Diagrammatically, the reallocation represents a movement along a production possibility frontier in which the two output possibilities are published science and patentable innovations and in which the total research budget is held constant. Complementarity prevails where the frontier has positive slope. Essentially, bioscience in these zones acts more as an input to than as a co-output with biotechnology. In a world of decreasing returns, decision makers push beyond such complementarity zones and operate where outputs substitute for one another. But in the presence of agglomeration or network economies, or where the supply function of productive scientists slopes upward, administrators might rationally operate where basic and applied research are complements (Rausser 1999).

The sample variation necessary for estimating aggregate model (1) and (2) or (1′) and (2′) is provided by inter-year and inter-university differences in research budgets and productivity. An aggregate production function of this sort differs from conventional ones in which inputs are rival and tradable. Here, a firm buys science information at zero market price (because it is publicly available in journals), but at a shadow cost equaling the resources expended to evaluate and exploit the information. Such a cost is a function of the firms' fixed investments in market position, location, and science know-how. Hence, our model will reflect a weighted average of individual firms' and universities' knowledge-creation technologies. Nevertheless, it can readily by used to draw inferences about the impacts of individual university and biotech firm characteristics. Commercial, Patent Office, and university data bases offer information on many of the shift variables represented above by X_{univ} and X_{firm} , including unit size, overhead expenditure, geographic location, and specialization. These can be used to test hypotheses about the principal factors affecting scientific output, biotechnological innovation, and the synergy between them.

Empirical Model

Drawing a clear line between what is "basic" and what is "applied," either in patented innovations or in publications, is difficult. Furthermore, both private firms and universities conduct both types of research. Nevertheless, most agricultural biotechnology patents are awarded to the private sector and most basic scientific research is conducted in universities. And, as discussed above, biotech firms pursue basic research primarily to enhance their absorptive capacity for evaluating and using scientific research published in the public sector (Lim 1999). For this reason, we will assume that private-sector expenditures are intended primarily to produce patentable innovations, and will ignore scientific publications of private-sector employees unless they are also university employees. In contrast, universities' non-overhead expenditures often can be divided between their applied and basic research programs.

Consistent with most of the recent literature, we will use patent awards as our measure of applied research output (Aghion and Howitt 1992; Harhoff, Narin, Scherer, and Vopel 1999; Henderson, Jaffe, and Trajtenberg 1998) and published scientific articles as our measure of basic research output (Lim 1999). The strengths and weaknesses of these measures have been discussed extensively (e.g. Cockburn, Henderson, and Stern 1999). Patents represent the end of a discovery phase in the development of either a research process or a candidate seed or compound. Many of these discoveries perform unsuccessfully in the subsequent field- or clinical-trial phase of R&D, or even if they are successful there, prove later to be commercially unprofitable. On the other hand, patent awards can also understate productivity inasmuch as some biotech firms – especially larger ones – retain certain discoveries as trade secrets, developing and marketing them on their own rather than patenting and licensing them to other entities. The U.S. Patent Office requires a patent document to list the patented inventions which the discovery has utilized, since permission must be obtained from the owners of these patents before the invention in question can be commercially exploited. Thus, a frequent way of accounting for patent quality is to weight each patent by the number of subsequent patents which cite it (Trajtenberg, Henderson, and Jaffe 1997; Lerner 1994). Scientific publications can be quality-weighted in similar fashion, namely by accounting for the number of times they are cited in subsequent publications.

With the above considerations in mind, our empirical model will take the following general form. Let

$A_{j,it}$ be the number of bioscience publications authored by the j^{th} scientist at the i^{th} university in the t^{th} year;

$P_{\tau}^{j,it}$ be the number of agricultural biotechnology patents awarded in the τ^{th} year which cited a publication authored by the j^{th} scientist at the i^{th} university in the t^{th} year;

r_{τ} be the discount rate in the τ^{th} year.

We can then define the magnitude of scientific innovations at the i^{th} university in the t^{th} year as

$$(6) \qquad I_{b,it} = \sum_{j} A_{j,it}$$

that is, the unweighted sum of its scientists' journal publications. The magnitude of biotechnological innovations subsequently linked to authors at the i^{th} university in the t^{th} year is

$$(7) \qquad I_{a,it} = \sum_{j} \sum_{\tau} P_{\tau}^{j,it} / (1 + r_{\tau})$$

that is, the time-discounted number of patent citations in year τ to the j^{th} scientist's year-t publications, summed over years $\tau = t+1, \ldots, T_{\tau}$ following publication, then summed over all J^{it} authors at the i^{th} university in the t^{th} year.

Quality-Weighting the Research Outputs

We can vary these definitions in such a way that each publication and patent is weighted by the frequency of its subsequent citations. For these purposes, define

$C_{t'}^{mj,\,it}$ as the number of times in the t'^{th} year that a scientific article cites the m^{th} publication in the t^{th} year of the j^{th} scientist at the i^{th} university;

$D_{\tau'}^{n\tau,\,jit}$ as the number of times in the τ'^{th} year that a patent document cites the n^{th} patent awarded in the τ^{th} year which had cited a scientific article authored by the j^{th} scientist at the i^{th} university in the t^{th} year.

The first definition allows us to specify a quality-weighted measure of the magnitude of scientific innovations at the i^{th} university in the t^{th} year, namely

$$(6') \qquad I_{b,\,it}^{*} \;=\; \sum_{j}\sum_{t'}\sum_{m} C_{t'}^{mj,\,it} \,/\, (1+r_{t'})$$

In (6′), Σ_m is the number of times the j^{th} scientist was cited in the t'^{th} year for articles he published in the t^{th} year. $\Sigma_{t'}\,\Sigma_m$ is the number of times this scientist was eventually cited for all articles he published in the t^{th} year. Summing the latter over all J^{it} scientists at the i^{th} university gives that university's t^{th}-year scientific output in terms of the number of times any article published from that university in that year was subsequently cited.

The second definition above allows us in similar fashion to specify a quality-weighted measure of the magnitude of agricultural biotechnological innovations linked to scientists at the i^{th} university in the t^{th} year. The measure is

$$(7') \qquad I_{a,\,it}^{*} \;=\; \sum_{j}\sum_{\tau}\sum_{\tau'}\sum_{n} D_{\tau'}^{n\tau,\,jit} \,/\, (1+r_{\tau})$$

In (7′), Σ_n is the number of times in the τ'^{th} year that any patent cited an earlier patent awarded in the τ^{th} year which had cited the jit^{th} publication. Summing over all years τ' gives the total number of times that any patent cited a τ^{th} –year patent which in turn had cited the jit^{th} publication. Summing again over all years τ gives the time-discounted number of patents that ultimately referenced the jit^{th} publication, and Σ_j sums this number over all scientists at the i^{th} university in the t^{th} year. Measure (7′) reflects a given university's effectiveness in generating scientific publications which will be cited in highly-cited patents. In certain circumstances other quality-weighting procedures might be more appropriate and can easily be developed with the present tools.

In the context of this research, unweighted measure (6) of a university's scientific output is not as naive as it might appear. Estimating equation (1) even with unweighted variables (6) and (7) constitutes a way of judging the quality of a university's bioscience publications, because it estimates the effectiveness of those publications in producing patentable innovations. Employing weighted measure (6′) for such purpose instead is a way of answering the question: Does weighting a scientist's publications by the volume of their subsequent literature citations improve our ability to forecast the effectiveness of those articles in generating patentable biotechnology innovations? Preliminary evidence suggests it does. That is, bioscience publications highly cited in patent documents tend also to be highly cited in the publicly accessible scientific literature (CHI Research).

Econometric Estimation

We can now specify econometrically estimable versions of (1) and (2) or (1′) and (2′). Employing weakly separable form (1′) and (2′), for example, in conjunction with unweighted measure (6) of bioscience output and weighted measure (7′) of the patents linked to them, gives

$$(1'') \qquad I_{a,it} \;=\; I_{a,it}\,(\mathrm{E}^{\ell}_{a,\,i}\;,\;\; I^{*}_{b,\,it}\;,\;\; X^{\,i}_{firm}) \qquad i \;=\; 1, \ldots, I\,;\;\; t \;=\; 1, \ldots, T$$

$$(2'') \qquad I^{*}_{b,\,it} \;=\; I^{*}_{b,\,it}\,(E^{\ell}_{b,\,i}\;,\;\; E^{\ell}_{a,\,i}\;,\;\; X^{\,i}_{univ}) \qquad i \;=\; 1, \ldots, I\,;\;\; t \;=\; 1, \ldots, T$$

where $E^{\ell}_{a,\,i}$ is a weighted average of the applied technology expenditures at the firms receiving patents which cited a scientist at the i^{th} university, X^{i}_{firm} is the set of characteristics of these firms, $E^{\ell}_{a,\,i}$ are applied technology expenditures at the i^{th} university, and ℓ superscripts indicate the appropriate lags. University applied technology expenditures would reasonable include outreach expenditures. The sample frame in this model consists of annual observations on the bioscience inputs and publications of a set of universities, and of the patent outputs, expenses, and characteristics of the set of firms which used those publications in their applied biotechnology programs. The model can be estimated with standard simultaneous equations methods.

One might expect the econometric results to indicate that complementarity between bioscience and biotechnology is greater in large universities than in small ones. The communication essential for synergy between basic and applied research usually is less costly within than between organizations (Zucker and Darby 1998). Because fixed costs of molecular biology research are high, returns to size in biotechnology R&D probably are increasing in output. If so, large universities can operate both basic and applied research programs more cheaply than can small universities, and hence take advantage of the low cost of in-house communication between the two programs. This simply is a variant of the argument that size provides agglomeration economies. On the other hand, recent breakthroughs in remote communication technology may have eliminated these size advantages: scientists working in the same sub-field at two different universities may communicate more easily with one another than do two scientists in less related fields at the same university. In any event, we would expect university bioresearch to be more complementary with the biotechnology at small start-up firms than with that at larger firms such as Novartis, since start-up firms' physical proximity and ownership connections with university scientists should enhance the communication of tacit knowledge (Zilberman, Yarkin, and Heiman 1999).

Apart from permitting tests of these hypotheses, our results will provide a basis for university decision-making in both the short and long run. The short-run issue is how to allocate annual university expenditures between applied and basic science. The long-run issue is how to design the university's research strategy given the university's location and other fixed features.

Data

The data for the econometric model divides into research outputs (patents and scientific papers) and inputs to the research process. To derive observations on the research output data, we draw a large sample of agricultural biotechnology patents from the United States Patent Office database and observe the identity of the awarded firms or other institutions and the scientific publications cited on the patent documents. We then identify the authors of those publications and the universities or labs at which they worked at time of publication. Because of the tedium of determining ag-biotech patents, discriminating between science and non-science references on a patent, and matching alternative forms of a scientist's or a firm's names, we hire CHI Research of Haddon Heights, New Jersey to conduct the above data search and cleaning process for this study. Finally, from other sources, including NSF and the Bureau of Census, we collect data on the research input allocations at the identified firms and universities, such as the R&D expenditures and technologists' and scientists' FTEs, and match them with the research outputs at the same institutions, taking account of the requisite lag structure.

Consider, for example, a case in which a bioscience article listed in a given patent document was authored by two scientists, one at university i and the other at university i'.

Upon encountering this article, we increment unweighted measures $I_{a,\, it}$ and $I_{a,\, i't}$ of applied biotechnology output by one unit each. If quality-weighted measures $I^*_{a,\, it}$, $I^*_{a,\, i't}$ are to be used instead of unweighted ones, these unit increments are replaced with the number of times the given patent was cited in subsequent patents. We then increment unweighted measures $I_{b,\, it}$ and $I_{b,\, i't}$ of basic bioscience output by one unit each if the indicated article had not earlier been counted as part of that university's science output in year *t*. That is, in the unweighted bioscience output measure, the fact of being cited in at least one patent qualifies a publication to be counted once, and only once, as part of the i^{th} and i'^{th} universities' science output in year *t*. If quality-weighted measures $I^*_{b,\, it}$ of bioscience output are to be used instead of unweighted ones, that unitary observation is replaced with the number of times the article was cited in subsequent scientific articles. The indicated output variables are then matched to the respective research inputs $E^{\ell}_{b,\, i}$, $E^{\ell}_{a,\, i}$, X^{i}_{univ} at the i^{th} and i'^{th} universities and to inputs $\mathrm{E}^{\ell}_{a,\, i}$, X_{firm} at the patenting firms.

References

Aghion, P., and P. Howitt. "A Model of Growth Through Creative Destruction." *Econometrica* 60 (March 1992): 323 – 351.

Alston, J.M., G.W. Norton, and P.G. Pardey. *Science Under Scarcity: Principles and Practice for Agricultural Research Priority Setting and Evaluation*. Ithaca: Cornell University Press, 1995.

Arora, A., and A. Gambardella. "Evaluating Technological Information and Using It." *J. Econ. Behav. and Organization* 24 (1993): 91 – 114.

__________________________. "The Changing Technology of Technological Change: General and Abstract Knowledge and the Division of Innovative Labor." *Research Policy* 23 (1994): 523 – 532.

Brennan, M.F., C.E. Pray, A. Courtmanche. "Impact of Industry Concentration on Innovation in the U.S. Plant Biotech Industry." Paper presented at the NE-165 Conference on Transitions in AgBiotech, Washington, D.C., June 1999.

Cockburn, I., R. Henderson, and S. Stern. "Balancing Incentives: The Tension Between Basic and Applied Research." National Bureau of Economic Research, Working Paper No. 6882, 1999.

David, P.A., D. Mowery, and W.E. Steinmueller. "Analysing the Economic Payoffs from Basic Research." *Econ. Innov. New Tech*. 2 (1992): 73 – 90.

Doll, J.J. "The Patenting of DNA." *Science* 280 (May 1, 1998): 689 – 690.

Fuglie, K., N. Ballenger, K. Day, C. Klotz, M. Ollinger, J. Reilly, U. Vasavada, and J. Yee. Agricultural Research and Development: Public and Private Investments Under

Alternative Markets and Institutions. AER – 735, Econ. Res. Service, U.S. Dept. of Agriculture, 1998.

Harhoff, D., F. Narin, F.M. Scherer, and K. Vopel. "Citation Frequency and the Value of Patented Inventions." *Rev. Econ. Stat*. 81 (August 1999): 511 – 515.

Heller, M., and R. Eisenberg. "Can Patents Deter Innovation? The Anti-Commons in Biomedical Research." *Science* 280 (May 1,1998): 698 – 701.

Henderson, R., A.B. Jaffe, and M. Trajtenberg. "Universities as a Source of Commercial Technology: A Detailed Analysis of University Patenting, 1965 - 1988." *Rev. Econ. Stat*. 80 (1998): 199 – 227.

Huffman, W.E., and R.E. Evenson. *Science for Agriculture*. Ames: Iowa State University Press, 1993.

Jaffe, A.B. "The U.S. Patent System in Transition: Policy Innovation and the Innovation Process." National Bureau of Economic Research, Working Paper No. 7280, 1999.

Kalaitzandonakes, N., and M. Hayenga. "Structural Change in the Biotechnology and Seed Industrial Complex: Theory and Evidence." Paper presented at the NE-165 Conference on Transitions in AgBiotech, Washington, D.C., June 1999.

Khanna, J., W.E. Huffman, and T. Sandler. "Agricultural Research Expenditures in the United States: A Public Goods Perspective." *Rev. Econ. Stat*. 76 (May 1994): 267 – 277.

Koo, B., and B.D. Wright. "Dynamic Implications of Alternative Intellectual Property Rights for Crop Genetic Resources." Paper presented at the NE-165 Conference on Transitions in AgBiotech, Washington, D.C., June 1999.

Lerner, J. "The Importance of Patent Scope: An Empirical Analysis." *Rand J. Econ*. 25 (September 1994): 319 – 333.

Lim, K. “The Concentration of Basic and Applied Research in the Semiconductor and Pharmaceutical Industries: Implications for Theories of Knowledge Spillovers.” Sloan School of Management, Massachusetts Institute of Technology, 1999.

Mansfield, E. “Academic Research Underlying Industrial Innovations: Sources, Characteristics, and Financing.” *Rev. Econ. Stat*. 77 (February 1995): 55 – 65.

Moschini, G., and H. Lapan. “Intellectual Property Rights and the Welfare Effects of Agricultural R&D.” *Amer. J. Agr. Econ*. 79 (November 1979): 1229 – 1242.

Narin, F., K.S. Hamilton, and D. Olivastro. "The Increasing Linkage between U.S. Technology and Public Science." *Research Policy* 26 (No. 3, 1997): 317-330.

Nelson, R.R. “The Simple Economics of Basic Scientific Research.” *J. Political Economy* 67 (June 1959): 297 – 306.

Nelson, R.R., and R. Rosenberg. “American Universities and Technological Advance in Industry.” *Research Policy* 23 (1994): 323 – 348.

Oehmke, J.F., D.D. Weatherspoon, C.A. Wolf, A. Naseem, M. Maredia, and A. Hightower. “Is Agricultural Research Still a Public Good?” Paper presented at the NE-165 Conference on Transitions in Ag Biotech, Washington, D.C., June 1999.

Pardey, P.G., and B.J. Craig. “Causal Relationships Between Public Sector Agricultural Research Expenditures and Output.” *Amer. J. Agr. Econ*. 71 (February 1989): 9 – 19.

Rausser, G. “Private/Public Research: Knowledge Assets and Future Scenarios.” Invited Fellows Address, American Agricultural Economics Association Annual Meetings, Nashville, TN, August 1999.

Segerstrom, P.S., T.C.A. Anant, and E. Dinopoulos. “A Schumpeterian Model of the Product Life Cycle.” *Amer. Econ. Rev*. 80 (December 1990): 1077 – 1091.

Trajtenberg, M., R. Henderson, and A. Jaffe. “University Versus Corporate Patents: A Window on the Basicness of Invention.” *Econ. Innov. New Tech*. 5 (1997): 19 – 50.

Traxler, G., and J.B. Falck-Zepeda. “Surplus Distribution from Biotechnology Innovations.” Paper presented at the NE-165 Conference on Transitions in AgBiotech, Washington, D.C., June 1999.

Zilberman, D., C. Yarkin, and A. Heiman. “Agricultural Biotechnology: Economic and International Implications.” Department of Agricultural and Resource Economics, University of California, Berkeley, 1999.

Zucker, L.G., and M.R. Darby. “Virtuous Circles of Productivity: Star Bioscientists and the Institutional Transformation of Industry.” National Bureau of Economic Research, Working Paper No. W5342, 1995.

________________________. “Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises.” *Amer. Econ. Rev*. 88 (1998): 290 – 306.