

Staff Paper

Is Agricultural Research Still A Public Good?

James F. Oehmke, Dave D. Weatherspoon, Christopher A.
Wolf, Anwar Naseem, Mywish Maredia
and Amie Hightower

Staff Paper 99-49

October 1999



Department of Agricultural Economics
MICHIGAN STATE UNIVERSITY
East Lansing, Michigan 48824

MSU is an Affirmative Action/Equal Opportunity Institution

Is Agricultural Research Still A Public Good?

James F. Oehmke, Dave D. Weatherspoon, Christopher A. Wolf, Anwar Naseem,
Mywish Maredia and Amie Hightower

oehmke@msu.edu

28 pages

Abstract

The nature of public agricultural research changed in 1980 when the Bayh-Dole Act allowed universities to retain title to inventions that were created with Federal funds, and the court case *Diamond v. Chakrabarty* allowed patenting of living tissue and eventually other bio-engineered products. In 1997, over 2,300 new licenses and options were executed on academic life-sciences property. This raises the question: is agricultural research still be a public good?

This paper is a critical first step in understanding how increasingly private ownership of intellectual property affects the agribusiness environment and the evolving role of public agricultural research institutions. The innovative step in this paper is the development of a formal economic model which represents the role of applied biotech research in the agricultural life sciences. The model is built around neo-Schumpeterian ideas of endogenous innovation and growth.

The most salient implications for the role of the public sector are (1) The private sector underinvests in applied R&D activity. (2) Concentration in the large-firm, life-science R&D industry increases over time. (3) The life-science revolution is reducing the number of markets, in the short run. This reduction in the number of niche markets diminishes the role of the public sector. (4) There is a role for the public sector in conducting R&D in niche markets. (5) In the long run, the life-science revolution may also create new niche markets. (6) There is a role for the public sector in the provision of basic research which increases the productivity of applied R&D.

Copyright © 1999 by James Oehmke. All rights reserved. Readers may make verbatim copies of this documents for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Is Agricultural Research Still A Public Good?

James F. Oehmke, Dave D. Weatherspoon, Christopher A. Wolf, Anwar Naseem, Mywish

Maredia and Amie Hightower

Paper prepared for

Transitions in Agbiotech: Economics of Strategy and Policy

Washington, DC

June 24-25, 1999

Organized by Regional Research Project NE-165: Private Strategies,

Public Policies, and Food System Performance.

Conference Steering Committee Chair: William Lesser, Cornell University.

Is Agricultural Research Still A Public Good?

The closing years of this millennium have witnessed a paradigmatic shift in the roles of public and private agricultural research institutions as producers of new agricultural inputs, with the latter playing a more dominant lead role than in the past. The agricultural life-sciences industry is emerging as a dominant player, attempting to replace most non-mechanical agricultural inputs by private-sector bio-engineering. These structural changes have given rise to two distinct pressures on public agricultural research: accountability to the public for expenditures and impact from those expenditures, and increasing privatization of research with private ownership of intellectual property rights and other research results. One of the most popular responses to these pressures is for public research institutions to patent or otherwise protect their intellectual property (IP) and use patent revenues to fund additional research. Many universities are utilizing the Bayh-Dole Act to work with small and medium university-related firms (SMURFs), that often include faculty members who have made an innovation. To critics, this response simply makes public institutions look increasingly similar to private firms. This raises the question: is agricultural research still be a public good?

This paper is a critical first step in understanding how increasingly private ownership of intellectual property affects the agribusiness environment and the evolving role of public agricultural research institutions.

The innovative step in this paper is the development of a formal economic model which represents the role of applied biotech research in the agricultural life sciences. Specifically, a neo-Schumpeterian model is utilized to analyze the role of private and public research in the future along with an estimation of the overall investment level for R&D. SMURFs are assumed to have

a link to a university, hence, they are in fact part of the public research domain but with the profit motive of a regular firm. Results derived from the model show that there is a continued, albeit diminished, role for public agricultural research as the life-science revolution progresses.

THE MODEL

Overview

Current models of investment in public agricultural research rely largely on economic models which fail to represent the changing nature of intellectual property protection, and the potential dynamic growth of biotechnology. In particular, the types of models summarized in the excellent reviews of Alston, Norton and Pardey and Evenson fail to recognize the dynamic pattern of product obsolescence and replacement that occurs with increasing rapidity in agriculture, and they provide inadequate conceptualization of the interaction between public and private innovative activity. On the other hand models of innovation by private firms ignore public sector research and hence are not directly applicable to agriculture (with the exception of Dinopoulos and Oehmke (D-O)). Some movement towards filling this gap is provided by Moschini and Lapan (M-L) and Alston, Sexton and Zhang (A-S-Z). However, these two papers use before- and after-innovation comparisons to model returns to research, in what are essentially discrete (non-differential) comparative static exercises. The current model remedies these weaknesses.

The model is built around neo-Schumpeterian ideas of endogenous innovation and growth. The defining characteristics of the neo-Schumpeterian approach are that R&D is inherently a risky investment, that products are made obsolete and replaced by the next generation of higher-quality products, that successful researchers obtain some degree of monopoly power and rents from their

discovery of the next generation of products, and that the lure of monopoly profits draws firms into the R&D process (Dinopoulos, 1994). Each of these assumptions accurately represents a part of the life-science industry.

The representation of R&D and innovation in this paper follows the neo-Schumpeterian approaches of Segerstrom, Anant and Dinopoulos, Grossman and Helpman, Aghion and Howitt (1992, 1998) and Barro and Sala-i-Martin, in modeling R&D as a sequence of stochastic innovation races. In each race, firms conduct R&D in an effort to be the first to discover the next-generation product. The winner is granted an exclusive patent on this product, and earns monopoly rents. Schumpeter's 'creative destruction' occurs as the 'creation' of each successive product 'destroys' the competitive advantage held by the previous-generation product.

The introduction of heterogeneous firms is a second distinctive feature, motivated by the gross empirical regularity that the life-science industry is composed largely of two types of firms. The first type of firm is the large, multinational corporation with expensive but well-funded research in a variety of biotechnological areas. Examples of such firms include Monsanto, DuPont, and Novartis. These 'life-science' companies attempt to maximize profits by applying biotech to the historical pharmaceutical, agriculture and nutrition industries. The second type of firm is a small, start-up life-science firm. These firms often arise from the inspiration and discovery of a single or a small team of scientists, and are frequently associated with state universities and land-grant colleges and universities. For example, since the Bayh-Dole Act of 1980, 2,214 new companies have been formed based on protected, academic, intellectual property. In 1997, 3,328 new licenses and options on academic property were executed, many by

existing companies; 70% of these new licenses and options are reported as in the life-sciences area (AUTM).

The primary difference between the two types of firms is the areas in which they conduct research. Production of the agricultural life-science product, in the model denoted by z , requires the use of two inputs, x and y . Small firms conduct R&D to improve the efficiency of the x input, large firms conduct R&D to improve the efficiency of the y input. The decision on where to target R&D is an endogenous outcome of differential R&D cost structures across small and large firms, and different profit opportunities for successful innovators in the different input industries.

Heuristically, the x input will be interpreted as having strong public-good characteristics, and may include niche-market inputs. The y input does not have strong public-good characteristics. That is, private firms who discover a better y input are able to capture many of the benefits from this improvement, but it would be difficult for a private firm to capture the benefits from improved x inputs due to their public-good characteristics (e.g. non-excludeability or non-appropriability). There is a role for the public sector in conducting research on inputs with public-good aspects (Ruttan). There is less role for the public sector in y -industry R&D, where the profits motivate private firms to conduct R&D and capture rents from innovation.

Over time, increases in scientific knowledge and commensurate increases in intellectual property rights (IPRs) have altered the public-good characteristics of many agricultural inputs. For example, open-pollinated varieties are generally storable, replicable and transferable by farmers. Private companies have little hope of generating sufficient profits from open-pollinated seed sales to justify a substantial R&D investment. The development of hybrid varieties and annual seed purchases stimulated development of a substantial private-sector seed industry in the

1950s, competing in large part on the basis of which firm had the latest and best varietal improvement. The nature and intensity of public-sector seed breeding and research also changed. For example, over this period state agricultural experiment station expenditures on cereals research fell from 5.3% of total public agricultural research expenditures in 1951 to 3.6% in 1964 (Huffman and Evenson). Another significant change in the public/private nature of agricultural R&D arose in 1980, when life-science technology took on characteristics of excludability. In *Diamond v. Chakrabarty*, the US Federal Court of Appeals ruled that living tissue could be patented (Huffman and Evenson). In other words, the set of agricultural inputs which have strong public-good characteristics is shrinking over time (similar arguments can be made for production and post-harvest activities, but are omitted from the current model).

The nature of public-sector R&D changed in 1980. The Bayh-Dole Act of 1980 allowed universities to retain title to inventions that were created with Federal funds, in effect allowing universities to compete with private industry in R&D. Universities are not reluctant to protect their intellectual property. Between 1993 and 1997 universities were issued 10,050 patents, including 2,645 in 1997. Also in 1997, universities filed 4,267 new patent applications and reported 11,303 invention disclosures (AUTM, 1999).

The 'public good' question is based on the observation that biotechnology has potential to improve or replace most non-mechanical agricultural inputs, and that the private sector is actively engaged in R&D to do just that. Much public-sector agricultural research also seeks to generate improvements in agricultural inputs. The most important public-sector results are patented or otherwise protect. This begs the question: Is agricultural research still a public good?

This question is most topical when raised concerning applied R&D activities. The model is interpreted correspondingly. The R&D undertaken by both large and small firms is assumed to be applied in nature, with the objectives of developing and commercializing innovations and generating profits from patents, licenses, or technology fees. Universities are assumed to be initiators of small firms based on academic research findings. This assumption is consistent with the specifications of the Bayh-Dole Act, and with the evidence on protection and commercialization of universities' intellectual property (AUTM). The public sector may also choose to engage in major research efforts oriented towards y-inputs—the same high-profit inputs which large firms are seeking to improve. Following development of the model, the paper examines the role of the public sector in each type of innovative activity.

Formal exposition of the model follows.

Production

The agricultural life-sciences product, z , is produced in a competitive industry, using two inputs, x and y . The unit cost of z production is defined by the function

$$c_z = \left(\frac{p_x}{A_x} \right)^\theta \left(\frac{p_y}{A_y} \right)^{1-\theta},$$

where p_x and p_y are the prices of inputs, and A_x and A_y are the currently available technology levels, associated with x and y , respectively. Production of the z good can be thought of as

farming, or pharming. The x and y inputs are combined to produce food, fiber, pharmaceuticals, nutraceuticals, or other high-tech products on the farm.

Technological advances result from R&D, which (if successful) discovers higher-quality inputs. Following Schumpeterian models of quality improvement (for discussion see Dinopoulos, 1994), each innovation augments the quality of input x or y by a proportion λ_x or λ_y , respectively.

Thus,

$$A_x(t) = \lambda_x^j A_x(0) \text{ and } A_y(t) = \lambda_y^k A_y(0),$$

where j and k denote the number of innovations between time 0 and time t in the x and y inputs, respectively (the index j will be reserved for x -industry innovations or applied R&D races, and k for the y -industry). For simplicity, set $A_x(0) = A_y(0) = 1$.

Market Structure

The demand for z is assumed to be perfectly inelastic. Some degree of inelasticity is a common characteristic of demand for agricultural products, and pharmaceuticals. The assumption of perfect inelasticity is made for computational ease: the fundamental results do not depend on the degree of inelasticity. M-L and A-S-Z allow for inelastic demand; D-O study a model with unitary elasticity of demand. The primary difference between the two assumptions is that unitary-elastic demand implies a constant output market size over time, allowing steady-state solutions with constant R&D industry structure over time, as in D-O. With inelastic demand, market size (in value terms) shrinks over time. Consequently, inelastic demand gives rise to dynamic equilibrium paths rather than steady states (although neither M-L nor A-S-Z has true dynamics).

The market for good z is competitive. The price of z , p_z , is thus equal to the cost of production. Factor demands are

$$x = z \frac{\partial c_z}{\partial p_x} = z \theta \frac{p_x^{\theta-1}}{A_x^\theta} \left(\frac{p_y}{A_y} \right)^{1-\theta} \quad \text{and} \quad y = z \frac{\partial c_z}{\partial p_y} = z (1-\theta) \left(\frac{p_x}{A_x} \right)^\theta \frac{p_y^{-\theta}}{A_y^{1-\theta}}$$

Owners of the current-generation innovations price the x and y goods to maximize profit. From equations (3), the demand for each of these goods is inelastic. Consequently, the IP owners will try to restrict quantity and raise price. The continued existence of the past generation of technology limits how high the price can rise. Following Dinopoulos, Oehmke and Segerstrom, we assume Bertrand competition among the competitors. Firm profits for the owner of the current-generation IP are maximized by charging prices $p_x = \lambda c_x$ and $p_y = \lambda c_y$, where c_x and c_y are the constant unit costs of production of the x and y goods, respectively. This limit-pricing structure results in firm profits:

$$\begin{aligned} \Pi_j &= \gamma (p_x - c_x) = \gamma (\lambda_x - 1) c_x = \gamma \alpha_z z \left(\frac{\lambda_x - 1}{\lambda_x} \right) \quad \text{and} \\ \Pi_k &= y (p_y - c_y) = y (\lambda_y - 1) c_y = \alpha_z z \left(\frac{\lambda_y - 1}{\lambda_y} \right), \end{aligned}$$

for the winners of race j and k , respectively. These profits can be obtained if the IP owner produces the input itself (which is usually the case for large agricultural input supply firms), or

licenses the technology to other firms to produce with a licensing fee equal to the markup λ (which is how small firms may operate). The insertion of γ , $0 < \gamma \leq 1$, represents the public nature of the x input: the innovator may not be able to appropriate 100% of the potential profits.

R&D and Innovation

The x and y inputs are subject to Schumpeterian innovation. That is, new inputs of higher quality are discovered and replace the current quality of inputs. Research and development (R&D) is by definition the attempt to discover new inputs. The emphasis on development and commercialization (R&D) is best interpreted as applied R&D. Basic R&D does not enter the model directly, but will be discussed later.

We assume that only small firms engage in R&D on good x , and only large firms engage in R&D on good y . The idea behind this assumption is that θ is small, so that the market for x is small and it is not worthwhile for large firms to invest in this research (their fixed costs are too high). Thus, $(1-\theta)$ is large, and the lower marginal cost curve for large firm R&D gives them a comparative advantage in this market. We formalize this intuition in the remainder of this subsection.

R&D is a costly activity. Assuming a lean cost structure for small firms, the cost to firm i of producing a level of research activity in race j , R_j , is given by

$$c_s(R_j) = \frac{w}{\delta} R_j.$$

The small firms' constant unit cost structure represents the case that the dominant input for the

firm is skilled labor (D-O). The parameter δ_x represents the productivity of a skilled worker in a small firm. For simplicity, the wage rate for skilled scientists, w , will be the numeraire.

For large firms, the cost of research activity R_k directed to producing an innovation that improves the quality of good y is:

$$c_L(R_k) = F + \frac{R_k^\alpha}{\delta_y}, \quad \alpha > 1.$$

F represents fixed costs, δ_y represents large-firm labor productivity for R&D, and α is a parameter that represents decreasing returns to scale as the level of research activity gets large relative to the fixed costs (for low levels of R_k , amortizing fixed costs over R_k results in increasing returns to scale), so that the firm has the usual U-shaped average cost curve. The fixed costs represent the higher transactions costs of starting and maintaining research activities in a large firm, such as organizing and coordinating a large number of research activities with production, marketing and other activities. The fixed costs also represent the costs of maintaining physical plant sufficient to allow flexibility to pursue evolving research agendas. However, if $\delta_y > \delta_x$, the large firm will have lower marginal costs than the small firm at low levels of research activity.

For each R&D race, the instantaneous probabilities of innovation are

$$\phi(R_i) = \frac{R_i}{1 + R} \quad , \quad \Phi(R) = \frac{R}{1 + R} \quad ,$$

for firm i and the industry, respectively (the subscripts j and k have been suppressed). Equation (7) describes the memory-less Poisson processes with intensities ϕ and Φ (see Tolley, Hodge,

Thurman and Oehmke for a discussion of the Poisson process with respect to R&D). These equations imply increasing but diminishing returns of research activity on innovation probabilities. This particular specification is taken from D-O; Dinopoulos, and Segerstrom(1995) provide alternative specifications of instantaneous diminishing returns to R&D. At the industry level, the instantaneous probability of innovation approaches unity as the level of research activity approaches infinity, but there is a nonzero probability of failure (not discovering the next-generation product) for any finite level of R&D.

The Effects of Innovation on the x- and y-Input Markets.

Differentiating the first set of equations in **(3)** shows

$$\frac{\partial x}{\partial A_x} < 0 \quad \text{and} \quad \frac{\partial x}{\partial A_y} < 0;$$

a similar result holds for y. These results indicate that use of x and y decreases with technological progress in x or y, holding p_x and p_y constant. This result occurs because of the inelastic demand for z. As A_x or A_y increases, the amount of x used to produce the same level of z decreases.

Were the quantity z to rise in response to a decline in the price of p_x or p_y and consequently in the price p_z , then the quantity demanded of x or y could increase.

The inelastic derived demand for inputs (inherited from the inelastic demand for z) results in diminished innovator profits over time. Substituting from **(1)** and **(2)** into **(4)** results in

$$\Pi_j = \frac{\gamma z \theta p_x^{\theta-1} p_y^{1-\theta} (\lambda_x - 1)}{\lambda_x^{\theta j} \lambda_y^{(1-\theta)k}} \quad \text{and} \quad \Pi_k = \frac{z(1-\theta) p_x^{\theta} p_y^{-\theta} (\lambda_y - 1)}{\lambda_x^{\theta j} \lambda_y^{(1-\theta)k}}$$

Thus,

$$\lim_{j \rightarrow \infty} \Pi_j = \lim_{j \rightarrow \infty} \Pi_k = \lim_{k \rightarrow \infty} \Pi_j = \lim_{k \rightarrow \infty} \Pi_k = 0$$

That is, profits to successful innovators decrease with each successive innovation.

Y-industry R&D Structure

The value of the firm that wins race k is determined by the arbitrage equation

$$(r + \Phi(R_{k+1}))V_k = \Pi_k.$$

Equation ? states that the profits earned by the winner of the kth race equal the risk-free rate of return plus a risk premium (per unit) equal to the probability that the next-generation innovation will be discovered and make the current technique obsolete.¹ Large firm i will invest in race k until the expected marginal return from R&D—the probability that firm i will innovate successfully times the value of being the innovator—equals the marginal cost of R&D:

$$\varphi'(R_{i,k})V_k = c'_L(R_{i,k}).$$

¹For simplicity, we have abstracted from complications due to the fact that profits will decrease if the next generation x innovation is discovered. The right-hand side of the equation is technically the expected profits, taking into account the probabilities of x-innovation. Since race-k entrants take expected profits as given, this simplification does not change the results.

The zero-profit condition for y-industry R&D is

$$\Phi(R_k)V_k = CR_k.$$

The upper case C represents the industry per-unit cost of producing R&D; that is, C is the minimum average cost of R&D for large firms.

Substituting for V_k from (13) into (12) and solving for $R_{i,k}$ results in

$$R_{i,k} = \left(\frac{\delta_y C}{\alpha} \right)^{\frac{1}{\alpha-1}}.$$

This result simply states that firms entering y-innovation races conduct the same level of R&D in each race—where the level is determined by their minimum average cost (here we neglect the integer problem).

Substituting for V_k from (13) into (11) results in

$$\frac{R_{k+1}}{1 + R_{k+1}} = \frac{\Pi_k - rC(1 + R_k)}{C(1 + R_k)}.$$

Equation (15) is a nonlinear difference equation in Π and R , and it is at best very difficult to find a closed form solution. However, further examination does generate results on the y-R&D industry structure.

One consequence of equation (15) is that there is no steady-state level of y-R&D expenditures. To see this, assume the contrary: that y-R&D expenditures are constant over time,

so $R_{k+1}=R_k$. Solving for R_k results in : $R_k = \frac{\Pi_k - rC}{(1+r)C}$. But this means that R_k decreases as Π_k

decreases, which is a contradiction. Thus y-R&D expenditures cannot be constant over time.

However, if λ_y is very small, so that Π_k decreases very slowly, then it might be possible to generate a sequence $\{R_k\}$ which varies little from one innovation race to the next. This intuition will be confirmed momentarily with simulation results.

Further manipulation of (15), using (2), results in

$$\frac{r + \Phi(R_{k+1})}{r + \Phi(R_{k+2})} = \frac{(1 + R_{k+1})\lambda_y}{1 + R_k}$$

If λ_y is large relative to $1 + R_{k+1}$, meaning that the productivity increase is large relative to the amount of research, then the right hand side of (16) is greater than one. Therefore the left hand side is greater than one, so $\Phi(R_{k+1}) > \Phi(R_{k+2})$, and thus $R_{k+1} > R_{k+2}$. In other words, when innovation generates large productivity increases, then research expenditures will be monotonically decreasing with each innovation race. If λ_y is relatively small, and R_k is larger than R_{k+1} , then the right hand side of (16) can be less than one. In this case $R_{k+1} < R_{k+2}$ and research expenditures exhibit cyclic behavior: they decrease and then increases. A similar result can be obtained if R_k is sufficiently greater than R_{k+1} , even for large λ_y (although a large λ_y would cause these cycles to dampen quickly). For $k=0$, the case of $R_k \gg R_{k+1}$ is interpreted to correspond to initial investments in agri-biotechnology. Initial research expenditures may be very high relative

to later expenditures if companies are overly optimistic about market size and consumer acceptance (for example).²

Numerical solutions to **(16)** exhibit each of the behaviors noted above (Table 1). In the first example, $r=10\%$, $C=600$, $\lambda_y=1.1$, and the initial conditions are $\Pi_0=200$ and $R_0=0.25$. These parameter values are chosen to give a reasonable instantaneous probability of success in any time interval (0.20 dt). Research activity exhibits a strong declining trend: by the 10th race, activity is less than 1/6 of the initial value.

Cyclic behavior can be introduced by increasing the initial value for research to $R_0=2.0$, keeping the other parameter values unchanged. Research activity during innovation race 1 falls to 0.01, recovers to 0.25 in race 2, and then declines monotonically. Eventually, the path for this example converges to the path in example 1. That is, the effects of the different initial condition for research last only a few races.

With a small value of λ_y , 1.0001, the third example shows how research expenditures can follow a prolonged cyclical pattern. This cyclical pattern is centered around a declining trend, and eventually dampens to the trend, although the low value of λ makes it difficult to see this trend. The low value of λ_y —with productivity increases of only 1/100 of a percent per innovation—also means that interpretation of this type of cyclical behavior as representative of life-science research behavior is improbable.

² The EU restrictions on transgenic organisms and the products thereof, consumer reaction to bovine growth hormone, potential difficulties relating to to bT corn poisoning monarch butterflies, and possible premature aging of cloned sheep are all examples of unforeseen, negative events that might have reduced research investments had they been predicted.

X-R&D Industry Structure

The firm that wins race j has a value determined by

$$(r + \Phi(R_{j+1}))V_j = \Pi_j.$$

This equation is directly analogous to (11): the profits earned by the winner of the j^{th} race equal the risk-free rate of return plus a risk premium (per unit) equal to the probability that the next-generation innovation will be discovered and make the current technique obsolete.

Due to the constant returns to scale nature of x -industry R&D, it is impossible to determine the number of firms engaged in x -R&D, or the level of R&D undertaken by each firm. It is possible to determine the industry level of x -R&D, from the zero-profit condition

$$\Phi(R_j)V_j = \frac{R_j}{\delta_x},$$

which is analogous to equation (13). Equations (7), (17) and (18) determine the x -industry levels of R&D activity. These equations can be combined to form the difference equation

$$R_{j+1} = \frac{\delta_x \pi_j}{1+r} R_j + \frac{\delta_x \pi_j - r}{1+r},$$

which governs the evolution of x -industry R&D expenditures over time. Iteration of (19) and repeated substitution results in an expression for R_{j+1} as a function of model parameters and the initial values Π_0 and R_0 , but it is more intuitive to derive results directly from (17) and (18).

From equation (18), it must be that $V_{j+1} < V_j$ if and only if $R_{j+1} < R_j$. Since $\Pi_j > \Pi_{j+1}$, equation (17) shows that for all j , at least one of the following is true:

$$\text{i) } V_{j+1} < V_j, \quad \text{ii) } \Phi(R_{j+2}) < \Phi(R_{j+1}) .$$

The second condition implies $R_{j+2} < R_{j+1}$, since Φ is a monotonically increasing function. If both conditions of (20) hold for all j , then it is straightforward to show that the sequences $\{V_j\}$ and $\{R_j\}$ are monotonically decreasing. This corresponds to the case in which each x -innovation has a lower value (due to the inelastic demand for x), and the industry consequently devotes fewer resources to each R&D race.

It is not necessarily the case that both conditions in ? hold. Suppose there exists a j such that $V_{j+1} > V_j$. Firm value V_{j+1} could increase over V_j if R_{j+2} –research to replace product $j+1$ –is sufficiently small so that the owner of product $j+1$ expects to earn monopoly rents for a longer period than had the owner of the innovation j . In this case, (20) implies that $R_{j+2} < R_{j+1}$, and so (18) implies $V_{j+2} < V_{j+1}$. That is, firm value exhibits some degree of cyclical behavior.

Numerical solutions of (19) exhibit the behaviors described above (Table 2). The first example has $\lambda_x=1.02$, $\gamma=1$, $r=10\%$, $\delta_x=0.15$, and the initial conditions are $\Pi_0=5$ and $R_0=2.2$. In this case, research expenditures decline monotonically over time. In the second example, $\delta_x=0.2$; the other parameters are unchanged. In this example, research activity increases through the 6th innovation race, and declines monotonically thereafter. Finally, it is possible to get an explosive solution to (19), as exhibited in the third example with $\delta_x=0.2$ and $\Pi_0=10$. Such solutions are neglected as infeasible on economic grounds: they imply that research expenditures would tend toward infinity as innovator profits tended to zero.

THE ROLE OF THE PUBLIC SECTOR

The ‘public good question’ can be motivated in terms of equation ?. The diminishing importance of x-inputs with strong public-good characteristics can be represented by a decrease in the share of x-inputs in total cost of production, θ . The public sector’s increasing protection of intellectual property is represented by modeling technology advances in both the x- and y-input industries as competitive R&D races, motivated by profits.

Examination of equation (4) shows that a decrease in Θ increases Π_k and decreases Π_j for all j and k, ceteris paribus. If the life-sciences revolution is as far reaching as some predict, the magnitude of this reduction could be substantial. In other words, the first major result is that the life-sciences revolution has reduced the role for public-sector applied R&D in generating improvements in agricultural inputs. In particular, the role of the public sector in generating research results and facilitating their commercialization and use through small private businesses, as provide for in the Bayh-Dole Act, is diminished by the life-sciences revolution. This diminution arises because increases in the protection of intellectual property increase the potential profits from such innovations, making them targets for large-firm R&D activities.

However, the high fixed costs which large firms face in competing in life-sciences R&D guarantees a role for the public sector as a provider of R&D for niche input-markets. As inelastic demand for agricultural inputs results in decreasing profits for large firms which discover the next-generation y input, these firms eventually decide that the returns to some components of y-industry R&D are insufficient to cover their fixed costs. Research on these components then falls within the realm of the public good, and there is a role for public sector R&D.

Traditionally, the role of the public sector in agricultural R&D has been to increase the level of research in areas in which the private sector is under-investing. This role remains.

Underinvestment by the private sector can be demonstrated formally. The socially optimal level of x-industry research is determined by the conditions

$$\rho v_j = \Pi_j / \gamma$$

and

$$\Phi(S_j) v_j = S_j / \delta_x,$$

where ρ is the social discount rate, v_j is the social value of the j^{th} innovation of the x input, and S_j is the socially optimal level of research on the j^{th} innovation. Since demand is perfectly inelastic, potential profits equal the social gain (there is no consumer's surplus since it is all extracted as monopoly rents), except that society captures all of the potential gain, not just the γ proportion that would be captured by a small firm. Since $\gamma \leq 1$, the right-hand side of (1) is less than the right-hand side of (2). With competitive capital markets $\rho = r$, but some authors argue that the market interest rate excessively discounts future generations, so that $\rho < r$. In either case, comparison with (2) shows that $\rho < r + \Phi(R_j)$. Therefore $v_j > V_j$. In other words, the social value of innovations exceeds the private value of innovations.

Substituting from (1) into (2) results in

$$S_j = \frac{\Pi_j}{\gamma \rho \delta_x} - 1$$

This equation differs from (19) in two important ways. First, since society as a whole captures all of the benefits from the innovation, shown by the presence of γ in the denominator on the right-hand side, the socially optimal level of research tends to be higher. Second, the probability of discovering the $j+1^{\text{st}}$ innovation does not enter the equation. This is because the social benefits of innovation are cumulative, and do not vanish when a competitor is the first to discover the next-generation improvement.

A similar expression can be derived for y -input innovations:

$$S_k = \frac{\Pi_k}{\rho C} - 1,$$

where S_k is the socially optimal level of R&D activity, which is oriented to discovering the k^{th} -generation y input.

For concreteness, socially optimal values of S_j and S_k are calculated for each of the numerical solutions presented in **Table 1** and **Table 2**, under the assumption that $\rho=r$. These values are presented in **Table 3**. In every case, the socially optimal level of R&D exceeds the level undertaken by the private sector.

CONCLUSIONS

The innovation in this paper is a Schumpeterian model of life-science R&D, innovation, and growth. Although the model is complex, it is rich in detail and implications about industry

structure and about the role of the public sector. The most salient implications for the role of the public sector are

1. The private sector underinvests in applied R&D activity.

This underinvestment is the result of continual innovation races, and the loss of profits to the current innovator when a competitor discovers the next-generation innovation. There is a potential role for the public sector in conducting or stimulating research to fill this gap.

2. Concentration in the large-firm, life-science R&D industry increases over time.

This is the result of the nature of life-science R&D, which can entail large fixed costs.

3. The life-science revolution is reducing the number of markets, in the short run.

This reduction in the number of niche markets diminishes the role of the public sector.

4. There is a role for the public sector in conducting R&D in niche markets.

Niche markets are those in which the profits from successful innovation are insufficient to lure large firms with high fixed costs of R&D into conducting innovative activities. Innovation in niche markets may still serve the public good. There is a role for the public sector in providing or promoting this research.

5. In the long run, the life-science revolution may also create new niche markets.

These niche markets arise as inelastic demand diminishes profits from future innovations in major inputs, causing large firms to cease R&D on these inputs. This creates a niche market. The long-run, net effect is not clear.

The final conclusions comes not from the model of the algebra, but from an underlying assumption. Specifically, the model is based on the premise that fundamental breakthroughs in agricultural biotechnology generated a vigorous applied R&D sector. The resulting innovations benefit both firms and consumers. However, the level of R&D activity diminishes over time.

Another major breakthrough could re-invigorate the sector. Thus,

6. There is a role for the public sector in the provision of basic research, which increases the productivity of applied R&D.

REFERENCES:

- Aghion, P. and P. Howitt, 1992. A Model of Growth Through Creative Destruction. *Econometrica* 60.2:323-352.
- Aghion, P. and P. Howitt, 1998. Endogenous Growth Theory (MIT Press).
- Alston, J.M. G.W. Norton, and P.G. Pardey. *Science Under Scarcity: Principles and Practice for Agricultural Evaluation and Priority Setting*. Ithaca, NY: Cornell University Press, 1995.
- Alston, J.M., R.J. Sexton, and M. Zhang “The Effects of Imperfect Competition on the Size and Distribution of Research Benefits.” *Amer. J. Agr. Econ* 79(November 1997):1252-1265.
- Association of University Technology Managers (AUTM), 1999. “The Bayh-Dole Act.” Available online a <http://autm.rice.edu/autm/publications/survey/facts.htm>.
- Association of University Technology Managers (AUTM). “Licensing Survey FY 1997: Executive Summary” Available online at <http://autm.crpc.rice.edu/autm/publications/survey/1997/execsumm.html>.
- Barro, R. and X. Sala-i-Martin, *Economic Growth*. New York, NY: McGraw-Hill, Inc, 1995.
- Evenson, R.E. Private and Public Research and Extension. In B. Gardner and G. Rausser, eds., *Handbook of Agricultural Economics* (forthcoming, North-Holland).
- Dinopoulos, E. “Schumpeterian Growth Theory: An Overview.” *Osaka City Univ. Econ. Rev.* 29(January 1994):1-21.
- Dinopoulos, E. and J. Oehmke, 1997. “A Neo-Schumpeterian Model of Agricultural Innovation and Growth ” paper presented at the Congress of the International Association of Agricultural Economists, Sacramento, CA, 1997.

- Dinopoulos, E., J. Oehmke, and P. Segerstrom. "High-Technology-Industry Trade and Investment: The Role of Factor Encowments." *J. Int. Econ.* 34(1993):49-71.
- Grossman, G.M. and E. Helpman, "Quality Ladders and Product Cycles." *Quarterly J. Econ.* 106(1991):557-586.
- Huffman, W. and R.E. Evenson, 1993. *Science for Agriculture* (Ames: Iowa State University Press).
- Huang, S. and R.J. Sexton. "Measuring Returns to an Innovation in an Imperfectly Competitive Market: Application to Mechanical Harvesting of Processing Tomatoes in Taiwan." *Amer. J. Agr. Econ.* 78(August 1996):558-571.
- Moschini, G. and H. Lapan "Intellectual Property Rights and the Welfare Effects of Agricultural Economics." *Amer. J. Agr Econ.* 79(November 1997):1229-1242.
- Ruttan, V. W., 1982. *Agricultural Research Policy* (Minneapolis: University of Minnesota Press).
- Segerstrom, P. T.C.A. Anant and E. Dinopoulos, "A Schumpeterian Model of the Product Life Cycle." *Amer. Econ. Rev.* 80(December 1990):1077-1091.
- P. Segerstrom, 1995. *A Quality Ladders Growth Model with Decreasing Returns to R&D*. Dept. of Economics, Michigan State University, East Lansing MI.
- Tolley, G. S., Hodge, W. Thurman and J. Oehmke, 1985. *The Economics of R&D Policy* (Prager Press).

Table 1. Numerical Solutions for the Differential Equation Determining the Industry Level of Y-R&D, for Selected Parameter Values and Initial Conditions, with Instantaneous Probability of Innovation and Expected Time to Innovation.

| | Parameter Values and Initial Conditions | | | | | | | | |
|-----------------|--------------------------------------------------------|-------------|------------------|-------------------------------------------------------|-------------|-----|----------------------------------------------------------|-------------|-----|
| | $\lambda=1.1, \Pi_0=200,$ $r=10\%, C=600, R_0=0.25$ | | | $\lambda=1.1, \Pi_0=200,$ $r=10\%, C=600, R_0=2.0$ | | | $\lambda=1.0001, \Pi_0=200,$ $r=10\%, C=600, R_0=0.4$ | | |
| Innovation Race | R_k | $\Phi(R_k)$ | ETA ^a | R_k | $\Phi(R_k)$ | ETA | R_k | $\Phi(R_k)$ | ETA |
| k=0 | 0.2500 | 0.200 | | 2.0000 | 0.667 | | 0.4000 | 0.286 | |
| 1 | 0.2000 | 0.167 | | 0.0112 | 0.011 | | 0.1602 | 0.138 | |
| 2 | 0.1800 | 0.153 | | 0.2495 | 0.200 | | 0.2304 | 0.188 | |
| 3 | 0.1540 | 0.133 | | 0.1370 | 0.120 | | 0.2061 | 0.171 | |
| 4 | 0.1325 | 0.117 | | 0.1367 | 0.120 | | 0.2140 | 0.177 | |
| 5 | 0.1123 | 0.101 | | 0.1115 | 0.100 | | 0.2113 | 0.174 | |
| 6 | 0.0941 | 0.086 | | 0.0943 | 0.086 | | 0.2122 | 0.175 | |
| 7 | 0.0775 | 0.072 | | 0.0775 | 0.072 | | 0.2119 | 0.175 | |
| 8 | 0.0624 | 0.059 | | 0.0624 | 0.059 | | 0.2120 | 0.175 | |
| 9 | 0.0486 | 0.046 | | 0.0486 | 0.046 | | 0.2119 | 0.175 | |
| 10 | 0.0361 | 0.035 | | 0.0361 | 0.035 | | 0.2119 | 0.175 | |

ETA=Expected time of arrival of innovation k, measured from the start of the innovation race.

Table 2. Numerical Solutions for the Differential Equation Determining the Industry Level of X-R&D, for Selected Parameter Values and Initial Conditions, with Instantaneous Probability of Innovation and Expected Time to Innovation.

| | Parameter Values and Initial Conditions | | | | | | | | |
|-----------------|----------------------------------------------------------------------|-------------|------------------|---------------------------------------------------------------------|-------------|-----|---------------------------------------------------------------------|-------------|-----|
| | $\lambda=1.02, \gamma=1, \Pi_0=5,$ $r=10\%, \delta=0.15, R_0=2.2$ | | | $\lambda=1.02, \gamma=1, \Pi_0=5,$ $r=10\%, \delta=0.2, R_0=2.2$ | | | $\lambda=1.02, \gamma=1, \Pi_0=5,$ $r=10\%, \delta=0.2, R_0=2.2$ | | |
| Innovation Race | R_k | $\Phi(R_k)$ | ETA ^a | R_k | $\Phi(R_k)$ | ETA | R_k | $\Phi(R_k)$ | ETA |
| k=0 | 2.2000 | | | 2.2000 | | | 2.20 | | |
| 1 | 2.1818 | | | 2.9091 | | | 5.82 | | |
| 2 | 2.1269 | | | 3.4840 | | | 12.15 | | |
| 3 | 2.0492 | | | 3.9181 | | | 22.99 | | |
| 4 | 1.9591 | | | 4.2131 | | | 41.10 | | |
| 5 | 1.8639 | | | 4.3783 | | | 70.71 | | |
| 6 | 1.7686 | | | 4.4284 | | | 118.09 | | |
| 7 | 1.6762 | | | 4.3821 | | | 192.28 | | |
| 8 | 1.5885 | | | 4.2595 | | | 305.92 | | |
| 9 | 1.5063 | | | 4.0808 | | | 476.28 | | |
| 10 | 1.4300 | | | 3.8649 | | | 726.13 | | |

ETA=Expected time of arrival of innovation k, measured from the start of the innovation race.

Table 3. Socially Optimal Levels of X-input and Y-input R&D, for Selected Parameter Values and Initial Conditions.

| | Parameter Values and Initial Conditions | | |
|-----------------|---------------------------------------------------|---------------------------------------------------|------------------------------------------------------|
| | y-input R&D | | x-input R&D |
| | $\lambda=1.1,$ $\Pi_0=200,$ $r=10\%, C=600$ | $\lambda=1.1,$ $\Pi_0=200,$ $r=10\%, C=600$ | $\lambda=1.0001,$ $\Pi_0=200,$ $r=10\%, C=600$ |
| Innovation Race | | | |
| k=0 | 3.33 | 3.33 | 3.33 |
| 1 | 3.03 | 3.03 | 3.33 |
| 2 | 2.75 | 2.75 | 3.33 |
| 3 | 2.50 | 2.50 | 3.33 |
| 4 | 2.28 | 2.28 | 3.33 |
| 5 | 2.07 | 2.07 | 3.33 |
| 6 | 1.88 | 1.88 | 3.33 |
| 7 | 1.71 | 1.71 | 3.33 |
| 8 | 1.56 | 1.56 | 3.33 |
| 9 | 1.41 | 1.41 | 3.33 |
| 10 | 1.29 | 1.29 | 3.33 |

ETA=Expected time of arrival of innovation k, measured from the start of the innovation race.