

**Setting Efficient Incentives for
Agricultural Research: Lessons
from Principal-Agent Theory**

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Abstract

by Wallace E. Huffman and Richard E. Just

This paper presents a conceptual analysis of important issues in management of agricultural research drawing on principal-agent theory and derives implications for funding and management of agricultural research. Building on well known attributes of research, whereby research results are risky, outputs are uncertain and sometimes unanticipated, more than one approach has validity for a given topic, we consider how incentives should be structured to elicit optimal research effort and directions, whether research directions should be set at a centralized or decentralized level, and the optimal duplication of effort. The results suggest that (i) the current trend toward replacement of formula funding by competitive grants allocation may be ill conceived, (ii) a mixed system with some research funding and direction at the federal level, some at the state level, and perhaps some at regional levels is advantageous, and (iii) funding of competing scientists working on the same problem at different institutions has merit.

Key words: research management, research funding, agriculture, principal-agent theory, research incentives, scientist's effort, noncompetitive funding, competitive funding, duplicative effort

Setting Efficient Incentives for Agricultural Research: Lessons from Principal-Agent Theory

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Setting Efficient Incentives for Agricultural Research: Lessons from Principal-Agent Theory

At least since the 1950s, studies have shown unusually high productivity of public agricultural research (e.g., Griliches; Huffman and Evenson; Ruttan; Schultz). In response, many have asked why more funds are not allocated to public agricultural research. More recently, following the large budget deficits of the 1980s, funding conditions have tightened and forced both the research agencies of the U.S. Department of Agriculture and many of the state agricultural experiment stations (SAES) into a contracting mode. Under unprecedented budget pressures, administrators and public decision makers have struggled to set priorities to reduce budgets without significant loss of productivity. In response, considerable debate has emerged over the last decade about how to manage public agricultural research (e.g., Alston, Norton, and Pardey; Huffman and Just 1994; Just and Huffman).

One school argues that priorities should be set at a national level and then competitive grant programs should be used to allocate funds according to these priorities. Another school argues that national priority setting may ignore research opportunities with local specificity or non-national groups of benefactors, and that competitive grants programs have high transactions costs and foster too many projects with short-term and relatively certain payoffs. Some limited empirical work has been offered supporting the latter view (Huffman and Just 1994). Interestingly, the analysis of these issues to date has not produced either rigorous empirical or theoretical results. Progress has been largely to identify issues, canvass views, and express a priori impressions and intuition.

This debate renews a longer-term concern about how best to foster, organize, and manage agricultural research. Almost two decades ago, T. W. Schultz (1980, 1982, 1983, 1985) spoke out against the tendencies for national priority setting and central planning of agricultural research, over-organization of institutional research, directed research from the top, elaborate

documentation/justification of research efforts, and treating/managing research as a routine activity. He concluded that “Although money, facilities and competent agricultural scientists are necessary to do worthwhile research, it is not a routine activity. It is, indeed, a subtle, elusive human activity that is difficult to foster, promote and maintain” (Schultz 1980, p. 16).

This paper presents a conceptual analysis of some of these important issues in management of agricultural research drawing on principal-agent theory. The analysis highlights some of the characteristics of the public agricultural research establishment whereby research results are risky, outputs are uncertain and sometimes unanticipated, more than one approach has validity for a given research topic, etc. The paper derives implications for funding and management of agricultural research. Based on the identified characteristics, we consider how incentives should be structured to elicit optimal research efforts and directions, whether research directions should be set at a centralized or decentralized level, and the optimal duplication of effort, for example, by competing scientists or competing research facilities. Results suggest that (i) the current trend toward replacement of formula funding by competitive grants allocation may be ill conceived, (ii) a mixed system with some research funding and direction at the federal level, some at the state level, and perhaps some at regional levels is advantageous, and (iii) funding of competing scientists working on the same problem at different institutions under different direction has merit.

Before beginning the conceptual analysis, we first set the stage by reviewing some recent trends in agricultural research funding and management. Then we introduce the principal-agent model of decision making in agricultural research along with its asymmetric information characteristics. Based on the features of uncertainty affecting agricultural research, we turn to design of incentive mechanisms to optimize performance. The resulting framework naturally lends itself to investigating questions of effort duplication.

The Changing Structure of Incentives for Agricultural Research

Some dramatic changes have taken place in the funding of agricultural research in the United States since establishment of the U.S. Department of Agriculture, the founding of the land-grant college system under the Morrill Act of 1862, and the institution of agricultural experiment stations under the Hatch Act of 1887.

Displacement of Federal Funding by State Funding. In 1887, when the state agricultural experiment station (SAES) system was first given formal federal funding by passage of the Hatch Act, at least 82 percent of the funding was from the federal government. This share dropped dramatically to 65 percent in 1900, 29 percent in 1960, and 26 percent in 1990. As the share of federal support has declined, the share of state support has increased. The state funded share of SAES budgets increased from 20 percent in 1900 to 58 percent in 1960. Since then, the state share of funding has decreased somewhat to 55 percent in 1980 and 1990, and further to 50 percent in 1995.

An important point about implementation of state funding was that it was provided through institutional block grants or program grants to agricultural experiment stations or land-grant universities, thus leaving the setting of directions and research program implementation to local land-grant or experiment station authority (Huffman and Evenson). A major force behind the increase in state funding was the requirement instituted in 1935 of matching regular federal funding with other, including state, funding. To receive regular USDA funding of the SAES, states were required to match regular federal funds. An important effect of this requirement was to provide long-run diversification in the SAES funding portfolio, which generated a very diversified public agricultural research system compared to other countries.

Displacement of Regular Federal Funding by Competitive Grant Programs. While funding for the USDA has continued to be essentially all from the federal government (USDA), the

composition of the funding and mechanism for allocating federal funds to the SAES system has changed (Huffman and Evenson, pp. 21-23; Alston and Pardey, Ch. 2; Committee on the Future of the Colleges of Agriculture in the Land-Grant University System, Ch. 6). Historically a legislated formula for allocating federal appropriations to the SAES system was used. Initially all states received equal appropriations, but the formula was modified over the period 1935-55 to depend on each state's share of total U.S. farm population and total U.S. rural people.

After strong encouragement from the National Research Council, the USDA initiated a Competitive Grants Programs to finance a small share of public agricultural research in 1977. With serious federal budget deficit problems beginning in the 1980s, public pressure mounted to increase scrutiny of the efficiency and social usefulness of all public expenditures. An outgrowth of pressure has been greater interest in and emphasis on priority setting at the federal level. Arguments were advanced that SAES formula funding did not adequately reward productivity (or penalize non-productivity). One response was a substantially increase in funding for the National Research Initiative (NRI) in 1986. Competition for NRI grants is open to all public and private researchers.

In 1900, virtually all of the 64 percent of SAES funding from the national government came in the form of USDA formula funds. By 1960, the share of SAES system funding coming from regular USDA (CSRS or CSREES administered) sources had declined to 22 percent. By 1980, the share was 17 percent and declined further to about 15 percent in 1990 and 1995. In 1982, only 3.3 percent of regular federal funds for SAES were distributed by competitive grants, but this share increased to 8.7 percent in 1990 and 15.7 percent in 1995 (Huffman and Evenson; USDA). Hence, the funding of agricultural research by regular or formula funds has been largely displaced by competitive grant funding.

Increased emphasis on private funding and public-private cooperation. Increasingly, in the midst of budget crises, public agricultural research scientists have been encouraged by administrators to pursue nontraditional sources of funding such as agencies other than departments of agriculture, private corporations, and commodity groups. Over the past two decades, SAES scientists in the U.S. have turned increasingly to non-regular federal and private sector sources. In 1980, the share of SAES system funding coming from nontraditional federal government sources was 11 percent. These funds were distributed by the USDA in contracts and cooperative agreements and by the National Institutes of Health, the U.S. Agency for International Development, the National Science Foundation, the U.S. Department of Health and Human Services, the Public Health Service, and other agencies primarily by competitive grants. This share increased to 12 percent in 1990 and 15 percent in 1995 (USDA).

Public agricultural scientists are increasingly being encouraged to obtain funding from private corporations and producer groups, including cooperatives. The private sector share of SAES funding was 7.0 percent in 1960, and increased to 9.2 percent in 1980 and 13 percent in 1995.

Summary. This brief account reveals that SAES funding has become increasingly diversified first to state as well as federal sources, then to non-agricultural government sources and the private sector. As this change has taken place, the traditional formula allocation mechanism of both federal and state governments has been increasingly displaced by competitive grant funding both from the USDA as well as other federal agencies and by the private sector.

Asymmetric Information and the Principal-Agent Problem of Academic Research

To understand the implications of current trends in public agricultural research funding and management according to principal-agent theory, R&D must first be recognized as a productive

process that has unusual attributes relative to the production process for manufactured goods. First, the R&D payoff is most accurately measured by the “best” of its scientists’ outputs, rather than their total output of models, designs, inventions, plant or animal varieties, etc.

Second, the research production process is subject to a large amount of ex ante uncertainty. This arises in large part because output is appropriately measured by the “best” rather than “total” output. For example, much of what is “discovered” may be of no social value because it does not improve upon existing innovations sufficiently to merit practical application. On the other hand, something new and of significance may be discovered that is not anticipated.

Third, the payoff or value of a research project is often unknown at the outset. In fact, the ultimate value of some R&D discoveries may be largely unknown even at the conclusion of the research projects that generated them. For example, more than sixty years after Atanasoff discovered the electronic digital computer and twenty-five years after Cohen and Boyer discovered the basic technique of recombinant DNA, society continues to uncover new and valuable applications that add to their respective payoffs. For many projects, however, the discovery of particular innovations, such as a new and successful wheat variety, will have characteristics that lend themselves to credible estimates of their value.

Fourth, asymmetric information exists in the relationship between scientists and their research institutions or administrators. When a research or funding institution contracts with a scientist for a research project, they can anticipate asymmetric information about the scientist’s level of “effort” or “hours of work” on the project. This arises because monitoring scientists’ effort or hours of work is very costly and most likely ineffective. Even a scientist may be unable to measure the amount of time devoted to thinking about a problem during casual or “non-working” hours (see Ladd). Clearly, given ex ante uncertainty in the research production process, a scientist’s effort or hours of work

cannot be accurately inferred from the output produced. This raises a “moral hazard” concern in setting research incentives: scientists’ effort may not be subject to effective contracting because an administrator may not be able to verify that a scientist’s effort has met the terms of a contract.

Principal-agent theory can provide insight into setting efficient incentives and contracting within organizations when the research administrator (the principal) and scientist (the agent) anticipate asymmetry of information about the scientist’s effort (Holmstrom; Mas-Collel, Whinston, and Green, Ch 14). In general, this problem is typical whenever an administrator or principal hires someone to take some action as an “agent” of the administrator when effective monitoring is not possible. Furthermore, considerable empirical evidence exists that principals and agents in a wide range of nonmarket circumstances are able to work out incentive schemes to mitigate the problems caused by asymmetric information and uncertainty (e.g. see Holmstrom; Holmstrom and Milgrom).

Modeling Research Incentives with Uncertain Payoffs

Before assessing implications of recent trends in agricultural research, we sketch the basic model. First, the research administrator is assumed to observe the research payoff at the end of a project, to compensate scientists for their effort, possibly with a compensation package including a fixed salary and a performance incentive, and to be risk neutral about R&D payoffs.¹ For the purpose of this paper, a research project is an attempt to develop a particular innovation or an annual contract to conduct research in a particular area. The administrator’s objective is to maximize expected R&D payoff net of scientists’ compensation.

Second, scientists are assumed to obtain utility from income, disutility from effort or work, to be risk averse, and to have a reservation utility (associated with activities that are not under the control of the research administrator). More specifically, each scientist (denoted by the subscript i)

is assumed to have a quadratic cost of effort, $c_i(e_i) = k_i e_i^2/2$ (which generates a positive-sloped effort schedule with respect to compensation) where e_i is effort, to have constant absolute risk aversion N_i , to have a fixed certainty-equivalent reservation utility (μ_i), and to choose effort on research to maximize individual expected utility subject to attaining at least the reservation utility.

Third, each scientist is assumed to work alone (to avoid team or easy-rider problems) and to undertake one project that produces exactly one indivisible unit of output, but with random quality depending on his effort. Hence, the research output is one-dimensional. For notational simplicity, the non-stochastic component of the production process is assumed identical across scientists — an assumption that is easily relaxed later — so the quality index can be simply defined as effort plus random components. To examine the implications of random quality, we let

$$(1) \quad y_i = e_i + \epsilon_i + \eta^*$$

where y_i is quality of research produced by scientist i , ϵ_i is a scientist-specific random component with zero mean and variance F_i^2 , and η^* is a random component affecting all scientists with zero mean and variance F_*^2 . The scientist-specific random term may represent the effects of individual ability, creativity and efficiency of mental processes (Ladd). The common shock might represent unanticipated problems associated with the particular innovation toward which all the scientists' efforts are directed, or it could represent unanticipated exogenous advances in the public stock of knowledge during the research project. Assuming that ϵ_i and η^* are uncorrelated, the variance of research output is the summation of the two variances, $T_i^2 = F_i^2 + F_*^2$ (note that if the two are correlated, a suitable redefinition can make them uncorrelated).

The effort level, e_i , is the source of asymmetric information. It is unobservable to the research administrator but treated as observable to the scientist. Research quality, y_i , is assumed to be observable to both the administrator and scientist but only at the end of the research project. We

permit more than one scientist to work independently on identical research projects, but only the highest quality output contributes to the administrator's R&D payoff. This might arise through the publication process where an editor publishes the "best" paper on a topic given that it adds significantly to the state of knowledge, or farmers use only the crop variety or animal breed that has the "best" anticipated performance.

Optimal Compensation of Public Research Scientists

An important research policy question is: What is the optimal scientist compensation scheme and how does it depend on characteristics of scientists and research projects? To convey some basic results about optimal compensation and the associated R&D payoff, we initially consider contracting between a research administrator (or funding agency) and one scientist. According to principal-agent theory, when contracting is repeated many times and the agent has discretion in actions including the level and timing of effort, the structure of the optimal pay scheme is linear in the observed principal's payoff (Holmstrom and Milgrom; Levitt). Hence, we consider Pay Scheme I consisting of two parts: (i) a guaranteed payment, w_i , that is independent of the observed R&D payoff, and (ii) an incentive payment that amounts to a positive share, β_i , of the observed R&D payoff,

$$(2) \quad w_i = w_i + \beta_i y_i.$$

A larger β_i implies a "higher powered" incentive scheme. Substituting equation (1) into (2), the structure of this pay scheme is linear in the scientist's effort,

$$(3) \quad w_i(e_i) = w_i + \beta_i e_i + \beta_i \epsilon_i + \beta_i^*.$$

Equation (3) depicts how ex ante uncertainty in the research production process is transmitted into ex ante wage uncertainty for the scientist. From equation (3), the expected wage conditional on effort is $E(w_i) = w_i + \beta_i e_i$ and the wage variance is $V(w_i) = \beta_i^2 T_i^2$. Where the scientist's utility is

$U_i(e_i) / U_i^*[w_i(e_i) - c_i(e_i)]$, the scientist's expected utility maximization problem is

$$\text{Max}_{e_i} E[U_i(e_i)] = \mu_i + \beta e_i - .5k_i e_i^2 - .5N_i \beta^2 T_i^2$$

for which first order conditions imply the optimal effort choice, $e_i^* = \beta/k_i$.²

With one scientist, the optimal compensation scheme for the administrator is obtained by choosing μ_i and β to maximize the administrator's expected R&D payoff net of scientist's compensation subject to (i) the scientist allocating effort to maximize his expected utility and (ii) the resulting certainty-equivalent utility being at least as large as the scientist's certainty-equivalent reservation utility μ_i ,

$$(4) \quad \text{Max}_{\mu_i, \beta} E[e_i^* - w_i(e_i^*)] = e_i^* - \mu_i - \beta e_i^* \quad \text{s.t.} \quad E[U_i(e_i)] \geq \mu_i.$$

Note that conditioning the administrator's problem insures that the scientist will be offered a compensation package that he will accept. In our model, it is unproductive for the administrator to offer a compensation scheme that the scientist will reject because the administrator's expected payoff is zero when the scientist rejects his compensation package, i.e., $e = 0$. Kuhn-Tucker conditions (or direct examination) reveal a boundary solution, $E[U_i(e_i)] = \mu_i$, implying

$$(5) \quad \mu_i^* = \mu_i - .5(\beta^*)^2/k_i + .5N_i(\beta^*)^2 T_i^2.$$

Substituting (5) into (4) and maximizing with respect to β , or substituting (5) into the corresponding first-order condition for β , reveals the optimal scientist performance incentive,

$$(6) \quad \beta_i^* = \frac{1}{1 + N_i k_i T_i^2},$$

which, when substituted into (5), gives the optimal guaranteed payment,

$$\mu_i^* = \mu_i + \frac{N_i k_i T_i^2 + 1}{2k_i(1 + N_i k_i T_i^2)^2}.$$

With this optimal pay scheme, some notable results follow: First, the administrator

compensates the scientist for effort and provides partial insurance against income risk from ex ante income uncertainty. With asymmetric information, the administrator does not provide full insurance because it would create a moral hazard problem for the administrator — the scientist would be fully insured against income risk and, thus, tend to shirk on effort.

Second, the guaranteed component of pay is positively related to the scientist's reservation utility μ_i , but the reservation utility has no impact on the incentive component of pay.

Third, as the riskiness of the research process increases, i.e., T_i^2 increases, the importance of the incentive component of pay relative to the guaranteed component decreases. The optimal pay guarantee is increasing (decreasing) in riskiness of the research process if $N_i k_i T_i^2 < (>) 3$. Thus, high risk, high risk aversion and/or high opportunity cost of time is sufficient to cause the guaranteed payment to increase in research risk. If research is infinitely risky ($T_i^2 \geq 4$), then $w_i^* = 0$, and the optimal pay scheme is a guaranteed or fixed wage equal to the certainty-equivalent reservation utility (and $w_i = w_i^* = \mu_i$).

Fourth, when scientists are heterogeneous in their reservation utility, degree of risk aversion, opportunity cost of effort, or riskiness of research output, the optimal pay scheme differs across scientists. The incentive-performance factor is higher for a scientist with less risk aversion, lower opportunity cost of effort, and lower scientist-specific research risk. The guaranteed component of the wage is higher for scientists who have a larger reservation utility (e.g., higher salary offers elsewhere). The guaranteed component is also higher (lower) for a scientist with higher risk aversion if $N_i k_i T_i^2 < (>) 3$, and for a scientist with higher opportunity cost of effort if $N_i k_i T_i^2 < (>) 1.78$.

To examine these implications further, note that the expected R&D payoff for the research administrator after paying wages is

$$(7) \quad A_1 = (1 - \beta) e_i \left(\frac{1}{2k_i(1 - \beta) N_i k_i T_i^2} \right) \mu_i,$$

and the expected wage of the scientist is

$$(8) \quad E(w_i) = \beta e_i \left(\frac{1}{2k_i(1 - \beta) N_i k_i T_i^2} \right) \mu_i.$$

These expressions reveal, not surprisingly, that a research administrator is better off contracting with a scientist that has low research risk, low risk aversion, and low opportunity cost of effort. Also, the scientist who has these characteristics fares better in terms of expected compensation. Perhaps, the result that scientists with low opportunity cost and low risk earn greater compensation is surprising, but it is explained by the fact that more is traded away for purposes of risk avoidance by those with high opportunity cost and high risk aversion. Among the pool of talent represented by scientists, at least two of these three attributes (research risk, risk aversion, and opportunity cost) are likely negatively correlated, which adds to the research administrator's dilemma of choosing scientists. The implications for research institutions where changes in employment are infrequent (research institutions with permanent employees and universities with tenure systems) is that hiring decisions are crucial and potentially the most crucial element of successful and efficient R&D administration.

In this model, an increase in ex ante R&D payoff uncertainty, say due to an increase in the variance of the common shock F^2 , causes the scientist to allocate less effort to the research project which reduces the expected quality of research and the expected R&D payoff. Because of asymmetric information regarding effort and incomplete insurance against the scientist's income risk, the scientist's expected compensation is also reduced. Furthermore, the expected R&D payoff net

of scientists compensation is reduced. Thus, in this model where an optimal compensation policy is in place and the research administrator employs only one scientist per research project (i.e., there are no duplicate projects), it is never optimal for the administrator to take actions that will increase ex ante uncertainty for scientists unless they lead to counter veiling effects on research quality.

One research policy change where the scientist could perceive increased risk is where formula funding is replaced by competitive grant funding. For example, this change might increase the risk that a scientist will receive adequate funding to carry out or complete planned research. An increase in perceived risk would lead a scientist to allocate less effort to research, which in turn lowers expected quality and expected net R&D payoff from research. Thus, any switch from formula funding to competitive grant funding should be verified to have a sufficiently positive effect on project quality, for example by weeding out frivolous projects or channeling funds to higher quality scientists (accounting for imperfect correlation between quality of project proposals and ultimate research discovery quality), to offset the effect of increased risk perceived by scientists.

Duplication of Effort

Another important issue is whether a research administrator should employ multiple scientists working independently on the same research objective. In a certain world, if a research administrator were interested in minimizing the cost of an innovation (with given quality), he would hire only one scientist. Employing a second scientist to do the same work doubles the cost of the research. Adding individual uncertainty and asymmetric information to the discovery process, however, an administrator can increase the expected R&D payoff in two ways by adding duplicative scientists and efforts.

First, when the output of two scientists comes from overlapping statistical quality

distributions, adding a second scientist has a benefit from the “sampling effect.” The research payoff to the administrator can be viewed as the expected value of the maximum of multiple draws from the quality distribution. Adding a second draw increases the expected value of the maximum payoff (Gumbel). The marginal payoff benefit from the sampling effect is increasing in F_i^2 and decreasing in the correlation between ϵ_1 and ϵ_2 (as is clear below). The sampling effect has no value when the random component of scientists’ research output is perfectly positively correlated. Hence, the benefit of the sampling effect reduces to a marginal expected cost and return comparison.

Second, adding another scientist to work on an identical research project may be an optimal action by a research administrator because, in an environment with imperfect information, the second scientist may provide useful information about relative performance that can be used in the optimal pay scheme of the first scientist, thus partially mitigating the moral hazard problem. This is the “insurance effect” of adding a second scientist.

To see that adding a second scientist can have positive value, consider Pay Scheme II where scientist i receives compensation according to the linear structure,

$$(9) \quad w_i(y_i, y_j) = \alpha_i + \beta_i y_i + \gamma_i y_j, \quad i = 1, 2,$$

where for simplicity of notation throughout $j = 2$ if $i = 1$, and $j = 1$ if $i = 2$. This pay scheme has three components: (i) a wage guarantee, α_i , (ii) an incentive component based on personal research quality, y_i , and (iii) a comparison standard due to outside information regarding research quality of the other scientist, y_j . Where the quality of each scientist’s research follows equation (1), the expected wage conditional on effort is $E(w_i) = \alpha_i + \beta_i e_i + \gamma_i e_j$ and the wage variance is $V(w_i) = \tau_i^2(\beta_i^2 + \gamma_i^2 + 2\beta_i\gamma_i D)$ where $D = F_*^2/(F_*^2 + F_i^2)$. If scientists have identical research risk ($F_i^2 = F_j^2$), then $D_i = D_j = D$ is the correlation of quality between scientists.

Each scientist has an expected utility maximization problem of the form

$$\text{Max}_{e_i} E[U_i(e_i)] = \mu_i + \beta_i e_i + (\gamma_i - .5k_i e_i^2 - .5N_i T_i^2 (\beta_i^2 + (\gamma_i^2 + 2\beta_i \gamma_i D_i)).$$

Taking the actions of others as given to find a Cournot-Nash equilibrium, the optimal effort choice for each individual scientist is again $e_i^* = \beta_i/k_i$.

With the introduction of a second scientist, the administrator's payoff depends on the maximum quality of research output over the two scientists. The research administrator maximizes the expected R&D payoff with respect to $\mu_i, \beta_i, \gamma_i, i = 1,2$, assuming each scientist maximizes expected utility and must receive at least the certainty-equivalent reservation utility μ_i ,

$$(10) \quad \text{Max}_{\mu_i, \beta_i, \gamma_i; i=1,2} E \left[\max(y_1^*, y_2^*) \right] \quad \text{s.t.} \quad E[U_i(e_i)] \geq \mu_i, i = 1,2,$$

where $y_i^* = \beta_i / k_i + \gamma_i + \mu_i$. While $\max(y_1^*, y_2^*)$ has no closed form representation, results from Levitt imply that

$$(11) \quad E[\max(y_1^*, y_2^*)] = e_1^* + \gamma_1 (e_1^* - e_2^*, F_1^2, F_2^2)$$

where

$$(12a) \quad k_1 \frac{\beta_1}{M\beta_1} + \frac{\beta_1}{M\gamma_1} + \frac{\beta_1}{M\gamma_2} + k_2 \frac{\beta_2}{M\beta_2} \neq 0, \quad k_1^2 \frac{\beta_1^2}{M\beta_1^2} + \frac{\beta_1^2}{M(\gamma_1^2)} + \frac{\beta_1^2}{M(\gamma_2^2)} + k_2^2 \frac{\beta_2^2}{M\beta_2^2} \leq 0,$$

$$(12b) \quad k_1 \frac{\beta_1}{M\beta_1} + \frac{\beta_1}{M\gamma_1} + \frac{\beta_1}{M\gamma_2} + k_2 \frac{\beta_2}{M\beta_2} + .5 \text{ and } \gamma_1 \leq .564 F_1^2 \text{ if } e_1^* < e_2^* \text{ and } F_1^2 < F_2^2 > 0.$$

Kuhn-Tucker conditions again reveal a boundary solution, $E[U_i(e_i)] = \mu_i$, i.e., the administrator will not pay a larger guaranteed component than necessary to retain a scientist's services, which implies

$$(13) \quad \mu_i^* = \mu_i - .5(\beta_i^*)^2/k_i - (\gamma_i^* \beta_i^*/k_i + .5N_i T_i^2 [(\beta_i^*)^2 + ((\gamma_i^*)^2 + 2\beta_i^* \gamma_i^* D_i]).$$

The Optimal Relative Performance Incentive

The introduction of a second scientist adds the opportunity to compensate scientists on the

basis of relative performance. Substituting (13) into (10) and maximizing with respect to C_i reveals that the optimal choice for the relative performance incentive is

$$(14) \quad C_i^* = -D_i S_i^*.$$

Thus, when multiple scientists are funded to work on the same research objective they are compensated on a relative performance basis where the strength of the performance comparison depends on the extent to which common random components effect research outputs. In one extreme, if the entire random component is common to both scientists ($F_i^2 = 0$ which implies $D_i = 1$), then the non-fixed component of compensation is proportional to the quality difference in research output ($C_i^* \propto S_i^*$). In the other extreme, if the random components of research quality are uncorrelated among scientists ($F_i^2 = 0$ which implies $D_i = 0$), then there is no insurance information from adding the second scientist and, thus, no comparison incentive is used ($C_i^* = 0$).

Optimal Asymmetry of Scientist Compensation Schemes

We now consider whether scientists should face the same or different pay schemes when two scientists are assigned the same task. Substituting both (13) and (14) into (10) for $i = 1, 2$, and maximizing with respect to S_1 and S_2 obtains first-order conditions that imply

$$(15) \quad S_1^* = \frac{(1 - k_1 M) / M S_1^*}{1 - N_1 k_1 T_1^2 (1 - D_1^2)} = \frac{(1 - k_2 M) / M S_2^*}{1 - N_1 k_1 T_1^2 (1 - D_1^2)} \quad \text{and} \quad S_2^* = \frac{k_2 M / M S_2^*}{1 - N_2 k_2 T_2^2 (1 - D_2^2)}.$$

These conditions are necessary but not sufficient because concavity does not hold (Levitt).

Comparison of the results in (15) reveals that the incentive payments can be asymmetric for several reasons including heterogeneity of scientists with respect to risk aversion, opportunity cost, and/or risk of research quality. Interestingly, however, asymmetric incentive payments may be optimal even when these attributes are the same among scientists.

For example, if $k_1 = k_2$, $N_1 = N_2$, and $F_1^2 = F_2^2$, then $T_1^2 = T_2^2$ and $D_1 = D_2$ which implies from (15) that

$$(16) \quad \frac{\partial e_1}{\partial \Delta} \text{ \& \ } \frac{\partial e_2}{\partial \Delta} = \frac{1 + 2k_1M}{1 + N_1k_1T_1^2(1 + D_1^2)} \frac{\partial \Delta}{\partial \Delta} \quad \text{and} \quad \frac{\partial e_1}{\partial \Delta} - \frac{\partial e_2}{\partial \Delta} = \frac{1}{1 + N_1k_1T_1^2(1 + D_1^2)}.$$

Comparing this latter result to (6) reveals that a greater total effort is expended in the two-scientist problem than in the single-scientist problem. Levitt's results for this case further show that a symmetric incentive scheme is preferred if and only if $D_1 < 1$ and

$$\frac{M^2}{M(\Delta)^2} < \frac{1 + N_1k_1T_1^2(1 + D_1^2)}{2k_1}.$$

Thus, a research administrator will find offering different compensation schemes to identical scientists advantageous when the second-order effects of incentives on the sampling effect are large.

The intuition of this result is evident by rearranging the first relationship in (16),

$$(17) \quad (\frac{\partial e_1}{\partial \Delta} \text{ \& \ } \frac{\partial e_2}{\partial \Delta}) [1 + N_1k_1T_1^2(1 + D_1^2)] = 1 + 2k_1M \frac{\partial \Delta}{\partial \Delta}.$$

The left-hand side of equation (16) represents the marginal cost to the administrator of increasing asymmetry in the incentive component of the compensation schemes, holding total effort of the two scientists ($e = e_1 + e_2$) constant. The expected total wage bill is increasing in asymmetry for a given total effort because of convexity in the opportunity costs of effort for scientists, i.e., the administrator must incur more cost to induce a marginal unit of effort from a scientist who is already working hard than one who is working less.

The right-hand side of equation (17) represents the marginal expected benefit to the administrator of increasing asymmetry while holding total effort constant. The first right-hand term represents the direct benefit from increasing the first scientist's effort while the second right-hand term reflects the reduction in value of the sampling effect as a result of the greater incentive difference. Thus, as the incentive differential widens, the marginal value of the sampling effect

decreases. Although the second scientist faces a lower powered incentive, the probability is still positive that the lower effort of the second scientist will produce the “best” output. With stochastic production, “good luck” combined with low effort can lead to a higher quality output than the high effort of the first scientist with “bad luck.” This probability, however, declines as the incentive and effort differentials widen. Furthermore, even when the output of the low-effort scientist is dominated by the output of the high-effort scientist, the low-effort scientist has value to the administrator as information about relative performance given asymmetric information on effort.

These results illuminate the key economic issues behind an administrator’s decision to employ one versus multiple scientists working independently on identical research objectives. The administrator chooses the number of scientists that maximizes expected R&D payoff net of the total wage bill. The sampling-effect advantage of using multiple scientists is increasing in the ex ante uncertainty of the research production process, T_i^2 , assuming production shocks across scientists are not too highly correlated. The administrator’s benefit from the “sampling effect” of an additional scientist is decreasing in this correlation and is zero when shocks across scientists are perfectly positively correlated (i.e., $D_i = 1$). The insurance effect advantage of adding an additional scientist because of information contained in a second scientist’s research output, however, is increasing in this correlation. It is of no value when output across scientists is uncorrelated ($D_i = 0$).

In effect, if y_2 contains new information about the first scientist’s level of effort, then y_2 can be used to induce more effort and, thus, attain higher quality output and increased expected R&D payoff. Hence, the administrator receives a marginal expected payoff for the “insurance effect” of Pay Scheme II relative to Pay Scheme I. The economic issue behind the insurance effect of employing a seemingly redundant scientist reduces to a comparison of the marginal expected cost of the additional information and marginal expected return from it.³

Impact of Duplication on Scientist Compensation

An interesting issue, especially to the first scientist, is whether his optimal performance incentive will be higher with one or two scientists assigned to the same task. When the output across scientists working on identical tasks is not too highly correlated, the optimal power of the incentive component of the first scientist's compensation will be higher when only one scientist is assigned to the task.

Two effects explain the difference in (15) and (6). First, the "insurance effect" of relative performance evaluation disappears when only one scientist is employed and makes inducing extra effort more expensive because of the positive marginal cost of each scientist's effort to the administrator. Comparing (15) and (6), this effect is represented by $D_1 \dots 0$. Second, the "sampling effect" associated with multiple draws from the same distribution disappears when only one scientist is employed. Comparing (15) and (6), this effect is represented by $k_2 M) / M \$_2^* \dots 0$.

To consider the expected impact of adding multiple scientists on scientist compensation, first note using (13) and (14) that the expected compensation for each scientist is

$$(18) \quad E(w_i) = \mu_i^* + \frac{(\sigma_i^*)^2}{k_i} + \frac{N_i (\sigma_i^*)^2 T_i^2 (1 - D_i^2)}{2k_i [1 + N_i k_i T_i^2 (1 + D_i^2)]}$$

Substituting (15) into (18) yields

$$E(w_1) = \mu_1 + \frac{[(1 + k_2 M) / M \$_2^*]^2}{2k_1 [1 + N_1 k_1 T_1^2 (1 + D_1^2)]} \quad \text{and} \quad E(w_2) = \mu_2 + \frac{[k_2 M) / M \$_2^*]^2}{2k_2 [1 + N_2 k_2 T_2^2 (1 + D_2^2)]}$$

Comparing to (7), the first scientist may be better or worse off when a second scientist is added. The first scientist will receive higher expected compensation if the relative incentive effect (represented by the correlation coefficient) is stronger, but will receive less if the sampling effect (represented by $k_2 M) / M \$_2^*$) is stronger. Comparing the two cases, an administrator with only one scientist only needs to compensate a single scientist for extra effort. In the two-scientist case, he must compensate both scientists for extra effort but receives the benefit of the effort from only one of them (the one with

the “best” output). With a higher-powered compensation incentive in the single-scientist case, the optimal guaranteed compensation will be lower because the administrator needs to offer more incentive to offset lack of information about whether effort is appropriate (the moral hazard explanation). The first scientist will lose with the addition of a second scientist in the case where elimination of shirking is the main purpose of adding the additional scientist. On the other hand, the first scientist will gain in those cases where the primary impact is healthy competition among scientists (the sampling effect explanation).

Some additional insight is revealed by considering further the special case where scientists have identical opportunity cost functions and the administrator chooses to offer identical incentives. In this case, a first scientist is better off when another scientist is added if $D_1^2 > (3/4) + (3/4k_1N_1T_1^2)$. This condition is less likely to hold if opportunity cost, risk aversion, and/or research risk are low, and will not hold in any case if $D_1^2 < .75$. This case suggests that duplication of efforts is likely to lower compensation in a wide variety of cases.

The Choice to Employ Multiple Scientists on the Same Research Objective

To determine whether the administrator is better off employing more than one scientist on the same research objective, the optimal expected R&D payoff must be determined in the multiple-scientist case and compared with the single-scientist case. Substituting into (10) and using (11) reveals the expected net R&D payoff for the two-scientist case,

$$(19) \quad A_2 = \frac{\$1}{2k_1} [1 - k_2M] / M\$2 + \frac{\$2}{2k_2} [k_2M] / M\$2 + \mu_1 + \mu_2 \text{)} .$$

While this expression is quite difficult to compare with (7) in general, a useful special cases gives insight. Suppose, for example, that the administrator chooses to use a symmetric incentive

scheme after correcting for differences in the opportunity cost of effort. For example, suppose the opportunity cost of effort represents the expense of research facilities and support that must be allocated to finance a scientist's effort and the administrator chooses to reward effort relative to the scale of opportunity costs, i.e., $\$/k_i$ are equalized across scientists. In this case, use of (11b) in (19) implies

$$(20) \quad A_2 \cdot \frac{1}{2k_1[1 - \rho N_1 k_1 T_1^2(1 - D_1^2)]} \cdot (\mu_1 + \mu_2) \cdot F_1^2$$

The first term of (20) is identical to (7) except for the correlation which reduces the denominator and increases the administrator's payoff due to the relative performance incentive. The second term of (20) is identical to (7) but the third term represents an additional reservation certainty equivalent that must be paid to an additional scientist. Finally, the last term represents the sampling effect of employing two scientists. If both scientists have similar research risk, then $\rho = .564 F_1^2$ from (11b).

Thus, adding a second scientist is preferred if and only if

$$A_2 - A_1 \cdot \frac{1}{2k_1[1 - \rho N_1 k_1 T_1^2(1 - D_1^2)]} + \frac{1}{2k_1(1 - \rho N_1 k_1 T_1^2)} \cdot (\mu_2) \cdot .564 F_1^2 > 0.$$

Thus, a second scientist is more likely to be preferred if the opportunity cost of effort is low, risk aversion is low, the correlation of research quality is high, and the certainty-equivalent reservation utility of the second scientist is low.

Value of Decentralized Research Institutions

When an administrator chooses multiple scientists to work independently on the same task, further advantages may be gained by encouraging risk taking and trying new approaches by some of the scientists, which increases the variance of their output. The results of this paper have two important

applications in this context. First, the framework can be re-interpreted to apply to the case where agents are individual research institutions and the administrator is, say, the federal government. Thus, duplication of efforts among research institutions may be practical and desirable.

Second, the framework of this paper has important implications with respect to two common concerns regarding the competitive grants process. One criticism of competitive grants processes is that funds are typically distributed by a small committee or according to the recommendations of such a small committee. Because a small committee is typically more narrow in its perceptions of “appropriate research approaches” than the scientific community as a whole, such a process may result in a narrow range of research perspectives among funded projects. This narrowing most likely reduces the value of the sampling effect. If the sampling effect is the primary reason for research duplication, then a greater sampling effect and thus greater R&D payoff are likely obtained by funding scientific approaches that cover the widest possible range for achieving a discovery. On the other hand, if the information effect is the primary reason for research duplication, then restricting the range of research approaches may be best.

Another criticism of the competitive grants process is that it tends to fund those projects that have more immediate and thus more certain payoffs that will demonstrate early productivity of research administrator’s programs. Where many of the players are risk averse, a tendency toward certainty has advantages. However, in the framework of this paper the risk averse players are the scientists; their risk aversion would presumably be reflected in the research they propose. On the other hand, when research efforts are duplicated, administrators can benefit by funding more risky projects if the sampling effect dominates the information effect [if β adds more to equation (20) than D_1^2 takes away]. Thus, choosing more risky projects is preferred, other things equal, if the correlation among research outputs is low.

As another approach to increasing the value of the sampling effect, an administrator may want to limit interactions among scientists because interactions tend to lead to similar research approaches and thus increase the correlation across scientists' output. The administrator is better off limiting interaction provided the increased value of the sampling effect outweighs the increase in the wage bill to compensate scientists for bearing greater risk and the benefits of knowledge enhancement by exchange that might otherwise take place.

If having multiple scientists work in different institutions and locations on the same task reduces the correlation of their outputs, then the value of the "sampling effect" increases thereby. At the same time, the "insurance effect" of each administrator employing multiple scientists on the same research objective may not be weakened if administrators can successfully share information on the performance of scientists. Additionally, although not reflected in the model, low morale problems that tend to arise in public institutions from large differences in compensation schemes can be mitigated by having large differences in compensation across research institutions but small intra-institution differences. This line of reasoning suggests advantage to the multi-institutional organization of public agricultural research in the United States and Germany relative to the single-institutional approaches of France and Italy.

We also note that the benefits of the multi-institutional organization can be lost if excessive communication among administrators leads to too much similarity of direction. That is, if individual administrators each seek to minimize the cost of an innovation and thereby restrict individual scientists to the same research approach on the same research objective, then much of the sampling effect may be lost (although the insurance effect is strengthened).

Implications for Management of Research and Setting of Priorities

The possibility that multiple workers can be optimally employed to undertake duplicative tasks is unique to R&D and similar activities. Such an approach is the antithesis of optimality in management of typical industrial production problems. In industrial production, ex ante payoff uncertainty is relatively low, output produced by workers on the same task is highly correlated, and asymmetric information is not much of a problem because shirking becomes quickly apparent in a well-known production process that has been repeated many times, e.g., on an assembly line. More importantly, in typical industrial production problems, output of workers is additive rather than determined by the best among workers. These differences in the attributes of R&D production relative to industrial production imply that different principles of management must be considered and that priority setting and strategic planning must address different issues.

In industrial production, a carefully structured strategic plan and set of priorities are valuable tools to management and can usually be implemented with simple compensation schemes. In particular, they permit sound management of large or loosely structured companies. In research management, however, plans and priorities are much less valuable unless carefully adapted to the opportunity for implementation when major considerations are ex ante uncertainty of output quality, asymmetric information regarding effort, and where best rather than average output matters.

For example, given that effort is unobservable and undirectable, a carefully structured set of priorities is useless if not tied to observable payoffs and not implemented through a feasible compensation scheme. These considerations suggest that priorities must be relatively general and specified in terms of payoffs that are observable by the research administrator. Priorities must be related to scientists' effort and consider the possibility of discovery by scientists' efforts and results moving in unanticipated directions. For example, if incentives are specified too narrowly and do not

take account of unanticipated peripheral discovery, the risk of the research to the scientist will be higher than it needs to be and, thus, call forth less than optimal effort. Thus, priority setting and planning can provide only useful broad goals or general direction for the efforts of scientists. For example, priority setting may be usefully linked to the compensation scheme by defining the attributes of importance in evaluating the R&D payoff of concern to the administrator (in a way that could be specified in the compensation scheme), rather than listing the set of R&D discoveries that the administrator would like to obtain (some of which may be discovered in peripheral research).

Conclusions

The results of this paper have some basic implications for how best to transfer resources from research-financing institutions to research-performing institutions and scientists. Typically, a research institution or government agency operating on behalf of a political jurisdiction or clientele group receives institutional, program, or formula funding and the administrator must decide how to allocate the funds among other research institutions or scientists. The leading alternatives are institutional or program grants, research contracts, and peer-reviewed competitive grants. We consider the economic efficiency of each.

If a research institution uses funds to employ scientists, the principles of optimal contracting imply that scientists should be compensated to conduct research consistent with the institution's research payoff. More specifically, the administrator should implement a partial incentive contract with scientists that involves both an optimal compensation guarantee and an optimal performance incentive. The performance incentive should be defined by the characteristics that matter in valuing the R&D payoff to the institution. More basically, what matters in valuing the R&D payoff may be rooted in the values of the political jurisdiction or clientele financing the institution. Scientists then

exert the optimal level of effort and the research institution maximizes its expected R&D payoff net of the wage bill for scientists.

In the case of research funding institutions (including those in the private sector) which contract with scientists and research institutions for research, the theory of contracting in this paper implies that the optimal contract should have a quality-based incentive. Costs may also be an important part of the contract to the extent they affect the scientist's opportunity cost. Particularly for more basic research, incentives should be defined in terms of broad performance attributes that reflect value of the research payoff to the funding institution rather than specifications of a particular innovation. Thus, the scientist can have more avenues available for attaining success, which reduces riskiness of the project and induces increased effort. Alternatively, if the contract simply assures "minimum cost," the scientist has too strong an incentive to cut effort as well as cost, which reduces quality and payoff.

Applying the principles of optimal contracting, this paper shows that peer-reviewed and peer-ranked competitive research funding is socially inefficient relative to optimal incentive contracts. Competitive funding detracts from research productivity because it adds to uncertainties faced by scientists. Furthermore, if the standards or personal views of the decision making body are more narrow, conservative, or short-sighted than the broad scientific community, then funded research may be too similar or low-risk to capture an optimal sampling effect of duplicative research. Chubin and Hackett summarize empirical evidence showing that peer review allocation of research funds is quite subjective. By nature, the process of peer and panel recommendations on acceptable procedures for attaining a project's objectives and on assessment of attainability of objectives tend to be too conservative. This leads to a socially excessive correlation of output across scientists receiving awards, thus reducing the value of the "sampling effect" on research payoff. This problem is

especially serious when research payoffs are very risky as in basic and pretechnology science research.

This paper also points out the value of the information effect which is strengthened by similarity (correlation) of research output. However, the information effect is only of value as it is incorporated into incentive schemes that induce higher quality research. We suggest that sufficient duplication of objectives among research projects exists so that the information value of duplication is low compared to the sampling value. If so, then the inducement of similarity of research through competitive funding has a detrimental effect when the ultimate social payoff depends on best rather than average quality of the research output.

The rationale for these conclusions is based on ex ante uncertainty in the research production process and asymmetric information on scientists' effort. Crucial assumptions for practical application are as follows. First, a research proposal has no direct value in the R&D payoff of a project. Second, a peer-reviewed grant system gives an incentive only for the quality of the proposal rather than for the ultimate research output (the latter of which is observable only after the award and is imperfectly correlated with the former). This is a crucial flaw because, with uncertainty, no one including the author of a proposal, knows what can be discovered. Alternatively, the obvious incentive is to "promise a lot and deliver a little."

An additional problem with competitive grants is that they impose heavy externalities on scientists and their employing institutions. The externalities are due to a system in which the funding institutions typically do not explicitly finance all of scientists' time. If scientists receive no compensation for proposal writing, or are compensated only for successful proposals, then income risk to scientists for undertaking research is increased. Alternatively, the incentive is to write proposals for work that has already been partly completed but not released, which distorts incentives. Second, if scientists are compensated by their home institution for writing a proposal, then these

resources likely come with high opportunity cost (e.g., teaching time or alternative research). Third, given asymmetric information about scientists' effort, a more likely scenario is that effort planned and compensated by already-funded projects will be redirected to proposal writing, thus reducing the payoff to those projects. For example, significant scientist effort may be going into NRI and other competitive proposal writing and evaluation that is being paid for by state-government-provided institutional research grants. Fourth, the proposal evaluation and ranking process for competitive grant programs consumes scientists' time that also is not compensated by research granting institutions. This time has opportunity costs similar to proposal writing. These externalities are sometimes characterized as the transactions costs of scientists' time spent in writing and reviewing project proposals (Just and Huffman, 1992; Huffman and Just 1994). The size of these inefficiencies is increasing in the share of proposals that are not funded.

Given the principles developed in this paper, we suggest that social efficiency of public agricultural research is likely to be best captured by formula, program, and institutional funding of diverse research institutions that offer optimal incentives to the scientists they employ. Short research proposals (e.g., a few pages in length) and covering reasonably long periods of time (e.g., 3 - 5 years) serve sufficiently to permit administrators to monitor, review, and manage — if the more crucial steps are taken to implement optimal incentives based on attributes of value to the institution. Research proposals need to state the objectives sufficiently to allow the decision maker to verify that anticipated payoffs fit the criteria that are used in valuing the R&D payoff of the institution. Describing details about approaches may be wasteful and even counter-productive if it tempts decision makers to limit scope and approaches. In this way, scientists' effort and time for reviewing and evaluating could be allocated exclusively to assessing the quality of research output, e.g., reviewing manuscripts for publication and evaluating research payoff. Interestingly, this

characterization of an optimal system appears to be much like the traditional agricultural experiment station system.

By comparison, the funding of public agricultural research in the United States has moved substantially toward competitive grant funding and away from formula and program funding over the past few decades. The premise is that competitive funding raises (average) research output quality. Before this trend continues further, a careful assessment seems prudent to determine whether the claimed merits of competitive funding outweigh the detractions from research productivity illustrated conceptually in this paper. Several critical questions must be answered. How much is the quality of the best research raised by eliminating poorer scientists and projects? How do these gains, if they exist, compare to the magnitude of quality lost through the mechanisms highlighted in this paper. The answers to these questions depend crucially on the effectiveness of the competitive evaluation process, the breadth of perception of funding panels, the correlation of quality of research proposals with ultimate research output quality, the extent of ex ante uncertainty in research quality, the asymmetry of information between scientists and funders, and the extent to which research payoffs depend on best versus average quality of research output. None of these issues have received much empirical attention.

Footnotes

¹ A risk neutral preference for administrators can be justified by thinking of them as managing a large portfolio of projects. The assumption of risk neutrality can be modified but at significant cost in additional complexity of the presentation but little change the basic conceptual conclusions provided scientists are more risk averse than administrators.

² As a utility function for scientists (the agents), we use the one that has attracted the most attention in the principal-agent literature (see Mas-Colell, Whinston, and Green, p. 479-80).

³ We assume the joint distribution of y_1 and y_2 exists and is represented by $f(y_1, y_2 | e_1, e_2) = f_2(y_2 | y_1, e_1, e_2) f_1(y_1 | e_1, e_2)$ by the theory of conditional probability. If $f_2(y_2 | y_1, e_1, e_2) \dots f_2(y_2 | y_1, e_2)$, i.e., $f_2(y_2 | y_1, e_1, e_2)$ depends on e_1 , then y is not a sufficient statistic for e which means that y contains “new information” about e_1 that is not contained in y . This is the condition in which “outside information” is useful in an optimal pay scheme for the first scientist (see Holmstrom; Mas-Colell, Whinston, and Green, Ch. 14).

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