DO FORMULA OR COMPETITIVE GRANT FUNDS HAVE GREATER IMPACTS ON STATE AGRICULTURAL PRODUCTIVITY?

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This article examines the impact of public agricultural research and extension on agricultural total factor productivity at the state level. The objective is to establish whether federal formula or competitive grant funding of agricultural research has a greater impact on state agricultural productivity. A pooled cross-section time-series model of agricultural productivity is fitted to annual data for forty-eight contiguous states over 1970–1999. Our results show that public agricultural research and agricultural extension have statistically significant positive impacts on state agricultural productivity. In addition, Hatch formula funding has a larger impact on agricultural productivity than federal competitive grant funding, and a reallocation of Hatch formula funds to competitive grant funding would lower agricultural productivity. This seems unlikely to be a socially optimal policy. Furthermore, from a cost–benefit perspective, our study shows that the social marginal annualized real rate of return to public resources invested in agricultural research is 49–62%, and to public agricultural extension, the rate is even larger.

Key words: agricultural productivity, agricultural research funding, competitive grants, extension, formula funding, Hatch funds, pooled cross-section time-series model, productivity analysis, research, states.

The federal government in 1887 established the State Agricultural Experiment Station (SAES) system to conduct original research and verify experiments bearing directly on the U.S. agricultural sector. Each State was entitled to an equal amount annually of federal funds to support this research (Knoblauch, Law, and Meyer 1962, p. 219). These stations were established under the direction of the Land Grant Universities, and the Hatch Act specified that the States or stations were to choose a program of research that fitted local needs. Hence, under the original Hatch Act, funds were allocated by a simple formula—an equal amount to each State. Under the 1906 Adams Act and 1925 Purnell Act, federal agricultural research funds were also allocated equally among States, but under the 1935 Bankhead-Jones Act, agricultural research funds were allocated by a new formula—each State received an amount in proportion to its share of the U.S. population (Knoblauch, Law, and Meyer 1962, pp. 224–25).[1] In addition, States were required "to match" these federal funds with state or other funds.

In 1955, agricultural research programs administered by the Office of Experiment Stations were consolidated into the Amended Hatch Act, and the allocation scheme was modified. Funds were allocated to three types of research: 20% for agricultural marketing research, 25% for regional research, and 52% for projects determined by the states. The remaining 3% went to federal administration of these funds. For the 52% component, funds were allocated to the States as follows: 20% equally to States, 26% allocated according to each state's share of the U.S. rural population, and 26% according to each state's share of the U.S. farm population (Knoblauch, Law, and

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We acknowledge useful comments obtained from a presentation at the National Meeting of State Agricultural Experiment Station Directors, Baltimore, MD, Sept. 24, 2002 and Oklahoma City, OK, September 2004. We also acknowledge helpful comments from two anonymous referees and Editor B. Wade Brorsen. Also, funding was provided by ESCOP through David MacKinzie and the University of Maryland and the Iowa Agriculture and Home Economics Experiment Station, project NC1003. Valuable research assistance was provided by Xing Fan and Dong Yan and editorial assistance from Cindy Pease.

[1] Later, the criterion was based on the rural population.

Amer. J. Agr. Econ. 88(4) (November 2006): 783–798

Table 1. Current and Constant Dollar Revenue of U.S. State Agricultural Experiment Stations and Distribution by Major Sources, 1980–2003

	Current Dol., Millions				Constant 2000 Dol.[a], Million			
Sources	1980	1990	2000	2003	1980	1990	2000	2003
Regular federal appropriations-CSRS/CSREES administered	136.9	223.6	292.6	393.0	322.1	304.6	292.6	350.3
Hatch and other formula funds	121.2	163.3	186.9	179.9	285.2	222.5	186.9	160.4
Special grants	9.6	39.7	47.0	72.2	22.6	54.1	47.0	64.3
NRI competitive grants	–	20.0	44.7	58.7	–	27.2	44.7	52.3
Other	6.1	0.6	14.0	82.2	14.4	0.8	14.0	73.3
Other non-CSRS/CSREES administered federal government research funds	91.8	193.3	360.4	537.9	216.0	263.7	360.4	479.4
Contracts, grants, and cooperative agreements with USDA agencies	24.4	49.5	75.0	107.2	57.4	67.5	75.0	95.5
Contracts, grants, and cooperative agreements with non-USDA federal agencies	67.4	143.9	285.4	430.7	158.6	196.3	285.4	383.9
State government appropriations	446.9	877.9	1,117.8	1,124.8	1,051.5	1,197.7	1,117.8	1,002.2
Industry, commodity groups, foundations[b]	74.0	210.0	340.9	387.1	174.1	286.5	340.9	345.0
Other funds (product sales)	55.2	91.6	118.0	128.3	129.8	125.0	118.0	114.3
Grand total	804.8	1,596.5	2,229.7	2,571.0	1,893.6	2,178.0	2,229.7	2,291.4

[a]Obtained by deflating data in first three columns using the Huffman and Evenson (1993, pp. 95–97 and updated to 2003) agricultural research price index with 2000 being 1.00.
[b]Amount received from industry and "other nonfederal sources," excluding state appropriations and product sales or self-generated revenue.
Source: U.S. Dept. Agr. 1982, 1991, 2001, 2004.

Meyer 1962, pp. 232–33).[2] Federal agricultural research funds allocated by this latter mechanism to the states are known as "formula funds" (CSREES 2005b).

In 1977, the USDA established its first competitive grants program which was for high priority research. However, funds available through this program remained quite small for a number of years. In 1990, it was renamed the National Research Initiative (NRI) Competitive Grants Program. Over 1980–2003, the amount of federal formula funds for SAES research declined by 57% or $124 million (2000 dollars) (see table 1). NRI funds going to SAES research increased by only $25 million (2000 dollars) over this period. Hence, Cooperative States Research Service (CSRS)—or its successor, the Cooperative State Research, Education, and Extension Service (CSREES)—funding of SAES research has fallen dramatically over the past twenty-five years.[3] Moreover, in the 2006 Federal Budget, President George W. Bush proposed eliminating federal formula funding of agricultural research and replacing it with a new competitive grant program for the SAES system (CSREES 2005a).[4]

Much debate has surrounded external peer-reviewed competitive grant funding of public agricultural research and federal formula funding. Key issues in favor of formula funding and against competitive grants are as

[2] Later, the marketing research requirement was eliminated.

[3] CSRS replaced the Office of Experiment Stations in 1961, and in 1995, CSREES replaced CSRS.

[4] Table 2 does show that the SAES system has been successful in obtaining grant and contract funding from non-USDA agencies. The increase from 1980 to 2003 was by $225 mil (2000 dol.).

follows. First, programmatic funding, e.g., formula funds, represents steady funding that can support core, base, or foundation research. Many important scientific discoveries take more that a decade to achieve. Hence, if scientists must pursue extramural funding, they face a large amount of uncertainty. A large share of extramural proposals are not funded in any given year, e.g., the NRI success rate in any year seldom exceeds 12%, and funding cycles are twelve months in length, which means that there is a long wait between submission dates. Moreover, this may require considerable effort to orchestrate a successful award, and the award is only for short-term funding—two to four years.

Second, federal formula funds carry no general university overhead or indirect cost. Thus, 97% of the total federally appropriated formula agricultural research funds go to the SAES system. In contrast, grant-funded SAES research includes significant off-the-top indirect cost collected by the upper administration at the receiving institution. The revenue from indirect cost has been used to develop a new layer of administrative bureaucracy in the form of extramural contract and grants offices, grant-seeking and writing activities, and employee training, and turnover associated with fluctuating competitive grant revenues. Upper administration also uses indirect costs to pay for renovating some expensive research laboratories and facilities. However, only a small share of overhead from SAES projects is channeled back to the agricultural experiment station or principal investigator. Hence, the university indirect cost is a tax on public agricultural research funds—driving a wedge between the amount appropriated by Congress and the amount received by the scientists for discovery and effort.

Third, competitive grant funding tends to favor institutions that have the research infrastructure to undertake research that is typically national in scope and will appeal to reviewers from many different regions. In the Land Grant University world, the favored universities tend to be those that have the largest research infrastructure and, in particular, those that have expert resources for writing grant proposals, such as the University of California, Big Ten universities (e.g., Wisconsin, Michigan State, Purdue, Illinois, Minnesota), and a few other universities. Proposals that address problems of concern to a single state or small group of states are under-funded in the national competitive-grant process, despite the fact that such research problems are of critical concern to these areas and may have a large net social payoff. This intramural-funded research does require annual plans of work, annual reports, and periodic review to ensure accountability, but does not overburden scientists with these activities (Huffman and Just 2000). This is especially important to small states—New Hampshire, Vermont, and West Virginia—that have depended heavily upon Hatch funding, obtaining more than 45% of their funds from this source, and on the state government matching funds.

Fourth, national competitive grant programs also tend to reallocate research resources within Land Grant Universities away from research that scientists see as vitally important to their individual states and toward research with national appeal. In the competitive grant process, preliminary results and other parts of a project are frequently unfunded. This has the practical effect of leveraging national agricultural research priorities, because state government appropriations pay for this research. At a minimum, a significant amount of state-appropriated agricultural research funds are used in writing (and evaluating) research grant proposals for national competitive grant programs, whereas those same resources could be used to study important state problems (Huffman and Just 1999).

The counter-argument goes something like the following. Under the Hatch Act, federal formula funds can be allocated to research on a wide range of problems in agriculture, marketing, forestry, home economics, and rural and community development. Washington bureaucrats have sometimes suggested that there is limited accountability.[5] In addition, a claim sometimes made is that this research is not subject to rigorous research methods and projects are reviewed infrequently. Scientists working on these projects, however, are university tenure-track and tenured faculty who undergo regular performance assessments for university pay increases and, in some cases, for

[5] The scope of the agricultural research under the Hatch Act includes research on all aspects of agriculture, including soil and water conservation and use; plant and animal production, protection, and health; processing, distribution, safety, marketing, and utilization of food and agricultural products; forestry, including range management and range products; multiple use of forest rangelands and urban forestry; aquaculture; home economics and family life; human nutrition; rural and community development; sustainable agriculture; molecular biology; and biotechnology. Research may be conducted on problems of local, state, regional, or national concerns (CSREES 2005b).

promotion in rank. Thus, the expectations set by the university are a critical factor affecting scientists' rigor and diligence in research and other activities (Huffman and Just 2000).

If fewer dollars were allocated across the Land Grant system for formula funding, for example, by eliminating formula funds to small SAESs, those dollars could be used to increase the research funds available for competitive grant programs. This rationale suggests that the U.S. might not "need" more than twenty colleges of agriculture, and perhaps we could get by with even fewer. However, reducing dramatically the number of states receiving federal agricultural research funds would greatly change the political economy of federal agricultural research funding. A likely prospect is that, over time, the currently strong congressional support for formula funds would wane and federal appropriations would decline. Another possibility is that the excluded Land Grant Universities would pursue congressionally earmarked research funds on a grand scale (note that these ear-marks or special grant funds exceed NRI funding in each year, table 1) (National Research Council 2003, pp. 71–72). Hence, attempts to concentrate public agricultural research funds in a few large Land Grant Universities might have major unintended and adverse consequences over the long run.

Prior studies of public agricultural research and extension impacts on state or regional agricultural productivity include Griliches (1963); Huffman and Evenson (1993); Alston, Craig, and Pardey (1998); Alston and Pardey (2001); and Yee et al. (2002). Huffman and Just (1994) used state productivity data for 1948–1982 to show that federal formula funding has a larger impact on agricultural productivity than competitive grant funding, owing to the high transaction costs associated with external competitive grant programs. However, since 1982, many changes have occurred in the frontiers of science, in funding mechanisms, and in the technology of agriculture.

The objective of the current paper is to estimate whether federal formula or competitive grant funding of agricultural research has a greater impact on state agricultural productivity. A pooled cross-section time-series model of agricultural productivity is fitted to annual data for forty-eight contiguous states over 1970–1999. Hypotheses tested are that the amount and composition of public agricultural research funding has no effect on state agricultural productivity. Findings include that programmatic funding, including federal formula funds, has a larger impact on state agricultural productivity than federal grant and contract funding. Moreover, a reallocation of federal formula funding to competitive grant funding lowers state agricultural productivity and, in this sense, is a non-optimal agricultural science policy.

More about Agricultural Research Funding and Productivity

Over the past twenty-five years, the rate of growth of funding for the state agricultural experiment station (SAES) system has slowed dramatically, and its composition has changed—with rapidly growing funds from nontraditional sources. The constant dollar funding for the SAES system grew at an average annual rate of 1.4% during the decade of the 1980s. However, over the next thirteen years, the average annual rate of growth was only 0.39% (table 1).

Looking across the forty-eight states, we see differences in the composition of SAES funding (table 2). In New England and the Appalachian states, a large share—20 to 55%—of SAES funding is from federal formula funding. In contrast, the Pacific region has an unusually small share of SAES funding from federal formula programs (table 2). California and Florida are states that stand out for their unusually low share of SAES funds from federal formula moneys—about 5%. Turning to federal grants, contracts, and cooperative agreement funding, the New England, Northeast, Northern Plains, Appalachian, Southeast, Delta States, and Southern Plains regions obtain a small share of SAES funds through these federal programs. States that stand out because of their large share—over 17%—of funding from these federal competitive sources are Wisconsin, Oregon, Indiana, Colorado, Rhode Island, California, Michigan, New York, and Utah. These states established relatively early the institutional infrastructure and scientific skills that would make them competitive in programs where the research agenda is set in Washington, D.C. and not locally.

Turning to a description of agricultural sector total factor productivity records at the state level from 1970 to 1999, total factor productivity grew at an average annual rate of 2% or more in Connecticut, Michigan, North Dakota, South Dakota, North Carolina, Georgia, Florida, Arkansas, Washington, and Oregon (table 2). All of these states, except Connecticut and Michigan, had agricultural output growth rates of 2% per year or more. States with very low average TFP growth

Table 2. Average Annual Growth Rate for Farm Output, Input, Multifactor Productivity and Public Agricultural Research Capital and Composition of SAES Funding, 1970–1999

Region/State	TFP Relative Level 1996	Average Annual Growth Rate, 1970–1999 (%) Total Output	Total Input	TFP	Public Ag. Research Capital	Avg. SAES Share from Federal Formula	Comp. Grants
New England							
Maine	1.026[a]	0.08	−1.50	1.42	1.43	0.33[b]	0.07[c]
New Hampshire	0.865	0.13	−1.17	1.30	0.77	0.55	0.01
Vermont	1.131	0.74	−0.15	0.89	1.49	0.47	0.03
Massachusetts	0.991	0.29	−1.43	1.72	0.02	0.36	0.05
Connecticut	1.168	1.45	−0.90	2.35	0.18	0.20	0.13
Rhode Island	0.959	−0.18	−1.69	1.50	1.18	0.38	0.18
Northeast							
New York	1.070	0.50	−0.91	1.41	2.12	0.11	0.17
New Jersey	0.948	0.83	−0.60	1.43	0.96	0.16	0.08
Pennsylvania	1.032	1.69	0.17	1.52	2.24	0.29	0.08
Delaware	1.198	2.82	1.75	1.08	1.57	0.35	0.06
Maryland	1.072	1.51	0.19	1.33	2.38	0.24	0.06
Lake States							
Michigan	0.852	1.94	−0.68	2.26	3.38	0.17	0.17
Minnesota	1.053	1.94	0.00	1.94	2.49	0.18	0.11
Wisconsin	0.977	1.09	0.68	1.77	2.25	0.15	0.25
Corn Belt							
Ohio	0.846	1.33	−0.57	1.90	0.79	0.23	0.02
Indiana	1.025	1.59	−0.33	1.92	1.64	0.16	0.20
Illinois	1.057	1.29	−0.58	1.87	1.56	0.20	0.11
Iowa	1.192	1.08	−0.75	1.83	3.19	0.18	0.14
Missouri	1.002	0.78	−0.59	1.37	3.39	0.22	0.10
Northern Plains							
North Dakota	1.181	2.15	−0.09	2.24	4.06	0.18	0.05
South Dakota	1.187	1.96	−0.11	2.07	2.60	0.24	0.04
Nebraska	1.257	2.49	0.69	1.80	4.42	0.11	0.09
Kansas	1.169	2.24	0.60	1.65	3.35	0.13	0.10
Appalachia							
Virginia	0.962	1.42	−0.27	1.69	3.25	0.21	0.14
West Virginia	0.607	1.19	−0.36	1.55	2.15	0.48	0.05
Kentucky	0.984	1.56	−0.03	1.60	2.23	0.35	0.00
North Carolina	1.181	2.15	−0.09	2.23	4.50	0.18	0.14
Tennessee	0.825	1.30	−0.45	1.75	2.95	0.28	0.14
Southeast							
South Carolina	1.057	1.07	−0.81	1.88	2.13	0.32	0.00
Georgia	1.465	2.25	0.20	2.04	5.53	0.19	0.04
Florida	1.525	2.27	0.27	2.00	3.47	0.06	0.06
Alabama	1.000	1.85	−0.05	1.90	1.63	0.23	0.06
Delta States							
Mississippi	1.222	1.51	−0.39	1.90	2.69	0.26	0.07
Arkansas	1.375	2.66	0.60	2.06	3.30	0.21	0.03
Louisiana	1.188	1.12	−0.23	1.35	1.69	0.13	0.04
Southern Plains							
Oklahoma	0.845	1.65	0.37	1.28	1.67	0.22	0.11
Texas	0.929	1.99	0.42	1.57	2.88	0.16	0.09

(Continued)

Table 2. *(Continued)*

Region/State	TFP Relative Level 1996	Average Annual Growth Rate, 1970–1999 (%) Total Output	Total Input	TFP	Public Ag. Research Capital	Avg. SAES Share from Federal Formula	Comp. Grants
Mountain States							
Montana	0.851	1.17	−0.03	1.20	2.49	0.18	0.09
Idaho	1.278	2.43	0.51	1.92	3.38	0.22	0.05
Wyoming	0.826	1.17	0.28	0.89	0.92	0.30	0.07
Colorado	1.076	1.57	0.06	1.51	3.77	0.23	0.18
New Mexico	0.964	1.98	0.43	1.55	2.49	0.28	0.10
Arizona	1.251	1.41	−0.16	1.57	4.63	0.12	0.12
Utah	0.890	1.87	0.45	1.42	2.60	0.23	0.17
Nevada	0.985	1.48	0.39	1.09	4.17	0.27	0.11
Pacific							
Washington	1.358	3.04	0.72	2.32	2.35	0.17	0.10
Oregon	0.837	2.67	0.29	2.38	2.59	0.12	0.22
California	1.445	2.64	1.18	1.46	3.02	0.05	0.17

[a]The TFP level is relative to Alabama.
[b]Share of SAES funds from Hatch and other federal formula programs.
[c]Share of SAES funds from federal competitive grants, contracts, and cooperative agreements lagged twelve years (see table 3).

were Vermont and Wyoming (0.89), Delaware (1.08), and Nevada (1.09). Over this period, it has been common for input growth to be negative. Nevertheless, among the four states with slowest TFP growth, three had positive input growth.

States in close proximity have, for the most part, agro- and geo-climatic conditions and economic factors that may make them respond similarly to new technologies. Hence, looking at regional groups of states may show another dimension of agricultural sector TFP growth. Consider the forty-eight contiguous states grouped into the eleven USDA regions. Total factor productivity growth was relatively high in the Lake States, Southeast, Northern Plains, and Pacific region, but low in the Mountain region (table 2).[6]

A hypothesis is that public agricultural research capital is one important determinant of total factor productivity in agriculture. Table 2 shows that the annual average growth in public agricultural research capital over 1970–1999 was high, at over 3% in Michigan, Iowa, Missouri, North Dakota, Nebraska, Kansas, Virginia, North Carolina, Georgia, Florida, Arkansas, Idaho, Colorado, Arizona, and California. However, it was less than 1.5% per year in the six New England States, New Jersey, Ohio, and Wyoming. Furthermore, the simple correlation between state annual average TFP growth over 1970–1999 and annual average growth of public agricultural research capital is 0.25.

An Econometric Model of Total Factor Productivity for Agriculture

Assume a state aggregate production function with disembodied technical change where Q is an aggregate of all types of farm outputs from farms within a state aggregated into one output index, $\mathrm{A}(RPUB, RPRI, EXT)$ is the associated technology parameter, and $\mathrm{F}(\cdot)$ is a well-behaved production function (Chambers 1988, p. 181). K is state aggregate quality-adjusted physical capital input, L is state aggregate quality-adjusted labor input, and M is state aggregate quality-adjusted materials input. The technology parameter $\mathrm{A}(\cdot)$ is hypothesized to be a function of state public agricultural research capital ($RPUB$), private agricultural research capital ($RPRI$), and public agricultural extension capital (EXT). The state aggregate production function is then:

$$(1)\quad Q = \mathrm{A}(RPUB, RPRI, EXT)\mathrm{F}(L, K, M).$$

Now we define TFP as

$$(2)\quad TFP = Q/\mathrm{F}(L, K, M) = \mathrm{A}(RPUB, RPRI, EXT).$$

[6] See Ball et al. (1999) for a discussion of the relationship between state levels of total factor productivity and the national level.

Taking natural logarithms of both sides of equation (2) and adding a random disturbance term μ, we obtain the rudimentary econometric model of agricultural productivity

$$(3)\quad \ln TFP = \ln \mathrm{A}(RPUB, RPRI, EXT) + u.$$

For this study, one goal is to test the impact of public agricultural research capital and its composition, e.g., shares due to major funding sources, on state aggregate total factor productivity (see Huffman and Just 1994). To accomplish this, the funding shares are interacted with the public agricultural research capital variable, and we add a time trend (*trend)* to effectively de-trend the dependent variable and all regressors (Wooldridge 2003, pp. 350–51). Hence, the embellished version of the econometric model of state agricultural *TFP* is

$$\begin{aligned}(4)\quad \ln TFP_{ilt} = {} & \beta_1 + \beta_2 \ln RPUB_{ilt} \\ & + \beta_3[\ln RPUB_{ilt}]SFF_{ilt} \\ & + \beta_4[\ln RPUB_{ilt}](SFF_{ilt})^2 \\ & + \beta_5[\ln RPUB_{ilt}]GR_{ilt} \\ & + \beta_6[\ln RPUB_{ilt}](GR_{ilt})^2 \\ & + \beta_7 \ln RPUBSPILL_{ilt} \\ & + \beta_8 \ln EXT_{ilt} \\ & + \beta_9 \ln RPRI_{ilt} + \beta_{10} trend \\ & + \delta_l + u_{ilt}\end{aligned}$$

where i refers to a particular state in region l and year t. In addition, SFF_{ilt} is a given state's share of SAES funding from federal formula and state government appropriations (i.e., programmatic funding) in year t; GR_{ilt} is a given state's share of SAES funding from federal grants, contracts, and cooperative agreements (i.e., federal grants and contracts) in year t; and $RPUBSPILL_{ilt}$ is a given state's public agricultural research capital spillin in year t,[7] and δ_l is a regional fixed effect.[8] Given the specification of equation (4) including an intercept term, the unconditional expected value of the random disturbance term u_{ilt} is zero.

Taking equation (4) and ignoring subscripts, the elasticity of state agricultural total factor productivity with respect to *RPUB*, *RPUBSPILL,* and *EXT* is

$$\begin{aligned}(5)\quad & \partial \ln(TFP)/\partial \ln(RPUB) \\ & = \beta_2 + \beta_3 SFF + \beta_4 (SFF)^2 \\ & \quad + \beta_5 GR + \beta_6 (GR)^2\end{aligned}$$

$$(6)\quad \partial \ln(TFP)/\partial \ln(RPUBSPILL) = \beta_7, \text{ and}$$

$$(7)\quad \partial \ln(TFP)/\partial \ln(EXT) = \beta_8.$$

The elasticity of state agricultural productivity (*TFP*) with respect to a change in a state's own public agricultural research capital, given by equation (5), clearly takes different values as the composition of SAES funding changes, i.e., *SFF* or *GR*. The elasticity of a state's agricultural *TFP* with respect to the public agricultural-research-capital spillin is given by equation (6) and with respect to public agricultural-extension capital is given by equation (7).[9]

The unique feature of equation (4) is that the productivity of a state's public agricultural-research capital depends on and is proportional to the composition of SAES funding sources—*SFF* and *GR*:

$$\begin{aligned}(8)\quad & \partial \ln(TFP)/\partial(SFF) \\ & = (\beta_3 + 2\beta_4 SFF) \ln RPUB\end{aligned}$$

$$\begin{aligned}(9)\quad & \partial \ln(TFP)/\partial(GR) \\ & = (\beta_5 + 2\beta_6 GR) \ln RPUB.\end{aligned}$$

Equations (8) and (9) show how the composition of public agricultural research funding affects state agricultural *TFP*. The proportional change of state agricultural *TFP* due

[7] Note that empirically, *TFP* has a weak lower bound roughly at zero, i.e., when there is a total "crop failure." However, it has no such tendency for any particular upper limit. Hence, by making the dependent variable of equation (4) the natural logarithm of *TFP*, we have created a transformed dependent variable and a disturbance term u that are approximately normal. In contrast to a production function, there are very weak priors about the exact functional form of the productivity equation. We follow Evenson (2001, p. 583) and choose a double-logarithmic model modified so that we can test hypotheses about the effects of the composition of agricultural experiment station funding on agricultural productivity. We also test for significant interaction effects between public and private agricultural research capital, but no significant impact is identified.

[8] The inclusion in equation (4) of a public research spillin variable reduces potential problems with spatial correlation of disturbances.

[9] In experiments, an interaction term between public agricultural research and extension was considered. The estimated coefficient of this term was negative, but it was not strong statistically. We excluded this variable from our final specification of the productivity model.

to a one percentage point change in *SFF*—a state's share of SAES funding from federal and state programmatic funding—is given in equation (8). Likewise, the proportional change of state agricultural *TFP* due to a one percentage point change in *GR*—a state's share of SAES funding from federal grants and contracts—is given by equation (9). The inclusion of squared terms in these equations $[(SFF)^2, (GR)^2]$ permits us to examine potential nonlinear impacts of funding composition on the productivity of public agricultural research at the state level.

The elasticity of state agricultural *TFP* with respect to private agricultural research capital (*RPRI*) is:[10]

$$(10)\quad \partial \ln(TFP)/\partial \ln(RPRI) = \beta_9.$$

With public funds allocated to agricultural research having nonresearch alternatives, it is interesting to ask what the social rate of return is on these investments. For example, if one million dollars of additional public funds were invested today in an average state, it would have direct benefits distributed over the next thirty-five years in this state and spillover benefits in other states in the same geo-climatic region. By setting the net present value of the benefits equal to the cost, we can solve for the marginal annualized internal rate of return (MIRR). When benefits and costs are in constant prices, we obtain a real rate of return on the public investment. The computation is

$$(11)\quad 1 = \left[\frac{\partial \ln(TFP)}{\partial \ln(RPUB)} Q/R + (n-1) \times \frac{\partial \ln(TFP)}{\partial \ln(RPUBSPILL)} Q/S\right] \times \sum_{0}^{m} w_i[1/(1+r)^i]$$

where Q is the sample mean value at the state level for gross agricultural output, R is the sample mean of a state's own public agricultural research capital, and $(n-1)$ is the number of states into which agricultural research-spillin effects flow. S is the sample mean of the public agricultural research capital spillin, m is the number of periods over which the input of public agricultural research impact agricultural productivity, w_i's are timing weights used to derive the public agricultural research capital variable, and r is the real MIRR including impacts of R&D capital spillovers (see Yee, Ahearn, and Huffman 2002, p. 191).

The Data

The data set is a panel for the forty-eight contiguous states and thirty years, 1970 through 1999, giving 1,440 total observations. We use the new annual state total factor productivity (*TFP*) data obtained from the USDA (see Ball, Butault, and Nehring 2002). The science of constructing research capital variables from research expenditures remains in its infancy (Griliches 1979, 1998). However, Griliches established a tradition forty years ago of using real public agricultural research expenditures or a research stock variable to proxy the "true" measure of agricultural research discoveries that impact productivity.[11] Our data on public agricultural research expenditures with a productivity focus were prepared by Huffman, McCunn, and Xu (2006), and they are converted to constant dollar values using the Huffman and Evenson (2005, pp. 106–07) research price index.[12]

Although a few researchers have included free-form or many lags of public agricultural research expenditures without much structure in aggregate productivity analyses (e.g., Alston, Craig, and Pardey 1998), this generally asks too much of the data in the sense that too many coefficients must be estimated.[13] Hence, by imposing prior beliefs about the shape of timing weights, we impose smoothness of the marginal impacts of successive real research expenditures on ln *TFP* and reduce the demands on the data to identify parameters. For example, Griliches (1998) concludes that the impact of research and development (R&D) on productivity or output most likely has a short gestation period, then blossoms, and eventually becomes obsolete. Following his guidance, we approximated this pattern with the following pattern of timing weights. First, a gestation period of two years

[10] Significant public and private agricultural research-capital interaction effects did not exist.

[11] A note is available upon request from the authors showing how a good proxy variable results in minimal errors in variable bias.

[12] Because the real agricultural research expenditures with a productivity orientation are in constant dollars, they do not have a strong trend over the sample period.

[13] Free-form lag estimates are unsatisfactory generally because with high correlation between lagged real research expenditures, the estimated coefficients on successive lagged research expenditures tend to oscillate between positive and negative values, which is difficult to rationalize (Evenson 2001, p. 588).

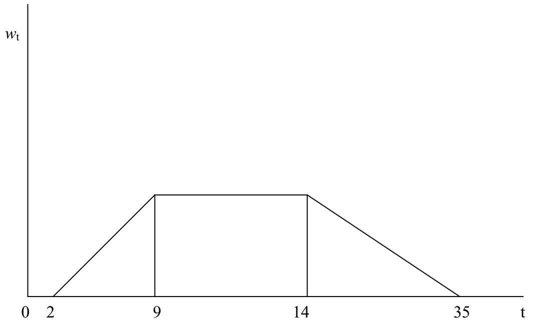

Figure 1. Public agricultural research timing weights

is imposed, during which the impacts of public agricultural research capital on productivity are negligible. Second, impacts are then assumed to be positive over the next seven years and are represented by increasing weights, followed by six years of maturity during which weights are high and constant. Then, twenty years of declining weights follow that go to zero eventually. This weighting pattern is known as "trapezoid-shaped time weights" (see figure 1, and Evenson 2001, pp. 584–88).[14]

We, however, can reduce the bias and decrease the size of the standard error associated with our research capital variables by choosing, among alternative proxy variables, one that is most highly correlated with *true* public agricultural research capital. One measure of research that has been used by some researchers is the total agricultural research expenditures across all agencies, research commodities, and research problem areas (U.S. Department of Agriculture 1993). However, if we ignore research expenditures that are remotely related to agricultural productivity, we can create a research capital variable that is more highly correlated with the *true* public agricultural research capital variable. We do this by choosing the subset of all public agricultural research expenditures undertaken by the Agricultural Research Service (ARS) and Economic Research Service (ERS) of the USDA and SAES, and Veterinary Medicine Schools/Colleges of the Land Grant system that have an agricultural productivity focus. We selected all research commodities that are farm output, farm input, or farm pest and research problem areas (RPAs) that are focused on biological efficiency, mechanization, protection/maintenance, and management. In particular, we excluded research on post-harvest activities and on research commodities denoted as households, families, or communities. This remaining subset of real public agricultural research expenditures is then used to construct the public agricultural research capital variable (*RPUB*).[15]

Interaction terms between a state's public agricultural research capital and SAES funding shares are created, i.e., the share of the SAES funds from federal formula and state government appropriations (*SFF*) and federal grants and contracts (*GR*) are multiplied by ln *RPUB*. However, given that the public agricultural research capital is derived using thirty-five years of data, we lagged *SFF* and *GR* by twelve years, to place them roughly at the weighted mid-point of the total lag length.

Although research spillin areas might be defined using state units (e.g., McCunn and Huffman 2000), we choose to use geo-climatic regions as defined in Huffman and Evenson (1993, p. 195). The regions are units that have similar climates and soils, leading to similar technological opportunities. For example, consider Iowa. It is covered by geo-climatic region 6, and it is surrounded by six states. For each of these states, we weight the amount of public agricultural research capital in each year by the share of the state that is also in region 6, and then we sum over these six weighted values.[16] Thus, the public agricultural research capital spillin for a given state does not include its own public agricultural research capital.

The public agricultural extension capital variable is constructed as follows. We take data on full-time equivalent professional extension staff years allocated to agricultural and natural resource extension to construct our public extension variable (Ahearn, Lee, and Bottom 2003). The instrument for public extension is a five-year weighted average of extension staff years, where the current year's input receives a weight of one-half and the weights decline geometrically over the next four years.

[14] Other trapezoidal weight patterns with a total lag of thirty-five years will also be highly correlated with the one we chose and be a good proxy variable. If the true timing weight pattern differs greatly from the trapezoidal shape, this would introduce measurement error that would make the least-squares parameter estimates inconsistent and biased toward zero (Greene 2003, pp. 83–85).

[15] A number of studies have used "a time trend" to proxy technical change or research capital, e.g., Capalbo and Denny (1986); Chavez and Cox (1992); and Lim and Shumway (1997). Our public agricultural research variable is a better proxy for technical change, and because it is constructed from real rather than nominal public agricultural research expenditures it is not strongly trended over the study period.

[16] The set of weights is available from the authors upon request.

To represent state private agricultural R&D capital, we also use a proxy variable. We take data on the annual flow of all private agricultural patents awarded in the U.S. to domestic and foreign inventors in four areas: field crops and crop services; fruits and vegetables; horticultural and green house crops; and livestock and livestock services (Johnson and Brown 2002). For each state, we apply local production weights to each of the four totals. Then the public agricultural research capital variable is created by applying trapezoidal timing weights over a nineteen-year period, and summing.

To take some account of the fact that federal and state agricultural science and economic policies follow natural boundaries around states and regional groupings of states, we define seven regional dummy variables. Starting from the eleven ERS production regions (table 2), we reduce them to seven by combining the New England and Northeast regions into a new *Northeast* region, the Appalachian region and the Southeast into a new *Southeast* region, the Lake States and Corn Belt into a new *Central* region, and the Southern Plains and Delta regions into a new *South Plains* region. Other regions are the *Northern Plains, Mountains*, and *Pacific*. If there are omitted variables, as there may be, the regional fixed effects and trend will partially account for these otherwise omitted effects. This will improve the quality of the final estimates. See table 3 for definitions of symbols and summary definitions of variables.

Method of Estimation

The methodology is one of a pooled cross-section time-series model of agricultural productivity that is fitted to annual data for forty-eight contiguous states over 1970–1999. Most likely disturbances are heteroskedastic and contemporaneously correlated across panels and auto-correlated within panels. Several strategies exist for estimating panel data models of this type. First, one could apply feasible generalized least squares (FGLS) where first-round OLS residuals are used to estimate one or more values of ρ in a first-order autoregressive process (AR(1)), a variance for each state and the contemporaneous correlation of disturbances across pairs of states.[17] However, Beck and Katz (1995) have shown that the full FGLS variance–covariance estimates are typically unacceptably optimist when used in panels of modest size and length. Second, one can apply the Prais–Winsten estimator (Greene 2003, pp. 325–26) to estimate the parameters in equation (4) and then use standard errors corrected for heteroscedasticity and contemporaneous correlation across states (PCSE).[18] This is an alternative to FGLS. Third, White (1980) and MacKinnon and White (1985) suggest another strategy where regression parameters are estimated by OLS and standard errors are corrected for a general, rather than a specific, form of heteroscedasticity. This latter methodology was extended by Newey and West (1987) to a general form of standard error correction for autocorrelation or combined general heteroscedasticity and autocorrelation. Given our data, the Newey–West standard errors ignore useful information that permits a major simplification of the variance–covariance matrix of the parameters. After weighing alternative strategies, we choose to pursue the Prais–Winsten estimator of regression coefficients and correct the standard errors and z-values for heteroscedasticity and contemporaneous correlation across states. The estimator for the regression coefficients is consistent and the estimate of the variance–covariance matrix of the parameters is asymptotically efficient under the assumed covariance structure of the disturbances.

The Results

Equation (4) is fitted with a panel structure for the forty-eight states and thirty observations over time with and without a time trend using the Prais–Winsten estimator and PCSE. The estimate of ρ used in the estimation is 0.76 for regression (1) and 0.69 for regression (2). These values are quite far away from 1 and suggest that weak dependency exists in the disturbances and that a unit root is unlikely to be a problem (Greene 2003, p. 636).

[17] For example, the OLS residuals $\hat{u}_{tl}$ for each state, $l = 1, \ldots, 48$, could be pooled to estimate a single value of ρ in $\hat{u}_{tl} = \rho_l \hat{u}_{t-1l} + \varepsilon_{tl}$, where ε_{tl} is a random disturbance term. Another option is to use residuals for each state to estimate state-specific values of ρ_l and then a single estimate of ρ can be obtained by taking a simple average over all forty eight state estimates of ρ_l, and it is used in computing the adjusted standard errors. Finally, one might use state specific estimates of ρ and transform each state separately. The options are available in the STATA xtgls routine (STATA 2005, pp. 102–11).

[18] Beck and Katz (1995, p. 121) made a case against estimating panel-specific AR(1) parameters rather than a single AR(1) parameter across all states. This estimation can be implemented in STATA 8.2 using xtpcse with the subroutine ar1 (STATA 2005, pp. 226–35).

Table 3. Variable Names and Definitions and Summary Statistics

Name	Symbol	Mean (SD)	Description
Total factor productivity	*TFP*	−0.205[a] (0.254)	Total factor productivity for the agricultural sector (Ball, Butault, and Nehring 2002)
Public agricultural	*RPUB*	16.129[a] (0.879)	The public agricultural research capital for an originating state. The summation of past research capital investments in agricultural research within a state having an agricultural productivity focus (Huffman, McCunn, and Xu 2006) in 1984 dollars (Huffman and Evenson 2005, pp. 106–07). Capital stock obtained by summing past research expenditures with a two- through thirty-five-year lag and trapezoidal shaped timing weights
Budget share from federal formula funds	$SFF1_{t-12}$	0.230 (0.112)	The share of the SAES budget from Hatch, Regional Research, McIntire-Stennis, Evans-Allen, and Animal Health (USDA), i.e., formula funds, lagged twelve years
Budget share from state government appropriations	$SFF2_{t-12}$	0.521 (0.123)	The share of the SAES budget from state government appropriations (USDA), lagged twelve years
Budget share from federal formula and state appropriations	SFF_{t-12}	0.751 (0.132)	The share of the SAES budget from programmatic funding, $SFF1_{t-12} + SFF2_{t-12}$
Budget share from federal grants and contracts	GR_{t-12}	0.096 (0.076)	The share of the SAES budget from the National Research Initiative, other CSRS funds, USDA contracts, grants and cooperative agreements, and non-USDA federal grants and contracts (USDA), lagged twelve years
Budget share from other funds	OR_{t-12}	0.165 (0.132)	The share of the SAES budget from private industry, commodity groups, NGO's, and SAES sales (USDA), lagged twelve years
Public agricultural research capital spillin	*RPUBSPILL*	17.763[a] (0.567)	The public agricultural research spillin stock for a state, constructed from state agricultural subregion data (see Huffman and Evenson 1993, p. 195)
Public extension capital	*EXT*	1.292[a] (0.976)	A state's stock of public extension, created by summing for a given state the public full-time equivalent staff years in agriculture and natural resource extension, applying a weight of 0.50 to the current year and then 0.25, 0.125, 0.0625, and 0.031 for the following four years. The units are staff-years per 1,000 farms.
Private agricultural capital	*RPRI*	6.076[a] (0.248)	A state's stock of private patents of agricultural technology. Each state's private agricultural research capital in the national total of agricultural patents awarded to U.S. and foreign inventors for each year (Johnson and Brown) obtained by weighting the number of private patents in crops (excluding fruits and vegetables and horticultural and greenhouse products) and crop services, fruits and vegetables, horticultural and greenhouse products, and livestock and livestock services by a state's sales share in crops (excludes fruits, vegetables, horticultural and greenhouse products), fruits and vegetables, horticultural and greenhouse products and livestock and livestock products, respectively. The annual patent totals are two- through eighteen-year lag using trapezoidal timing weights
Regional indicators	*Northeast*		Dummy variable taking a 1 if state is CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, or VT
	Southeast		Dummy variable taking a 1 if state is AL, FL, GA, KY, NC, SC, TN, VA, or WV
	Central		Dummy variable taking a 1 if state is IN, IL, IA, MI, MO, MN, OH, or WI
	North Plains		Dummy variable taking a 1 if state is KS, NE, ND, or SD
	South Plains		Dummy variable taking a 1 if state is AR, LA, MS, OK, or TX
	Mountains		Dummy variable taking a 1 if state is AZ, CO, ID, MT, NV, NM, UT, or WY
	Pacific		Dummy variable taking a 1 if state is CA, OR, or WA
Trend	*Trend*		Annual time trend

[a]Numbers reported in natural logarithms.

Table 4. Panel Estimates of Pooled Cross-Section Time-Series Model of Agricultural Productivity: Forty-Eight U.S. States, 1970–1999 ($N \times T = 48 \times 30 = 1{,}440$)

	Regression (1)		Regression (2)	
Regressors	Coefficient	z-Value[a]	Coefficient	z-Value[a]
Intercept	−6.865	5.91	−24.803	5.62
ln $(\mathit{Public\ Ag\ Res\ Capital})_t$	0.189	9.44	0.131	14.13
ln $(\mathit{Public\ Ag\ Res\ Capital})_t \times SFF_{t-12}$	0.037	1.54	0.035	1.67
ln $(\mathit{Public\ Ag\ Res\ Capital})_t \times (SFF_{t-12})^2$	−0.030	1.83	−0.028	1.92
ln $(\mathit{Public\ Ag\ Res\ Capital})_t \times GR_{t-12}$	−0.032	2.74	−0.034	3.01
ln $(\mathit{Public\ Ag\ Res\ Capital})_t \times (GR_{t-12})^2$	0.037	1.47	0.040	1.70
ln $(\mathit{Public\ Extension\ Capital})_t$	0.156	5.46	0.110	5.12
ln $(\mathit{Public\ Ag\ Res\ Capital\ Spillin})_t$	0.147	4.12	0.035	2.09
ln $(\mathit{Private\ Ag\ Res\ Capital})_t$	0.089	1.20	0.001	0.02
Regional Indicators				
Northeast (=1)	0.185	2.61	0.053	1.10
Southeast (=1)	0.037	0.79	0.005	0.13
Northern Plains (=1)	0.343	5.73	0.194	5.48
Southern Plains (=1)	0.103	1.88	0.062	1.51
Mountains (=1)	0.219	3.02	0.115	2.29
Pacific (=1)	0.117	1.91	0.057	1.25
Trend			0.011	4.75
R^2	0.328		0.421	

Note: The dependent variable is $\ln(TFP)_{ilt}$. Parameters are estimated by the Prais–Winsten estimator where the estimate of the AR(1) parameter ρ for regression (1) is 0.76 and for regression (2) is 0.69. The estimation was carried out in STATA 8.2 using the panel data routine "xtpcse" and subroutine "ar1."

[a]The z-values are constructed from standard errors that are corrected for heteroscedasticity across states and contemporaneous correlation of disturbances across pairs of states.

In table 4, all of the estimated coefficients have plausible signs. In regression (2), which includes trend, all of the adjusted z-values are smaller than for regression (1), which excludes trend, except for the direct effect of public agricultural research capital. This variable has a larger adjusted t-value in regression (2) than in regression (1). All of the direct effects of key variables are significantly different from zero at the 5% level in a two-sided test, except for the estimated coefficient of private agricultural research capital. All of the coefficients of interaction terms are statistically significant (positive or negative) at the 5% level in a one-sided test. In regression (2), the estimated coefficient of *trend* is 0.011, and it is significantly different from zero at the 5% level. It is a measure of the net effect of time trend in the dependent variable, all regressors, and even in other variables from outside the model that are correlated with ln *TFP* and (or) *trend*, including any technical change in research equipment or software. At face value, the coefficient of *trend* suggests that *TFP* is growing annually at 1.1% per year, holding other regressors in the econometric *TFP* model constant. The R^2 is 0.33 in regression (1) and 0.42 in regression (2), which indicates that we are capable of explaining one-third to almost one-half of the variation in ln *TFP* by the regression equations.

The point estimate of marginal effects represented by equations (5)–(9) and the associated 95% confidence intervals are reported in table 5.[19] Although the signs of these marginal effects are unaffected by the inclusion of *trend*, the marginal effects are smaller in absolute value when trend is included. The elasticity of *TFP* with respect to public agricultural research capital (*RPUB*) is 0.197 without *trend* and 0.139 with *trend*. The elasticity of *TFP* with respect to public agricultural research spillin capital (*RPUBSPIL*) is 0.146 without *trend* and 0.036 with *trend*. The elasticity of *TFP* with respect to extension capital (*EXT*) is 0.156 without *trend* and 0.110 with *trend*. These marginal effects, however, have tight 95% confidence intervals (table 5).

The central focus of this paper is the impact of the composition of SAES funding on the productivity of public agricultural research. These marginal effects are a little smaller after the inclusion of trend, and we focus on the

[19] When the marginal effect is not a constant, it is evaluated at the sample mean of the appropriate variable.

Table 5. Marginal Impacts on Agricultural TFP from a Policy Change (95% Confidence Interval Is in Parentheses)

	From Regression[a]	
Equation/Marginal Impact	(1)	(2)
(5) $\partial\ln(TFP)/\partial\ln(RPUB)$	0.197 (0.161, 0.234)	0.139 (0.124, 0.153)
(6) $\partial\ln(TFP)/\partial\ln(RPUBSPILL)$	0.147 (0.077, 0.217)	0.036 (0.002, 0.067)
(7) $\partial\ln(TFP)/\partial\ln(EXT)$	0.156 (0.100, 0.212)	0.110 (0.068, 0.153)
(8) $\partial\ln(TFP)/\partial(SFF)$	−0.130 (−0.253, 0.001)	−0.099 (−0.214, 0.016)
(9) $\partial\ln(TFP)/\partial(GR)$	−0.402 (−0.657, −0.146)	−0.431 (−0.684, −0.179)

[a]Estimated coefficients are taken from table 4 and marginal effects are evaluated at the sample mean of the data for (5), (8), and (9).

second set. An increase in programmatic funding by one percentage point decreases *TFP* by 0.9%. The 95% confidence interval for this impact is relatively tight and, conditional on the data, the marginal impact is most likely negative, but there exists some chance that it is positive (table 4).[20] In contrast, a marginal increase of SAES federal grants and contract funding by one percentage point reduces *TFP* by 4.3%. Conditional on the sample, this latter impact is almost certainly negative. Recall that at the sample mean, the share of federal formula funds in total SAES funds is 23% (and of state government funding is 0.52) and the share in federal grants, contracts, and cooperative agreements is 9.6% (table 3). Hence, if federal formula funds are reduced by ten percentage points, and these funds are transferred to competitive grants (with an overhead rate of 20%), this will increase SAES funding from federal grants, contracts, and cooperative agreements by only about 2%. Hence, agricultural *TFP* will decline by 7.6%. This is a significant reduction.

To gain insight, we graph $\partial\ln(TFP)/\partial(SFF)$ against *SFF.* Given that β_3 is positive and β_4 is negative, as SFF increases, $\partial\ln(TFP)/\partial(SFF)$ first increases, peaks at SFF = 0.62 under either regression, and then decreases for larger values of SFF (figure 2). The marginal relationship between $\partial\ln(TFP)/\partial(GR)$ and GR is convex rather than concave. At small (or large) values of GR, $\partial\ln(TFP)/\partial(GR)$ is large. Starting from a small value of GR, $\partial\ln(TFP)/\partial(GR)$ decreases to GR = 0.43 under regression (1) and (2), and then increases for larger values of GR (see figure 3). *Hence, an incremental re-allocation of funds from SFF to GR, i.e., a decline in the share of programmatic funding offset by an equal increase in federal grants and contracts, will lower state agricultural TFP significantly.*

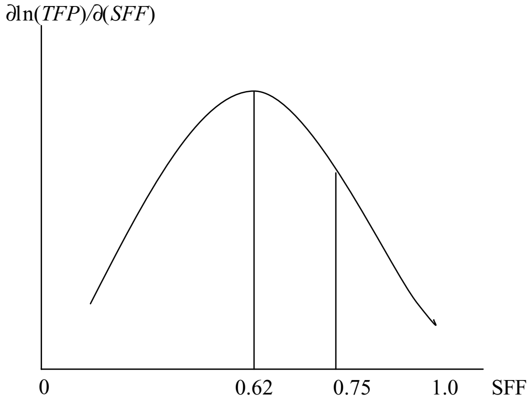

Figure 2. Marginal effect of *SFF* on ln *TFP*

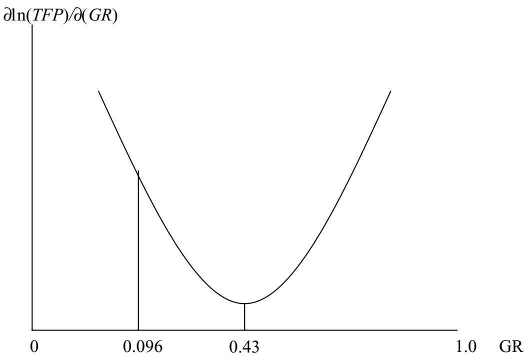

Figure 3. Marginal effect of *GR* on ln *TFP*

Conclusions

This study has presented new econometric evidence of the significant positive impact of public agricultural research and extension on state agricultural *TFP* over 1970–1999. The results also showed that programmatic funding, e.g.,

[20] This is a Bayesian and not a classical statistical interpretation, Greene (2003, pp. 429–30).

federal formula funding, has a larger impact on agricultural productivity than federal competitive grants and contracts. Why does this occur? Local SAES directors have the advantage of building reputations with state clientele and their scientists relative to national science program directors, and Huffman and Just (1999, 2000) have shown this increases efficiency of the public agricultural research organization. Furthermore, state legislators expect their Land Grant University to use state government-appropriated public agricultural research funds to solve local problems or to develop new technologies that will give local clientele a comparative advantage rather than to chase national competitive grant funds. Failure of State Agricultural Experiment Station directors to deliver on these expectations can be expected to weakening future state legislative support for public agricultural research, which has occurred in some states (e.g., Wisconsin and Colorado).

Our results provide evidence against President Bush's 2005 Federal Budget, which proposed eliminating Hatch and other formula funds for agricultural research and replaced them with a competitive grants program for the SAES system. Our results imply that transfers of federal formula funds or replacing federal formula funds with a competitive grants program for State Agricultural Experiment Stations would reduce state agricultural productivity significantly. These conclusions are unaffected by the inclusion of trend in the econometric *TFP* model. In addition, states, which have large experiment stations and have accumulated past experience competing for federal grants, would have an advantage over other states. Hence, the new science policy would imply major distributional effects among states, and State Agricultural Experiment Station directors as a group and the U.S. Congress seem unlikely to support President Bush's proposal to convert existing Hatch Act funding into a competitive grant program.

Returning to the broader issue of the social annualized marginal rate of return to public funds invested in agricultural research, our estimate ranges from 49 to 62%. The smaller of these numbers is associated with the *TFP* model that includes a time trend.[21] Both of these marginal real internal rates of return compare quite favorably with estimates reported by Evenson (2001). The implied first-year marginal product of public extension exceeds its cost. This marginal product is about \$29 per dollar of extension staff time, which clearly exceeds its costs.[22]

Until 1980, 70% of State Agricultural Experiment Station funding came from federal formula funds *and* state government appropriations, both of which are relatively unrestricted use funds. Today, that percentage has fallen to about 50%. A long lag exists from the initial investment in public agricultural research to obtaining useful discoveries and then to innovations available to farmers. If, for some reason, current public agricultural research investments would drop to zero, research benefits would continue for some time, but at a reduced rate. It, however, would be very difficult for future research ever to catch up on past foregone discoveries. Hence, it is critical to maintain, or even increase, funding for public agricultural research.

[Received November 2003; accepted November 2005.]

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[21] The marginal annualized internal rate of return is computed assuming a one-unit increment in public funding, and benefits are measured at the sample mean and distributed over time using timing weights (figure 1). The sample mean value of Q is \$3.513 billion per state per year in constant 1984 dollars.

[22] We used a sample mean number of farms per state of 49,900 and assumed that a staff-year of extension effort cost \$33,000 in 1984 prices, which may be large.

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