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New Econometric Evidence on Agricultural Total Factor Productivity Determinants: Impact of Funding Composition

by

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Abstract: This paper examines the impact of public agricultural research and extension on agricultural total factor productivity at the state level. The primary emphasis, however, is on testing the hypothesis that the composition of agricultural experiment station funding—the share from federal competitive grants and contracts and from federal formula and state government appropriations—affects the productivity of public agricultural research. We use an econometric model of total factor productivity for the agriculture sector, where instruments are created for key regressors and annual data for the 48 contiguous states over the 30-year period 1970-1999. Our results show that public agricultural research and agricultural extension have statistically significant positive impacts on state agricultural productivity. Also, the composition of SAES funding matters; an increase in federal competitive grant funding at the expense of federal formula funding for state agricultural experiment stations lowers the productivity of public agricultural research significantly. 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- to 62-percent, and to public agricultural extension, it is even larger.

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New Econometric Evidence on Agricultural Total Factor Productivity Determinants: Impact of Funding Sources

In 1980, 17% of the funding for the SAES system was from so-called "regular Cooperative State Research Service (CSRS) administered sources," and 15.1% were from Hatch Act and other formula funds. These are funds where the Congressionally-appropriated total amount of funds is distributed among the various states by a fixed formula.[1] No significant CSRS-administered competitive-grant program or funding existed at that time. Also, we refer to "other federal funds" as those that are not from CSRS or the Cooperative State Research, Education and Extension Service (CSREES). They include SAES funding obtained from the National Science Foundation and National Institutes of Health competitive grants and USDA cooperative agreements. In 1980, these funds accounted for 11.4% of SAES funding, state governments accounted for 55.5%, and private sources accounted for another 9.2 percentage points. Hence, in 1980, programmatic funding was roughly 70.6% of total SAES system funding (table 1).

Since 1980, the share of SAES system funds obtained from Hatch and other formula funds has steadily declined to 10.2% in 1990, 8.4% in 2000, and 7.9% in 2003. CSRS/CSREES administered competitive grant funds rose to 1.9% of the total SAES funding in 1990 and then to 2.3% in 2003. Other federal government agency funding has steadily risen in importance, from 12.1% of the total in 1990 to 20.9% in 2003. State government funding account for 55% of the total in 1990, but declined since then—50.1% in 2000 and 43.7% in 2003. Private sector funds increased in importance to the SAES system since 1980, being 13.2% in 1990 and 15.1% in 2003. Hence, since 1980, the share of SAES system funding that arises from programmatic funding declined to 50.7% in 2003, which is roughly 20 percentage points lower than in 1980.

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 follows. First, programmatic funds, e.g., Hatch formula funds, involve no overhead and, hence, about 97 percent of the total federally appropriated formula agricultural research funds go to SAESs. In contrast, grant and contract funded SAES research involve significant indirect cost or overhead being paid to the Office of the Provost or Vice President for Research at the university receiving the grant. Only a small share of the overhead funds is channeled back to the SAES or principal investigator. Hence, university overhead is a tax on public agricultural research funds—driving a wedge between the amount appropriated by Congress and the amount received by the SAES scientists.

Second, competitive grant funding tends to favor institutions that have the research infrastructure to undertake research that is typically national in scope and will have 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 Schools that are Land Grant Universities (e.g.,Wisconsin, Michigan, Purdue), and a few other Land Grant 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 states or regions and may have a large social payoff relative to cost. This is especially important to small states─New Hampshire, Vermont, and West Virginia—that have depended heavily upon Hatch funds, obtaining more than 45% of their funds from this source.

Third, national competitive grant programs also tend to reallocate research resources within Land Grant Universities away from research that researchers see as vitally important to their individual states and toward research that review panels and reviewers think will have national appeal in the competitive-grant process. In the competitive-grant process the federal government tends, on average, to under-fund the proposals that they do fund, including those asking for preliminary results. This has the practical effect of leveraging national agricultural research priorities, because other funds, for example, state-government appropriations, pay for the research that produces preliminary results and completes these projects. At a minimum, a significant amount of state government-provided 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 time spent writing proposals in an effort to obtain federal competitive grants represents an effort that could be productively used to research local agricultural problems.

The counter-argument goes something as follows. 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, and in this sense, some might suggest that they have limited federal accountability.[2] Some have argued that research conducted under these funds is not subject to rigorous research methods. Agricultural Experiment Station research projects are reviewed infrequently, but the scientists working on these projects are university tenure-track and tenured faculty, who undergo regular performance assessment for university pay increases and, some, for promotion in rank. Thus, the expectations set by the university are critical factors affecting scientists' rigor and diligence in research and other activities. Huffman and Just (2000) have argued that a diversity of incentives among scientists helps the research system reduce its risks in discovery, because nobody knows when and where the next important discovery will occur. One could suggest that scientists at small Land Grant Universities that generally operate under weaker incentives for discovery than those in the large universities are providing important diversity in the discovery process in the U.S. This does not mean that scientists at small universities will never make big discoveries, only that the expected frequency will be low. Hence, it is difficult to argue that "bad science" is an accurate description of agricultural research in the SAES system.

If fewer dollars were spread throughout the Land Grant system for formula funding, particularly to fund the many small (and inconsequential, from the big universities' perspective) Land Grant Universities, those dollars could instead be used to increase the research funds available for competitive grant programs. This rationale ties in with the argument that from a scientific discovery perspective, the U.S. might not "need" more than 20 Colleges of Agriculture, and perhaps we could get by with even fewer. However, reducing the number of states receiving federal agricultural research funds to 20 or so would greatly change the political economy of funding agricultural research in the U.S. Congress. A likely prospect is that, over time, the amount of Congressionally appropriated funds for public agricultural research would decline. Another possibility is that the 28 or so Land Grant Universities that would be cut out of formula funds might pursue Congressionally ear-marked research funds (National Research Council, p. 71-72). Hence, it is not clear that an attempt to concentrate public agricultural research funds in a few large Land Grant Universities would actually be successful over the long run.

Prior studies that have examined the impacts of public agricultural research and extension on state or regional agricultural productivity include Griliches (1963); Huffman and Evenson (1993); Alston, Craig and Pardey; and Yee, Huffman, Ahearn, and Newsome (2002). Huffman and Just (1994), however, were the first to test econometrically the hypothesis that the composition of public agricultural research funding affects the productivity of research. They examined the Huffman and Evenson TFP data for 1948-1982 and tested the hypothesis that grants, contracts and cooperative agreement funded agricultural research; federal formula; and state funded research are equally productive. They rejected this hypothesis and concluded that federal formula funding is more productive than competitive-grant funding, possibly owing to the high transaction costs associated with external competitive grant programs. Much has happened in the technology of agriculture and the funding of agricultural research since 1982. In particular, the USDA's competitive grant program has grown from a few million dollars to about a $100+ million dollar program and the SAES system has experienced a large increase in federal grant funds from non-USDA agencies.

The objective of the current paper is to present a new econometric examination of the impacts of public agricultural research and extension, and of the composition of public agricultural research funding on the productivity of agricultural research in the 48 contiguous states for the more recent time-period 1970-1999. In particular, it reports on tests of the hypothesis that the composition of public agricultural research funding, i.e., shares from federal competitive grants and federal formula funds, has no effect on state agricultural productivity. The alternative hypothesis is that composition does affect the productivity of public agricultural research. To accomplish these objectives, we use an econometric model of agricultural productivity, new annual state productivity data constructed by the USDA (see Ball, Butault and Nehring), new public agricultural research data by Huffman et al., new private R&D data associated with patenting by Johnson and Brown, and new extension data by Ahearn, Lee and Bottom. We show that the composition of SAES funding affects the size of the impacts of public agricultural research on state agricultural total factor productivity (TFP). We also show that a reallocation of federal formula funding to competitive-grant funding will lower state agricultural productivity and, in this sense, be a non-optimal agricultural science policy.

More about Agricultural Research Funding and Productivity

Over the past 25 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 non-traditional 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 13 years, the average annual rate of growth was only 0.39% (table 1).

Looking across the 48 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 percent—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 percent. 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 percent—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 1970-1999, total factor productivity grew at an average annual rate of 2 percent 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 two percent per year or more. States with very low average TFP growth 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 48 contiguous states grouped into the 11 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).[3]

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 to 1999 was high, at over 3% percent 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 percent 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, $A(RPUB, RPRI, EXT)$ is the associated technology parameter, and $F(\cdot)$ is a well-behaved production function (Chambers, 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 $A(\cdot)$ 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) $Q = A(RPUB, RPRI, EXT)\, F(L, K, M)$.

Now we define *TFP* as:

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

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

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 (also, 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, p. 350-351). Hence, the embellished version of the econometric model of state agricultural *TFP* is

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

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*,[4] and δ_l is a regional fixed effect. 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

(5) $\partial \ln(TFP)/\partial \ln(RPUB) = \beta_2 + \beta_3\, SFF + \beta_4\, (SFF)^2 + \beta_5\, GR + \beta_6\, (GR)^2$,

(6) $\partial \ln(TFP)/\partial \ln(RPUBSPILL) = \beta_7$, and

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

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).[5]

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*

(8) $\partial \ln(TFP)/\partial(\mathrm{SFF}) = (\beta_3 + 2\beta_4\, SFF) \ln RPUB$,

(9) $\partial \ln(TFP)/\partial(\mathrm{GR}) = (\beta_5 + 2\beta_6\, \mathrm{GR}) \ln RPUB$.

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 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 1 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 given by equation (10):[6]

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

With public funds allocated to agricultural research having non-research 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 was invested today in an average state, it would have direct benefits distributed over the next 35 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:

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

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, p. 191).

The Data

The data set is a panel for the 48 contiguous states and 30 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). The data on public agricultural research expenditures with a productivity focus were prepared by Huffman *et al*., and they are converted to constant dollar values using the Huffman and Evenson (2005, p. 106-107) research price index. 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.

The science of constructing research capital variables from research expenditures remains in its infancy (Griliches 1979, 1998). However, Griliches established a tradition 40 years ago of using real public agricultural research expenditures to proxy the "true" measure of agricultural research discoveries that impact productivity. With this proxy (instrumental variable) approach, the important issue is not that we do not have a *perfect measure* of public agricultural research capital, but that we have a measure that is *correlated with the true measure* and with ln *TFP* (Greene, p. 86-88).[7] Under this condition, the estimated coefficient of the agricultural research capital variable in equation (4) will be consistent (and no errors in variable problems exist).

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, this generally asks too much of the data, in the sense that too many coefficients must be estimated.[8] Hence, by imposing prior beliefs about the shape of timing weights, we reduce the demands on the data to identify parameters, and we get rid of parameter-estimate oscillation. For example, Griliches (1998) concludes that the impact of 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 follow pattern of timing weights. First, a gestation period of two years 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, p. 584-588).[9]

We, however, can reduce the size of the standard error associated with our research capital variables by choosing, among alternative instruments, 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. Dept. Ag. 1993). However, if we delete research expenditures that are, at best, 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*).[10]

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 35 years of data, we lagged *SFF* and *GR* by12 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, 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 6 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 6 weighted values.[11] 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). 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.

To represent state private agricultural R&D capital, we also apply the instrumental variable method. 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). 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 19-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*. See table 3 for definitions of symbols and summary definitions of variables.

Method of Estimation

Equation (4) is to be fitted to panel data for 48 states. At one time, it was somewhat common to undertake some type of feasible-generalized-least-squares estimation (FGLS) using quasi-first differences when fitting models over time (e.g., see McGuirk, Driscoll, and Alwang). For our particular estimation problem, recommended practices currently are different. It is acceptable to estimate the model by OLS, but to correct the standard errors for heteroscedasticity and/or autocorrelation.

One adjustment suggested by Greene (p. 217-219) is to incorporate prior information on plausible forms of heteroscedasticity and/or autocorrelation. For example, it is most likely that the random disturbance in equation (4), u_{ilt}, is heteroskedastic across states and follows a first-order autoregressive process over time.[12] Another adjustment is proposed by White (1980) and MacKinnon and White (1985) where standard errors are adjusted for a general form of heteroscedasticity. The latter methodology was extended by Newey and West to a general form of autocorrelation or combined general heteroscedasticity and autocorrelation. Also see Davidson and MacKinnon (p. 548-556); Woodridge (2002, p. 148-152); and Cameron and Trevide. After weighing these options, we decided to pursue the simplest but most plausible correction to the standard errors. This uses the "xtpcse" routine in STATA8.2 to estimate the regression coefficients of equation (4) and adjust the standard errors of these coefficients for heteroscedasticity across states and a single AR(1) process on the time dimension (Stata Corp, p. 150-159).

Although we know that OLS will be inefficient, good reasons exist for taking this approach. First, all of the explanatory variables may not be strictly exogenous in equation (4). If they are not, FGLS is not consistent. However, the OLS estimator is consistent provided

$E(u_{ilt} \mid X_{ilt}) = 0$, which permits feedback, where $E(\cdot)$ is the expectation operator and X_{ilt} is the set of regressors in equation (4),. Second, in most applications of FGLS, the model's disturbances are assumed to follow a first-order autoregressive process [AR(1)] and the variables of the model undergo quasi-first differences before estimation of coefficients. Since rho (ρ), the first-order autocorrelation coefficient and the variance of the disturbances are unknown, they must be estimated, and this changes greatly the properties of the estimator. The best-case scenario with FGLS is a consistent estimator, which requires that the sample size over time go to infinity.[13] In panel-data over time, however, we will be in the small sample situation in the time dimension. In this case, FGLS has unknown statistical properties and can hardly be claimed to be better than OLS. Third, given the specification of equation (4), the mean and the variance of the disturbance in equation (4), u_{ilt}, can be assumed reasonably to be finite constants over time, and if the disturbances are weakly dependent over time, the disturbances are covariance stationary. With a few added assumptions, we can draw upon the Gordin's Central Limit Theorem for asymptotic normality of the OLS estimator (Greene, p. 263-265, 463; White, p. 122-133).

The Results

Equation (4) is fitted in STATA8.2 with a panel structure for the 48 states and 30 observations over time with and without a time trend and coefficient estimates and standard errors are reported in table 4.[14] The residuals from regressions (1) and (2) in table 4 produce a single summary estimate of ρ, the first-order autocorrelation coefficient, of 0.76 and 0.69, respectively. 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, p. 636). Moreover, we are in the small length of the time series and large number of cross-sectional observations, and hence, a large cross-section and relatively short time series let us be agnostic about the amount of temporal persistence in the data (Wooldridge 2002, p.175).

In regressions (1) and (2), table 4, all of the estimated coefficients have plausible signs. In regression (2), which includes trend, all of the adjusted t-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 regression (1). All of the direct effects of key variables are significantly different from zero at the 5 percent 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 percent 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 percent 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 percent 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 associated 95-percent confidence intervals are reported in table 5.[15] 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-percent 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 second set. An increase in programmatic funding by one percentage point decreases *TFP* by 0.9 percent. The 95-percent 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).[16] In contrast, a marginal increase of SAES federal grants and contract funding by one percentage point reduces *TFP* by 4.3 percent. 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 23.0 percent (and of state government funding is 0.52) and the share in federal grants, contracts and cooperative agreements is 9.6 percent (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 two percent. Hence, agricultural *TFP* will decline by 7.6 percent. 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*.

Discussion

The current blend of federal formula and state appropriations and federal competitive grants, contracts and cooperative agreements provides SAES directors with considerable flexibility in using the resources and providing direction for public agricultural research that meets local and regional needs. Directors have the advantage of building reputations with state clientele and their scientists, which tends to increase the efficiency of the public agricultural research organization (Huffman and Just 1999, 2000). Generally, state legislators expect their Land Grant University to use state government appropriated public research funds to solve local problems or to develop new technologies that will give local farmers a comparative advantage. Failure of State Agricultural Experiment Station directors to deliver on these discoveries will most likely result in a future weakening of state legislative support for public agricultural research, which has occurred in some states, e.g., Wisconsin and Colorado.

In Febuary 2005, the President of the United States recommended a major change in public agricultural science policy; the elimination of federal formula funds for experiment station research. In its place, he proposed a new competitive grants program for the state agricultural experiment stations (CSREES 2005a). This proposed policy is a complete contradiction of the Congressional sentiment underlying the original Hatch Act of 1887 and most acts up to the Amended Hatch Act of 1955 (Kerr).[17] Also, our econometric results imply that this new agricultural science policy would reduce agricultural total factor productivity, which is one of the major benefits of public agricultural research.[18] Recall that, when public agricultural research is funded by federal competitive grants and contracts, part of the granted resources goes to university overhead, and the research agenda that is to be undertaken is set by the funding agency, i.e., CSREES. Furthermore, the funding decisions use information presented in research proposals rather than completed projects. In addition, the federal competitive-grant programs do not pay for research proposal writing, so the risk of federal research grant programs is borne by the competing scientists or their employing institutions, and the somewhat distorted incentive structure increases transactional costs, while lowering the scientists' productivity. Moreover, federal funding agencies tend to fund less than 100 percent of the resources needed to complete a research project. Other resources, most notably state government-appropriated funding, needed to complete these projects. Hence, this policy change would greatly increase the funding uncertainty faced by SAES scientists and Agricultural Experiment Station directors. These are reasons why, from a social perspective, federally funded competitive grants do not look nearly as attractive economically as they do to the federal funding agencies, that generally take a “private benefits” perspective.

Social scientists have periodically noted that public agricultural research, cooperative extension, farmers' education, private agricultural research, infrastructure and government all contribute to agricultural productivity change. Over the past two decades, a number of studies have examined the effect of public investments in agricultural research and development, and all have demonstrated a positive and significant impact on agricultural productivity (Evenson 2001).

Conclusions

This study has presented new econometric evidence of the significant impact of public agricultural research and extension on state agricultural *TFP* over 1970 through 1999. The results also showed that complex interaction effects exist between a state’s public agricultural research capital and SAES funding composition—shares of federal formula and state appropriations (programmatic funding) and of federal grants and contracts. These results imply that transfers of federal formula funds or replacing federal formula funds with a competitive grant programs 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, have an advantage over other states. Small states would most likely lose state matching funds if their Hatch funds were eliminated. Many of these states would be forced to close their state agricultural experiment station, or to form alliances with other stations. The first option seems likely to be quite detrimental to long-run federal funding of SAES research because it would undermine Congressional support. The latter re-organization could result in some economies of scale in the organization of agricultural research and be beneficial to the long-run strength of the SAES system. In any case, major distribution effects would be implied by the eliminating Hatch funding of SAES research. Hence, State Agricultural Experiment Station directors as a group and the U.S. Congress seem unlikely to support 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-percent. The smaller of these numbers is associated with the *TFP* model that includes a time trend.[19] 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.[20]

Until 1980, 70 percent of State Agricultural Experiment Station funding came from federal formula funds *and* state government appropriations, both of which are relatively unrestricted. Today that percentage has fallen to about 50 percent. Due to the nature of agricultural research, a long lag exists from the initial investment in a project to the time when useful discoveries lead to innovations for farmers. It is easy to overlook the important role of timing in public agricultural research. 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 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 research, given the large dividends paid on addressing local agricultural problems and associated issues. In research, lost time is difficult to recover.

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Table 1. Relative Distribution of U.S. State Agricultural Experiment Station Revenue by Major Source, 1980-2003

Sources	Distribution(%)			
	1980	1990	2000	2003
Regular federal appropriations	17.0	14.0	13.1	15.3
Hatch and other formula funds	[15.1]	[10.2]	[8.4]	[7.0]
CSRS/CSREES special grants	[1.2]	[2.5]	[2.1]	[2.8]
NRI Competitive grants	--	[1.2]	[2.0]	[2.3]
Other CSRS/CSREES administered funds	[0.7]	[0.1]	[0.6]	[3.2]
Other federal government research funds	11.4	12.1	16.2	20.9
Contracts, grants, and cooperative agreements with USDA agencies	[3.0]	[3.1]	[3.4]	[4.2]
Contracts and grants with non-USDA federal agencies	[8.4]	[9.0]	[12.8]	[16.7]
State government appropriations	55.5	55.0	50.1	43.7
Industry, commodity groups, foundations	9.2	13.2	15.3	15.1
Other funds (product sales)	6.9	5.7	5.3	5.0
Grand total:%	100.0	100.0	100.0	100.0
Grand total amount:				
Current dollar., millions	804.8	1,596.5	2,229.7	2,571.0
Constant dollar., millions 2000	1,893.6	2,178.0	2,229.7	2.291.4

Source: CSREES

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	Ave. 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
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 12 years (see table 3).

Table 3. Variable Names and Definitions and Summary Statistics

Name	Symbol	Mean (Sd.)	Description
Total factor productivity	*TFP*	-0.205* (0.254)	Total factor productivity for the agricultural sector (Ball et al., 2002)
Public agricultural research capital	*RPUB*	16.129* (0.879)	The public agricultural research capital for an originating state. The summation of past investments in agricultural research within a state having an agricultural productivity focus (Huffman, McCunn, and Xu) in 1984 dollars (Huffman and Evenson 1993). Capital stock obtained by summing past research expenditures with a 2 through 35-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 12 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 12 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 12 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 12 years
Public agricultural research capital spillin	*RPUBSPILL*	17.763* (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* (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, apply a weight of 0.50 to the current year and then 0.025, 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* (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 2- thru 18-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 to buy 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

*Numbers reported in natural logarithms.

Table 4. Least-squares Panel Estimate of the Econometric Agricultural Total-factor Productivity Model: 48 U.S. States, 1970-1999[a] [N x T = 48 x 30 = 1,440]

Regressors	Regression (1) Coefficient	Regression (1) t-value[b]	Regression (2) Coefficient	Regression (2) t-value[c]
Intercept	-6.865	5.91	-24.803	5.62
ln (*Public Ag Res Capital*)$_t$	0.189	9.44	0.131	14.13
ln (*Public Ag Res Capital*)$_t$*SFF_{t-12}	0.037	1.54	0.035	1.67
ln (*Public Ag Res Capital*)$_t$*$(SFF_{t-12})^2$	-0.030	1.83	-0.028	1.92
ln (*Public Ag Res Capital*)$_t$*GR_{t-12}	-0.032	2.74	-0.034	3.01
ln (*Public Ag Res Capital*)$_t$*$(GR_{t-12})^2$	0.037	1.47	0.040	1.70
ln (*Public Extension Capital*)$_t$	0.156	5.46	0.110	5.12
ln (*Public Ag Res Capital Spillin*)$_t$	0.147	4.12	0.035	2.09
ln (*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	

[a] The dependent variable is ln $(TFP)_{ilt}$.

[b,c] The t-values are obtained by taking a regression coefficient and dividing it by its standard error. The standard errors include adjustments for heteroscedasticity across states and a single first-order autoregressive structure on the disturbances ordered over time. The estimate of ρ, the first-order autocorrelation coefficient, for regression (1) is 0.76 and for regression (2) is 0.69. The estimated coefficients and adjusted t-values are computed in STATA8.2 using the panel data routine "xtpcse."

Table 5. Marginal Impacts on Agricultural TFP from a Policy Change (95-Percent Confidence Interval for each Impact is in Parentheses)

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

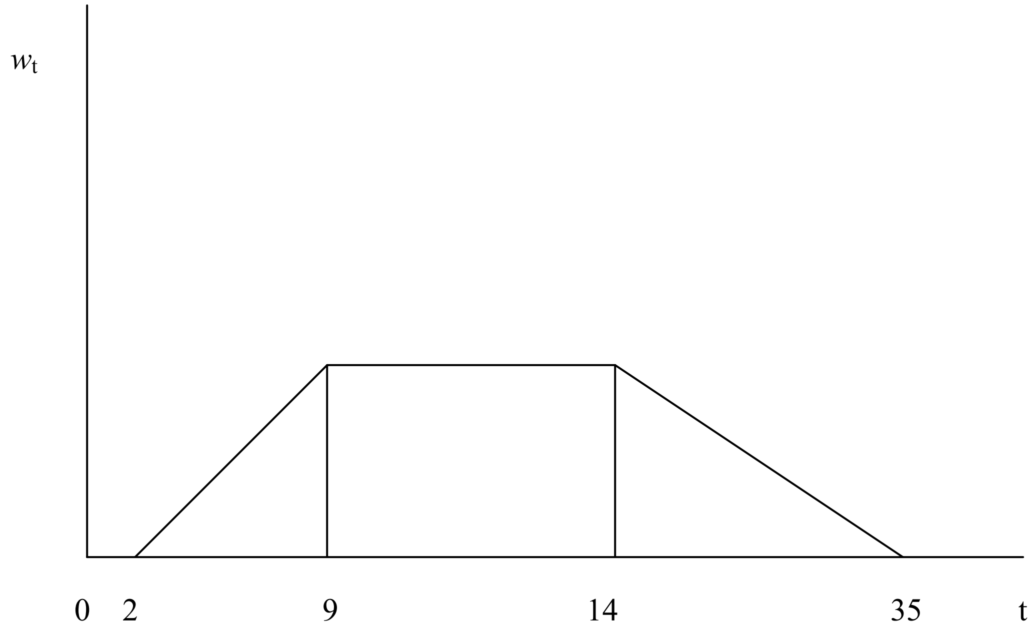

Figure 1. Public Agricultural Research Timing Weights.

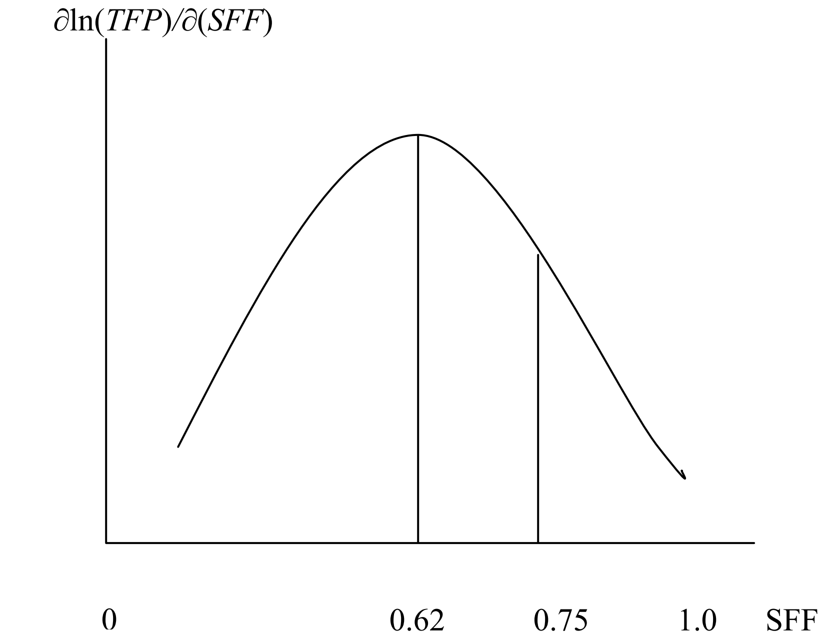

Figure 2. Marginal effect of *SFF* on ln *TFP*

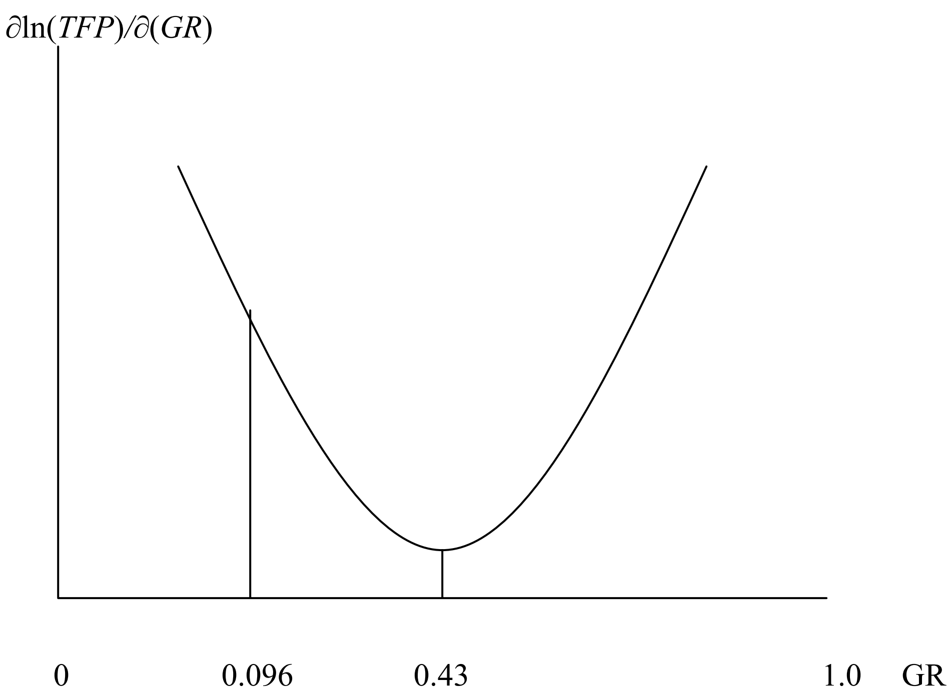

Figure 3. Marginal effect of *GR* on ln *TFP*

Table A1. Ordinary Least-squares Estimate of Econometric Model of State Agricultural Total Factor Productivity, 48 States: 1970-1999[a] [N x T = 48 x 30 = 1,440]

Regressors[b]	Regression (1) Coefficient	Regression (1) t-value[c]	Regression (2) Coefficient	Regression (2) t-value[d]
Intercept	-6.438	21.59	-25.753	20.84
ln (*Public Ag Res Capital*)$_t$	0.162	13.94	0.118	10.60
ln (*Public Ag Res Capital*)$_t$**SFF*$_{t-12}$	0.111	4.09	0.082	3.27
ln (*Public Ag Res Capital*)$_t$*(*SFF*$_{t-12}$)^2	-0.080	4.44	-0.059	3.51
ln (*Public Ag Res Capital*)$_t$**GR*$_{t-12}$	-0.079	6.16	-0.063	5.30
ln (*Public Ag Res Capital*)$_t$*(*GR*$_{t-12}$)^2	0.153	4.45	0.107	3.36
ln (*Public Extension Capital*)$_t$	0.188	14.78	0.129	10.52
ln (*Public Ag Res Capital Spillin*)$_t$	0.120	9.94	0.026	2.11
ln (*Private Ag Res Capital*)$_t$	0.108	4.16	0.031	1.29
Regional Indicators				
Northeast (=1)	0.111	3.87	0.025	0.94
Southeast (=1)	-0.005	0.26	0.015	0.81
Northern Plains (=1)	0.287	9.97	0.170	6.18
Southern Plains (=1)	0.048	2.10	0.032	1.50
Mountains (=1)	0.151	6.50	0.083	3.80
Pacific (=1)	0.093	3.46	0.058	2.32
Trend			0.011	16.03
R^2	0.512			0.586

[a] The dependent variable is ln (*TFP*)$_t$.

[b] The *Central Region* is the excluded region.

[c,d] The t-values are computed without regard to possible heteroscedasticity or autocorrelation.

Endnotes

[1] The "formula" is as follows: 20% of each year's appropriation is distributed equally among states, 26% is distributed to states based on their share of the U.S. farm population, and 26% is distributed based on a state's share of the U.S. rural population (Huffman and Evenson 2005; CSREES 2005b). Twenty-five percent of the total is allocated to regional or multi-state research, and 3% are allocated for federal administration. Sometime formula funding is used to describe only the parts based on the shares of the farm and of the rural population, but this seems a bit conservative here. States must also match Hatch and other formula funds from state and other sources.

[2] 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).

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

[4] 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 (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 tested for significant interaction effects between public and private agricultural research capital, but no significant impact was identified.

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

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

[7] The instrument should also be uncorrelated with the disturbance term in equation (4).

[8] Free-form lag estimates are generally not very satisfactory because with correlation between lagged real research expenditures, the estimated coefficients tend to oscillate between positive and negative values and only make sense when smoothed (Evenson, p. 588).

[9] Although we could use a somewhat altered shape of the lag pattern to construct the research capital

variable, other trapezoidal shapes with a total lag of 35 years will yield a new research capital variable that is highly correlated with the one we chose, and hence, meet the instrumental variable criterion.

[10] A number of studies have used "trend" to proxy technical change or research capital, e.g., Capalbo and Denny; Chavez and Cox; and Lim and Shumway. Our public agricultural research variable is a is a better proxy or instrument technical change. Because it is constructed from real public agricultural research expenditures it is not strongly trended over the study period.

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

[12] A first-order autoregressive process on the disturbance u_t is represented as $u_t = \rho\, u_{t-1} + \varepsilon_t$ where ρ is the first-order autocorrelation coefficient and ε_t is a zero mean and fixed finite variables disturbance term.

[13] If actual-first differences exist, i.e., $\rho = 1$, rather than quasi-first differences are appropriate, this problem does not arise.

[14] See Appendix A for OLS estimates of the coefficients of the model and t-values outside the panel structure and without adjustments for heteroscedasticity or autocorrelation.

[15] When the marginal effect is not a constant, the evaluated is at the sample mean.

[16] This is a Bayesian, and not a classical statistical, interpretation, Greene (p. 429-430).

[17] Up do the Bankhead-Jones Act of 1935, all state agricultural experiment stations shared equally in federally appropriated SAES research funding (Kerr, p. 73-74), but in this Act for the first time funds were distributed among states on the basis of each state's share of the rural population of the United States. The first major attempt by the Executive Branch to take control of Hatch Act funding occurred in 1953 under the Eisenhower administration. For a few years the Office of Experiment Stations was under a newly organized Agricultural Research Service (ARS), and ARS supervised all federal agricultural research and allocated funds to the states for agricultural research (Kerr, p. 95-96). This ended in 1961 under the Kennedy Administration when the Cooperative State Research Service was formed to take charge of the state agricultural experiment stations and be parallel to ARS in the USDA organizational structure (Kerr, p. 103-104).

[18] Other outputs , e.g., the number of basic scientific discoveries from public agricultural research, might increase. However, we do not have a direct way of obtaining an estimate of this effect. Our results do suggest that these other impacts of public agricultural research would need not only to be positive, but relatively large, to offset the negative *TFP* effects.

[19] 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.

[20] 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.