12-2003

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December 2003

Working Paper # 03029

Department of Economics Working Papers Series

Ames, Iowa 50011

June 18, 2004

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 and private agricultural research and extension on agricultural total factor productivity at the state level. We test the hypothesis that the composition of agricultural experiment station funding—share of funding from impact of federal competitive grants and contracts and from federal formula and state government appropriations---affects the productivity of public agricultural research using data for the 48 contiguous states over 1970-1999. Our results show not only that sources of funding matter, but that an increase in federal competitive grant funding at the expense of federal formula funding would lower the productivity of public agricultural research. Furthermore, our simulation results show that a few states would most likely gain by a re-allocation of federal formula to grant and contract funding but most would lose.

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

The distribution of state agricultural experiment station (SAES) resources has undergone a dramatic shift in recent decades. The share of SAES funding from federal formula funds administered by the USDA--dollars that are allocated to individual states for agricultural research based in part on rural population and farm numbers--has decreased from 16 percent in 1980 to 9 percent in 2000. During that same period, USDA-administered competitive grant funding grew only 2 percent.

Although state appropriations have remained a dominant source of SAES funding, those resources also have declined, from 55 percent of total experiment station funding in 1980 to 50 percent in 2000. This shift in funding takes place at a time when public officials are increasingly challenged to make the most of every dollar they invest, whether it's in education, infrastructure, welfare programs, or research. It is possible that further shifting may not be in the best interest of farmers, consumers, or even society in general.

Although the U.S. agricultural experiment station system has over 1970-1999 had modest dependence on federal grants and contracts, some states, e.g., Indiana, Oregon, and Wisconsin, have obtained more than 20 percent of their experiment station funds from these sources over the long run. In contrast, the experiment stations in New Hampshire, Vermont, and West Virginia have depended heavily upon federal formula funds—obtaining more than 45 percent of their funds from this source. Huffman and Just (1994) is the only study to examine specifically the effect of different public agricultural research funding composition on state agricultural productivity, but it used data for an earlier period 1948-1982. They found that formula funding was more effective than competitive-grant funding at increasing state agricultural total factor productivity. The reason that they gave was possibly owing to high transaction costs for grant funds and misallocations of pork barrel funding

By all accounts, U.S. agriculture has had an amazing rate of total factor productivity increase in the post-World War two eras. Using a newly constructed data set of state agricultural accounts, Ahearn, Yee, Ball, and Nehring (1998) report an average annual rate of aggregate agricultural TFP growth of 1.94 per cent over 1948 to 1994. Over the period 1980 to 1999, the rate is approximately three percent per year. Jorgenson and Stiroh (2000), using their own data sets for 37 sectors of the U.S. economy over 1958 to 1999, show that the U.S. agricultural sector ranks third among 37 sectors in TFP grow. Furthermore, U.S. agriculture accounts for 21 percent of aggregate U.S. TFP growth over this time period but only two percent of GDP.[1]

Prior studies that have examined the impacts of public agricultural research and extension on agricultural productivity using regional or state level data include Griliches (1963), Huffman and Evenson (1993), Alston, Craig and Pardey (1998), and Yee, Huffman, Ahearn, and Newsome (2002). Evenson (2001) provides a review and critique of these and many other studies that report empirical evidence for the impacts of public agricultural research and extension on agricultural productivity. All of these studies have found positive and significant impacts of public agricultural research on agricultural productivity. The empirical evidence for public extension is somewhat mixed, some showing a positive effect and others not showing any effect. The work by Huffman and Evenson (1993) which uses state aggregate data for 1948-1982 for crop and livestock sub-sectors and an aggregate agricultural sector, is the only one to include private agricultural R&D as a determinant of TFP for the agricultural sector. Their research focused on identifying impacts of the scientific composition on productivity---pre-invention versus applied research and applied crop versus livestock research. Although they found that private agricultural research had a positive impact on TFP, excluding it did not have much impact on the impact of public agricultural research on TFP.

The current paper presents a new econometric examination of the impacts of public agricultural research, private agricultural R&D, and public extension on state agricultural productivity for the period 1970 to 1999. In particular, it reports tests of the hypothesis that the composition of public agricultural research funding i.e., share from federal competitive grants and contracts and from federal formula and state government appropriations, has no effect on state agricultural productivity. The alternative is that the composition has a non-linear impact on productivity. We also report simulations of a new agricultural science policy—one that shifts federal formula funds to competitive grant funding, or the reverse. To accomplished these objectives, we use a new annual state productivity data set constructed by the USDA (see Ball et al. 2002), new public agricultural research data by Huffman et al., new private R&D data associated with patenting by Johnson and Brown (2002), and new extension data by Ahearn, Lee, and Bottom (2002). We show that composition of SAES funding matters for determining the impact of public agricultural research funds on state agricultural TFP. Also, our simulation results show that a few states would gain by a re-allocation of federal formula funds to grant and contract funds but most would lose.

The Model of State Aggregate Total Factor Productivity

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

Now we define state total factor productivity (*TFP*) as:

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

Taking natural logarithms of both sides of equation (2) and adding a random disturbance term μ, we have

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

For this study, we want to test that both the impact of the level of the public agricultural research stock and its composition, e.g., shares due to major funding sources, impact state aggregate total factor productivity (also, see Huffman and Just 1994). To accomplish this, the funding shares are interacted with the public agricultural research stock. Hence, the embellished version of the state agricultural *TFP* equation is:

$$\begin{aligned}(4)\ \ell n\ TFP = {} & \beta_1 + \beta_2\,\ell n\ RPUB + \beta_3\,[\ell n\ RPUB]SFF + \beta_4\,[\ell n\ RPUB](SFF)^2 \\ & + \beta_5\,[\ell n\ RPUB]GR + \beta_6\,[\ell n\ RPUB](GR)^2 + \beta_7\,\ell n\ EXT + \beta_8\,[\ell n\ PRUB]\ \ell n\ EXT \\ & + \beta_9\,\ell n\ RPUBSPILL + \beta_{10}\,\ell n\ RPRI + u\end{aligned}$$

where *SFF* is a state's share of SAES funding from federal formula and state government appropriations (i.e., programmatic funding), *GR* is a state's share of SAES funding from federal grants, contracts, and cooperative agreements (i.e., federal grants and contracts), *RPUBSPILL* is a state's public agricultural research capital spillin.[2] The elasticity of state agricultural total factor productivity with respect to *RPUB*, *RPUBSPILL*, *EXT*, and *RPRI* is:

$$(5)\quad \frac{\partial \ell nTFP}{\partial \ell nRPUB} = \beta_2 + \beta_3\,SFF + \beta_4\,(SFF)^2 + \beta_5\,GR + \beta_6\,(GR)^2 + \beta_8\,\ell n\ EX\mathrm{T},$$

$$(6) \qquad \frac{\partial \ell nTFP}{\partial \ell nRPUBSPILL} = \beta_9,$$

$$(7) \qquad \frac{\partial \ell nTFP}{\partial \ell nEXT} = \beta_7 + \beta_8 \, \ell n \, RPUB,$$

$$(8) \qquad \frac{\partial \ell nTFP}{\partial \ell nRPRI} = \beta_{10}.$$

The elasticity of state agricultural productivity (*TFP*) with respect to a charge in the state's own public agricultural research capital is given in equation (5), and clearly this elasticity takes on different values as the composition of state agricultural experiment station funding change, i.e., *SFF* and *GR*, and the amount of local extension activity (*EXT*).[3] The elasticity of a state's agricultural *TFP* with respect to the public agricultural research capital spillin is displayed in equation (6), and it is a constant. The elasticity of state agricultural *TFP* with respect to public agricultural extension input is given by equation (7), and it clearly varies as stock of local public agricultural research changes (*RPUB*). In particular, if state public agricultural research and extension are "compliments," β_8 is expected to be positive, or if they are "substitutes," it will be negative. The elasticity of state agricultural *TFP* with respect to private agricultural research capital (*RPRI*) is given in equation (8) and it is a constant.[4]

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

$$(9) \qquad \frac{\partial \ell nTFP}{\partial SFF} = (\beta_3 + 2\beta_4 \, SFF) \, \ell n \, RPUB,$$

$$(10) \qquad \frac{\partial \ell nTFP}{\partial GR} = (\beta_5 + 2\beta_6 \, \mathrm{GR}) \, \ell n \, RPUB.$$

Equations (9) and (10) show how 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 (9). 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 (10). 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.

We test the null hypothesis that SAES funding composition has no impact on state agricultural *TFP*; i.e., discoveries from all types of funds---federal formula and state government appropriations, federal grants and contracts, and "other" funding---are equally productive for causing technical change leading to growth in state agricultural *TFP*. This is the joint null hypotheses: $\beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$. If this hypothesis is accepted, then the state agricultural *TFP* equation, equation (4) will be of a traditional form. If, however, this hypothesis is rejected, a public agricultural research policy that changes both the size of a state's public agricultural research capital and its composition, as reflected in *SSF* and *GR*, will have affect state agricultural *TFP*. The total impact of a marginal change of Rn*RPUB*, *SFF*, and *GR* on *TFP* is:

$$(11)\quad d\ \mathrm{Rn}TFP = [\mathrm{MRn}TFP/\mathrm{MRn}RPUB]\ d\ \mathrm{Rn}RPUB + [\mathrm{MRn}TFP/\mathrm{M}SFF]\ d\ SFF + [[\mathrm{MRn}TFP/\mathrm{MRn}\ GR]\ d\ GR.$$

However, if changes are larger than marginal ones, taking differences between beginning and ending values of Rn *TFP* gives results that are more reliable. First, evaluate equation (4) at the sample mean values for each state to establish a baseline. Second, define new values of the public R&D policy variables as $\mathrm{Rn}\ RPUB' = \mathrm{Rn}\ RPUB^{o} +)\ \mathrm{Rn}\ RPUB$, where an "o" superscript is used to designate the starting value of a variable or baseline and a "′" is used to designate the new value of a variable. Likewise, let $SFF' = SFF^{o} + \Delta SFF$, and $GR' = GR^{o} + \Delta GR$. Third, compute the difference between new and baseline estimates as:

$$
\begin{aligned}
(12)\quad \Delta \ell n TFP &= \ell n TFP' - \ell n TFP^{o} = \beta_2 \ell n RPUB' + \beta_3 (\ell n RPUB')\, SFF' \\
&+ \beta_4 (\ell n RPUB')(SFF')^2 + \beta_5 (\ell n RPUB')\, GR' + \beta_6 (\ell n RPUB')\, (GR')^2 \\
&+ \beta_8 (\ell n RPUB')\, \ell n EXTF^{o} - \beta_2 \ell n RPUB^{o} - \beta_3 (\ell n RPUB^{o})\, (SFF^{o}) \\
&- \beta_4 (\ell n RPUB^{o})\, (SFF^{o}) - \beta_5 (\ell n RPUB^{o})\, (GR^{o})^2 - \beta_8 (\ell n PRUB^{o})\, \ell n EXT^{o}
\end{aligned}
$$

With the use of public funds allocated to agricultural research having alternative uses, it is interesting to ask what the social rate of return on these investments is. For example, if one million dollars of additional public funds is invested today in an average state, it will have benefits distributed over the next 34 years in this state and other states in the same area, which are recipient of spillin effects. By setting the net present value of the benefits equal to the cost, we can solve for the internal rate of return. When benefits are in constant prices, we obtain a real rate of return on the public investment. The internal rate of return (r) computation is:

$$
(13)\quad 1 = \left[\frac{\partial \ell n TFP}{\partial \ell n RPUB} Q/T + (n-1)\ \frac{\partial \ell n TFP}{\partial \ell n RPUBSPILL}\ Q/S\right] \sum_{0}^{m} w_i [1/(1+r)^t]
$$

where Q is the sample mean value for state agricultural output, T is the sample mean for a state's own public agricultural research capital, (n -1) is the number of state into which agricultural research spillin effects flow. S is the sample mean of the public agricultural research spillin capital, w_is are timing weights used to create the stock of public agricultural research, and r is the internal rate of return including impacts of R&D spillover (see Yee et al. 2002, p. 191).

The Data and Results

The data set is a state panel on aggregate agriculture, 1970 to 1999, for 48 contiguous states, or 1,440 observations. We use the new annual state total factor productivity (*TFP*) data obtained from the USDA (see Ball et al. 2002). 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 (1993) research price index. These real research expenditures with a productivity orientation are not strongly trended over the sample period. The science of constructing research stock variables from expenditures remains in its infancy (Griliches 1979, 1998). Although a few researchers have included many lags of public agricultural research expenditures without much structure, e.g., Alston, Craig, and Pardey (1998), this generally asks too much of the data. Hence, by imposing priors about the share of timing weights, we reduce the demands on the data to identify parameters.

Griliches (1998) concludes that R&D most likely has a short gestation period, then blossoms, and is eventually obsolete. We approximate these patterns with a gestation period of 2 years during which the impacts are negligible, impacts are then assumed to be positive over the next 7 years and are represented by increasing weights, followed by 6 years of maturity during which weights are high and constant, and then 20 years with declining weights where weights fade out to zero.[5] This weighting pattern is known as trapezoid-shaped time weights (see figure 1), and they are used to translate the real public agricultural research expenditures into a real public agricultural research stock (*RPUB*).[6] Although regional grouping of states in which spillin effects might occur are arbitrary, we choose to define spillovers using the geo-climate sub-region map of Huffman and Evenson (1993, p. 195).[7]

To construct state private agricultural R&D capital, we apply similar shaped but shorter in length timing-weights. The total length is 19 years, which is consistent with U.S. patent length. The number of agricultural patents issued (see Johnson and Brown 2002) is used to approximate private agricultural R&D in each state. A measure of public agricultural extension capital is constructed from staff days of agricultural and natural resource extension activity (Ahearn, Lee, and Bottom 2002). We assume that one-half of the impact of extension occurs in the current year, and the balance is allocated with declining weights over the next four years. See table 1 for definition of symbols and summary definitions.

Interaction terms between a state's public agricultural research stock and SAES funding shares were created, i.e., the share of the SAES funds from federal formula and state government appropriations (*SFF*) and federal grants and contracts (*GR*) were multiplied by Rn*RPUB*. However, given that the public agricultural research stock was derived using 34 years of data, we lagged *SFF* and *GR* by12 years to place them roughly at the weighted mid-point of the total lag length. We also created an interaction term between the stock of public agricultural research and stock of agricultural extension, i.e., Rn*RPUB* x Rn*EX*T.

Data for 48 states, 1970-1999, giving a total number of 1,440 observations, are pooled together and used to fit equation (4). Although more than a decade ago, it was somewhat common to undertake some type of feasible generalized least squares estimation (FGLS) using quasi-first differences when fitting a model to a panel set of observations over time (e.g., see McGuirk, Driscoll, and Alwang 1994), the state of knowledge and the standard has changed is then. In recent years, it has become popular and acceptable to estimate models by OLS but to correct the standard errors for a general form of autocorrelation and heteroscedasticity (see Davidson and MacKinnon 1993, p. 548-556; White 1980; MacKinnon and White 1985; Wooldridge 1989, 2003, p. 410). Even though we know that OLS will be inefficient, good reasons exist for taking this approach. First, the explanatory variables may not be strictly exogenous. If they are not, FGLS is not even consistent, let alone efficient. Second, in most applications of FGLS, the errors are assumed to follow a first-order autoregressive process [AR(1)] and quasi-first differences applied before estimation. Since rho (D), the first-order autocorrelation coefficient, and variance of the disturbances are unknown, the best-case scenario with FGLS is a consistent estimator, which requires that the sample size go to infinity. In panel-data over time, we will, however, be in the small sample situation. In this case, FGLS has unknown statistical properties and can hardly be claimed to be better than OLS. Hence, it may be better to compute standard errors for the OLS estimates that are robust to general forms of serial correlation and heteroscedasticity (Wooldridge 2003, p. 410). This is the route that we take in this paper; we report OLS parameter estimates for equation (4) and t-values computed from autocorrelation- and heteroskedastic-robust standard errors using the SAS program.

Table 2 displays least squares estimates of the parameters of the model. All of the coefficients are significantly different from zero at the 1 percent level.[8] The R^2 is 0.52, and a joint test of no explanatory power of the equation gives a sample F-statistic of 140. This test has 15 and 1,424 degrees of freedom, and the tabled F-value is about 2.0 at the 1 percent significance level. Hence, the state aggregate *TFP* model has significant explanatory power.[9]

Using sample mean values of the data, the elasticity of *TFP* with respect to *RPUB*, *RPUBSPILL*, *EXT*, and *RPRI* is 0.231, 0.123, 1.267 [=1.364 – 0.075(1.292)], and 0.113, respectively. These elasticities are all positive. Public agricultural research capital and extension capital interact negatively, i.e., the estimate of β_8 is -0.075. Hence, public agricultural research and extension are substitutes which is similar to what Huffman and Evenson (1993) found for the livestock sub-sector. Hence, public agricultural research and extension seem to have become stronger substitutes over time. The coefficients of the variables describing the composition of SAES agricultural research funding, $\$_3$, $\$_4$, $\$_5$, and $\$_6$ are each significantly different from zero individually at the 1 percent level. Also, the joint test of no funding composition effects, i.e., $\beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$, is soundly rejected. The sample F-statistic for this joint test is 16.8, and the critical value of the F-statistic with 4 and 1424 degrees of freedom at the one percent significance level is about 3.4. Hence, the productivity of the state public agricultural research capital is affected significantly by the composition of SAES funding, i.e., all types of funding are not equally effective with respect to impacts on state agricultural productivity.

To gain insight, we graph MRn*TFP*/M*SFF* against *SFF.* If the marginal effect is zero, then a change in the share of state agricultural experiment station funding coming from federal formula and state appropriations (block grants) would not affect the productivity of public agricultural research. If MRn*TFP*/M*SFF* is a constant and positive (negative), then any incremental changes in *SFF* and dMRn *TFP* will move in the same (opposite) direction. If the marginal effect of *SFF* on *TFP* is initially low and then it increases over some range of SFF, eventually topping out, and turning downward again, then dMRn*TFP*/M*SFF* will have an inverted "U" shape pattern as *SFF* increases. This type of pattern has an easily computable value of *SFF* that gives maximum marginal effect of *SFF* on dRn*TFP.* Similar statements can be made about how MRn*TFP*/M*GR* changes as GR increases. The patterns of marginal effects of *SFF* and *GR* on dMRn *TFP* are displayed in figures 2 and 3.

The empirical estimates of the marginal impact of *SFF* on Rn *TFP* has in fact an "inverted U shape," which peaks at 0.702 (see figure 2) and of *GR* on Rn*TFP* has a "U shaped" (see figure 3), which has a minimum at 0.237. In contrast, the sample mean value of SFF_{t-12} is actually 0.75 and of GR_{t-12} is 0.096. Hence, at the sample mean, the evaluation of equation (9) gives a marginal effect of changing *SFF* on Rn *TFP* of -0.124 [= -0.073 + 2(0.154)0.751] 16.29 and of *GR* on Rn *TFP* of -0.701 [= -0.073 + 2 (0.154)0.096] 16.129. *Hence, an incremental re-allocation of funds from SFF, say 5 percentage points, 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.*[10]

Simulations

The current blend of federal formula and state appropriations, as opposed to federal competitive grants, contracts, and cooperative agreements, provides SAES directors with considerable flexibility in using the resources and providing direction for research programs that meet 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. Generally, state legislatures expect their land-grant universities to spend state appropriations on finding solutions to local problems. Failure of state agricultural experiment station directors to deliver on discoveries needed locally will most likely result in a future weakening of state legislative support, which has occurred in some states, e.g., Wisconsin and Colorado.

Some officials have suggested reducing federal formula funds for experiment station research. One option is to offset the reduction of federal formula funds with increases in competitive grant programs, although Congress has been reluctant to pursue this scenario. We will show that such a shift would lower agricultural productivity in general and benefit only a few states while reducing funds and agricultural productivity for all the other states.

One possible scenario would be to reduce total federal SAES funding from federal-formula funding (*SFF1*) by 10 percentage points, and, hence, reduce *SFF* ()*SFF* =)*SFF*1). These funds then could be re-allocated to the USDA's competitive grant programs, e.g., to the National Research Initiatives, i.e., to increase *GR*. We assume that these funds actually go to the state agricultural experiment stations.[11] Two things are of significant interest, the long-run impact on SAES funding (and the stock of public agricultural research, *RPUB*) and on state agricultural *TFP*.

To implement this policy at the state level, we assume that each state will have their baseline federal formula funds rescaled by 13/23 and their federal grants and contracts funding will increase by a factor of 2.04 times the baseline value.[12] Following this policy, twenty-six states would have an increase in their public agricultural research stock, and six states (California, Indiana, Michigan, New York, Oregon, and Wisconsin) would have more than a 10 percent increase. Twenty-two states would have a decline, and in six states (Kentucky, Massachusetts, New Hampshire, South Carolina, Vermont, and West Virginia), the decline would be by more than 10 percent. Using equation (12), we compute the implied change in Rn *TFP* for each state.[13] This change is not proportional to the change in the public agricultural research capital (*RPUB*) because the share of SAES funding from federal formula and state government appropriations (*SFF*) and federal grants, contracts, and cooperative agreements (*GR*) are also changing, and we have shown that they impact Rn*TFP*, too. Forty-five states would experience a decline in Rn*TFP* from this policy change; the largest—approximately an 8 percent decline would occur in Alabama, Nebraska and West Virginia.[14] Only three states would experience an increase in state agricultural productivity—California, Oregon, and Wisconsin. These latter states have a history of significant reliance on federal grants and contract for SAES funding (see Appendix table 1 for more details).

When public agricultural research is funded by federal competitive grants and contracts, the research agenda is set by the funding agency in Washington, D.C., and decisions are based on proposals rather than completed projects. In addition, the federal competitive-grants programs do not pay for research proposal writing, so the risk of federal research grant programs is borne by the competing scientists or their institutions and the somewhat distorted incentive structure increases transactional costs, while lowering the scientists' productivity. Furthermore, federal funding agencies tend to fund less than 100 percent of funded research project costs, so other funds, most notably state-appropriated or federal formula funds, are used to subsidize research sponsored from outside the state. 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 who 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 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. This is thought to be, in part, because the state agricultural experiment stations have a long-term focus on addressing local problems. As a result, the positive reputation earned through these long-term relationships creates strong incentives for discovery (Huffman and Just 1999, 2000) and incentives that are different for one-time or inconsistent funding (or contracting) from a federal competitive grant program.

Conclusions

This study has presented new econometric evidence of the determinants of state *TFP*, placing special emphasis on the composition of SAES funding on state agricultural *TFP* growth over 1970-1999. The results showed that complex interaction effects exist between a state’s public agricultural research capital stock and SAES funding composition—shares of federal formula and state appropriations (programmatic funding) and of federal grants and contracts. These results showed that a marginal percentage point transfer of federal funds from formula to competitive grant programs, holding total funding constant, would on average reduce state agricultural productivity. A more complex simulation, e.g., a 10-percentage point reduction in federal formula funds (a rescaling by the amount by 13/23) and transfer to federal competitive grants program (a rescaling of amount by 2.04), would cause non-marginal adjustments in Rn TFP across the states. The results showed that only 3 states would experience an increase in Rn*TFP*, but the other 45 would face a decrease. Hence, it is not hard to imagine that most agricultural experiment station directors would be opposed to this re-allocation.

Returning to the broader issue of the social rate of return to public funds invested in agricultural research, our estimate is of a 56 percent real marginal return. This number 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. This value compares favorably with estimates reported by Evenson (2001).

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 59 percent. Due to the nature of research, a long lag exists from the initial investment in a project to the time when useful discoveries result. It is easy to overlook the important role of timing in public agricultural research. If for some reason, current investments would drop to zero, research benefits would continue for some time, at a reduced rate, but it would be very difficult for future research to ever 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 problems and issues. In research, lost time is difficult to recover.

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Table 1. Variable Names and Definitions

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* (0.870)	The public agricultural research stock for an originating state. The summation of past public sector investments in agricultural research with a productivity enhancing emphasis (Huffman, McCunn, and Xu) in 1984 dol (Huffman and Evenson 1993). Stock obtained by summing past research expenditures with a 2 through 34 year lag and trapezoidal shaped timing weights
Private agricultural research capital	*RPRI*	6.076* (0.248)	A state's stock of private patents of agricultural technology. The number of patents 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, horticulture and greenhouse products, and livestock and livestock services by a state's 1982 sales share in crops (excludes fruits, vegetables, horticultural and greenhouse products), fruits and vegetables, horticulture and greenhouse products and livestock and livestock products, respectively. The annual patent total are summed with a 2 thru 18 year lag using trapezoidal timing weights.
Public extension capital	*EXT*	1.292* (0.976)	A state's stock of public extension is created by summing public full-time equivalent staff in agriculture and natural resource extension applying 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.
Budget share from federal grants and contracts	GR_{t-12}	0.096 (0.076)	The share of the SAES budget from National Research Initiative, other CSRS funds, USDA contracts, grants and cooperative agreements, and nonUSDA federal grants and contracts (USDA), lagged 12 years.

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), 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)	$SFF1_{t-12} + SFF2_{t-12}$
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
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 variables 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
Public agricultural Research Spillin	*RPUBSPILL*	17.763* (0.567)	The public agricultural research spillin stock for a state is constructed from state agricultural subregion data (see Huffman and Evenson, 1993, pp. 195)

*Numbers reported in natural logarithms.

Table 2. Least-Squares Estimate of Total Factor Productivity Equation, 48 States: 1970-1999[a/] [n=1,440]

Regressors[b/]	Coefficient	t-Values[c]	
		White	Traditional
Intercept	-8.701	17.60	18.38
Rn (*Public Ag Res Capital*)$_t$	0.290	10.39	12.15
Rn (*Private Ag Res Capital*)$_t$	0.113	3.42	4.40
Rn (*Public Extension Capital*)$_t$	1.364	8.83	7.07
Rn (*Public Ag Res Capital*)$_t$*SFF_{t-12}	0.123	5.46	4.60
Rn (*Public Ag Res Capital*)$_t$*$(SFF_{t-12})^2$	-0.087	5.61	4.85
Rn (*Public Ag Res Capital*)$_t$*GR_{t-12}	-0.073	6.58	6.11
Rn (*Public Ag Res Capital*)$_t$*$(GR_{t-12})^2$	0.154	5.36	4.55
Rn (*Public Ag Res Capital*)$_t$*Rn (*Public Extension Stock*)$_t$	*-0.075*	3.46	6.11
Rn (*Public Ag Res Capital Spillin*)$_t$	0.123	12.55	10.33
Regional Indicators			
Northeast (=1)	0.176	10.02	5.84
Southeast (=1)	0.066	4.03	2.89
Northern Plains (=1)	0.342	6.44	11.48
Southern Plains (=1)	0.079	5.59	3.41
Mountain (=1)	0.226	5.79	8.70
Pacific (=1)	0.112	3.24	4.20
R^2	0.524		

[a/] The Central Region is the excluded region.
[b/] The dependent variable is Rn (*TFP*)$_t$
[c/] White t-values are computed using White (1980) and Wooldridge (1989) for heteroscedasticity- and autocorrelation- robust standard errors (Wooldridge 2002, p. 57).

Appendix Table 1. Baseline and Simulation Results: Re-allocation of 10 percentage points of federal formula funds to federal grants and contracts[a]

	Mean Values, 1970-1999					Simulated Outcome			
STATE	SFF1t-12	SFF2t-12	GRt-12	ORt-12	REV1P[b]	ΔlnPRUB3	ΔGRt-12	ΔSFFt-12	ΔlnTFP
AL	0.2327	0.4141	0.0564	0.2967	19777.07	-0.0435	0.0636	-0.0769	-0.0841
AR	0.2087	0.5313	0.0333	0.2267	19657.41	-0.0581	0.0381	-0.0532	-0.0508
AZ	0.1203	0.6202	0.1157	0.1437	20078.46	0.0654	0.1038	-0.0944	-0.0358
CA	0.0520	0.6967	0.1662	0.0850	95084.71	0.1402	0.1286	-0.1209	0.0104
CO	0.2290	0.4831	0.1753	0.1126	18937.18	0.0487	0.0751	-0.0657	-0.0080
CT	0.2022	0.6167	0.1266	0.0545	7591.56	0.0394	0.1119	-0.1091	-0.0135
DE	0.3461	0.4132	0.0570	0.1836	4255.42	-0.0962	0.0695	-0.0883	-0.0660
FL	0.0625	0.7594	0.0600	0.1180	52301.81	0.0344	0.0571	-0.0531	-0.0284
GA	0.1913	0.5937	0.0427	0.1721	31351.12	-0.0397	0.0480	-0.0564	-0.0453
IA	0.1766	0.4234	0.1444	0.2557	31220.50	0.0709	0.1297	-0.1126	-0.0615
ID	0.2169	0.5562	0.0520	0.1749	10357.87	-0.0443	0.0495	-0.0568	-0.0467
IL	0.2049	0.4889	0.1137	0.1925	22467.72	0.0285	0.1107	-0.1059	-0.0602
IN	0.1562	0.3719	0.1980	0.2740	29789.08	0.1295	0.1568	-0.1236	-0.0318
KS	0.1285	0.5142	0.0991	0.2583	25025.89	0.0456	0.0919	-0.0804	-0.0617
KY	0.3454	0.6314	0.0023	0.0210	15319.23	-0.1603	0.0031	-0.0068	-0.0432
LA	0.1290	0.7666	0.0350	0.0694	25123.29	-0.0198	0.0379	-0.0392	-0.0241
MA	0.3629	0.5227	0.0464	0.0680	6012.92	-0.1184	0.0529	-0.0573	-0.0419
MD	0.2382	0.6250	0.0638	0.0729	10431.63	-0.0406	0.0626	-0.0657	-0.0333
ME	0.3264	0.3967	0.0660	0.2110	7038.70	-0.0786	0.0730	-0.0884	-0.0725
MI	0.1653	0.4958	0.1731	0.1658	30027.38	0.1026	0.1443	-0.1286	-0.0207
MN	0.1750	0.6304	0.1052	0.0894	32194.02	0.0328	0.1017	-0.0986	-0.0266
MO	0.2186	0.4676	0.1036	0.2102	20672.59	0.0124	0.1040	-0.1011	-0.0672
MS	0.2587	0.4480	0.0657	0.2275	22716.40	-0.0454	0.0753	-0.0851	-0.0790
MT	0.1819	0.4495	0.0900	0.2786	10514.76	0.0142	0.0899	-0.0862	-0.0764
NC	0.1804	0.5510	0.1350	0.1335	41020.45	0.0601	0.1234	-0.1157	-0.0335
ND	0.1776	0.6347	0.0528	0.1349	15453.58	-0.0226	0.0575	-0.0599	-0.0421
NE	0.1081	0.3799	0.0947	0.4174	29478.07	0.0500	0.0880	-0.0681	-0.0877
NH	0.5510	0.3618	0.0062	0.0811	2877.41	-0.2669	0.0084	-0.0333	-0.0331
NJ	0.1551	0.6264	0.0836	0.1349	14620.41	0.0189	0.0824	-0.0809	-0.0403
NM	0.2752	0.5318	0.0960	0.0970	7335.32	-0.0212	0.0998	-0.1022	-0.0412
NV	0.2740	0.4841	0.1055	0.1364	5072.64	-0.0102	0.1087	-0.1111	-0.0476
NY	0.1121	0.5443	0.1685	0.1750	44864.97	0.1185	0.1342	-0.1121	-0.0249
OH	0.2300	0.7187	0.0230	0.0283	23238.50	-0.0793	0.0275	-0.0294	-0.0338
OK	0.2204	0.5730	0.1081	0.0985	15940.21	0.0162	0.1069	-0.1058	-0.0337
OR	0.1207	0.4549	0.2232	0.2012	23783.39	0.1640	0.1576	-0.1291	0.0053
PA	0.2894	0.5384	0.0836	0.0886	20678.89	-0.0398	0.0934	-0.0970	-0.0465
RI	0.3765	0.3625	0.1791	0.0819	2678.67	0.0194	0.1700	-0.1694	-0.0099
SC	0.3242	0.6072	0.0033	0.0653	14304.31	-0.1495	0.0043	-0.0178	-0.0234
SD	0.2439	0.5530	0.0359	0.1671	8441.07	-0.0714	0.0420	-0.0542	-0.0492
TN	0.2811	0.3434	0.1395	0.2360	16770.50	0.0168	0.1181	-0.1181	-0.0730
TX	0.1616	0.5076	0.0895	0.2413	50730.37	0.0225	0.0889	-0.0836	-0.0693
UT	0.2343	0.4819	0.1743	0.1095	9576.64	0.0762	0.1538	-0.1464	-0.0076
VA	0.2059	0.4897	0.1423	0.1622	24834.60	0.0569	0.1318	-0.1228	-0.0418
VT	0.4728	0.4322	0.0299	0.0651	3172.35	-0.1953	0.0374	-0.0460	-0.0545
WA	0.1698	0.5274	0.0993	0.2035	21602.13	0.0279	0.0943	-0.0880	-0.0596
WI	0.1512	0.4933	0.2490	0.1065	36581.87	0.1765	0.1755	-0.1582	0.0594
WV	0.4821	0.3523	0.0512	0.1144	5300.50	-0.1700	0.0724	-0.0937	-0.0790

WY	0.2993	0.5706	0.0655	0.0645	4731.49	-0.0648	0.0752	-0.0793	-0.0415

[a] See text for full discussion of the context of the change.

[b] Total value of SAES funds for all uses in 1984 dollars (1,000s)

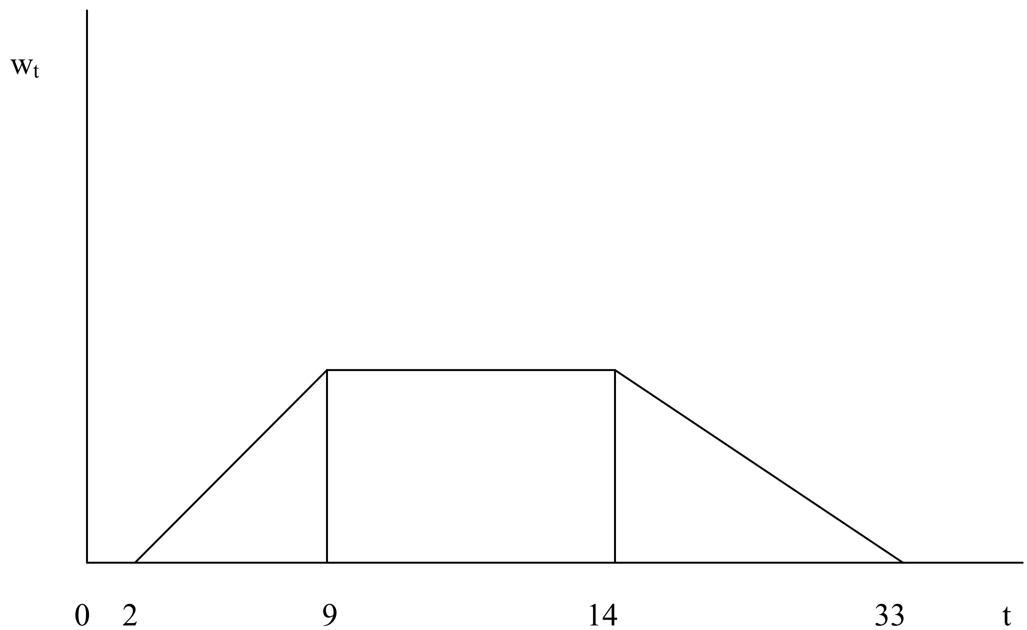

Figure 1. Public Agricultural Research Timing Weights.

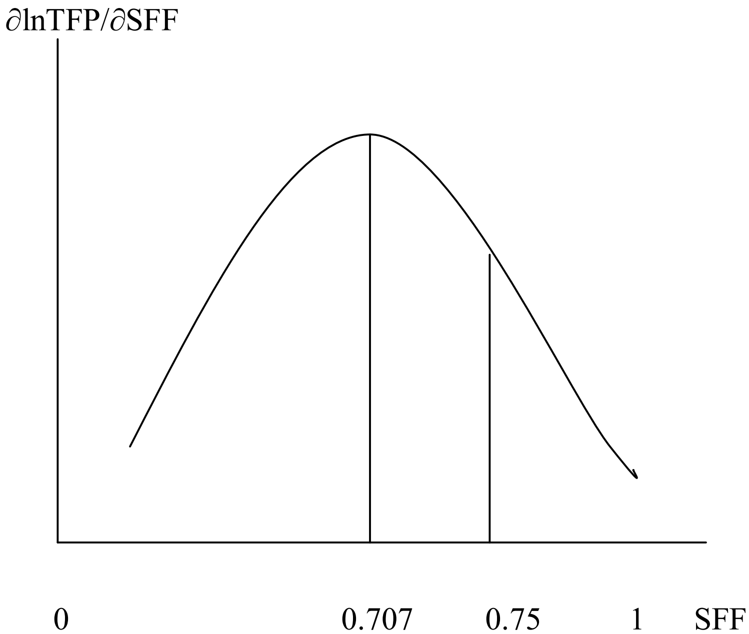

Figure 2. Marginal Effect of SFF on lnTFP.

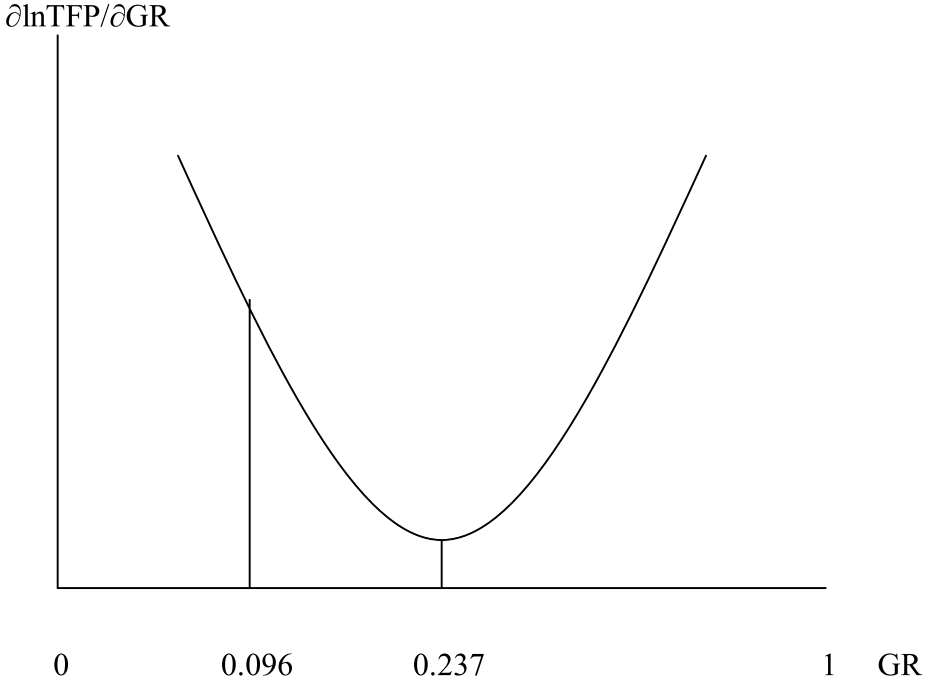

Figure 3. Marginal Effect of GR on lnTFP.

Endnotes

[1] See Acquaye, Alston, and Pardey (2003) for an another perspective on U.S. agricultural TFP growth over the period 1948 to 1991.

[2] Note that empirically *TFP* has a weak lower bound roughly at zero, i.e., when there is a total "crop failure." It, however, 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. The one we choose is double-logarithmic 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 stocks but no significant impact was identified.

[3] In particular, Huffman and Evenson (1993) found that public agricultural research and extension stock interacted positively in the crop sub-sector and negatively in the livestock sub-sector.

[4] Significant public and private agricultural research stocks interaction effects did not exist.

[5] See Evenson (2001) and Alston and Pardey (2001) for a discussion of timing weights.

[6] A number of studies have used "trend" to proxy technical change, e.g., Capalbo and Denny (1986), Chavez and Fox (1992), and Lim and Shumway (1997). Our public agricultural research variable is a much better proxy for useful technical change and because it is constructed from real public agricultural research expenditures it is not strongly trended over the study period.

[7] Similar weights were used by Huffman and Evenson (1993). We have followed a common convention in constructing interstate public agricultural research spillover variables using all productivity-oriented public agricultural research expenditures, e.g., see Huffman and Evenson (1993), Khanna, Huffman, and Sander (1994), and McCunn and Huffman (2000). Of course other options are possible, but federal grant funds are frequently insufficient to complete a project which means that federal formula and state appropriated funds may be diverted to these objectives. Our use of spatial weights derived from geo-climatic regions (see Huffman and Evenson 1993) performed better than the regional weights limited to state boundaries which Khanna, Huffman, and Sandler (1994) and McCunn and Huffman (2000) have used.

[8] If heteroscedasticity and or autocorrelations were serious in our data, we would expect the "robust t-values" to be much smaller in absolute value than for the traditional t-values. In contrast, for our data these two t-value are on average approximately the same—about 7.13.

[9] Using the residuals from this equation, the estimate of rho, the first-order autocorrelation

coefficient, averaged across all 48 states is only 0.11, which is near zero and far from 1, the unstable value.

[10] See Huffman and Evenson (2003) for a model of the determination of funding shares for the state agricultural experiment stations, i.e., making funding share endogenous.

[11] Given that the National Research Initiate (NRI) Program is a national competitive program, some of the funded projects are for individuals who are not at a land-grant university an, hence, not associated with a state agricultural experiment station. In only two cases, a state agricultural experiment station is not directly affiliated with a land-rant university.

[12] The percentage change in RPUB and the size of the total real SAES budget in 1984 dollars is assumed to be the same.

[13] We treat this scenario as a non-marginal change, and apply the difference equation (12).

[14] We have ignored the impact of the policy change on public agricultural research spillin, RPUBSPILL, because it is difficult to approximate how it would change. In addition to public agricultural research impacting state agricultural productivity, it may have other largely independent effects, including basic scientific discoveries, which are socially valuable but not related to agricultural productivity (Committee on Opportunities in Agriculture, 2003). Hence, our simulation results may not capture all of the social benefits of a re-allocation of federal funds between formula and grants and contracts.