Rates of Return to Public Agricultural Research in the Presence of Research Spillovers

by

Jet Yee, Economic Research Service

and

Wallace Huffman, Iowa State University

Selected Paper for Presentation at the
American Agricultural Economics Association Meetings
Chicago, Illinois
August 5-8, 2001

Abstract

This study uses new state data to examine the contributions of public agricultural research, extension, and infrastructure to agricultural productivity. The estimated social rates of return (which take into account spillover effects) are high and imply a need for federal or regional institutions to coordinate public agricultural research funding.

Address for Correspondence:

Jet Yee
Economic Research Service
1800 M Street, NW
Washington, DC - 20036
Phone: (202) 694-5611
E-mail: jyee@ers.usda.gov

The level of knowledge in any one state or industry depends not only on its own research investment, but is also affected by the knowledge borrowed from other states or industries. That is, the productivity of the agricultural sector in a state depends also on the research investments of other industries and states. For example, a new variety of corn developed in Iowa may be available to the farmers in Illinois. Similarly, U.S. agricultural productivity may benefit from spillovers of technology developed by foreign research expenditures. A few studies (e.g., Evenson, 1989) have found cross-state spillovers from agricultural research to be significant.

Prior efforts to explain the sources of state agricultural productivity growth have been undertaken by Huffman and Evenson (1993) and Alston, Craig, and Pardey (1998). Huffman and Evenson (1993) constructed a state level productivity data set for 42 states for the period 1950-1982. They used public and private research stocks and agricultural extension stocks to explain TFP. They used public agricultural research expenditures focused on discoveries to enhance and maintain agricultural productivity to create one public agricultural research stock variable for each state that contained both a state's own contribution and spill-in contributions from adjacent states. The impacts of public agricultural research on agricultural productivity were generally positive.

Alston, Craig, and Pardey (1998) constructed another state level productivity data set for 48 states, 1949-1991 which they used to examine the impact of a single combined public agricultural research and extension variable on TFP. They used essentially all of the public agricultural research expenditures of state agricultural experiment states to construct the research and extension stock variable, irrespective of whether the research was focused on production agriculture. Interstate spillovers were not considered. They found positive effects of the combined public agricultural research and extension variable on agricultural productivity.

Our problem in this paper is to measure the spillover effects of the research performed in other geographical areas on a state's agricultural productivity. Using newly-constructed data on agricultural productivity (TFP), production-oriented public agricultural research expenditures, production-oriented agricultural extension expenditures, and other variables at the state level, we estimate the separate contribution of a state's own public agricultural research and spill-ins from agricultural research in adjacent states to agricultural productivity. Our productivity model also takes into account public agricultural extension, infrastructure in highways, and weather. In addition, we examine the interaction effects between a state's own public agricultural research and agricultural extension. Our results add new information about the relative importance of a state's own public agricultural research, research spillovers, extension, infrastructure, and weather and the interaction effects between public agricultural research and extension. Having a better understanding of the sources of productivity growth and the rates of return to public resources invested in research, extension, and infrastructure is important to good public policy decision making.

The Model

In previous econometric studies of agricultural productivity, public and private research, extension, and farmers' schooling have been identified as the primary sources of productivity growth. Our productivity model also allows for spillin of research results from other states. Instead of pooling all 48 contiguous states for the period 1960-1993, we divide the states into several regions. We estimate a pooled regression for each region. In our model, the level of productivity in a state depends on the state's own research stock as well as the stock of research in the other states in the same region.

Assume a single, output aggregate production function with disembodied technical change:

$$(1)\quad Q = AF(K,L,M)(ownrd)^{\delta_1}(spillin)^{\delta_2}(ext)^{\delta_3}(hiway)^{\delta_4}$$

where Q is all types of outputs aggregated into one index of output, A is a constant, F(•) is a well-behaved function, K is physical capital input, L is quality adjusted labor input, M is quality adjusted materials input, ownrd is a state's own public research stock, spillin is the public research stock from other states, ext is public extension stock, and hiway is highway stock. (Since the measure of labor input we use accounts for the changing educational attainment of the farm workforce over time, we do not explicitly consider education as a determinant of output growth.)

Now define total factor productivity (P) as

$$(2)\quad P \equiv \frac{Q}{F(K,L,M)} = A(ownrd)^{\delta_1}(spillin)^{\delta_2}(ext)^{\delta_3}(hiway)^{\delta_4}.$$

Taking natural logarithms of both sides of equation (2) and adding an interaction between ownrd and ext, dummy variables for extreme weather conditions, and a random disturbance term, we obtain the following model that is linear in the unknown parameters (δ_j's):

$$(3)\quad \begin{aligned} \ln P = \ln A + \delta_1 \ln(ownrd) + \delta_2 \ln(spillin) + \delta_3 \ln(ext) + \delta_4 \ln(hiway) + \delta_5 \ln(ownrd)\cdot\ln(ext) \\ + \delta_6 drought + \delta_7\, flood + u. \end{aligned}$$

With the interaction term included, the output elasticity of ownrd is now $\delta_1 + \delta_5$ ln(ext) and of ext is $\delta_3 + \delta_5$ ln(ownrd). This specification of the research-extension interaction incorporates the hypothesis that stronger two-way flows of information occur between public agricultural research and extension conducted within a state than between spill-in research from other states and local extension. In particular, if farmers' production problems get transmitted to researchers through public extension personnel, we would expect the interaction effect to be positive. If public agricultural research and extension within a state function independently, we would expect the coefficient of the interaction term to be insignificant. If public research and extension effectively are substitutes in affecting agricultural productivity, we would expect δ_5 to be negative. Since we estimate equation (3) for each of seven regions, we also include state dummy variables in equation (3) to obtain our final econometric model.

Given estimates of the parameters in equation (3), own-state (private) and social (including inter-state spillovers) impacts of public agricultural research on agricultural productivity/output can be evaluated. The numbers can then be used to compute rate of return estimates to an increment in public agricultural research.

For simplicity, first assume no interstate spillover effects of public agricultural research investment in one state on agricultural productivity in other states occurs. The internal rate of return (r) for an additional research expenditure of ΔR_t in period t is the discount rate which results in the following equality:

$$(4) \quad \Delta R_t = \sum_{i=0}^{m} \frac{\Delta Q_{t+i}}{(1+r)^i}$$

or

$$(5) \quad 1 = \sum_{i=0}^{m} \frac{\Delta Q_{t+i}}{\Delta R_t} \cdot \frac{1}{(1+r)^i} = \sum_{i=0}^{m} \frac{\Delta Q_{t+i}}{\Delta T_{t+i}} \cdot \frac{\Delta T_{t+i}}{\Delta R_t} \cdot \frac{1}{(1+r)^i}$$

where Q is a state's output and T is its own public research stock (ownrd). Since the output elasticity of ownrd is $\delta_1 + \delta_5$ ln(ext),

$$(6)\quad \frac{\Delta Q_{t+i}}{\Delta T_{t+i}} = \left[\delta_1 + \delta_5 \ln(ext_{t+i})\right] \cdot \frac{Q_{t+i}}{T_{t+i}}$$

and

$$(7)\quad \frac{\Delta T_{t+i}}{\Delta R_t} = w_i$$

where the w_i's are the weights used to construct the research stock in equation (3). Hence, we can rewrite equation (5) as

$$(8)\quad 1 = \sum_{i=0}^{m} \left[\delta_1 + \delta_5 \overline{\ln(ext)}\right] \cdot \frac{\overline{Q}}{\overline{T}} \cdot w_i \cdot \frac{1}{(1+r)^i} = \left[\delta_1 + \delta_5 \overline{\ln(ext)}\right] \cdot \frac{\overline{Q}}{\overline{T}} \cdot \left[\sum_{i=0}^{m} w_i \cdot \frac{1}{(1+r)^i}\right]$$

where we have replaced ln(ext_{t+i}), Q_{t+i}, and T_{t+i} with their respective sample mean values.

With spillovers, equation (8) must be modified. An additional research expenditure of $\Delta R_{i,t}$ by state i in period t has two impacts. First, it affects state i's own research stock with a direct impact on state i's output. Second, it affects the research spillover stock available to all other states in the same region as state i with indirect impacts on those other states' outputs. By a similar derivation, we obtain

$$(9)\quad 1 = \left[\left[\delta_1 + \delta_5 \overline{\ln(ext)}\right] \cdot \frac{\overline{Q}}{\overline{T}} + (n-1) \cdot \delta_2 \cdot \frac{\overline{Q}}{\overline{S}}\right] \cdot \left[\sum_{i=0}^{m} w_i \cdot \frac{1}{(1+r)^i}\right]$$

where $\overline{S}$ is the average research stock from other states in the same region (spillin) and n is the number of states in the region. With positive interstate spillovers effects of public agricultural research on productivity of other states and other things equal, we see that the internal rate of return, r, must increase from equation (9) relative to equation (8). That is, the social (accounting for impacts in all states) rate of return from the investment in public agricultural research by one state must be greater than the private rate of return, or return as any one state sees it. Furthermore in equation (9), the internal rate of return must increase as n, the number of states in the region, increases, other things equal. This is just the regional public good attribute playing itself out. When Q, T, and S are in real terms, the r's computed are marginal real internal rates of return.

Data Sources and Variable Construction

Considerable effort has gone into the construction of the new data used in this study. We expect the level of productivity in a state to depend on the state's own research stock as well as the stock of research in some subset of other states, i.e., agricultural research discoveries are impure public goods (Huffman and Just 1999; Huffman and Evenson 1993). Much of agricultural production, especially crop production, is strongly affected by geoclimatic conditions. The geoclimate determines day length, precipitation amounts and patterns, and soil types. The movement of plant diseases and insects also has a strong spatial component. These are some reasons why research spillovers might be expected to have a strong spatial component. Much of non-grazing livestock production is, however, less affected by geoclimate, and fruit and vegetable production tend to occur in rather unique local environments which might be located long distances apart. These are some reasons why research spillovers might have a specie component that is transferred over long distances.

Several groupings of states were considered in our work. First, the old Economic Research Service (ERS) farm production regions date back to the 1950s. It consists of the 10 regions where states within a region are contiguous. The regions are: Northeast, Lake States, Corn Belt, Northern Plains, Appalachian, Southeast, Delta, Southern Plains, Mountain, and Pacific. Second, a National Research Council (NRC) study on colleges of agriculture at the land grant universities (Committee on the Future of the Colleges of Agriculture in the Land Grant University System 1995) conducted a cluster analysis to classify state agricultural experiment stations (SAES's) expenditures into 9 commodity research clusters.[1] In this grouping, some clusters consist of contiguous states and others do not. Third, McCunn and Huffman (2000) group the 48 states into seven regions, each containing contiguous states. Their grouping builds on earlier work by Khanna, Huffman, and Sandler (1994). The McCunn and Huffman (MH) regional grouping worked well for a study of convergence in state agricultural TFP growth rates, The earlier Khanna, Huffman, and Sandler paper examined state government decisions on funding state agricultural experiment stations in a model of impure public good provision.

The NRC regions differ from the ERS and MH regions in not having states which are contiguous. For example, California, Oregon, and Washington are in the same ERS region (Pacific), while California and Florida are in the same NRC region. The ERS and MH grouping are more similar to each other than to the NRC grouping. In fact, the Pacific, Mountain, Northern Plains, and Northeast regions are the same for both the ERS and MH groupings.[2] Based upon some preliminary experimentation, the MH grouping of states into regions gave the best empirical results, and it is the one used for creating research spillovers in this paper.

Data on total factor productivity (TFP) by state are new ERS estimates prepared by Ball and Nehring (ERS Staff Paper Number 9804).[3] The TFP numbers for each state are spatially adjusted so that they are comparable across states.

Public agricultural research expenditures were compiled by Huffman, McCunn, and Xu (2001), after making some improvements in the earlier Huffman and Evenson (1993; 1994) approach. The Huffman and Evenson research variables stopped in 1982, and the new series is extended to 1995, uses refined methods, incorporates new historical data on non-USDA federal expenditure on SAES research 1955-65, and builds on actual annual SAES expenditure/receipts over the 1927-1948 period.

Public agricultural research sector in each state consists of the state institutions--state agricultural experiment stations and schools/colleges of veterinary medicine--and the USDA agencies of the Agricultural Research Service and Economic Research Service.[4] Using the USDA's Current Research System (CRIS; see U.S. Dept. Agr. 1993) classification of research, agricultural research expenditures to enhance and maintain agricultural productivity are taken to be a subset of all CRIS research commodity categories (see USDA 1993). They are research expenditures on all farm commodities (e.g., corn, wheat, fruits, vegetables, beef, swine, dairy) in CRIS research problem areas (RPA's) that have a focus on enhancing or maintaining productivity (see Huffman and Evenson 1994, p. 120-121), plus all expenditures on the research commodity categories of structures and inputs, farm management, insects, and general science. Although there is undoubtedly some reporting errors by public scientists in their CRIS reports, we do not consider these errors to be serious in major aggregates.[5] The annual nominal agricultural research expenditures by state are converted to real (1984 = 1.00) expenditures using Huffman and Evenson's agricultural research price index (Huffman and Evenson 1993, Table 4.1 and p. 236-37).[6]

Research expenditures in a given year are expected to have an impact on productivity for many years. We can include as separate variables a finite number of lagged research expenditures in a production function such as equation (1). However, the large number of lagged research expenditures uses up a large number of degrees of freedom. Also, the lagged values of the research expenditures tend to be highly correlated. Griliches (1979; 1998) emphasizes that near-multicollinearity problems make it impossible to estimate research timing weights without some type of prior restrictions. What is usually done is to construct a research stock using current and past research expenditures:

$$(10) \quad T_t = \sum_{i=0}^{n} w_i R_{t-i}.$$

The science of research stock variables construction remains in its infancy (Griliches 1998, Ch. 12). The main reason is that the "true research stock" is unknown, so we need a good proxy or instrumental variable for it (Greene 1997, pp. 441-443). In studies of the impact of private research in manufacturing, the stock of research capital is frequently created from research expenditures using the perpetual inventory method. Griliches (1998) concludes the usual declining balance or geometric depreciation doesn't fit very well the likely gestation, blossoming, and eventual obsolescence of knowledge. In agriculture, where none of the public agricultural research is conducted on farms or under the direct control of farmers, the perpetual inventory approach is implausible (see Evenson 2000). Huffman and Evenson (1993; 1994) use a trapezoid-shaped timing weights after a short gestation period to approximate an agricultural research stock. There are 7 years of rising weights, followed by 6 years of constant weights, and then 20 years of declining weights; and the summation of the weights is one. Here we adopt the Huffman and Evenson trapezoidal timing weight pattern to derive the proxy variable for the public agricultural research stock.

It would be useful at this point to make a few comments concerning technological spillovers. The level of knowledge in any one sector or industry depends not only on its own research investment but is also affected by the knowledge borrowed or spilling in from other industries. That is, the productivity of the agricultural sector depends also on the research investments of other industries. The problem is to measure the spillover effects of the research performed by other industries on agricultural productivity.

There are several ways to proceed. Let T_j be the stock of technical knowledge in industry j. We can treat the T_j's as separate variables in a production function. However this is not feasible due to degrees of freedom and perhaps multicollinearity problems. We thus need to aggregate (similar to the research time lag problem). A measure of borrowed knowledge by the agricultural sector from other industries is

$$(11) \quad T_a = \sum_j w_j T_j$$

where T_a is the amount of knowledge borrowed by the agricultural sector from all other sectors. The weights (w_j's) differ by sector and reflect the fact that not all knowledge are equally useful to the agricultural sector. W_j becomes smaller as the technological "distance" between the agricultural sector and sector j increases. Measures of technological "distance" could be based on inter-sectoral purchases under the assumption that borrowed research is embodied in purchased inputs or could be based on research in common scientific fields (e.g., Jaffee 1986).

In addition to technological spillovers from private research, there are also geographical spillovers from public agricultural research performed by one state to other states. For example, some of the public agricultural research discoveries in Iowa may spillover to some or all of the surrounding states, i.e., spills in, or Iowa benefits from some or all the public agricultural research conducted in surrounding states. Similarly, U.S. agricultural productivity may benefit from spillovers of technology developed by foreign research expenditures. The techniques used to treat spillovers from private research can also be used to treat geographical spillovers. The weights (w_j's) in equation (11) reflect the fact that application of research results from another state or country is limited by the location-specific nature of much agricultural research.

We use two public research stock variables in our work. One is a state's own stock and the second is a spillin/spillover stock. Consistent with our regional grouping of states, we assume that discoveries from public agricultural research in a given state are an impure public good (Cornes and Sandler 1996; Khanna, Huffman, and Sandler 1994). In particular, we impose the simplifying assumption that benefits are regionally confined and apply a simple aggregation technology for the publicness of agricultural research. That is, we assume the weights (w_j's) are the same for all states in a given region and equal to zero for states outside the region. For a given state in a region, the spillover (or spillin) stock is defined as the total public agricultural research stock of all states in the region less the state's own public agricultural research stock.

Spillovers from private research is also a possibility. If an improved product is used as an input in the production of another product, its contribution will show up in the productivity measure of the industry that purchased it. So it is possible for research performed in the agricultural chemical industry to have no impact on its own productivity, but have an impact on agricultural productivity as traditionally measured.

We, however, do not directly consider private research in this study. The omission is due to several factors. Only national level data on private agricultural research expenditures exist, e.g., see Huffman and Evenson 1993, Klotz, Fuglie, and Pray 1995. Although Huffman and Evenson (2000, 1993) have applied a weighting system, which incorporates impure public good attributes of discoveries, to appropriate potential impacts to the individual states, their data set has not been revised or extended. Hence, state level data on private research are difficult to obtain or construct.

Finally, private agricultural research is performed because firms hope to appropriate most of the benefits of their research by increasing the prices of their products. These price increases should be reflected in quality changes in quality-adjusted price and quantity indexes. If the private firms were able to capture all the benefits of their discoveries and the quality adjustments were perfect, there would be no need for a private research stock variable. However, private firms cannot expect to capture all the benefits from their innovations. In the case of Bt-cotton, Falck-Zepeda, Traxler, and Nelson (2000) show that the input supply industry captured a little less than one-half of the total social benefits in 1996. Huffman and Evenson (1993), also, showed significant effects of private research on state agricultural productivity. Thus, we are undoubtedly missing some private research effects on state agricultural productivity.

There are really two types of technological spillovers that should be distinguished. The first type involves improved inputs purchased from another industry at less than its quality-adjusted price. These are really not pure spillovers, but are the result of measurement problems we just alluded to. The second type involves knowledge borrowed from industry j which is used to enhance (make more productive) the research efforts of industry i. This borrowing of knowledge may have very little relation to input purchases. For example, two industries may buy very little from each other, but are working on similar projects and hence can benefit from each other's research.

Our agricultural extension variable is constructed from estimates of production-oriented agricultural extension expenditures in each state per farm. Over 1955-1993, extension was organized into four program areas: agriculture and natural resources (ANR), community resource development (CRD), 4-H youth (4-H), and home economics (HE). The ANR program area includes crop production and management, livestock production and management, farm business management, agricultural marketing and supply, and natural resources. We collected data on professional extension full-time equivalents (FTE's) by state and major program areas from annual State Accomplishment Reports. To obtain an estimate of agricultural production related extension expenditures for a state, we multiplied the state's total expenditures on extension by the share of ANR full-time equivalent staff to total professional staff in all areas. An extension stock measure is obtained by applying the perpetual inventory method and a 50 percent depreciation rate.

Infrastructure refers to federal highways in this study. Data are available for 1931-1992 on capital stock from capital outlay and capital stock from maintenance (both in 1987 dollars) from the U.S. Department of Transportation, State Transportation Economic Division.[7] The Federal Highway Administration's composite price index was used to deflate the capital expenditure and maintenance outlay series to 1987 dollars. In this data set, the standard perpetual inventory technique was used to generate the highway capital stock from expenditures data. Following Eberts, Park, and Dalenberg (1986) discards are assumed to follow a truncated normal distribution, with the truncation occurring at one half the average life and one and one half times the average life. We extended the highway capital series to 1993. Our highway capital stock measure is total highway capital stock, which equals capital stock from capital outlays plus capital stock from maintenance.[8]

Extreme weather conditions (droughts and floods) affect agricultural productivity, and if they are controlled for, we may get better estimates of the impacts of other sources of productivity.[9] We employed the USDA's precipitation data weighted by harvested crop acreage to create a variable (pre-plant) equal to cumulative February to July rainfall. We then created a drought dummy variable (drought) equal to 1 if pre-plant is less than 1 standard deviation below normal (and 0 otherwise) and a flood dummy variable (flood) equal to 1 if pre-plant is more than 1 standard deviation above normal (and 0 otherwise).

The Empirical Results

We discuss in this section econometric estimates of the total factor productivity (TFP) equation for each of the 7 regions, and estimates of the marginal internal rate of return to investments in public agricultural research.

The TFP equations

Econometric estimates of the TFP equation (3) are estimated for each region, with and without an interaction variable between the stock of own public research and stock of extension. The equations were first estimated by ordinary least squares with state dummy variables included. Where first-order autocorrelation was a significant problem (as judged by the Durbin-Watson statistic), the productivity equation was re- fitted as a time series model with an AR(1) process with ρ allowed to differ across states. The Southern Plains was the only region which did not require a first-order autocorrelation correction. The estimation procedure also took into account within state heteroscedasticity as well as contemporaneous correlation of disturbances across states in the same region. (Tables containing the estimated results can be obtained by sending an e-mail to jyee@ers.usda.gov.)

For the Northeast region, all the estimated coefficients of the public policy variables are significantly different from zero at the 5 percent level when the research-extension interaction variable is included, and the estimated coefficients of spillin research and highways are positive. When the research-extension interaction variable is excluded, extension performs poorly. Thus, the TFP model with the research-extension interaction variable is judged to be the best. The estimated coefficient of the research-extension interaction variable is, however, negative, suggesting own research and extension are substitutes for impacting agricultural productivity in the Northeast region. Also, as expected, drought and flood have statistically significant negative impacts on agricultural productivity.

For the Southeast region, the TFP equation including the research-extension interaction variable performs poorly in the sense that the coefficients of the public policy variables are not significantly different from zero at the 5 percent level, except for spillin research. When the research-extension interaction term is excluded, the coefficients of own research, spillin research, and extension are positive and each significantly different from zero at the 5 percent level. We conclude that this is the best specification for the Southeast region. However, highways have a positive but not statistically significant effect on agricultural productivity in the Southeast region. Also, drought has a statistically significant negative impact on productivity here.

In the Central region, when the own-research and extension interaction variable is excluded from the TFP equation, the estimated coefficients of own research and highways are not significantly different from zero at the 5 percent level. However, when the research-extension interaction variable is included, all of the public policy variables have coefficients that are significantly different from zero and the estimated coefficients for spillin research and highways are positive. Furthermore, the estimated coefficient of the interaction variable is positive, suggesting that own research and extension are complements for impacting agricultural productivity in the Central region. In this region which has very little irrigation, both drought and flood variables have statistically significant negative impacts on agricultural productivity.

In the Northern Plains region, the own research and extension variables perform poorly when no own research-extension interaction variable is included. The estimated coefficients of own research and extension are not significantly different from zero. However, when the research-extension interaction variable is included, all the estimated coefficients of the public policy variables are significantly different from zero at the 5 percent level. The interaction model is the preferred model for the Northern Plains region. Furthermore, own research and extension are complements in the Northern Plains region. Drought has a statistically significant negative impact on productivity here.

In the Southern Plains region, all the estimated coefficients of the public policy variables are positive and significantly different from zero when no research-extension interaction variable is included in the TFP equation. When the interaction variable is included, its estimated coefficient is negative but not significantly different from zero at the 5 percent level. Hence, we conclude that in the Southern Plains region, the TFP regression without the research-extension variable is best. The impacts of droughts and floods on TFP are negative, but drought is statistically stronger and more frequently occurring in this region.

In the Mountain region, the estimated coefficient of own research is not significantly different from zero and that of extension is negative (and significant) when no research-extension interaction variable is included. However, when the interaction variable is included, the estimated coefficients of all research and extension variables are significantly different from zero, and the coefficient for own research is positive. For the Mountain region, we conclude that the TFP equation including the research-extension interaction variables is best. However, the estimated coefficient for the research-extension interaction variable is negative, suggesting that own research and extension are substitutes. Here, highways do not have a statistically significant effect on agricultural TFP, and drought has a statistically significant negative impact on agricultural productivity.

For the Pacific region, neither TFP model performs well. In particular, extension does not have a statistically significant impact in either equation. Extension appears to be a different activity in this region than in the other six regions. Hence, among the two equations reported, the one without the research-extension interaction variable is best. In this equation, the estimated coefficients of own research and spillin research are positive, but the coefficient for own research is only significant at the 7 percent level. Highways have a positive, but not statistically significant impact on agricultural TFP in the Pacific region. With this region being one of normally low precipitation and heavy reliance on irrigation, the negative but not significant effects of the drought and flood variables is not too surprising.

Next, we summarize the TFP elasticities associated with the public policy variables (own research, spillin research, extension, and highways) and report them in table 1. In the models without the research-extension interaction variable, the TFP (or output) elasticities are the estimated coefficients. In the models containing interaction variables, the TFP (output) elasticity of ownrd is $\delta_1 + \delta_5$ ln(ext) and of ext is $\delta_3 + \delta_5$ ln(ownrd), and these elasticities are evaluated by region at the respective regional sample mean values.

For the non-interaction model, TFP elasticities for ownrd are positive for all regions, except for the Mountain region (where the estimated coefficient was not significant). The TFP elasticity of public research spillin is positive for all regions. Perhaps surprising, the TFP elasticity with respect to public research spillin is greater than for ownrd, except for the Northern Plains. The elasticity of TFP with respect to hiway is positive for all regions. Ext, however, has a negative TFP elasticity for three regions: the Northern Plains, Mountain, and Pacific regions.

In the TFP models including the research-extension interaction variable, the TFP elasticity of ownrd is positive for all regions, except for the Northern Plains. The TFP elasticity of spillin is positive for all regions. In general, the interaction model, when evaluated at the regional sample means, increases the TFP elasticities for ownrd and decreases the TFP elasticities for spillin, compared to the non-interaction model. Spillin, however, still has a higher TFP elasticity than ownrd. Hiway has a positive TFP elasticity for all regions. Ext has a negative TFP elasticity for two regions (Northern Plains and Pacific). Since the coefficient of the interaction term is positive (and significant) for the Northern Plains region, this implies that a greater level of investment in a state's own research and extension efforts is needed to make the TFP elasticities positive. As we have noted, the TFP model with the own research and extension interaction variable is preferred to the non-interaction model for most of the regions.

The social rate of return to public agricultural research

The private and social real internal rate of return is computed for each of the seven regions. For each region, we compute the sample mean of Q, T, S, and ln(ext) to obtain values for a "representative state in the region" and for a "representative spillover effect" from other states within the region. Table 2 presents the calculated rates of return for each of the 7 regions for both the non-interaction and interaction models.

The marginal private real rate of return is obtained using equation (8) [or equation (9) with δ_2 set to zero]. The marginal social real rate of return takes into account own-state and spillover effects and is obtained using equation (9). As expected, for all regions the marginal social real rate of return is always greater than the own-state/private real rate of return. The own-state/private rates of return are generally sizeable but less than 100 percent and within the range found by other researchers for the U.S. (see Evenson 2000). The social rates of return are several times the private rates of return. Some of the social rates of return are surprisingly high, e.g., for the Northeast and Central regions the real social rate of return exceed 600 percent. Regions having a large number of states and large farm output per state have the largest social rate of return, which is as expected with a regional public good (i.e., summation technology for publicness within the region).

Concluding Remarks

This paper uses new data to provide new evidence on the contribution of public own research, spillin research, extension, and infrastructure in highways to agricultural productivity change over 1960 to 1993. The results are a significant addition to the literature because few studies have focused on agricultural productivity at the state level, and none has considered the effects of infrastructure or the direct effect of public agricultural research spillovers.

Where our results overlap with prior studies, the results are largely as expected. Public agricultural research and highways have positive impacts on agricultural productivity, and the marginal real social rate of return to public agricultural research is large. The results for public agricultural extension are mixed, but this is consistent with Huffman and Evenson (1993), and extension does not have a positive impact on agricultural productivity in two regions (in the interaction model). The model containing an own-research-and-extension interaction variable was preferred to the non-interaction model for most regions.

Spillin research stocks also impact agricultural productivity positively in almost all regions. Furthermore, the computed real rates of return to investments in public agricultural research to any one state is less than the social rate of return to all states in its region. Thus, state level planning for public agricultural research would be socially suboptimal. This outcome is consistent with the regional public good nature of public agricultural research, and it implies a need for a regional institution to coordinate public agriculture research funding and provision. Furthermore, our estimates of the marginal social rate of return is large by comparison with other studies reported in Evenson (2000), but this seems to be due largely to the direct incorporation of research spillin in our model of state agricultural productivity.

In this study, we have not included private research variables. If good private research variables were available, it might alter the story somewhat. This is left to future work.

Table 1. TFP or Output Elasticities with respect to Public Policy Variables (interaction terms evaluated at the respective regional means)

	Non-interaction Term Model			
Region	**Own R&D**	**Spillin R&D**	**Extension**	**Highway**
Northeast	0.16	0.24	0.03	0.35
Southeast*	0.08	0.38	0.07	0.03
Central	0.01	0.53	0.07	0.04
Northern Plains	0.26	0.13	-0.13	0.35
Southern Plains*	0.10	0.25	0.14	0.17
Mountain	-0.06	0.36	-0.05	0.12
Pacific*	0.16	0.49	-0.07	0.13

	Interaction Term Model			
Region	**Own R&D**	**Spillin R&D**	**Extension**	**Highway**
Northeast*	0.19	0.33	0.05	0.26
Southeast	0.09	0.38	0.07	0.03
Central*	0.10	0.40	0.03	0.14
Northern Plains*	-0.01	0.35	-0.19	0.52
Southern Plains	0.09	0.24	0.16	0.15
Mountain*	0.13	0.24	0.004	0.01
Pacific	0.20	0.48	-0.06	0.08

Notes: The preferred model is denoted by (*).

In the models without the research-extension interaction variable, the TFP/output elasticities are the estimated coefficients. In the models containing interaction variables, the TFP/output elasticity of ownrd is $\delta_1 + \delta_5 \ln(\text{ext})$ and of ext is $\delta_3 + \delta_5 \ln(\text{ownrd})$ evaluated at the regional sample means.

Northeast - ct, de, ma, md, me, nh, nj, ny, pa, ri, vt
Southeast - al, fl, ga, ky, nc, sc, tn, va, wv
Central - in, il, ia, mi, mo, mn, oh, wi
Northern Plains - ks, ne, nd, sd
Southern Plains - ar, la, ms, ok, tx
Mountain - az, co, id, mt, nv, nm, ut, wy
Pacific - ca, or, wa

Table 2. Own-State/Private and Social Real Rate of Return (r) to Public Agricultural Research in a State (percent)

Region	Interaction Private	Interaction Social	Non-interaction Private	Non-interaction Social	Number of States in the region
Northeast	106	> 600*	92	> 600	11
Southeast	46	290	43	290*	9
Central	89	> 600*	12	> 600	8
Northern Plains	0.0	390*	510	> 600	4
Southern Plains	52	210	55	220*	5
Mountain	73	260*	0.0	250	8
Pacific	127	> 600	> 600	> 600*	3

Notes: The preferred model is denoted by (*).

See notes for Table 1.

In the Northern Plains and Mountain regions, when the estimated output elasticity was negative, the output elasticity is set to zero in the rate of return computation.

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ENDNOTES

1. See Figure 7.4 in the NRC report for the grouping of states by research cluster.

2. In addition, MH Central = ERS Corn Belt + ERS Lake States, MH Southern Plains = ERS Southern Plains + ERS Delta, and MH Southeast = ERS Southeast + ERS Appalachian.

3. The data in the publication are also available electronically from the ERS homepage at URL: http://usda.mannlib.cornell.edu/data-sets/inputs/98003

4. The project information reported to CRIS contains a location code for where the research is conducted. When an ARS or ERS project is conducted in Iowa for example, the funds would go into the public agricultural research expenditures in Iowa. If the location is given as Washington, DC, for ERS the funds are not counted in our public research expenditures data. Part but not all of the ARS research at Beltsville was included in the public research expenditures in Maryland.

5. The annual research expenditure series, 1970-95, were derived from USDA-CRIS electronic data files. For 1927-1969, the total public agricultural research expenditures series were derived from (1) reported expenditures by the state agricultural experiment stations to the USDA and (2) a projected ratio of total public agricultural research expenditures to total SAES expenditures by state. The projected ratios were obtained by fitting simple time series models to the actual data by state, 1970-95, and then projecting backward. A major adjustment was made 1948-1950 to reflect the dramatic shift in the share of U.S. total public agricultural research between state institutions and the USDA (see Huffman and Evenson 1993, Table 4.1 and Figure 4.1).

6. The Huffman and Evenson research price index gives about 70 percent weight to faculty salaries and behaves similar to Alston and Pardey's and Fuglie's agricultural research price index over 1970-1990.

7. The state highway database is located at the web page: http://www.bts.gov.

8. Alicia Munnell at Boston College also has a database on infrastructure including the components highways, water systems, and others by state. Munnell's database has been employed in several studies of the manufacturing sector (e.g. Morrison and Schwartz). We, however, do not employ Munnell's database in our study primarily because her database is only from 1970 to 1986.

9. Weather data are available from the ERS homepage as an ERS data product: Weather in U.S. Agriculture. Monthly temperatures and precipitation data for farm production

regions and States for 1950-94. (URL: http://usda.mannlib.cornell.edu/data-sets/general/92008). Weather for certain months (e.g. February to July) may be more important than other months in explaining agricultural productivity (Huffman and Evenson).