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# Measuring Public Agricultural Research and Extension and Estimating their Impacts on Agricultural Productivity: New Insights from U.S. Evidence

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**Abstract**: This paper provides new estimates of the marginal product of public agricultural research and extension on state agricultural productivity for the U.S., using updated data and definitions, and forecasts of future agricultural productivity growth by state. The underlying rationale for a number of important decisions that underlie the data used in cost-return estimates for public agricultural research and extension are presented. The parameters of the state productivity model are estimated from a panel of contiguous U.S. 48 states from 1970-2004. Public research and extension are shown to be substitutes rather than complements**.** The econometric model of state agricultural *TFP* predicts growth rates of *TFP* for two-thirds of states that is less than the past trend rate. The results and data indicate a real social rate of return to public investments in agricultural research of 67% and to agricultural extension of 100+%. The paper concludes with guidance for *TFP* analyses in other countries.

Key Words: agricultural productivity analysis, rate of return to research, public agricultural research, public agricultural extension, states, spillovers, forecasts, US states, econometric analysis, panel data

JEL Classification: D24, C51, Q16

In order to feed the growing population of the world, expected to reach 9.6 billion people by 2050 (United Nations, 2013), a 29% increase over 2013, without causing immense environmental damage and hunger, society must increase agricultural productivity. Two ways of doing this are to invest in public agricultural research and extension. Developed countries, like the United States, have been a leader in this area for most of the 20st century (Pardey, Alston, and Chan-Kang, 2013). For example, U.S. public agricultural research grew rapidly from 1960-1980, but its growth slowed considerably from 1980-1995, and then turned negative from 1995-1998 before flattening out to the end of the period in 2010 (figure 1; Fuglie et al., 2011). U.S. private agricultural research (agricultural input focused) expenditures tracked public agricultural-productivity oriented research closely over 1970-1994, and then private agricultural R&D expenditures shoot upward to 1997, being more than $ 1 billion (2006 dollars) larger. This was followed by a downturn over 1997-2001. Over 2005-2010, private agricultural R&D shot upward again and in 2010 was almost two times larger than public productivity-orient agricultural research (Fuglie et al., 2011).

A major concern about slowing investments in U.S. public agricultural research and extension is its adverse effects on future agricultural productivity and international competitiveness of U.S. agriculture. Rapidly developing countries, such as Brazil and China, are investing heavily in agricultural research (Pardey, Alston, and Chan-Kang, 2013). Hence, the future international competitiveness of U.S. agricultural exports is at risk. In addition, future investments in public and private agricultural research and extension may not be large enough to deliver declining real world food prices in the 21st century (Nelson et al., 2010), and this will make consumers worldwide worse off. Moreover, those currently engaged in the public agricultural science and agricultural extension policy debates need up-to-date estimates of the expected returns on investment of public funds in both of these activities, for example, if the expected return to

public agricultural research is larger than to extension, this would suggest increased funding for agricultural research relative to extension (Huffman, Norton, and Tweeten, 2011).

In the United States, agricultural research and cooperative extension are separate public programs, each jointly funded primarily by the federal and state governments, and impacting agricultural productivity.[1] The objective of this paper is to provide new estimates of the separate impacts of public agricultural research and extension on state agricultural productivity in the U.S., using updated data and definitions, and forecasts of future agricultural productivity growth by state. In addition, the new estimates are used to construct estimates of the rate of return to public agricultural research and extension separately and provide comparisons where possible. To do this, we: (1) first discuss measurement issues that underlie rate of return estimates, i.e., the important distinction between gross and net measures of public agricultural research and extension. The choice is shown to affect the size of rate of return estimates. (2) Update data on investments in public agricultural extension used by Huffman and Evenson (2006a,b), (3) update and extend data on public agricultural research investments over 2000-2010, which goes significantly beyond Huffman and Evenson (2006a,b), (4) examine alternative lag lengths, or sets of timing weights for constructing public agricultural research stocks, (5) report new estimates of the impact of public agricultural research and extension on state agricultural productivity for the 48 states from 1970-2004, and (6) present forecasts of agricultural productivity from 2004-2010.[2] Finally, we suggest how our methods might be adopted for use in other countries.

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[1] Public agricultural research received a small amount of funding from the private sector and from NGOs and public extension receives significant funding from county governments (Huffman and Evenson 1993).
[2] The forecasts reported by Heisey, Wang and Fuglie (2011) are for a model fitted to national aggregate data. New insights are gained by a state level analysis.

Our research differs from Plastina and Fulginiti (2012), Wang et al. (2012) and Andersen and Song (2013) provide estimates of the returns to public agricultural research at the state level using state level data from 1949-1991. They estimate a state aggregate cost function including the stock of own-state and area-type spillin stocks of public agricultural research as regressors. In constructing the agricultural research variable from annual data on USDA intramural and state agricultural experiment station research by state, they examine alternative shapes and lag length and conclude that an inverted V shape, having gestation period of zero weight for 7 years and a total length of 31 years, is best. They find significant spatial correlation of disturbances and obtain a social rate of return to public agricultural research of 29%.[3]

Wang et al. (2012) explore the contributions of within-state and area-type spillover of public agricultural research stocks and public agricultural extension on agricultural productivity in an aggregate cost function. Their model is fitted to data for the 48 contiguous states for the more recent period, 1980-2004. They find that within-state and area-type spillin stocks of public agricultural research undertaken by USDA and state agricultural experiment stations and veterinary medicine colleges enhance agricultural productivity. Public agricultural extension also enhances the benefits from public agricultural research.[4]

Andersen and Song (2013) examine the impact of public agricultural research undertaken by USDA and state agricultural experiment stations on agricultural productivity at the U.S. aggregate level. In converting these research expenditures to a stock variable, they assume a short

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[3] However, they did not have data on public agricultural extension or private R&D and did not include trend in their model.

[4] Using U.S. aggregate data, Ball, Schimmelpfenning, and Wang (2013) examine trends in agricultural productivity over 1948-2009. They conclude that structural breaks occurred in 1974 (perhaps due to the energy crisis) and 1985 (cause less well identified), suggesting some slowing of agricultural productivity. Wang et al. (2013) undertake an analysis of agricultural productivity at the U.S. aggregate level. Agricultural productivity was explained mainly by public agricultural research and no consistent impact of private agricultural research was uncovered.

gestation period followed by a total lag length of 50-years. Their best fitting model estimated over the years 1949-2002 and adjusted for first-order autocorrelation yields a productivity elasticity of public agricultural research capital of 0.373. This translates into a social real internal rate of return (IRR) of 21%, which is sizeable but on the low side of IRRs distribution summarized in Huffman, Norton, and Tweeten (2011)

In contrast these earlier studies, we undertake state productivity analysis using available USDA data on total factor productivity (*TFP*) for the farm sector by state from 1970-2004 (which is the latest productivity data at the state level that USDA has made available) and newly updated data on the investments and stocks of public agricultural research and extension. We produce conditional one-year ahead forecasts from our fitted model, both for the with-in-sample and out-of-sample periods. The out-of-sample *TFP* forecasts are interesting because public agricultural research and extension data are now available from 2005-2010, but the USDA has not released state agricultural productivity data by state for these years. The out-of-sample forecasts provide some optimism for future U.S. agriculture *TFP* growth. The real social annual IRR to agricultural-productivity-oriented public agricultural research is 67% and to public agricultural extension is over 100%.

**Issues in Measuring Agricultural Research and Extension**

Although it is widely accepted that public agricultural research and extension and private agricultural research are major determinants of agricultural productivity, a number of important issues arise in modeling this relationship. In addition, Huffman and Evenson (2006b) describe how public agricultural research produces scientific discoveries, an infinite-lived public good, and agricultural extension produces information for farmer and other adult education, which is an

impure public/private good. Hence, public agricultural research and extension are very different but likely complementary activities affecting agricultural productivity.

In the United States, public agricultural research is undertaken primarily by state institutions—state agricultural experiment stations (SAES) and veterinary medicine colleges/schools—and federal institutions—the USDA's Agricultural Research Service (ARS) and Economic Research Service (Huffman and Evenson 1993). Expenditures on research performed by these institutions are reported in the Current Research Information System (CRIS), starting in 1968 (CSRS 1991).[5]

Although state agricultural experiment stations (SAES) were established in 1887 to conduct original research on agriculture, the breadth of the research undertaken has increased over time to include research to improve the rural home and rural life (starting in 1925), on agricultural marketing and resource conservation (starting in 1935), on forestry and wildlife habitat (starting in 1962) and on rural development (starting 1972) (Huffman and Evenson, 1993). Hence, the breadth of the research agenda of scientists of the SAESs has expanded over time, and by the 1970s, research that was undertaken by SAES scientists was actually much broader than what could reasonably be expected to impact agricultural productivity. In addition, the breadth of research undertaken by the USDA has expanded and new institutions to shepherd this work have been developed. For example, the Bureau of Home Economics was established (1924) to undertake home economics research. It was later named the Bureau of Human Nutrition and Home Economics (1943), and in 1957, the Home Economics Division and Utilization Division, which

[5] In 1990, research expenditures of all veterinary medicine colleges and schools amounted to 15.8% of expenditures on animal disease research of SAES scientists (CSRS 1991). In addition, these veterinary colleges and schools, such as the Iowa State Veterinary Medicine College, are engaged in significant collaborative research with the livestock disease research conducted by ARS scientists, such as ARS's National Animal Disease Laboratory in Ames, IA. Hence, it is surprising that Alston et al. (2011) exclude research undertaken from the veterinary medicine colleges and schools from their set of state institutions undertaking public agricultural research.

focused on post-harvest agricultural research, were combined into one Nutrition, Consumer, and Industrial Uses Division (Huffman and Evenson 1993, p. 33). Hence, the breadth of "agricultural" research undertaken by the federal system has also expanded significantly over the past century.

As part of the federal-state partnership on funding of public agricultural research, the USDA's intramural research agencies, state agricultural experiment stations, state forestry schools and a few other cooperating institutions agree to provide CRIS data on research projects carried out. The collected data include a description of each new project by the principal investigator—the commodity or resource that is the target of the research and the research problem areas (RPAs). RPAs include goals of research to protect crops, livestock, and forests from insects, diseases and other hazards; and to produce an adequate supply of farm and forests products at decreasing real production costs.[6] Data reported to CRIS also include annual funding of each project by source, summarized in the annual *Inventory of Agricultural Research* (USDA, 1971-2012). Hence, the range of research topics covered by U.S. public agricultural research data span traditional crop and livestock production, including biological efficiency, diseases, pests, and resources, but also forestry research, post-harvest research (food processing, agricultural marketing and agricultural policy), rural and community development research, and home economics and human nutrition research (Huffman, 2010).[7] Thus, a gross measure of U.S. public agricultural research includes expenditures on a diverse set of research commodities and research problem areas that are only tangentially related to agricultural productivity.

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[6] Other major goals are to insure stable and productive agriculture for the future through wise management of natural resources, expand the demand for farm and forest products by developing new and improved products and processes and enhancing product quality; improving efficiency in marketing systems; expand export markets and assist developing nations; protect consumer health and improve nutrition and well-being of the American people; assist rural people to improve their level of living; and promote community improvement, including development of beauty, recreation, environment, economic opportunity, and public services (USDA 1993).

[7] In the U.S., forestry is a minor activity on farms and ranches and generally excluded from agricultural productivity measures.

However, with the details available in CRIS, it is possible to relatively accurately net out public agricultural research expenditures that clearly do not have a traditional agricultural productivity focus. Huffman (2010) provides those details. How much of a difference does it make? He estimates that in 1970, 70% of the U.S. total expenditures on public agricultural research reported to CRIS were on agricultural productivity-oriented research, and 30% were on all other types. Since then, the share having an agricultural productivity focus has been slowly declining. In ARS, a significantly larger share of research undertaken is agricultural productivity oriented than in the state public agricultural research system. Also, across regions of the U.S., there are significant differences in the share that is agricultural productivity oriented.

What are the consequences of using a gross measure of U.S. public agricultural research to explain U.S. agricultural productivity, when a net measure is most appropriate? Greene (2003, p. 84-85) and Fuller (1987) show that when a regressor contains measurement error the associated estimated regression coefficient exhibits attenuation or bias toward zero. Given the hypothesis that the "true model" is one where agricultural-productivity-oriented research explains agricultural productivity, using a research stock variable constructed from a gross measure of public agricultural research creates a measurement error problem. The outcome is attenuation in the productivity elasticity with respect to public agricultural research capital, which reduces the estimated benefits. Moreover, using the gross measure over-estimates the costs of enhancing agricultural productivity. Hence, with benefits underestimated and costs overestimated, the estimated rate of return to public agricultural research will predictably be biased downward.[8]

[8] Likewise, if productivity-oriented agricultural research of veterinary medicine colleges is omitted, this creates measurement error in the agricultural research stock variable.

The organization and location of the USDA's agricultural research operations have changed over time (Huffman and Evenson, 1994 pp. 31-32, 53-54). Before 1920, decisions were made in Washington, DC, and the research was also conducted there. Over 1920-1934, the USDA established field stations across the U.S. Over 1935-1972, the USDA's research took on increasingly a regional structure, with the U.S. split into four regions. In 1953, ARS was established to consolidate the biological, chemical, physical, and engineering research of the USDA. This agency has weathered many re-organizations in the USDA since then, and it remains the primary research unit of the USDA. In 1972, the management of ARS research was organized into four regions. Each regional headquarters took charge of the research agenda for its region.

In many states, ARS field stations and research centers are located near land-grant universities and their state agricultural experiment stations and veterinary medicine colleges/schools. This close proximity of ARS and SAES scientists facilitates joint research projects on locally and regionally important agricultural topics and problems (Huffman and Evenson, 1993, 1994). Thus, combining within-state agricultural research efforts of federal and state institutions into one variable to explain state agricultural productivity seems most plausible.[9]

Public agricultural research undertaken in one state produces discoveries that also spill over to the public and private agricultural research efforts in other states and to technologies available to farms and agri-businesses in other areas, i.e., are an impure public good (Cornes and Sandler, 1996). They can be represented by (1) similarity of agroecological zones, (2) output-mix similarities, or (3) geographical proximity. Agroecological zones are relatively homogeneous in

[9] The main alternative would be create separate accounts for public agricultural research performed by federal and state agencies in each state and try to identify separate impacts of these two sources of public agricultural research on state agricultural productivity. However, there seem to be more important issues in state agricultural productivity analysis.

geo-climates and ecology, but don't necessarily follow political boundaries. For example, in *Soils: the* 1957 *Yearbook of Agriculture*, Barnes (U.S. Department of Agriculture, pp. 452-455) reports that U.S. soils and climate follow definite regional patterns. Furthermore, geo-climates are a major factor in soil formations. Differences across regions are due to latitude, elevation and worldwide movement of air masses, and major differences in soils across regions result from the climate under which the soils developed, the parent materials from which the soils developed and the slope and drainage potential. Hence, across regions of the U.S., major differences exist in climates, soils and ecology. Since crop and livestock production are primarily open-air and open-field activities using the earth's surface, agricultural production, and associated problems, are very much affected by local agro-ecological zones, such as in figure 1, which has 16 geo-climatic regions and a number of sub-regions. This is the map used to define the potential for public agricultural research spillovers by Huffman and Evenson (2006a,b).

Different producers of the same commodity frequently face similar technologies and some of the same production problems. For private manufacturing companies, Jaffe (1986) developed a spillover weight that is based on similarity of private-sector patent-based technology clusters, which are not strictly commodity based to gage inter-firm private R&D spillovers on profits. However, all of his firms are engaged in enclosed and environmentally-controlled environments, so the nature of the technology and production problems are relatively similar. A commodity-similarity index for effects of public agricultural research conducted in one state on other states' agricultural productivity has been used by Alston et al. (2011) and Anderson and Song (2013). Because of the open-air, earth-surface-using nature of agricultural production, technology choice and production problems may follow more closely geo-climates than commodity mix. For example, consider milk production on dairy farms in Wisconsin under relatively small-scale

silage-grazing herds versus large-scale hay-based confined desert milk production on large dairy farms of California and Arizona. Although they are producing a similar product and using dairy cows to do this, their production problems are quite different.

When areas are close to one-another, geographical proximity, as in shared state boundaries, reduces the physical distance that discoveries and information must travel before they can be used by farmers and agribusiness in another area. This reduces one dimension of the costs of information transfers. For example, discoveries made by public agricultural research in Iowa on corn can easily travel to agribusinesses and farmers in Illinois and southern Minnesota. This is the type of method for measuring public agricultural research spillovers by Plastina and Fulginiti (2012). However, this type of spillover effect would most likely exclude the benefits of public corn research conducted in Iowa on Indiana and Ohio agribusinesses and farms, even though these states have a large area in the same geo-climatic zone (figure 1). Hence, across these three methods of measuring spillover benefits of public agricultural research, the use of agroecological zones represents a middle-ground solution between geographical proximity, as in shared state boundaries, and commodity-mix similarity, irrespective of distance and similar geoclimatic region. Hence, we prefer the one using agro-ecological zones. See Appendix figure (1).

Extension is primarily adult education for immediate decision making of farmers, households, and communities and youth activities. The Smith Lever Act (1914) established cooperative (federal and state) extension service, separate from agricultural research, to provide instruction, education, information and practical demonstration in agriculture and home economics through field demonstrations, popular publications and other methods (Huffman and Evenson, 1993, pp. 24). Broadly, the goal has been to provide information for better farm, agribusiness and home decision-making. The youth activities are comprised of “boys” and “girls” clubs, called “4-

H" clubs, where members undertake practical projects in agriculture, home economics and related subjects (4-H History).[10] In the 1960s, extension added programs in community development and natural resources.

Although a gross measure of cooperative extension is possible, it seems most likely that only agriculture and natural resource extension contribute significantly to state agricultural productivity. This requires netting out resources allocated to other types of extension activities, i.e., home economics, community development and 4-H. How much of a difference is their between the net and gross measures of cooperative extension? Over 1977-1992, only 55% of the gross was accounted for by agricultural and natural resource extension (Ahearn, Yee, and Bottom, 2003). The other 45% were allocated to the other activities. In addition in 1977, 30% of the gross extension was allocated to 4-H, but this share declined to 23% in 1992 and seemingly leveled off (Ahearn, Yee, and Bottom, 2003). Hence, gross measures of agricultural extension contain measurement error for explaining state agricultural productivity, leading to a downward bias of benefits and unduly inflating the costs and a reduction in the rate of return.

In addition, public agricultural research and extension are quite different activities, requiring different amounts and types of education and producing products for different purposes and having different useful lifespans.[11] Hence, it seems implausible to aggregate them together

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[10] These youth projects focused on developing a product to "show" and be "judged" at the local county fair, e.g., a fattened lambs, pigs or baby beefs; baked cookies, cakes, pies; canned fruits and vegetables; displays of fresh fruits, vegetables and grains; refinished cabinets, artistic photos, and paintings. The science of these 4-H projects has been roughly comparable to high school science classes and FFA (Future Farmers of America) and home economics classes, which are good for creating student interest in science but far from making or even reproducing discoveries.

[11] In the U.S. since the 1950s, the typical agricultural and natural resource extension staff members have had a BS degree in agriculture or resources, and more recently specialists have MS degrees and occasionally a Ph.D. degree in an agricultural and resource science field. However, extension agents are not expected to undertake original research but instead engage in a large amount of interpretative work, which translates technical scientific, market, regulatory and policy information into the bites of information needed and usable by modestly educated farmers and agri-businessmen. Much of this information is time dated, and obsolesces rapidly with the passage of time. Public

into one variable for state agricultural productivity analysis. Moreover, because public agricultural research and extension have different stakeholders, it is useful to have separate benefit-cost estimates.[12]

Agricultural and natural resource extension could be a private good or local public good, which has implication for the correct unit of measurement—state aggregate or state average per farm. To the extent that agricultural extension provides information in a timely manner for farmers' decision making in a changing environment (markets, weather, pest conditions) and each farmers' problems is somewhat unique and communication is frequently oral, extension information has private good attributes (Cornes and Sandler, 1996; Evenson, 2001) and undergoes rapid obsolesce as the decision-making environment changes. If we were to express agricultural extension as a state total rather than per-farm basis, another source of measurement error and attenuation bias in benefits would arise and costs would be incorrectly stated; the rate of return would be underestimated.

**Trends in U.S. Public Agricultural Research and Extension**

Real expenditures on public productivity-oriented agricultural research undertaken by state and USDA institutions grew at an average rate of 3.2%, from 1960-1980, but its growth slowed to 0.9%, from 1980-1990, and the growth rate turned negative, from 1990-2009 (-0.8%). In particular, real public agricultural research effort peaked in the U.S. in 1994, and public agricultural research effort was 22% lower in 2009. There is a significant year-to-year variation in agricultural research expenditures in each of the states.

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agricultural research requires scientists holding Ph.D. degrees and the ability to make discoveries regularly, a demanding activity.

[12] State level data on private agricultural R&D have many problems. We ran one regression with an imperfect measure of private R&D. Given that the ln(*TFP*) equation includes trend (and other variables), the estimated coefficient on private R&D was not significantly different from zero. Moreover, excluding the private R&D had very little impact on the other estimated coefficients or there standard errors. These results are available from the authors upon request.

To give little more perspective, we present data for four large agricultural states that differ in products produced and are in very different regions of the country: California, Iowa, North Carolina and Texas. In these states, productivity-oriented public agricultural-research expenditures peaked over the late 1980s and the early to mid-90s (see figure 1). In Panel A, we see that the peak came earlier in North Carolina (1988), with a later secondary peak in 2005. The peak in California came in 1992, with a later secondary peak in 2005, and the peaks in Texas and Iowa were from 1994-1995.

With a lag, the effects of a long-term change in the growth rates of public agricultural research expenditures are revealed in public agricultural research capital stocks. Under a 35 year total lag length and trapezoidal timing weights, panel B, figure 1, shows a smooth series for the stock of public agricultural research by state relative to research expenditures (panel A). In addition, the stocks peak later than for flows—in 2004 for North Carolina, in 2007 for Texas, and in 2010 for California and Iowa. After reaching a peak, the stock of public agricultural research started to slowly decline.[13] Huffman (2010) shows that the patterns are similar in other states.

At the state level, public agricultural extension stocks have a stronger upward trend than public state agricultural research stocks. The main reason is that the number of farms has been declining, and in some cases, the number is declining more rapidly than FTE agricultural extension staff days.[14] For example, in Iowa, agricultural extension capital has a slow upward trend over the whole period, 1970-2010 (figure 2). In North Carolina, the trend was strongly upward from 1970-1998, but significantly irregular from 1998-2010. In California, the agricultural

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[13] Trapezoidal timing weights and a total lag length of 35 years, starting with a zero weight for initial year and two following years (Huffman and Evenson, 2006, p. 271).

[14] The stock is computed using exponentially declining weights over 5 years, starting with a weight of 0.51 in initial year.

extension stock was largely unchanged from 1970-1990, but then declined slowly until 2010. For Texas, the extension stock increased from 1970-1978, declined slowly from 1978-1987, and then returned to a previous high level in 1990. It then drifted down from 1990-2004 before increasing a little from 2004-2010.

**The Econometric Model of State Agricultural Productivity:**

**The General Form**

With the variables in logarithms, agricultural productivity (*y*) in state *i* and time period *t* is explained by a set of regressors (*X*)—the stock of public agricultural research, stock of agricultural (and natural resource) extension and trend, and a zero mean random disturbance term ($\mu$) with a first-order autoregressive process:

(1) $y_{it} = X_{it}\beta + \mu_{it}, VAR(\mu_{it}) = \sigma^2_{\mu_i}$, for $i \in N$ and $t \in \{0,1,\cdots,T\}$

(2) $\mu_{it} = \rho_i\mu_{it-1} + \varepsilon_{it}, VAR(\,\varepsilon_{it}) = \sigma^2_{\varepsilon_i}$, for $i \in N$ and $t \in \{0,1,\cdots,T\}$.

Hence, the variance of the random disturbances $\sigma^2_{\varepsilon_i}$ and $\rho_i$ may differ across observation units, e.g., states. The coefficient $\beta_j$ represents the marginal effects of $\underline{x}_j$ on *y*, and is of considerable interest in equation (1).

If additional information exists on *X* but not on *y*, then equation (1) can be used for forecasting *y*. A one-period (year) ahead mean forecast, $\hat{y}^f_{iT+1}$, with known $X_{iT+1}$ and first-order autocorrelation is written as:

(3) $\hat{y}^f_{iT+1} = X_{iT+1}\hat{\beta} + \hat{\rho}_i\hat{\mu}_{iT}$

where $\hat{\beta} = (X'X)^{-1}X'y$, $\hat{\mu}_{iT} = y_{iT} - X_{iT}\hat{\beta}$, and $\hat{\rho}_i = (\hat{\mu}_i{}'\hat{\mu}_i)^{-1}\left(\hat{\mu}_i{}'\hat{\mu}_{i(t-1)}\right)$.

An important attribute of a forecast is its forecast error, and for (2), it is

$$\hat{v}_{iT+1} = \bar{y}^f_{iT+1} - \hat{y}^f_{iT+1} = X_{iT+1}\beta - X_{iT+1}\hat{\beta} - \hat{\rho}_i\hat{\mu}_{iT} = X_{iT+1}\left(\beta - \hat{\beta}\right) - \hat{\rho}_i\hat{\mu}_{iT}$$

and, assuming no correlation between $X_{iT+1}(\beta - \hat{\beta})$ and $\hat{\rho}_i \hat{\mu}_{iT}$, the estimate of the variance of mean one-step-ahead forecast in the $i^{th}$ state is:

$$EstVAR(\hat{v}_{iT+1}) = \hat{\sigma}^2_{\mu_i}[X_{iT+1}(X'X)^{-1}X_{iT+1}'] + \hat{\sigma}^2_{\varepsilon_i}\hat{\rho}^2_i$$

where $\hat{\sigma}^2_{\mu_i}$ and $\hat{\sigma}^2_{\varepsilon_i}$ are estimates of the variance of $\mu_i$ and $\varepsilon_i$, respectively.

With an estimate of the variance of the forecast, the confidence interval, a very important attribute of forecast, is constructed. Here, the 90% confidence interval of the mean one-step ahead forecast in the $i^{th}$ state is

(4) $$X_{iT+1}\hat{\beta} + \hat{\rho}_i \hat{\mu}_{iT} \pm 1.69[EstVAR(\hat{v}_{iT+1})]^{1/2}$$

The interpretation is that there is a 90% probability that the random interval covers the mean one-year ahead forecast $\hat{y}^f_{iT+1}$.[15] The general forecasting method can be extended to an m-step ahead mean forecast and its confidence interval.

**The Specific Empirical Form**

In the field of state agricultural productivity analysis, a ln-ln productivity function is widely used (Huffman and Evenson, 1993, 2006a,b; Alston et al., 2011; Andersen and Song, 2013).[16] In this study, agricultural productivity in state *i* and year *t* is represented as follows:

(5) $$\ln(TFP)_{it} = \beta_1 + \beta_2 \ln R(m)_{it} + \beta_3 \ln S(m,r)_{it} + \beta_4 \ln EXT(q)_{it} + \beta_5[\ln R(m)_{it} \bullet \ln EXT(q)_{it}]$$
$$+\sum_{k=1}^{K} \delta_k D_k + \tau t + \mu_{it},\ \mu_{it} = \rho_i \mu_{it} + \varepsilon_{it},\ i = 1,..,n,\ t = 1,...,T,$$

where total factor productivity, *TFP*, is a ratio of the quantity index for farm outputs divided by a quantity index for farm inputs under the control of farmers. $R(m)_i$ is the within-state stock of public agricultural research with a lag length of *m*, and $S(m,r)_i$ is the inter-regional spillin stock of

[15] A 95% confidence interval would be about 30% wider.
[16] The other primary approach is a cost function model, e.g., Huffman et al. (2002), Plastina and Fulginiti (2012) and Wang et al. (2012).

public agricultural research from other states, with lag length $m$ and geo-climate region $r$ for state $i$.[17] Hence, we consider only lag lengths for $R$ and $S$ that are the same, i.e., we use the stock of public agricultural research capital for each state in a geo-climatic region to construct the regional research stock spillover/spillin variable.[18] We include a separate variable for agricultural extension stock, $EXT(q)_i$ with lag length $q$.[19]

To capture un-modeled effects, a time trend is included in (5), including the impact of effects of private R&D not captured by trend. It also effectively de-trends the dependent variable and all of the regressors (Enders, 2010; Fuller, 2013). This is necessary to be able to draw causal inference.[20] In addition, de-trended time series have less autocorrelation and are more likely to be trend stationary (Enders, 2010). Other controls in (5) are dummy variables for regions composed of groups of states, $D_{\mathrm{k}}$. They reflect some of the regional nature in ARS decision making on projects and regional nature of some of the formula funding for state agricultural research institutions. In addition a random disturbance term, $\mu_{it}$, is included to capture other factors that might impact state agricultural productivity in a particular state $i$ and year $t$.[21]

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[17] With lags of significant length, including expenditures rather than stocks as regressors leads to estimated coefficients on successive lags that tend to oscillate in sign, to be statistically weak and are impossible to rationalize. Griliches (2000) suggests that it is useful in these situations to impose some structure on the lag pattern. Since we do not know the "true" lag pattern, we are involved in constructing plausible proxy variables for stocks (Greene 2003).

[18] Of course, one could use different lag lengths for constructing within-state and spillover research stock variables. That issue might be taken up in later research.

[19] Due to the very applied nature and high rate of obsolescence of agricultural extension information, we ignore any interstate spillovers.

[20] Ignoring the fact that two series are trending in the same or opposite directions can lead to a false conclusion that changes in one variable are actually caused by changes in another variable (Wooldridge 2009; Enders 2010). In many cases, two time series processes appear to be correlated, only because they are both trending over time for reasons related to other unobserved factors.

[21] We have not included a measure of stochastic spatial correlation in (4). In private communication, Wayne Fuller suggested to us that spillover effects and stochastic spatial effects are most likely related. For example, an error in the defining spillover regions could make the disturbances appear to be spatially correlated. More likely, however, is that plausible spillover measures dramatically reduce and perhaps eliminate significant stochastic spatial effects.

The elasticity of productivity with respect to *R*, *S*, and *EXT* are useful in computing the marginal product and rate of return to investments in these activities:

(6) $\partial \ln(TFP) / \partial \ln(R) = \beta_2 + \beta_5 \ln(EXT)$

(7) $\partial \ln(TFP) / \partial \ln(S) = \beta_3$

(8) $\partial \ln(TFP) / \partial \ln(EXT) = \beta_4 + \beta_5 \ln(R)$

Turning next to cost-benefit analysis of investments in public agricultural research and extension, the tradition has been to compute a current value of the marginal product and then assume the benefits are distributed over time using timing weights—determined by the research lag length and pattern—and then discount benefits back to the current period, e.g., see Yee et al. (2002). However, Alston et al. (2011) argue that there are conceptual problems in this calculation because the benefits really could not be invested in another project (but they do not discuss possibility of investing in more of the same—public agricultural research) and generate the traditionally compute IRR. However, their concerns vanish once we take a slightly different perspective on the IRR computation. Consider a public investment of $1 million in public agricultural research that is spread over the last *m* periods and generates the marginal product of public agricultural research today. This marginal product is derived using the productivity elasticities for *R* and *S*, equations (6) and (7) evaluated at the mean of ln(*EXT*) and ln(*R*).[22]

[22] Because the relevant productivity elasticities used in these computations have their narrowest confidence interval at the sample mean of the data, this is an advantageous place to perform the evaluation. Evaluations of marginal products at each point of the data set suffer from the fact that the confidence interval differs for each point, being generally much larger at the beginning and end of the series. This type of evaluation seems unnecessary in a linear model of state agricultural productivity.

The internal rate-of-return (IRR) to an incremental investment in public agricultural research, say $1 million, can be obtained by solving equation (9) for *r*:

$$(9)\quad -1\left[\sum_{i=3}^{m}\omega_i/(1+r)^i\right]^{-1}+\left[(\overline{\partial\ln(TFP)/\partial\ln(R)})\,\overline{Q}/\overline{R}+(N-1)(\overline{\partial\ln(TFP)/\partial\ln(S)})\,\overline{Q}/\overline{S}\right]=0.$$

$r$ is the interest rate used to accumulate costs to time period 0, $\overline{Q}$ is the mean annual value of gross agricultural output at the state level, $\overline{R}$ is mean within state stock of public agricultural research, and (N – 1) is the average number of states into which public agricultural research spillover-benefits flow. $\overline{S}$ is mean public agricultural research capital spillovers. The first set of terms on the left-hand side of equation (9) is the present discounted value as of today of the past investments in agricultural research needed to realize the marginal product of public agricultural research today—the second term is the marginal product of agricultural research from within state and spillover benefits.

In equation (9), *r* is the interest that the project *could pay* and still have a net present value of zero (Harberger, 1972). When costs and benefits are in constant dollars and benefits include interstate spillover benefits, a real social IRR is obtained. The distribution of costs (or benefits) over time in the "project" is nothing more or less than that determined by the particular set of timing weights used, the $\omega_i s$ in equation (9). Representing the public investment project as in (9) shows that it is unnecessary to think about the proceeds of a public agricultural research project somehow needing to actually be re-invested in another project.[23,24]

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[23] Even though politicians may like sound bites that benefit-cost ratios can generate, they are more problematic than IRR estimates. In computing the benefit-cost ratio one must have an estimate of the social opportunity costs of funds (interest rate) in each year of the project, and there is no reason to believe that these interest rates are the same in each year of a long-life investment project, and hence, are often exceeding difficult to estimate with any accuracy. This was shown by Harberger (1972, pp. 29-30). It is extremely arbitrary to assign a single value to this social opportunity funds every year of the project, e.g., 3%, and it would make a big difference if the rate were twice this large for more

For computing the real IRR for a $1 million investment in agricultural extension distributed over *m'* years, the computation is simpler because there is no interstate spillover effect included in (5):

$$(10)\quad -1\left[\sum_{i=0}^{m'}\omega_i^{'}/(1+r')^i\right]^{-1}+\left[(\partial\overline{\ln(TFP)}/\partial\ln(EXT))\overline{Q}/\overline{EXT}\right]=0$$

where $\overline{EXT}$ is the sample mean value of *EXT* and *r'* is IRR to an incremental investment in agricultural extension. The $\omega_i^{'}s$ are the usual time weight for benefits. Equations (9) and (10) show that the current payoff to public agricultural research (extension) can only be obtained by having an on-going long-term public agricultural research (extension) program.

**Data and Empirical Definitions of Variables**

Table 1 provides a brief summary of the variables in the empirical productivity equation. Data on agricultural productivity at the state level are the ERS data from Ball et al. (2010), and consist of annual data for the 48 contiguous states from 1970-2004. These are the official state agricultural productivity series of the USDA. Within-state public agricultural research with a productivity focus is converted into constant-dollar magnitudes, using the Huffman and Evenson (2006b) research price index, as updated. Constant dollar agricultural research expenditures are converted into stocks using a short gestation period of zero weight and then trapezoidal timing weights (Huffman and Evenson, 1993, 2006a,b). We permit some flexibility and consider alternative lag lengths of 30, 35, 40 and 45 years for within and spillin public agricultural research

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distant dates. Also, Evenson (2001, pp. 605-606) discusses some common problems in interpreting benefit-cost ratios, including the gross misinterpretation of Griliches (1958) estimate of the benefit-cost ratio for hybrid corn research.

[24] The use of equation (9) above or equation (11) in Huffman and Evenson (2006a) leads to the same IRR.

capital.[25] We suggest that our trapezoidal pattern of timing weights is broadly consistent with the shape of the most preferred gamma-lag pattern of Alston et al. (2010).[26]

The public agricultural extension variable is constructed as follows. First, we took data on full-time equivalent extension staff days per year in agricultural and natural resource extension from Huffman and Evenson (2006a,b) over 1970-1977 and from Ahearn et al. (2003) from 1977-1992. Because the state level data on FTE staff days in agricultural and natural resource extension end in 1992 and much of the decline in 4-H activities had already occurred, we developed a method for extending the agricultural extension series over 1993 to 2010 using Friedman's (Friedman 1962) method for creating a proxy for a missing series by using a related series. To do this we draw upon NIFA administrative data on FTEs of extension specialist per year from 1993-2010.[27] However, for each state we inflate the data on FTE extension specialists in 1992 so that it equals that of FTE extension staff time devoted to agricultural and natural resource extension. Applying this method, we are able to extend the series on agricultural extension by state from 1993-2010.[28] This is imperfect and we would like better data.[29] In all years, newly derived data on FTE agricultural extension staff years are divided by the number of farms in 1,000s, to put it on a per farm basis (Evenson 2001). To translate the flow of FTE agricultural extension staff years into a stock, we apply exponentially declining timing weights over *t* to *t*-4 of 0.5090, 0.2591,

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[25] For creating the research stock variable, there is broad agreement on the shape, except for how smooth it is, e.g.,see Alston et al. (2011) and Huffman and Evenson (2006b). There is some diverge in opinion about total lag length, but we consider a plausible range of values, given our data. Our lag length for creating extension capital matches evidence in country data, but differs from the assumption by Alston et al. (2011). Of course a more general search over shapes and length of lag could be undertaken. That might be taken up at a later time.

[26] They, however, arbitrarily aggregate SAES research and agricultural extension together.

[27] In Huffman and Evenson (2006a,b) a simple time series model was developed for each state's data on staff days allocated to agriculture and natural resource extension and it was used to forecast the missing data over 1993-1999.

[28] We cannot go beyond 2010 because NIFA discontinued the FTE extension specialist data with the release of the 2010 data.

[29] We imposed the restriction that FTEs of agricultural extension were the same in 1992 and 1993.

0.1319, 0.0671 and 0.0329, which are similar to those used by Huffman and Evenson (1993, 2006a,b). This pattern reflects the rapid rate of obsolescence of agricultural extension information.

The regional indicators of equation (5) reflect the regional dimension of state agricultural experiment station and USDA research. The Amended Hatch Act of 1955 mandated that 20% of Hatch Act funds going to state agricultural experiment stations be allocated to regional research—research expected to benefit more than one state (Huffman and Evenson, 1993 pp. 21, 104-105), and to carry out this program, the states (and territories) were grouped into the Northeast region, the Southern region, the North Central region and the Western region. Also, in 1972, the administration of research by ARS took a regional structure, grouping states into four regions (Huffman and Evenson, 1994 pp. 31, 54). Up until this time, research management decisions of ARS were made by an administrator in Washington, DC, with assistance from staff at the Beltsville (MD) Center. But starting in 1972, each of the four regions was assigned a regional administrator, and he/she planned the research within his/her region.[30]

The twelve states within the Northeast region are assigned to regional indicator $D_1$. The Southern region with thirteen states covers a large area, and it is split into an Eastern part consisting of eight states (with regional indicator $D_{2e}$) and Western part consisting of five states (regional indicator $D_{2w}$). The North Central Region with twelve states covers a large area and is split into an Eastern part consisting of eight states ($D_{3e}$, the reference region) and the Western part consisting of four states ($D_{3w}$). The Western Region consists of thirteen states, but we exclude Alaska and Hawaii for the analysis. The other eleven contiguous states cover a vast land area of

[30] In 1981, the regional research requirement of the Amended Hatch Act was discontinued, but the regional structure of ARS research continued.

the western United States. The Western region is split into the eight inland states (regional indicator $D_{4e}$), Washington and Oregon ($D_{4w}$) and California ($D_{4ca}$).[31]

We expect $\beta_2$ to $\beta_4$ and $\beta_6$ to be positive. One can think of scenarios when investments in public agricultural research and extension are complements, i.e., an increase the public agricultural research increases the productivity of agricultural extension, especially in developing countries (Evenson 2001). However, in prior research, Huffman and Evenson (2006a,b) found that for the U.S. public agricultural research and extension are (imperfect) substitutes, i.e., $\beta_5 < 0$.

**The Estimated Model of State Agricultural Productivity**

Econometric estimates of several versions of equation (5) are reported and discussed in this section. When $\rho$ is not constrained to be zero, the regression coefficients are estimated using the Prais-Winsten estimator, which retains the first observation by performing a different transformation on it than the pseudo-first differences of the other observations (Judge et al. 1985). All standard errors and associated z-values are adjusted for heteroscedasticity across states, i.e., clustering, and contemporaneous correlation of disturbances across pairs of states.[32]

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[31] Of course other regional grouping of states could be considered, or even state fixed effects could be considered. We leave that for future research.

[32] On the advice of Wayne Fuller of Dickey and Fuller (1979), we did not undertake unit-root tests on each continuous variable in equation (5) or co-integration tests (Engle and Granger, 1987). The reasons are as follows: (i) equation (5) contains a time trend and this greatly reduces autocorrelation, as in trend-stationary variables, (ii) the sample size in $t$ is "small," at most 34 observations, but unit-root and co-integration tests have only good large sample properties (i.e., $T \rightarrow \infty$), and small sample properties are unknown, (iii) the estimate of equation (5) where all states have the same autocorrelation coefficient gives a sample value of $\rho$ equal to 0.66, which is far from one (and zero), and (iv) the estimate of equation (5) where each state is permitted to have a different value of $\rho$ results in $\hat{\rho}_i$ values that have a wide variance, spanning values from -0.07 to 0.975, but only six of the forth-eight estimates (12.5%) are larger than 0.90 and the modal value is 0.66. A histogram of the $\hat{\rho}_i$s and plot of the normal kernel density function for these estimates is available from the authors on request. Under the above conditions, Fuller indicated that unit root and co-integration tests have very low power and tend to confuse rather than shed light on statistical properties of time series. Our approach implicitly assumes that key variables are integrated of order zero, or is not significantly different from zero.

First, we examine the effect of various lag lengths for $R(\bullet)$ and $S(\bullet)$ on explaining ln(*TFP*). As a metric for comparing models with different lag lengths, we choose $R^2$. Other meaningful metrics will be highly correlated with it since no formal statistical test exists. Equation (5), after excluding ln(*P*), is the general model of ln(*TFP*) used for choosing among the different lag lengths for public agricultural research. These combinations are: $m$ = 30, 35, 40 and 45.[33] The $R^2$ for the equation having $R(30)\&S(30)$ is 0.6364, $R(35)\&S(35)$ is 0.6400, $R(40)\&S(40)$ is 0.6395, and $R(45)\&S(45)$ is 0.6375. Hence, the lag length for public agricultural research that provides the largest $R^2$ is $m$ = 35. Moreover, these results are in agreement with the 35-year lag length used earlier by Evenson and Huffman (1993, 2006a,b) and Huffman (2010). However, the $R^2$ and parameter estimates are not very sensitive to small changes in the lag length.

Second, regression (1), table 2, reports estimates of the regression coefficients of the refined equation (5) where $\rho$ is constrained to be zero. The estimated coefficient for the direct impact on ln(*TFP*) of within-state public agricultural research capital (ln*R*) is 0.222, of spillin public agricultural research capital is 0.104, and of agricultural extension is 0.090. The estimated coefficient on the interaction term between within-state public agricultural research and public agricultural extension is -0.050. This last coefficient provides an added degree of substitutability between public within-state agricultural research and extension, relative to those that exist in a standard Cobb-Douglas production function (which excludes this interaction term).[34] See Chambers (1988). All of these coefficients are significantly different from zero at the 5% significance level. The estimated coefficients for the regional indicators in regression (1) are all

[33] This process is similar to looking for the choice of $m$ that maximizes the likelihood function.
[34] The simple correlation between ln(R) and ln(EXT) is -0.41, which is highly plausible. Consider investing $100,000 in public agricultural research and public agricultural extension. Given our lag patters, 90% of the benefits from the investment of extension will have been realized when the first positive benefits to public agricultural start to occur.

positive except for $D_{2w}$, and they are all significantly different from zero at the 5% significance level, except for the coefficient of $D_{4e}$. These productivity differences reflect inherent differences in funding and management of public agricultural research. Trended factors contributing 1.2 % per year to state agricultural productivity growth, other things equal.

Third, regression (2), table 2, reports estimates of the regression coefficients of equation (5) where $\rho$ is permitted to be positive, but is constrained to be the same across all 48 states. In fact $\hat{\rho}$ = 0.66. The estimated coefficient for the direct impact on ln(*TFP*) of within-state public agricultural research capital (ln*R*) is 0.194, of spillin public agricultural research capital is 0.106, and of agricultural extension is 0.073, which are all positive as expected. However, the estimated coefficient on the interaction term between within-state public agricultural research and public agricultural extension is -0.038. All of these coefficients are significantly different from zero at the 5% significance level. The estimated coefficients for the regional indicators in regression (2) are similar in size and significance as in regression (1). In regression (2), trended factors contribute 1.1 % per year to state agricultural productivity growth, other things equal, which is slightly smaller than for regression (1).

Fifth, regression (3), table 2, reports estimates of the regression coefficients of equation (5) where each state has a unique estimate for $\rho$. The estimated coefficient for the direct impact on ln(*TFP*) of within-state public agricultural research capital (ln(*R*)) is 0.161, of spillin public agricultural research capital is 0.084, and of agricultural extension is 0.025. The estimated coefficient on the interaction term between within-state public agricultural research and public agricultural extension is -0.025. All of these coefficients are significantly different from zero at the 5% significance level, but all are somewhat smaller in absolute value relative to regressions (1) and (2). The estimated coefficients for the regional indicators in regression (3) are all positive,

except for $D_{2w}$ and $D_{4e}$. However, the estimated coefficient for $D_{4e}$ as well as for $D_{2e}$ and $D_{4w}$ are now not significantly different from zero at the 5% significance level. Trended factors, including most likely private R&D capital, contribute 1.1% per year to state agricultural productivity growth, other things equal, which is the same as regression (2) and only slightly smaller than for regression (1). Hence, it would be unusual for future state average annual *TFP* growth rates to fall below 1% per year.

Looking across regression (1)-(3), we see that the absolute size of the estimate coefficients of the public agricultural research and extension stock variables and the statistical significance of the estimated coefficients of regional dummy variables decline as we release restrictions on the $\hat{\rho}_i$s. A key difference between regression (2) and (3) is the number of observations used to estimation $\rho$; equivalent to 1,500+ in the case of regression (2), or all of the residuals from regression (1) are pooled together across the 48 states to fit one equation $\hat{\mu}_t = \rho \hat{\mu}_{t-1} + \varepsilon_t^*$ , while in regression (3), only 34 observations are used to estimate each of the $\rho_i$s, i.e., it uses only residuals for state *i*. This is important because the estimates of $\rho$ have at best good large sample properties, with small sample properties being unknown (Wooldridge 2002). Hence, $z_2 = \hat{\rho}/s.e.(\hat{\rho}) \rightarrow N(0,1)$, an asymptotic standard unit normal distribution.[35] However, $z_{3i} = \hat{\rho}_i/s.e.(\hat{\rho}_i)$, $i = 1,..34$, has small sample properties and might not be standard unit normal. For these reasons, one might prefer the results reported in regression (2) over (3).

Table 3 provides a comparison of the agricultural productivity elasticity with respect to *R*, *S* and *EXT* across the three models reported in table 2, including an allowance for the interaction

[35] In a test of the null hypothesis that $\rho = 0$ vs. an alternative hypothesis that $\rho > 0$, the sample value of the z statistic is 4.44 and the tabled value is 1.96. Hence, we reject the null hypothesis and accept the alternative of positive autocorrelation.

of *R* and *EXT*. The productivity elasticity due to *R* is largest for regression (1), 0.152, and declines as we move to regression (2) and (3)—0.139 and then 0.126, respectively. This is a 19% decline from largest to smallest productivity elasticity. The productivity due to *S* is largest for regression (2), 0.106, slightly smaller in regression (1), 0.104, and smallest for regression (3), 0.085. The maximum difference is a little larger here, 22%. The productivity elasticity due to *EXT* is 0.107 in regression (1), 0.083 for regression (2), and 0.081 in regression (3), with the maximum difference being 28%. If we make the assumption that the estimates have a normal distribution, the 95% confidence interval for all of these estimates are quite tight (see table 3, numbers in parentheses).[36]

Taking the data on productivity elasticities from above and making a few added assumptions, we obtain estimates of the marginal cost of increasing *TFP*. Any one state controls only *R* and *EXT*, but not *S*, and the summation of the production elasticities over *R* and *EXT* is 0.259, 0.222 and 0.210 for regressions (1)-(3), respectively. Hence, a 25% increase in *R* and *EXT* by any one state would be expected to result in an increase of its *TFP* by only 5% (for any of the three estimates). Assuming the price of research and extension resources and farm input prices are unaffected, this relationship suggests that the marginal cost of producing additional *TFP* (or agricultural output) increases by roughly 20%. If prices of resources increase, then the marginal cost of increasing *TFP* will be even larger. In contrast, if all states were somehow to agree to the same proportional increase in *EXT* and *R*, which would lead to an equal proportional increase in *S*, then the summation of these elasticities would be a little larger, but then resource costs would most likely increase. Even with an unlikely cooperative agreement across all states, the empirical model of *TFP* shows only slightly smaller decreasing returns to scale in public agricultural

[36] However, one might consider the elasticities computed for regression (2) to be the best due to better large sample properties of the estimates.

research (*R* and *S*) and extension in the long run and rising marginal cost in producing agricultural productivity.

**Forecasting Agricultural Productivity**

To gain insights from our results, consider both one-year ahead within sample and out-of-sample forecasts of ln(*TFP*). The latter type of forecast is interesting because the USDA has not released its data on state agricultural *TFP* for the years beyond 2004, but we have data on the actual amount of public agricultural research and extension capital to 2010. Hence, we can make a true conditional forecast over 2005-2010. As always, the structure of the model might have changed over this period, but we are much more confident in forecasting over this 5 year out-of – sample period than a 50 year out-of-sample forecast as in Alston et al. (2010) and Heisey, Wang and Fuglie (2011).

When forecasting is the objective, equations (1)-(3) provide guidance. However, a choice must be made as to which model reported in table 2 to use. Regression (3) has some advantages, because each state has its own $\hat{\rho}_i$, and this added state specific information, results in a forecast that tracts ln($TFP_{it}$) better.[37]

The forecasts track actual ln(*TFP*) relatively well, except for a few states that have extremely noisy ln(*TFP*) values, e.g., Montana, North Dakota.[38] To gain additional perspective on how well our model of productivity performs, we consider the forecasts for the states of California, Iowa, North Carolina and Texas (figure 3). We use equation (3) and estimated parameters from regression (3), table 2, to make these forecasts. Panel A shows that one-year

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[37] However, the distribution of the one-year ahead forecasts used to construct the confidence interval might be compromised by small sample size used in estimating $\rho$.

[38] A multi-panel figure displaying these within-sample plots of ln(*TFP*) and one-year ahead forecasts of $\ln(\widehat{TFP})$ from 1970-2004 is available from the authors upon request.

ahead forecasts track actual ln(*TFP*) relatively well in California. California has most of its cropland irrigated, so this removes most of the noise in ln(*TFP*) associated with weather. Panel B displays the data for Iowa, and it shows that there is a relatively large amount of noise in ln(*TFP*). Iowa is an important agricultural state, but very little of the cropland is irrigated, so unusual weather events of 1983, 1988 and 1993 lead to large dips in ln(*TFP*), but one-year ahead forecast of ln(*TFP*) do a relatively good job of tracking the actual ln(*TFP*) series. Panel C displays the North Carolina data. It shows that ln(*TFP*) is relatively smooth, but with a few reversals of trend. The one-year ahead forecasts of ln(*TFP*) do a relatively good job of tracking ln(*TFP*) here. Panel D displays the Texas data. It shows some noisiness in ln(*TFP*), due mainly to unusual weather events, somewhat like Iowa, but the model of one-year ahead forecasts of ln(*TFP*) tracks the actual ln(*TFP*) series relatively well. Since the detail in small, it is difficult to accurately visualize what is going on in these figures. Hence, we construct table 4 to display the average rate of growth of ln(*TFP*) from 1990-2004, which is the last 15 years of our state agricultural productivity series and a period of substantial length so as not to be dominated by a few extreme observations.

We compute the average rate of growth for the mean forecast of ln(*TFP*) over 2004-2010 by state, and report these growth rates also in table 4. States are grouped by ERS Farm Production Regions and not necessarily by geo-climatic regions. A somewhat optimistic discovery is that the rate of growth of forecasted ln(*TFP*) is positive for 90% of the states. In 21% of the states (Rhode Island, Missouri, Kansas, Louisiana, Oklahoma, Texas, Montana, Wyoming, Washington and California), the growth rate of forecasted ln(*TFP*) during 2004-2010 is higher than for the actual rate of ln(*TFP*) over the most recent 15 year period, but for the other states it is lower. However, on the pessimistic side, in only 16 states (33% of the total) is the rate of growth of forecasted ln(*TFP*) larger than the estimated trend rate of increase in ln(*TFP*) over the sample period 1970-

2004 of 1.1% per year (table 2, regression 2). Hence, 67 percent of the states are paying the price for past underinvests in public agricultural research and extension (including possibly being located in one or more geo-climatic regions where public agricultural research spillins have not been growing).

To add perspective to the out-of-sample conditional forecast of ln($TFP_{it}$), we have constructed a 90% confidence interval for the mean forecast in the four target states from 2005-2010. Panel A, figure 5, shows that in California, the forecast of ln(*TFP*) is growing over time at almost 1% per year, which is faster than over the previous fifteen years. Moreover, the 90% confidence interval is relatively tight and does not widen much over 2005-2010; $\hat{\rho}_{CA}$ is small. Panel B shows that in Iowa, the growth of forecasted ln(*TFP*) is positive but low, relative to the previous fifteen years. Moreover, the 90% confidence interval is rapidly widening as the forecast moves forward over 2005 to 2010. Panel C shows than in North Carolina, the growth of forecasted ln(*TFP*) is large relative to the most recent fifteen years, and the 90% confidence interval is rapidly expanding as the forecast move forward from 2005 to 2010; $\hat{\rho}_{NC}$ is large. Panel E shows that in Texas, the growth rate of forecasted ln(*TFP*) is increasing rapidly relative to ln(*TFP*) growth over the most recent fifteen year period. The 90% confidence interval is also rapidly expanding as the forecast moves forward over 2005 to 2010.[39] Widening confidence intervals provide an indication that caution about forecasts is warranted.

How do our out-of-sample state *TFP* forecasts compare to those of others? Few other forecasts exists, and none for this period. However, after estimating a state agricultural productivity model using data for 1949-2002, Alston (2010, pp. 387) report some type of

[39] Although one might construct a decomposition of *TFP* growth by state into a contribution due to public agricultural research, public agricultural extension and trend, it is not critical to this paper. Later work might consider it.

projection for 2050. However, they do not present an econometric model of their forecast as in equation (2), which raises an issue about whether it is a true or ad hoc forecast. Given that their R&E variables stop in 2002, it seems that a valid forecast for 2050 should be labeled as a 48-year ahead forecast. Moreover, a key quality indicator of an out-of-sample forecast is its sampling error or confidence interval, but they do not report a confidence interval for their forecasts.

**Returns to Public Agricultural Research and Extension**

By choosing the IRR on investments of public agricultural research and extension, we not only have a number that is relatively easy to interpret, but also a number which is reported in other recent studies and can be easily compared. The real social IRR from an incremental investment in (productivity-oriented) public agricultural research is obtained using equation (9) with NPV set equal to zero. The IRR on this net measure of public agricultural research is 66.8% per year, which is 6 to 10 percentage points larger than in Huffman and Evenson (2006a).[40] Hence, the investment project could pay an interest rate of 66% on funds invested in public agricultural research and still generate a positive net present value. This is quite amazing. Roughly 40% of the return to public agricultural research is due to spillover effects outside the performing state, which is sizeable. Spillovers benefits, however, create an incentive for one state to free-ride on the investments of other states (in the same geo-climatic region), and this free-riding provides another justification for the high IRRs to public agricultural research.

As a check for robustness, we re-compute the social IRR at the low side of the 95% confidence interval for the productivity elasticities reported in table 3, column 3. This yields an

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[40] Note that $\omega_0, \omega_1,$ $\omega_2$ and $\omega_{35}$ are all zero to be consistent with the gestation lag and terminal period weight of zero. The value of $\overline{Q}$ used in this calculation is $3.513 billion per state per year in constant 1984 dollars.

IRR of 60% per year, reflecting the fact that the confidence interval is very tight.[41] This value falls within the three-fourths to one-fourth quartile range (83% to 28%) of a long history of IRR estimates for public agricultural research in the U.S. (Huffman and Evenson, 2006b pp. 294-295).

Alternatively, a comparison can be made to IRRs reported in recent studies, say 2006 and later. Table 5 summaries five such studies. Among the information provided is the type of analysis undertaken (TFP vs variable cost), unit of observation (states vs national level), time period covered in the statistical analysis, whether a gross or net measure of public agricultural research is used, the lag length for creating stocks of public research, and the time period over which research investment data were taken. We also record whether public agricultural extension was used to explain agricultural productivity, and if so, the type of measure (gross vs net), lag length, and time period over which investment data were taken.

The Plastina and Fulginiti (2010) and Andersen and Song (2013) studies use gross measures of public agricultural research and obtain real social IRR estimates of 29% and 21%, respectively. They do not include extension as an explanatory variable, which would tend to bias upward their estimate, but not likely as much as the downward bias caused by using a gross rather than net measure of public agricultural research. In these studies the gross measure of agricultural research likely overestimates the cost by roughly 30%. Wang et al. (2012), Huffman and Evenson (2006a) and the current study use net measures of public agricultural research (an a measure of agricultural extension) to explain TFP or variable cost, and obtain IRR estimates to public agricultural research of 45%, 49% and 67%, respectively, which are significantly larger, as expected. Huffman and Evenson (2006b) and the current study use a net measure of agricultural

[41] Recall that we showed earlier that the marginal cost of increasing productivity with an increment in public agricultural research rises sharply, dampening enthusiasm for non-marginal investments.

extension to help explain agricultural productivity, while Wang et al. (2012) uses a gross measure to explain variable cost. However, Wang et al. do not compute an estimate of the rate of return to public extension. For Huffman and Evenson (2006a) and the current study (using equation (10)), the real IRR is larger than 100%, i.e., the benefits of agricultural extension in the year that it is invested exceed its total cost, a very handsome return.

In contrast, Alston et al. (2011) have chosen gross measures of public agricultural research and extension, but to further complicate benefit-cost analysis comparisons, they attempt to estimate separate impacts of the USDA's intramural agricultural research, which is largely conducted in the various states, and SAES research. Also, they exclude the livestock research undertaken by the state veterinary medicine colleges from their analysis. Finally, they combine the gross measures of SAES research and extension within a state into one variable, creating a heterogeneous mixture, which they label "knowledge stocks." They apply the same long lag length of 50 years and pattern/timing weights (gamma distribution) to the combination of agricultural research and extension. Their report an estimate of the real social IRR of 22.7% (table 5).[42] In addition, in the text, they (Alston et al., 2010 pp. 1274) report a real social IRR to the USDA's agricultural research activities of 18.7%, which is four percentage points lower. Over the time-period covered by their data, it is a reasonable approximation to average the two rates of return to public agricultural research and extension, yielding a real social IRR of roughly 20%. Compared to studies that used net measures of public agricultural research and extension, this IRR is significantly lower as expected—over estimate of costs and under estimate of benefits. Moreover, their estimates do not permit an objective assessment of possible differences in the IRR to public

[42] They also report what they call a marginal IRR, which is significantly lower, but the idea that one should only include 3% of the benefits, as they do, is not convincing.

agricultural research and extension. Hence, one can conclude that measurement and methods matter in a significant way in trying to understand differences in IRR estimates across studies in the U.S. over long periods of time.

**Conclusion**

This paper has fulfilled its objective of providing up-to-date estimates of rates of return to public agricultural research and extension for the U.S. and placing them in context with respect to other recent studies. For public agricultural research with a productivity focus the estimated real IRR is 67%, and for narrowly defined agricultural and natural resource extension is over 100%. Stated another way, these public investment project could pay a very high interest rate (66% for agricultural research and 100% for extension) and still have a positive net present value. Hence, these IRR estimates are quite large relative to alternative public investments in programs of education and health. In addition, there is no evidence of a low returns to public agricultural extension in the U.S., or that public funds should be shifted from public agricultural extension to agricultural research. In fact, if any shifting were to be recommended, it would be to shift some funds from public agricultural research to extension. However, this conclusion is not generalizable to other countries, without new research.

We find a strong impact of trended factors on state agricultural productivity of 1.1 percent per year. The most likely reason is continued strong growth in private agricultural R&D investments. The size and strength of this trend makes it unlikely for average annual *TFP* growth for the U.S. as a whole to become negative in the near future. However, for two-thirds of the states, the forecast of the mean ln(*TFP*) over 2004-2010 is less than trend. The primary reason is under-investment in public agricultural research and extension in the past. For public agricultural

research where the lags are long, it will be impossible for these states to exceed the trend rate of growth for *TFP* in the near future.

We also include informative 90% confidence intervals for one-year ahead conditional forecasts of ln(*TFP*) from 2005-2010 for a selected set of states, and these intervals are quite large for some states and generally increasing as we forecast into the future. The growing width of these confidence intervals going out just a few years into the future suggests that the width of confidence intervals going out 25 or 50 years are so large that these forecasts are uninformative.

Other countries can learn from the research undertaken in the US to estimate rates of return to public agricultural research and extension. First, it is important to think carefully about and identify plausible benefits and costs. In particular, one should guard against creating variables that contain obvious forms of measurement error, such as inaccurately measuring the costs and benefits or aggregating public agricultural research and extension together. Econometric analysis should be used where possible to link aggregate *TFP* (or variable cost) to stocks of public agricultural research and extension derived, where possible, from net measures of investments in these activities. Furthermore, with research and extension as separate variables, it will be possible to test whether they are complements or substitutes. Second, we encourage IRR rather than cost-benefit ratio calculations. It is unlikely that reasonable discount rates to be used for computing the net present value of costs and benefits separately for a B/C ratio in developing countries will be the same as for the U.S., adding to the difficult of comparing them to the U.S. evidence.

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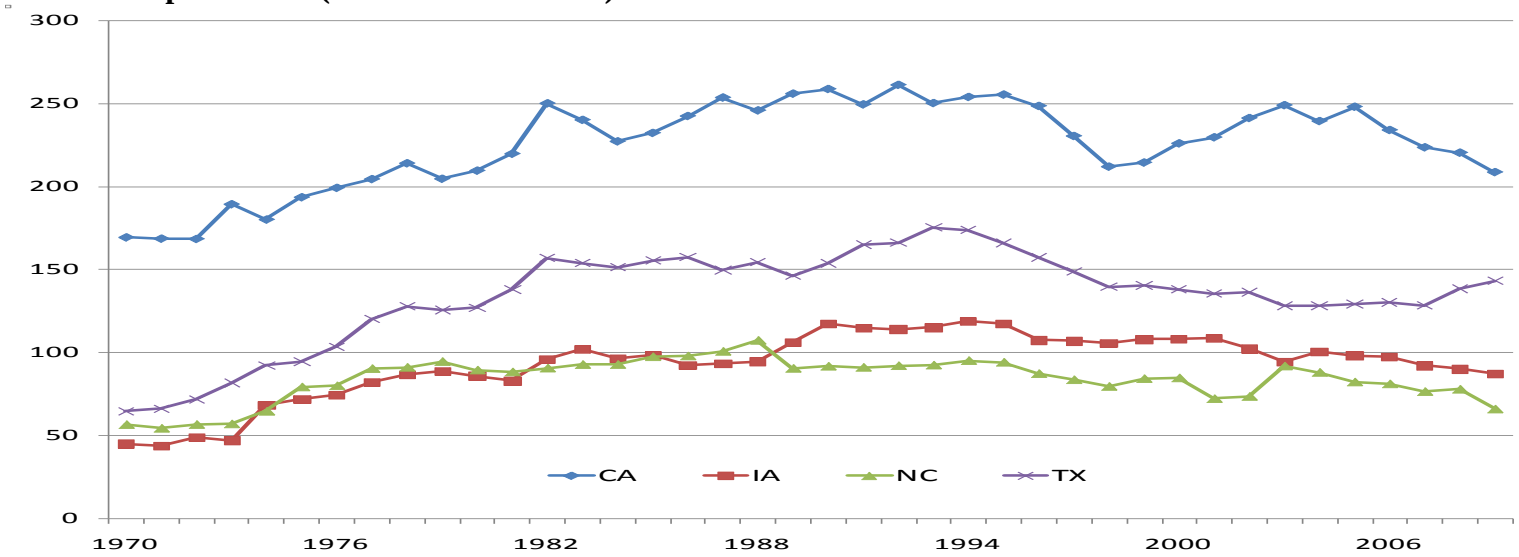
Figure 1. Real Public Agricultural Research, CA, IA, NC, and TX, 1970-2009 (millions of 2006 dol.)

**Panel A. Expenditures (millions of 2006 dol.)**




**Panel B. Capital (35-year lag)**

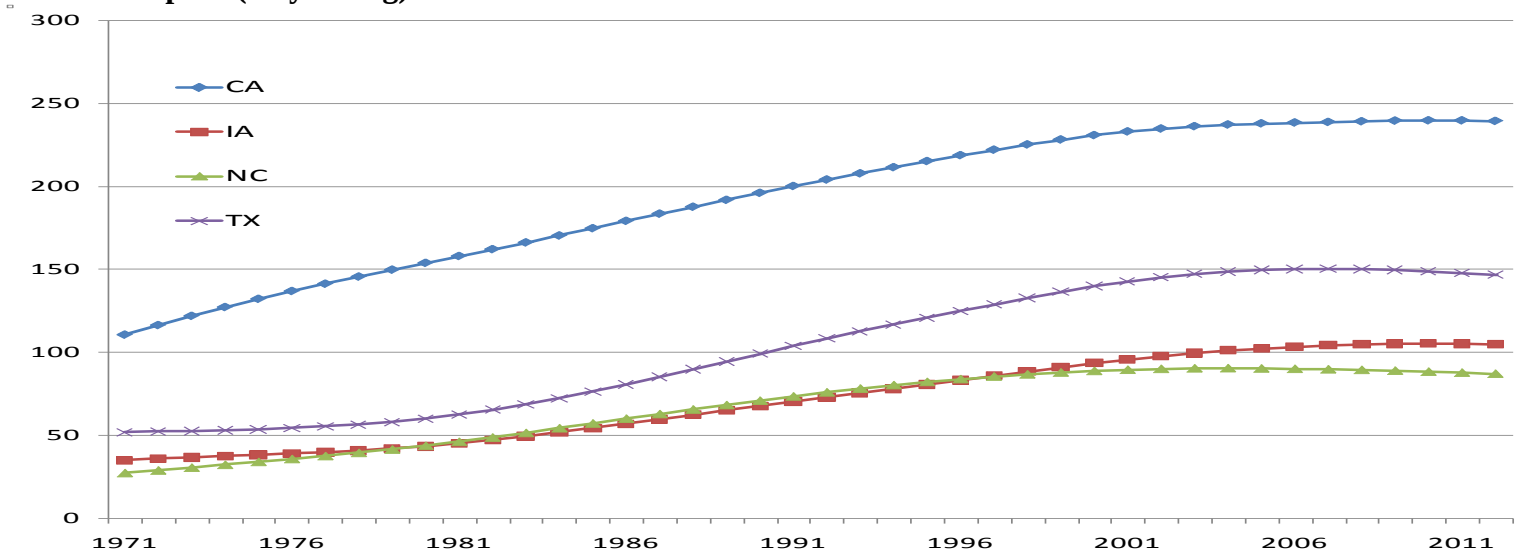


Figure 2. Public Agricultural Extension Capital in Full-Time Equivalent Staff Days per Year Relative to the Number of Farms (1,000s)

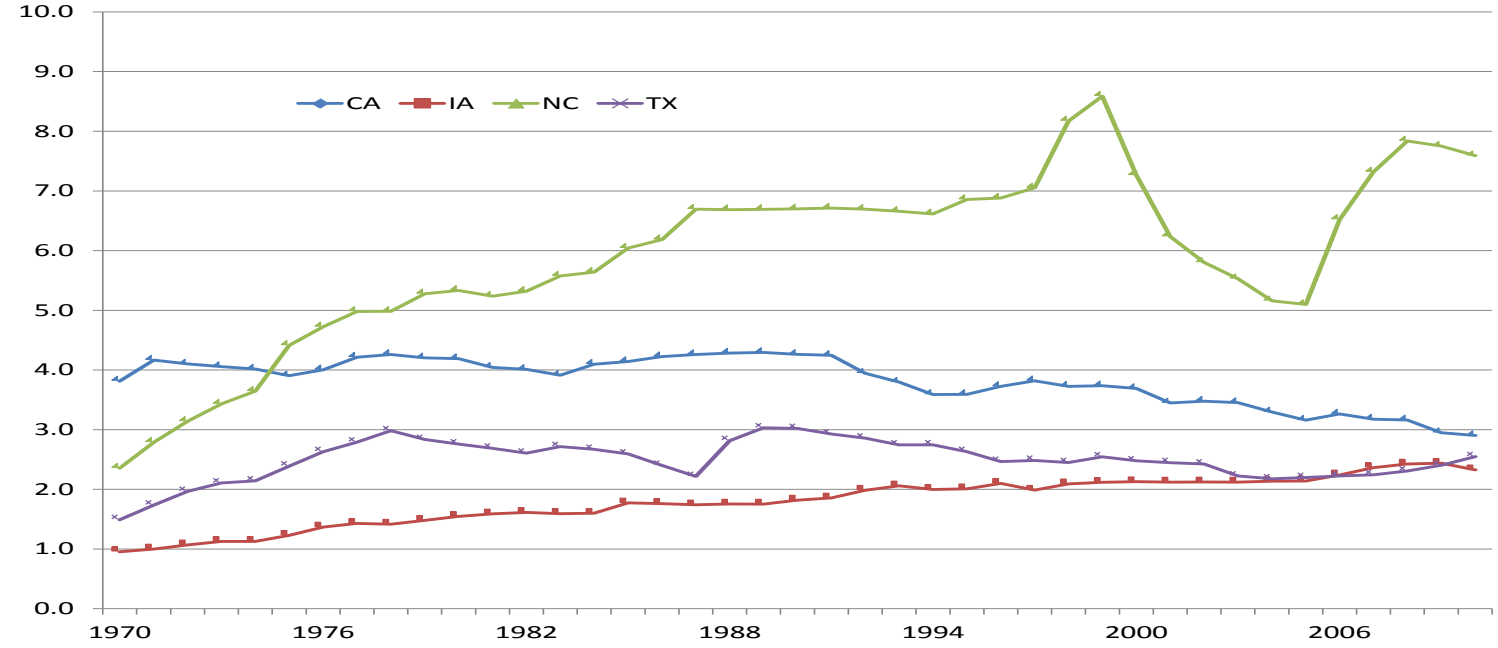
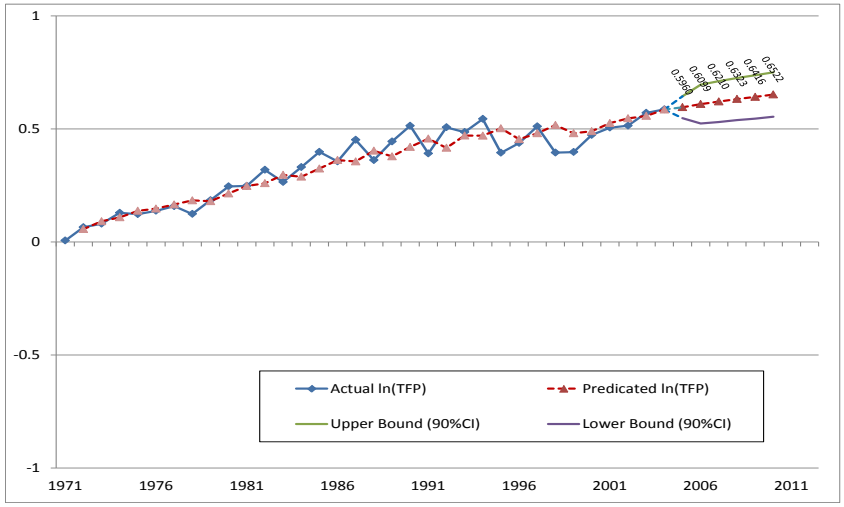
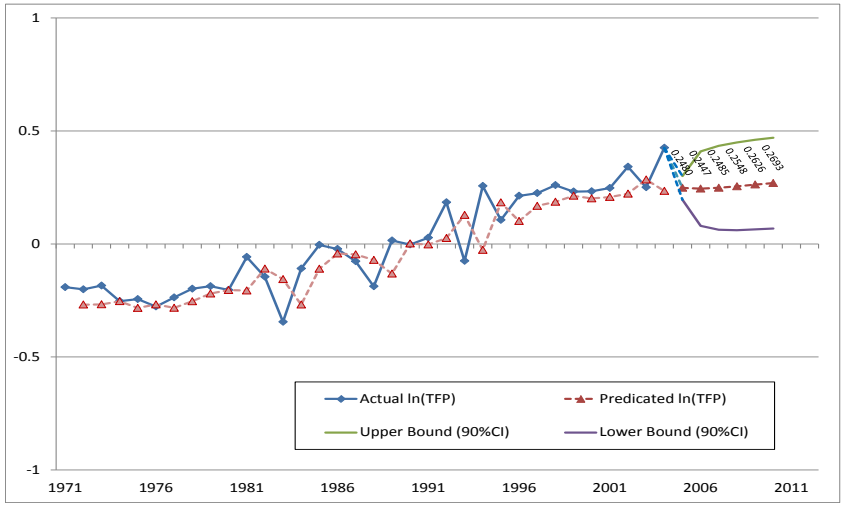


Figure 3. Plots of Actual ln(TFP) and One-year Ahead Forecasts of Mean ln(TFP) within Sample, 1971-2004, and Out-of-sample, 2005-2010, and 90% Confidence Interval, 2005-2011 (Regression 3, table 2)

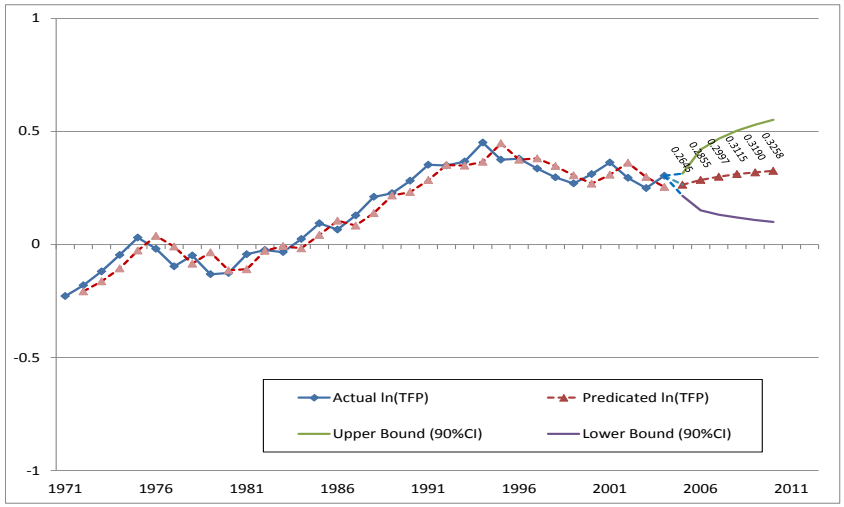
**Panel A. California**




**Panel B. Iowa**




**Panel C. North Carolina**




**Panel D. Texas**

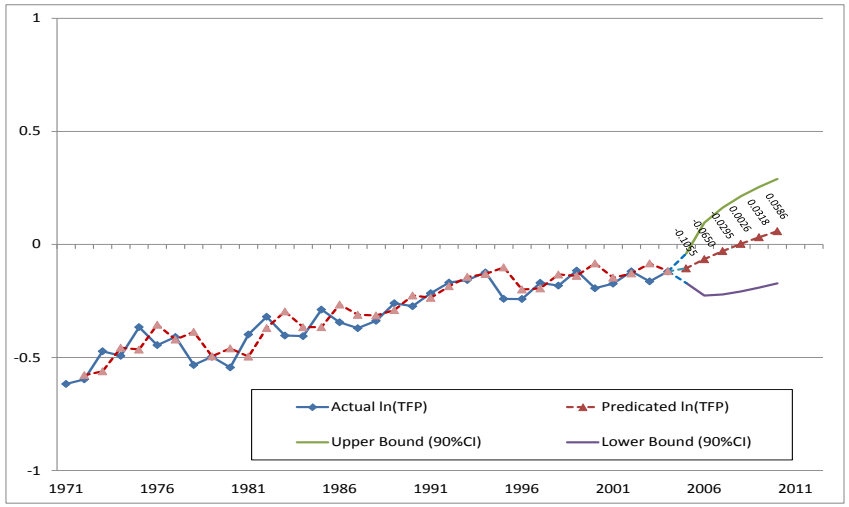


Table 1. Variable Names and Definitions for Annual

| Name | Symbol | Mean[1]/Sd | Description |
|---|---|---|---|
| Total factor productivity | *TFP* | -0.161 (0.279) | Total factor productivity for the agricultural sector relative to Alabama in 1996 |
| Public agricultural Research Capital | *R*(35) | -0.335 (0.891) | With-state productivity-oriented public-agricultural-research capital relative to Alabama in 1996. Trapezoidal shaped timing weights in 10 million. See Appendix Figure 1. |
| Spillin Public Agri-Research Capital | *S*(35) | 1.406 (0.493) | Spillin productivity-oriented public-agricultural-research capital in 10 million. Trapezoidal shaped timing weights. See Appendix Figure 2. |
| Public Agricultural Extension Capital | *EXT*(5) | 1.415 (0.611) | Public agricultural extension created by taking full-time equivalent staff years in agricultural and natural resource extension per 1,000 farms and converted to a stock using exponentially declining weights over five years starting with the current year. |
| Regional indicators | $D_1$ | | Dummy variable taking a 1 if state is the Northeast Region, plus WV (CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT or WV) |
| | $D_{2e}$ | | Dummy variable taking a 1 if state in Eastern part of Southern Region (AL, FL, GA, KY, NC, SC, TN, or VA) |
| | $D_{2w}$ | | Dummy variable taking a 1 if state is Western part of the Southern Region (AR, LA, MS, OK, or TX) |
| | $D_{3e}$ | | Dummy variable taking a 1 if state is Eastern part of the North Central Region (IN, IL, IA, MI, MO, MN, OH, or WI) |
| | $D_{3w}$ | | Dummy variable taking a 1 if state is Western part of the North Central Region (KS, NE, ND, or SD) |
| | $D_{4e}$ | | Dummy variable taking a 1 if state is in Eastern Part of Western Region (AZ, CO, ID, MT, NV, NM, UT, or WY) |
| | $D_{4w}$ | | Dummy variable taking a 1 if state is OR, or WA of Western Region |
| | $D_{4ca}$ | | Dummy variable taking a 1 if state is CA of the Western Region |
| Trend | *t* | | Annual time trend |

[1]Mean of ln values.

Table 2. Econometric Estimates of State Agricultural Productivity Equation: Contribution of Public Agricultural Research and Extension Capital, 48 U.S. States, 1971-2004 (N=1,632)

| | OLS Regression (1) | | FGLS Regression (2)[a/] | | FGLS Regression (3)[b/] | |
|---|---|---|---|---|---|---|
| Regressors | Coefficients | z-values | Coefficients | z-values | Coefficients | z-values |
| Intercept | -19.111 | 12.19 | -19.328 | 5.55 | -21.366 | 7.23 |
| ln *R*(35) | 0.222 | 15.77 | 0.194 | 7.91 | 0.161 | 7.00 |
| ln *S*(35) | 0.104 | 12.77 | 0.106 | 4.69 | 0.085 | 6.28 |
| ln *EXT*(5) | 0.090 | 10.05 | 0.073 | 4.34 | 0.073 | 4.91 |
| ln *R*(35) x ln *EXT*(5) | -0.050 | 7.16 | -0.038 | 3.19 | -0.025 | 2.21 |
| Regional Indicators | | | | | | |
| $D_1$ | 0.135 | 9.33 | 0.151 | 3.35 | 0.134 | 4.11 |
| $D_{2e}$ | 0.070 | 4.29 | 0.065 | 1.85 | 0.046 | 1.75 |
| $D_{2w}$ | -0.069 | 4.36 | -0.072 | 2.01 | -0.035 | 2.15 |
| $D_{3w}$ | 0.060 | 5.90 | 0.054 | 2.35 | 0.091 | 3.18 |
| $D_{4e}$ | 0.003 | 0.21 | 0.000 | 0.00 | -0.033 | 1.02 |
| $D_{4w}$ | 0.099 | 6.23 | 0.099 | 2.02 | 0.045 | 0.83 |
| $D_{4ca}$ | 0.285 | 21.00 | 0.298 | 9.52 | 0.334 | 8.28 |
| *Trend* | 0.012 | 11.84 | 0.011 | 7.59 | 0.011 | 7.59 |
| $R^2$ | 0.631 | | 0.640 | | 0.640 | |

Note : The dependent variable is ln(*TFP*). *R* = within-state constant dollar stock of public agricultural research; *S*= spillin constant dollar stock of public agricultural research; *EXT* = within state stock of agricultural and natural resource extension of FTE staff per 1,000 farms. Dummy variables are included for regions and the Central region, $D_{3e}$ (IN, IL, IA, MI, MO, MN, OH, and WI) is the excluded region in the regression equations. The absolute size of *z*-values are reported. They are constructed from standard errors that are corrected for heteroscedasticity across states, i.e., clustering, and contemporaneous correlation of disturbances across pairs of states.

[a/] One value of $\rho$ estimated along with parameters of equation (2) using Prais-Winsten estimator, which retains the first observation; $\hat{\rho} = 0.66$..

[b/] Forty eight different values of $\rho$ estimated, one for each state, along with parameters of equation (2) using Prais-Winsten estimator, which does an appropriate transformation to retain the first observation..

Table 3. Marginal Impact of Public Agricultural Research and Extension on State Agricultural Productivity and 95% Confidence Interval (Evaluated at the sample mean of the data for ln(*R*) and ln(*EXT*) from table 1).

| Equation being evaluated | Regression | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\partial \ln(TFP)/\partial \ln(R)$ | 0.152<br>(0.147, 0.157) | 0.139<br>(0.119, 0.159) | 0.126<br>(0.102, 0.149) |
| $\partial \ln(TFP)/\partial \ln(S)$ | 0.104<br>(0.026, 0.182) | 0.106<br>(0.062, 0.150) | 0.085<br>(0.059, 0.112) |
| $\partial \ln(TFP)/\partial \ln(EXT)$ | 0.107<br>(0.090, 0.124) | 0.083<br>(0.073, 0.093) | 0.081<br>(0.043, 0.120) |

*R* = within-state constant dollar stock of public agricultural research
*S*= spillin constant dollar stock of public agricultural research
*EXT* = within-state stock of agricultural and natural resource extension of FTE staff per 1,000 farms.

Table 4. Average Annual Rate of Agricultural *TFP* Growth, by State and Sub-periods

| Regions and States | Actual 1990-2004 | Predicted 2004-2010 |
|---|---|---|
| New England | | |
| Maine | 2.025 | 0.161 |
| New Hampshire | 2.585 | 0.984 |
| Vermont | 1.719 | -0.026 |
| Massachusetts | 2.193 | -0.554 |
| Connecticut | 2.364 | 1.086 |
| Rhode Island | 1.500 | 1.771 |
| Northeast | | |
| New York | 1.665 | 1.201 |
| New Jersey | 1.727 | 0.234 |
| Pennsylvania | 1.516 | 1.244 |
| Delaware | 1.214 | -1.403 |
| Maryland | 1.877 | 0.003 |
| Lake States | | |
| Michigan | 1.677 | 1.317 |
| Minnesota | 1.997 | 1.086 |
| Wisconsin | 2.249 | 0.900 |
| Corn Belt | | |
| Ohio | 1.822 | 0.577 |
| Indiana | 2.377 | 0.596 |
| Illinois | 2.112 | 0.461 |
| Iowa | 2.850 | 0.497 |
| Missouri | 2.079 | 2.550 |
| Northern Plains | | |
| North Dakota | 0.901 | 0.359 |
| South Dakota | 1.474 | 0.600 |
| Nebraska | 1.164 | 0.981 |
| Kansas | 0.863 | 2.264 |
| Appalachia | | |
| Virginia | 1.387 | 1.767 |
| West Virginia | 0.054 | 2.401 |
| Kentucky | 0.723 | 1.404 |
| North Carolina | 0.149 | 1.014 |
| Tennessee | 0.014 | 3.119 |

| Regions and States | Actual | Predicted |
|---|---|---|
| Southeast | | |
| S. Carolina | 1.469 | 0.720 |
| Georgia | 1.273 | 0.659 |
| Florida | 0.785 | 0.099 |
| Alabama | 1.267 | 0.067 |
| Delta | | |
| Mississippi | 1.532 | 0.717 |
| Arkansas | 1.857 | -0.951 |
| Louisiana | 0.994 | 1.671 |
| Southern Plains | | |
| Oklahoma | 0.655 | 2.219 |
| Texas | 1.025 | 2.523 |
| Mountain States | | |
| Montana | 0.949 | 3.103 |
| Idaho | 1.871 | -0.263 |
| Wyoming | -0.007 | 2.677 |
| Colorado | 1.295 | 0.969 |
| New Mexico | 1.805 | 1.524 |
| Arizona | 2.829 | -0.044 |
| Utah | 1.082 | 1.076 |
| Nevada | 1.267 | 0.789 |
| Pacific | | |
| Washington | -1.231 | 0.311 |
| Oregon | 2.133 | 0.537 |
| California | 0.485 | 0.953 |

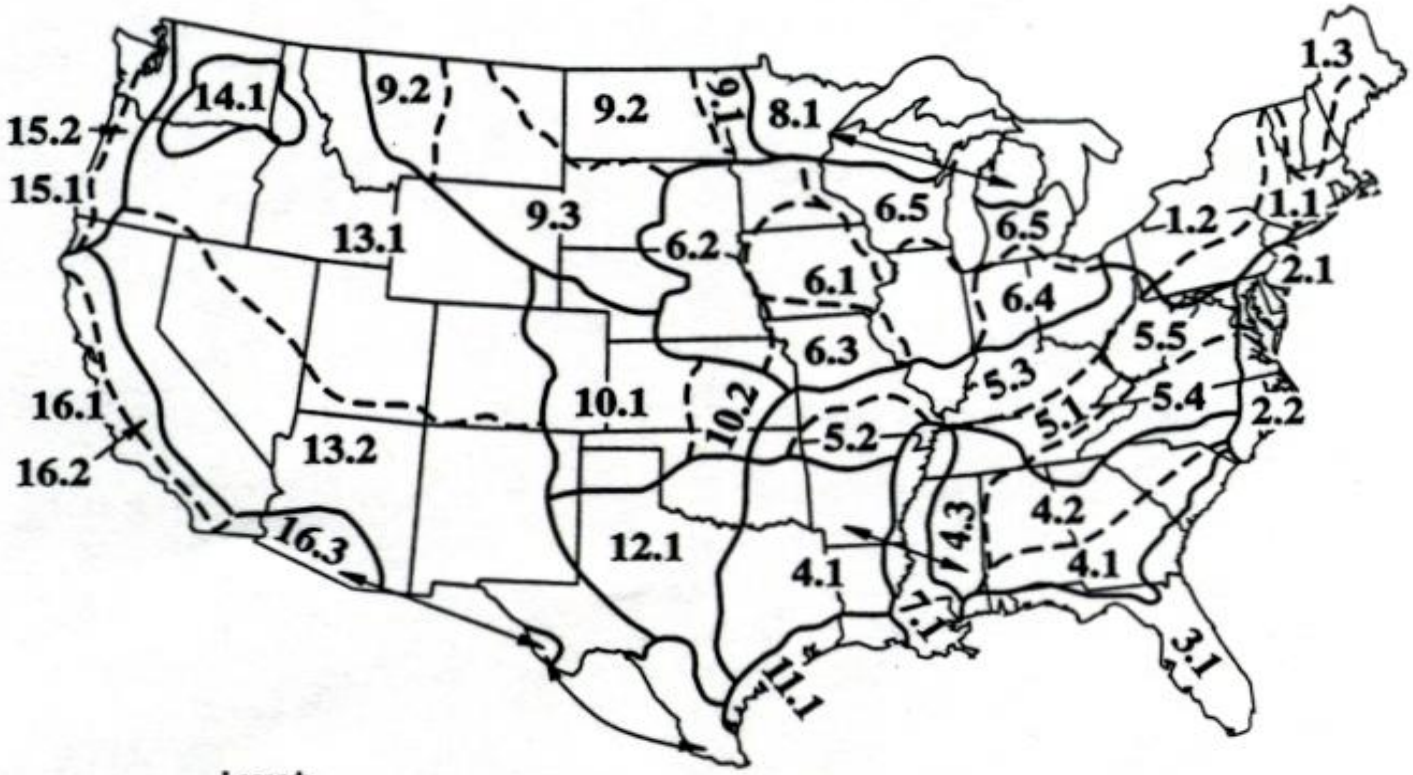
Derived in this study using regression 3, table 2.

Table 5. Characterization of Real Rates of Return (IRR) to Public Agricultural Research and Extension in the U.S.: Recent Evidence

| Source | Type of Analysis | Obs. Unit | Time Period Covered | Public Ag Research | | | Public Ag Extension | | | Real Social IRR | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Type | Lag | Time period | Type | Lag | Time period | Ag Research | Ag Extension |
| Huffman & Evenson (2006b) | TFP | States | 1970-1999 | Net | 35yrs | 1935-1997 | Net | 4yrs | 1966-1999 | 49% | > 100% |
| Alston et al., (2011) | TFP | States | 1949-2002 | Gross | 50yrs | 1900-2002 | Gross | 50yrs | 1900-2002 | 22.7% | Blend[a] |
| Plastina and Fulginiti (2010) | Var.Cost | States | 1949-1991 | Gross | 31yrs | 1918-1984 | None Included | | | 29%(8-37%)[b] | -- |
| Wang et al. (2012) | Var Cost | States | 1980-2004 | Net | 35yrs | 1945-2002 | Gross | None | 1980-2004 | 45% | Not Comp[c] |
| Andersen and Song (2013) | TFP | U.S. | 1949-2002 | Gross | 50yrs | 1900-2002 | None Included | | | 21% | None |
| Jin and Huffman (2014) | TFP | States | 1970-2004 | Net | 35yrs | 1935-2002 | Net | 4yrs | 1966-2004 | 67% | > 100% |

[a] Public agricultural research and extension are aggregated together into one variable.
[b] The range of IRR estimates across the 48 states.
[c] No estimate of IRR is computed.

**Appendix Figure 1**
**Geo-Climatic Region Map**




Legend:
1. Northeast Dairy Region
2. Middle Atlantic Coastal Plain
3. Florida and Coastal Flatwoods
4. Southern Uplands
5. East-Central Uplands
6. Midland Feed Region
7. Mississippi Delta
8. Northern Lake States
9. Northern Great Plains
10. Winter Wheat and Grazing Region
11. Coastal Prairies
12. Southern Plains
13. Grazing-Irrigated Region
14. Pacific Northwest Wheat Region
15. North Pacific Valleys
16. Dry Western Mild-Winter Region

Source: Huffman and Evenson (2006b, p. 271)

**Appendix Figure 2**
**Public Agricultural Research Timing Weights, Lag Lengths and Shapes for Distributing Cost or Benefits over an Investment Project of 1 mil (real dollars): Selected Lengths**