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Reduced U.S. funding of public agricultural research and extension risks lowering future agricultural productivity growth prospects

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Abstract
The objective of this paper is to examine the status of labor-saving mechanization in U.S. fruit and vegetable harvesting. Fruit and vegetable harvest mechanization has several potential advantages: reduced harvest costs, eliminate problems associated with finding good quality harvest labor, permit longer harvesting days, and reduce exposure of harvest to human bacteria. Commercial mechanical harvesters for processed tomatoes, cucumbers, peppers, carrots, tart cherries, apples, grapes, peaches, plums and grapes are in the hands of growers. To my surprise, considerable progress has been made on fresh market sweet cherry, apple and berry harvesters, and in the next few years commercial sales of these machines are expected. A negative shock to labor harvest-labor availability or jump in the harvester wage or piece rate could rapidly accelerate adoption of the best mechanical harvesting technologies by growers and processors.

Keywords
states, agriculture, returns to research, multifactor productivity, U.S., forecasts

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Reduced U.S. Funding of Public Agricultural Research and Extension Risks Lowering Future Agricultural Productivity Growth Prospects

by

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Abstract: The objective of this paper is to provide policy makers with new estimates of the separate returns to public agricultural research and extension and a perspective on future agricultural productivity growth. This requires fitting an econometric model that contains separate regressors for the stock of public agricultural research and public agricultural extension. We use net measures to create our public agricultural research and extension variables. Our model is fitted to data for the U.S. contiguous 48 states, 1970-2004. It yields statistically significant estimates of within-state and spillin stocks of public agricultural research and of within-state agricultural extension. The econometric model of state agricultural TFP yields somewhat optimistic forecasts for agricultural total factor productivity over 2004-2010. The social rate of return to public investments in agricultural research and extension are shown to remain large—both are in excess of 60 percent, which is large by any standard.

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Reduced U.S. Funding of Public Agricultural Research and Extension Risks Lowering Future Agricultural Productivity Growth Prospects

Public agricultural research in the U.S. grew rapidly from 1960-1980, but its growth slowed considerably from 1980-1990, and the growth rate turned negative from 1990-2009 (figure 1). Public agricultural extension peaked roughly at the same time and then flattened out. Private agricultural research expenditures have a strong upward trend, but there have been peaks in mid-1980s, late 1990s, and 2005, followed by valleys (figure 1). Private agricultural research is not a perfect substitute for public agricultural research. For example, private research is profit motivated and frequently builds on public agricultural research. Private agricultural research does not undertake socially important but unprofitable research such as research to advance basic or general sciences, genetic improvement of small grains and orphan crops, natural resources and environmental quality and agricultural policy (Huffman, Norton and Tweeten 2011). Likewise private information dissemination is not a substitute for public agricultural extension. Private information is closely associated with new inputs and the technology that private firms sell. However, public agricultural extension is largely focused on providing farmers with current market information on commodity and input prices, features of the government farm program and production problems, including those related to pest and weather.

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. 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 public agricultural science and agricultural extension policy debates need the most up to date estimates (Huffman, Norton and Tweeten 2011).

Plastina and Fulginiti (2012) 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 and examine alternative shapes of research lag length and conclude that an inverted V shape is best. Also, they do not include variables for public agricultural extension or private agricultural research. One of the main conclusions of their paper is that ignoring spatial correlation of the model's disturbance terms across states within close proximity most likely leads to upward biases in estimated returns to public agricultural research. With no extension or private R&D, the exclusion of a time trend may affect their results.

Wang et al. (2012) explore the contributions of public agricultural research and extension, research spillover, and roads on agricultural productivity in an aggregate cost function. They fit their model to data for the 48 contiguous states from 1980-2004 and find that public agricultural research enhances agricultural productivity and that agricultural extension, road density and public agricultural research spillovers enhance the benefits from public agricultural research.[1]

The objective of this paper is to provide policy makers with new estimates of the impacts of public agricultural research and extension on state agricultural productivity, where research and extension variables are separate explanatory variables, and forecasts of future agricultural productivity growth by state. To do this, we: (1) outline how choice of empirical definitions of

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[1] 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.

public agricultural research and extension can be the source of measurement error biases in estimating their impacts on agricultural productivity, (2) update investments in public agricultural extension over 1993-2010, which also replaces some crude data for 1993-1999 used by Huffman and Evenson (2006a,b), (3) update and extend data on public agricultural research investments from 2000-2010, which goes significantly beyond Huffman and Evenson (2006a,b), (4) examine the 35-year lag length for public agricultural research stocks, (5) report new estimates of the state agricultural productivity model fitted to data for 48 states from 1970-2004, (6) present forecasts of agricultural productivity for each of the 48 states from 2004-2010, and (7) present new estimates of the rates of return to investments in both public agricultural research and extension with comparisons.[2]

To do this 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 data that USDA data are available) and newly updated data on the investments and stocks of public agricultural research and extension. We conditional one-year ahead forecasts from our fitted model, both for with-in-sample and out-of-sample periods. The out-of-sample TFP forecasts are interesting because public agricultural research and extension data are available for this 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 agriculture TFP growth prospects.

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

[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.

issues arise in modeling this relationship. In addition, Huffman and Evenson (2006b) describe how public agricultural research produces discoveries and agricultural extension produces information, which leads to very different routes and timing issues associated with how they impact state agricultural productivity First, research means discovery, which requires top Ph.D. level trained and experienced scientists and supported with complementary resources. These are costly resources (Huffman and Evenson 1993). Discoveries are an infinite-life public good, although their direct usefulness may wax and wane and finally fade away. 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), and research expenditures by these institutions are reported in the Current Research Information System (CSRS 1991).[3] Moreover, since the mid-1930s, the research of ARS has been dispersed across the various U.S. states, and frequently the research facilities of ARS are located close to land-grant universities and work on joint projects with their SAES and veterinary medicine college scientists (Huffman and Evenson 1994, p. 29-32).

Although state agricultural experiment stations were established in 1887 to conduct original research on agriculture, the breadth of their research has increased over time to include research to improve the rural home and rural life (1925), on agricultural marketing and resource conservation (1935), on forestry and wildlife habitat (1962) and on rural development (1972) (Huffman and Evenson 1993). Hence, the breadth of the research agenda of scientists of the

[3] 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.

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 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 state and federal system has also expanded significantly over the past century.

We follow Huffman and Evenson (1993, 2006a,b) and the Current Research Information System (CRIS) choose as the set of institutions performing agricultural research state agricultural experiment stations (SAES), public veterinary medicine colleges/schools, and the USDA's Agricultural Research Service and Economic Research Service. In addition, CRIS provides both a gross measure of measure of broadly defined public agricultural research but also the details about the nature of the research—research commodities and research problem areas. With this latter information, we can net out public agricultural research that does not have an agricultural-productivity focus, for example, post-harvest (food processing, agricultural marketing and agricultural policy), rural and community development, and home economics and human nutrition (Huffman 2010, Huffman and Evenson 1993, 1994).[4] How much is the difference between gross

[4] The primary goal of these other types of research is to make discoveries that have limited implications for agricultural productivity.

and net measures? For example, in 1970, about 70% of the expenditures on public agricultural research reported in the CRIS were on agricultural productivity-oriented research (Huffman 2010).

The problems created by mis-measurement are predictable. Greene (2003, p. 84-85) and Fuller (1987) show that when a regressor contains measurement error the associated estimated regression coefficients will exhibit attenuation or is biased toward zero. Since we have firm beliefs that it is primarily agricultural-productivity-oriented research that impacts agricultural productivity using instead a gross measure of public agricultural research creates a measurement error problem. Likewise, excluding the research of the veterinary medicine colleges creates a measurement error. The outcome is attenuation in the associated estimated coefficients and underestimate of the true impact of public agricultural research on agricultural productivity and rate of return estimates.[5]

For more than 40 years, the USDA's agricultural research enterprise has had a regional structure (Huffman and Evenson 1994) and been distributed across four regions and 48 or more states. In many of these states, the major research centers of the USDA are on, or near land grant universities and their SAES and veterinary medicine colleges/schools (see Huffman and Evenson 1994, p. 54). Moreover, many joint interactions and projects exist between state and federal scientists (Huffman and Evenson 1993, 1994). This suggests combining agricultural research efforts of public institutions in each state.

Public agricultural research undertaken in one state frequently spill over to other areas, i.e., are an impure public good (Cornes and Sandler 1996), but spillovers do not necessarily following state political boundaries. The concept of spillovers is much simpler under our concept of agricultural productivity-oriented public agricultural research than for a gross measure of public agriculture research. The primary reason is that crop and livestock production is largely biological

[5] These expenditures are expected to have primary benefits elsewhere.

in nature and sensitivity to climate, soils and topography while other research is not. For example, in *Soils: the* 1957 *Yearbook of Agriculture*, Barnes (U.S. Department of Agriculture, pp. 452-455) argues that U.S. soils and climate follow definite regional patterns (but not state boundaries). 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 and soils and in associated production problems, which then impact expected farm profitability and create incentives for regional specialization. For example, farmers growing wheat in Texas, Kansas, North Dakota, Ohio and Washington are producing hard red winter, hard red spring and durum and soft red spring and white wheat. Likewise, growers of tomatoes for processing in California and Ohio and fresh tomatoes in Florida face many problems unique to their region. Even dairying in Wisconsin, with its small grazing-based dairies, has greatly different production problems than those of the very large scale, confined hay-based, desert dairies of California.[6]

In contrast, within a geo-climatic region, many forces of nature and the environment are similar and have special implications for local crop and livestock production. For example, consider the Midlands Feed region, region 6 (see figure 2). This region combines productive soils, gentle relief and moderate rainfall over a wide area. Summers are warm, but winters are cold. In this region, there is a great similarity of production problems. Farmers are producing feed grains,

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[6] Alston et al. (2011) define a state specific spill-in stock of knowledge (*SS*) federal expenditures on agricultural research anywhere in the U.S. plus other-state government spending on agricultural research and extension weighted together using similarity of state agricultural output mix and then 50 years of gamma timing weights. The use of interstate spillover weight based on composition of output has similarities to that applied in the industrial organization literature to private non-farm firm's research spillovers (Jaffe 1989). However, inter-area public agricultural research spillover in U.S. agriculture are quite different and more closely related to geo-climatic regions.

oilseeds and to a lesser extent hay, beef, swine and dairy under similar climate and soils.[7] Another important difference is that geo-climates do not recognize political or state boundaries. For these reasons, our public agricultural-research spillin variable for each state is constructed using the 16 geo-climate-region in figure 2.

Extension is primarily adult education for decision makers by farmers, households, and communities. The Smith Lever Act (1914) provided the formal legislation establishing the cooperative (federal and state) extension service 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, p. 24).

In addition to the farm and home focus of extension information, there was an early emphasis on youth activities. The original act included youth work in boys' and girls' clubs, called "4-H" clubs, involved with practical projects in agriculture, home economics and related subjects (4-H History). 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.

[7] We acknowledge that in some cases a discovery in one state and geo-climatic region may impact agricultural productivity in a distant state that is in another geo-climatic region, which, in some cases, might be a long distance away. This could be accomplished by using a type of product mix congruity index. However, this type of research index largely ignores the role of geo-climatic factors in determining production problems and spillovers, and the advantages of geographical proximity to information transfers.

In the early 1900s when extension started, farmers in the South were seeking solutions to a serious infestation of cotton boll-weevils, and in the North they were seeking information on practical farm management problems (Huffman and Evenson 1993). Extension was later extended to resources and community development, and natural resource issues in 1961. Since the 1960s, extension staff has been allocated across four program areas: agricultural and natural resources, community resource development, home economics and human nutrition and 4-H and youth activities. How much of extension is not focused on agricultural and natural resource issues? Over 1977-1992, 55% (Ahearn, Yee and Bottom 2003). Moreover, 30% of extension FTEs were allocated to 4-H in 1977, but this share declined to 23% in 1992 and seemingly leveled off (Ahearn, Yee and Bottom 2003).

Since the 1950s, the typical extension staff member has had a BS degree in agriculture, and more recently specialists have MS degrees and occasionally a Ph.D. degree in an agricultural science field. However, they 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 low educated farmers, agri-businessmen, and local communities. Much of this information is time dated, and obsolesces rapidly with the passage of time. Hence, a key hypothesis in how we proceed is that public agricultural research and extension are two separate and distinguishable activities, and in a credible model of state agricultural productivity, they should be separate and statistically significant explanatory variables.[8]

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[8] The private sector provides considerable information tied-in with sale of farm inputs and purchasing farm output. We argue that the cost of this information is reflected in prices that farmers pay for inputs and receive for outputs. However, there is private farm information that is for sale, e.g., by Doane’s Agricultural Services, John Deere, Pioneer. However, we do not have any data on this activity.

Extension could be a private good or local public good. 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 are somewhat unique and communication is frequently oral, extension information has private good attributes (Cornes and Sandler 1996) and undergoes rapid obsolesce as the decision-making environment changes. Consistent with this scenario, Huffman (1974), Huffman (1981), and Huffman and Evenson (2006a,b) report positive and statistically significant effects of agricultural extension capital constructed on a per farm basis using a relatively short time lag, farm output and on state agricultural productivity.[9] In contrast, if one were to use the gross measure of extension (expenditures or staff days across all four major program areas) or fail to express it on a per farm basis, we would expect attenuation or bias toward zero in the estimated coefficient on extension in a model explaining state agricultural productivity (Greene 2003, p. 84-85).[10]

Private agricultural research might be proxied by expenditures on R&D or by patents granted to private firms. Heisey, Wang and Fuglie (2011) and Wang et al. (2013) have used a U.S. aggregate measure of private agricultural research in a model to explain U.S. agricultural productivity (but it was not statistically significant). However, no consistent disaggregated data by state exists on private agricultural research. Huffman and Evenson (2006a, b) used a crude private R&D variable derived from annual flows of private sector patents awarded in the U.S. to domestic and foreign inventors in four areas: field crops and crop services; fruits and vegetables; horticultural and green house crops; and livestock and livestock services (Johnson and Brown 2002). The national aggregate patent data were then allocated among the states using each states'

[9] The very applied nature and high rate of obsolescence on extension information make significant interstate spillovers on agricultural productivity unlikely.
[10] We expect these expenditures to have primary benefits elsewhere.

production share of national output for crops and livestock, and then these patents for a given year are summed to give a total. The fact that a patent life is roughly 19 years seems relevant to the timing lag for private R&D.

Trends in 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 (see figure 2). There is a significant year-to-year variation in agricultural research expenditures in each of the states. For example, consider the broad trends in four major agricultural producing states that are geographically scattered across the country and have different climate and product mixes. In California, Iowa, North Carolina and Texas, productivity-oriented public agricultural-research expenditures peaked over the late 1980s and the early to mid-90s (see figure 3). However, 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, figure 4 shows great stability in the stock of public agricultural research relative to expenditures. In addition, the stocks peak later than for flows—in 2004 for North Carolina, in 2007 for Texas in 2007, and in 2010 in California and Iowa. After reaching a peak, the stock of public agricultural research started to slowly decline.[11] 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.[12] For example, in Iowa, agricultural extension capital has a slow upward trend over the whole period, 1970-2010 (figure 5). In North Carolina, the trend was strongly upward from 1970-1998, but significantly irregular from 1998-2010. In California, the agricultural 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 General Econometric Model

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

$$(1) \qquad \begin{aligned} y_{it} &= X_{it}\beta + \mu_{it}, VAR(\mu_{it}) = \sigma^2_{\mu_i}, \text{for } i \in N \text{ and } t \in \{0,1,\cdots,T\} \\ \mu_{it} &= \rho_i\mu_{it-1} + \varepsilon_{it}, VAR(\varepsilon_{it}) = \sigma^2_{\varepsilon_i}, \text{for } i \in N \text{ and } t \in \{0,1,\cdots,T\}. \end{aligned}$$

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

[11] Trapezoidal timing weights and a total lag of 35 years.
[12] The stock is computed using exponentially declining weights over 5 years, starting in *t*.

If we have additional information on *X* but not on *y*, we can use equation (1) as a basis 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:

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

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, if we ignore any correlation between $X_{iT+1}\left(\beta - \hat{\beta}\right)$ 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 μ_i and ε_i, respectively.

With an estimate of the variance of the forecast we provide a second important attribute of a forecast, which is sometimes overlooked. Here, the 90% confidence interval of the mean one-step ahead forecast in the *i*th state is

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

The interpretation is that there is a 90% probability that the random interval covers the mean one-year ahead forecast $\hat{y}^f_{iT+1}$.[13] The general forecasting method can be extended to an m-step ahead mean forecast and its confidence interval.

[13] A 95% confidence interval would be about 30% wider.

The Econometric Model of Agricultural Productivity

In the field of agricultural productivity analysis, a ln-ln multiproductivity function is widely used (Huffman and Evenson 1993, 2006a,b; Alston et al. 2011).[14] Agricultural productivity in state i and year t is represented as follows:

$$\text{(4)}\quad \ln(TFP)_{it} = \beta_1 + \beta_2 \ln R(m)_{it} + \beta_3 \ln S(m,r)_{it} + \beta_4 \ln EXT(q)_{it} + \beta_5[\ln R(m)_{it} \bullet \ln EXT(q)_{it}]$$

$$+\beta_6 \ln P(v)_{it} + \sum_{k=1}^{K} \delta_k D_k + \tau t + \mu_{it},\ \mu_{it} = \rho_i \mu_{it} + \varepsilon_{it},\ i = 1,..,n,\ t = 1,...,T,$$

where total factor productivity, *TFP*, is a ratio with the quantity index of farm outputs divided by a quantity index of 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 public agricultural research from other states, with lag length m and geo-climate region r for state i.[15] Both research stock variables are expected to have a positive impact on state agricultural productivity. Hence, we limit ourselves to lag lengths for R and S that are the same. We include a separate variable for agricultural extension stock, $EXT(q)_i$ with lag length q.[16] $P(v)$ is the stock of private agricultural research with lag length v. Because private agricultural research is more directly focused on developing and marketing new technologies to farmers, we expect the timing lag v is shorter than for R and S.[17]

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[14] The other primary approach is a cost function model, e.g., Huffman et al. (2002), Plastina and Fulginiti (2012) and Wang et al. (2012)

[15] 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 proxy variables for stocks (Greene 2003),

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

[17] If β_5 is zero, then equation (1) is simply a Cobb-Douglas production function, where TFP is produced using inputs of *R*, *S*, *Ext* and *P*. A Cobb-Douglas production function is well known for its inputs being substitutes, and the marginal products being positive.

We include a time trend in our model of state agricultural productivity analysis to (i) effectively de-trend the dependent variable and all of the regressors. This is necessary to be able to draw causal inference,[18] (ii) de-trended time series have less autocorrelation and are more likely to be trend stationary (Enders 2010). In addition, trend could pick up the effect of slowly and persistently changing inputs on farm outputs, which would lead to a conservative estimate of the impact of ln*R*, ln*S* and ln*EXT* on ln(*TFP*). Other control variables are dummy variables for regions composed of groups of states, D_k.   In addition a random disturbance term, μ_{it}, is included to capture other factors that might impact state agricultural productivity in a particular state *i* and year *t*.[19]

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 from Ball et al. (2010), and consist of annual data for the 48 contiguous states from 1970-2004. The input data have been adjusted for quality where possible, including the labor farm labor, land and pesticides. This is 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. We convert constant dollar expenditures into stocks using the general trapezoidal timing weight of Huffman and Evenson (1993 and 2006a,b), but we do

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[18] Ignoring the fact that two series are trending in the same or opposite directions can lead to 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.

[19] 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.

examine the impact of lag-length on the performance of the ln(*TFP*) equation.[20] Huffman and Evenson (1993, 2006a,b) have popularized trapezoidal shaped lags over 35 years. We permit some flexibility and consider alternative lag lengths of 30, 35, 40 and 45 years for within and spillin public agricultural research capital.[21] Figure 6 displaces the exact patterns for each lag length, which we argue is broadly consistent with the shape of the most preferred lag pattern of Alston et al. (2010).

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.[22] 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.[23] This is imperfect and we would like better data.[24] In all years, newly derived data

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[20] Alston et al. (2011) have used a gamma distribution to approximate timing weights on a bundle of state gross SAES research and public extension expenditures. Their most preferred shape is not greatly different from the shape of our timing weights, however, they choose a longer time lag of 50 years.

[21] Of course a more general search over shapes and length of lag could be undertaken.

[22] 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.

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

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

on FTE agricultural extension staff years are divided by the number of farms in 1,000s, to put it on a per farm basis. 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, 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 on agricultural extension information.

The private agricultural research stocks were imported from Huffman and Evenson (2006a, b). The only shortcoming is that these data from 1970 to 1999, but they are short on the upper end. They used a lag length (*v*) of 19 years and trapezoidal timing weights to obtain these stock variables.

The regional indicators of equation (4) 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, p. 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 the USDA's Agricultural Research Service (ARS) took a regional structure, grouping states into four regions (Huffman and Evenson 1994, p. 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.[25]

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

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 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}).

The Estimated Model of State Agricultural Productivity

Econometric estimates of several versions of equation (4) are reported and discussed in this section. When ρ is not constrained to be zero, we use 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.[26]

[26] On the advice of Wayne Fuller of Dickey and Fuller (1979), we did not undertake unit-root tests on each continuous variable in equation (4) or co-integration tests (Engle and Granger 1987). The reasons are as follows: (i) equation (4) 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 (4) where all states have the same autocorrelation coefficient gives a sample value of ρ equal to 0.66, which is far from one (and zero), and (iv) the estimate of equation (4) where each state is permitted to have a different value of ρ 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. See Appendix figure 1 for a histogram of the $\hat{\rho}_i$s and plot of the normal kernel density function for these estimates. Under the above conditions, Fuller indicated that unit root and co-integartion tests have very low power and tend to confuse rather than shed light on statistical properties of time series.

First, we examine the contribution of private R&D on state agricultural productivity. This regression uses data from 1970-1999, which is not quite the full length of the time period that we focus on in this paper, but these are the data available in Huffman and Evenson (2006a,b). The estimated coefficient of ln(*P*) is not significantly different from zero even at the 10% level, and adding an interaction term between private and within-state public agricultural research does not change the outcome (See Appendix table 1). Even if we had the missing data, we judge that this private agricultural research stock variable would not be a significant variable for explaining state's agricultural productivity.[27] Hence, ln(*P*) is dropped from further consideration.

Second, we examine the effect of various lag lengths for *R*(•) and *S*(•) on explaining ln(*TFP*). As a metric for comparing models with different lag lengths, we choose R^2. Equation (4), 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, and figure 7 displays the R^2 for each fitted model.[28] 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.

Third, regression (1), table 2, reports estimates of the regression coefficients of the refined equation (4) where ρ is constrained to be zero. The estimated coefficient for the direct impact on

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[27] Using U.S. aggregate data over 1970-2009 and private R&D capital constructed from private agricultural expenditure data, Wang et al (2013) also failed to fine a statistically significant effect of private agricultural research on agricultural productivity.
[28] This process has similarity to looking for the choice of m that maximizes the likelihood function.

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). 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 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.

Fourth, regression (2), table 2, reports estimates of the regression coefficients of equation (4) with the restriction that ρ_i is same across all 48 states; and $\hat{\rho}$ = 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. 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). 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 (4) where each state has a unique estimate for ρ_i (see Appendix figure 1 for a histogram of the $\hat{\rho}_i$ values). 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 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 state average annual *TFP* growth rates in the future to fall below 1%.

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 ρ; 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 ρ_is, i.e., it uses only residuals for state *i*. This is important because the estimates of ρ have at best good large sample properties, with small sample properties being unknown (Wooldridge 2002). Hence, $z_2 = \hat{\rho}/$

$s.e.(\hat{\rho})$ →N(0,1), an asymptotic standard unit normal distribution.[29] 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 elasticity of *TFP* with respect to *R*, *S* and *EXT* across the three models reported in table 2, including an allowance for the interaction of *R* and *EXT*. The elasticity of *TFP* 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 elasticity. The elasticity of *TFP* 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 elasticity of *TFP* 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 our estimates have a normal distribution, the 95% confidence interval for all of these estimates are quite tight (see table 3, numbers in parentheses).[30]

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

[29] 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.
[30] However, one might consider the elasticities computed for regression (2) to be the best due to better large sample properties of the estimates.

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 marginal cost of increasing *TFP* will be even larger than 20%. In contrast, if all states were somehow to agree to the same proportional increase in *R* and *EXT*, 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 research (*R* and *S*) and extension in the long run and rising marginal cost in producing agricultural productivity.

Forecasting Agricultural Productivity

To gain additional implications from our results, we 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 changed over this period, but we are much more comfortable making a forecast over this 5 year interval than making forecasts to 2050 that others have done by Heisey, Wang and Fuglie 2011 and Alston et al. (2010).

When forecasting is the objective, regression (3) has some advantages. For example, the additional flexibility in the choice of ρ giving each state its own value should result in a forecast that tracts ln(*TFP*) better.[31]

[31] 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 ρ.

Figure 8 displays within-sample plots of ln(*TFP*) from 1970-2004 and one-year ahead forecasts of $\ln\left(\widehat{TFP}\right)$ from 1970-2004. These forecasts track actual ln(*TFP*) relatively well, except for a few states that have extremely noisy ln(*TFP*) values, e.g., Montana, North Dakota. To gain additional perspective on how well our model of productivity performs, we consider the figures for California, Iowa, North Carolina and Texas. Panel A shows that one-year 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.

Figure 8 also display out-of-sample forecasts for ln(*TFP*) from 2005-2010 using parameter estimates from regression (3), table 2, using equation (2). Since the detail in small, it is difficult to accurately visualize what is going on in these figures. Hence, we construct table 3 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. The average rate of growth for one-year ahead forecasts of ln(*TFP*) over the 7 year period from 2004-2010, conditional on actual information on public research and extension capital. A somewhat optimistic discovery is that the rate of growth of forecasted ln(*TFP*) is positive for 90% of the states. Exceptions are Vermont, Massachusetts, Delaware, Arkansas, Idaho and Arizona. 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. In 16 states (33%), the rate of growth of forecasted ln(*TFP*) is larger than the estimated trend rate of increase in ln(*TFP*) over the sample period 1970-2004 of 1.1% per year (see regression 2).

Regionally, there is considerable diversity in the forecasts of *TFP* growth. The Southeast, New England and Pacific regions have unusually low predicted *TFP* growth (0.38%, 0.57% and 0.60%). Perhaps surprising is the finding that the Southern Plains and Appalachia have high forecasted *TFP* growth (1.94% and 2.37%). Hence, it is apparent that for some states and regions, the rate of growth of forecasted *TFP* from 2004-2010 is moderate.

To add a little more perspective on our out-of-sample conditional forecast of ln(*TFP*), we have constructed the 90% confidence interval for the forecasts for the states of California, Iowa, North Carolina and Texas. Figure 9, Panel A shows that in California, the forecast of ln(*TFP*) is growing at almost 1% per year, which is faster than over the previous fifteen years. Moreover, the 90% confidence interval is relatively tight and not changing much over 2005-2010 because $\hat{\rho}_{CA}$ 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 very wide. Panel C shows than in North Carolina, the growth of forecasted ln(*TFP*) is large relative to the most recent fifteen years, but the 90% confidence interval is rapidly expanding as the forecast move forward to 2010 because $\hat{\rho}_{NC}$ is large. Panel E shows that in Texas, the growth rate of forecasted *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 to 2010.

How do our out-of-sample state *TFP* forecasts compare to those of others? Not much exists. However, after estimating a state agricultural productivity model using data for 1949-2002, Alston (2010, pp. 387) report some type of 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

To summarize the returns to research and extension, we choose an internal rate of return (IRR) computation similar to Yee, Huffman, Ahearn and Bottom (2002), Huffman and Evenson (2006a,b), Wang et al. (2012) and Plastina and Fulginiti (2012) and not a marginal rate of return (MIRR) computation or benefit-cost ratio, as in Alston et al. (2011). Some are confused about the interpretation of the IRR. It is that uniform discount rate that yields a net present value of zero for an investment project, i.e., it is the interest rate that the project *could pay* and still have a net present value of zero (Harberger 1972). It is a misinterpretation that the proceeds of an investment project *must actually* be re-invested each year in another project. However, Alston et al. (2011) propose the MIRR based on the must pay interpretation, which leads to lower return estimates. Although they suggest that MIRR is a more plausible estimate than IRR estimates, the jury is still out. Although they express an overall preference for benefit-cost ratios, B-C ratios seem more problematic than IRR estimates.[32]

To estimate the social internal rate of return (IRR) to (productivity-oriented) public agricultural research, we use equation (9) from Yee et al. (2002, p. 189-191), the productivity elasticities from column (3), table 3, and the sample mean values of ln(*EXT*) from table 1.[33] Our estimate of the IRR to an incremental investment in (productivity-oriented) public agricultural research is 66.8% per year, which is 6 to 10 percentage points larger than in Huffman and Evenson (2006a).[34] Roughly 40% of the return to public agricultural research is due to spillover effects, 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 marginal rate of return to public agricultural research. This provides another justification of the large IRRs.

As a robustity check, we re-compute the IRR at the low side of the 95% confidence interval for the productivity elasticities reported in table 3, column 3. This yields an IRR of 60% per year, reflecting the fact that the confidence interval is very tight.[35] Moreover, given that these IRR estimates are adjusted for inflation, they are quite large, but they fall in the three-fourths to

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[32] 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 they are the same in each year of a long-life investment project, and hence, are often exceeding difficult to estimate with any accuracy (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%. 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.

[33] Evaluations of marginal products at each point of the data set suffer from the fact that the confidence interval differs for each value, 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 and we evaluate the productivity elasticity at the sample mean of the data where the confidence interval is narrowest.

[34] The sample mean value of output (Q) used in this calculation is \$3.513 billion per state per year in constant 1984 dollars.

[35] 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.

one-fourth quartile range for rate of return estimates on public agricultural research of 83% to 28% per year for studies in the U.S. summarized in Huffman and Evenson (2006b, p. 294-295).

How do our returns to public agricultural research compare to other estimates? Plastina and Fulginiti (2012) obtain an estimated social real IRR to public agricultural research of 29%, averaged across all states in models with stochastic spatial effects. Wang, Ball, Fulginiti and Plastina (2012) report an estimate of the social IRR of roughly 45% (modal value across states). Alston et al. (2010, 2011) report a social IRR to the bundle of agricultural research and extension or R&E of 22.3% (Alston et al., 2011, pp. 1272, top of column) and an MIRR of 9.9%.[36] We argue that a major factor contributing to lower return (IRR) estimates in Plastina and Fulginiti (2012) and Alston et al. (2011) than in our study is that they use gross measures of public agricultural research. Also, Alston et al. (2010, 2011) further muddy the interpretation by having aggregated public agricultural research and extension together into their R&E variables. The Wang et al. (2012) paper uses roughly the same data for public agricultural research and extension as our study, and different estimates of the IRR may be due largely to them taking a cost function rather than our multifactor productivity function approach.

Conclusion

This paper has fulfilled its objective of providing policy makers with up-to-date direct impacts and separate estimates of the returns to public agricultural research and extension, and a perspective on future agricultural productivity growth. We find econometric support for the 35-year lag length for public agricultural research stocks. We easily find separate statistically significant contributions of public agricultural research and extension to state agricultural

[36] Recall that they aggregated within-state gross SAES (only) research and extension together on a dollar-for-dollar basis and then applied a seemingly long lag length of 50 years to both. This aggregation occurs they suggest because of multicollinearity problems that arose when separate variables included.

productivity. A likely identifying factor is dramatically different lag lengths and lag patterns/shapes for these two types of investments. Also, extension is treated as private good and expressed on a per farm basis, which is different from the public good treatment of agricultural 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 US states to become negative in the near future.

Our one-year-ahead conditional forecasts show major forecasting power of our econometric model of state TFP, and out-of-sample forecasts over 2004-2010 provide some optimism for future agricultural TFP growth, but there is wide regional variation. Some regions can expect high rates of growth for forecasted *TFP*, e.g. more than 1.9% per year for the Southern Plains and Appalachia, but others less than 0.7% per year, e.g., the Southeast, New England and Pacific regions. In other regions, the forecasted rates are more modest. 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. Our new estimate of the social real annual IRR to (agricultural-productivity-oriented public agricultural research) is 60% and to agricultural extension is over 100%. These high rates of returns suggest that public agricultural research and extension are attractive investments of public funds. However, we show that there are very strong diseconomies of scale associated with increasing TFP (or agricultural output) by investing only in public agricultural research and extension. Hence, large IRRs do not necessarily imply large—non-marginal—investments are optimal.

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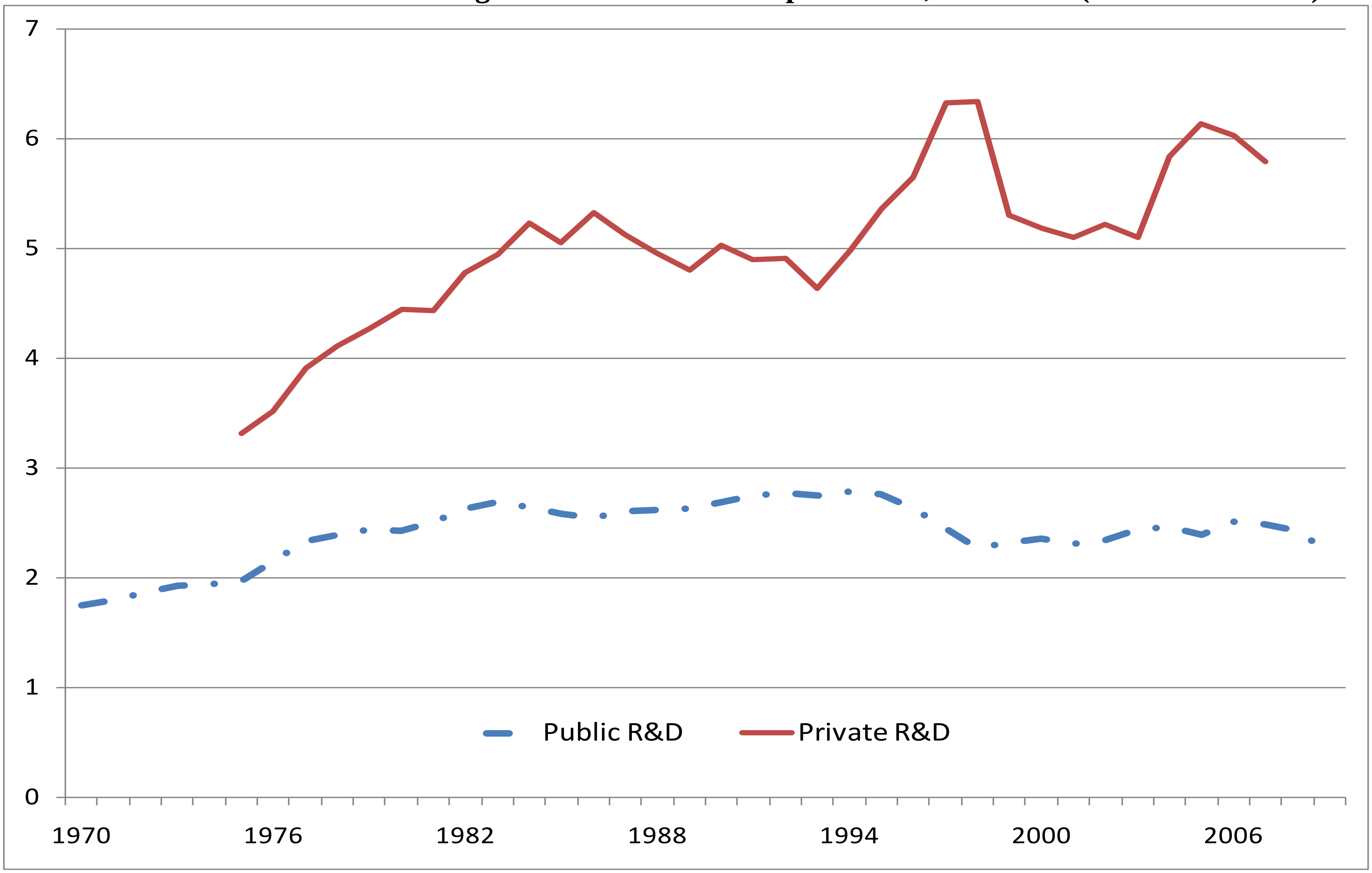
Figure 1

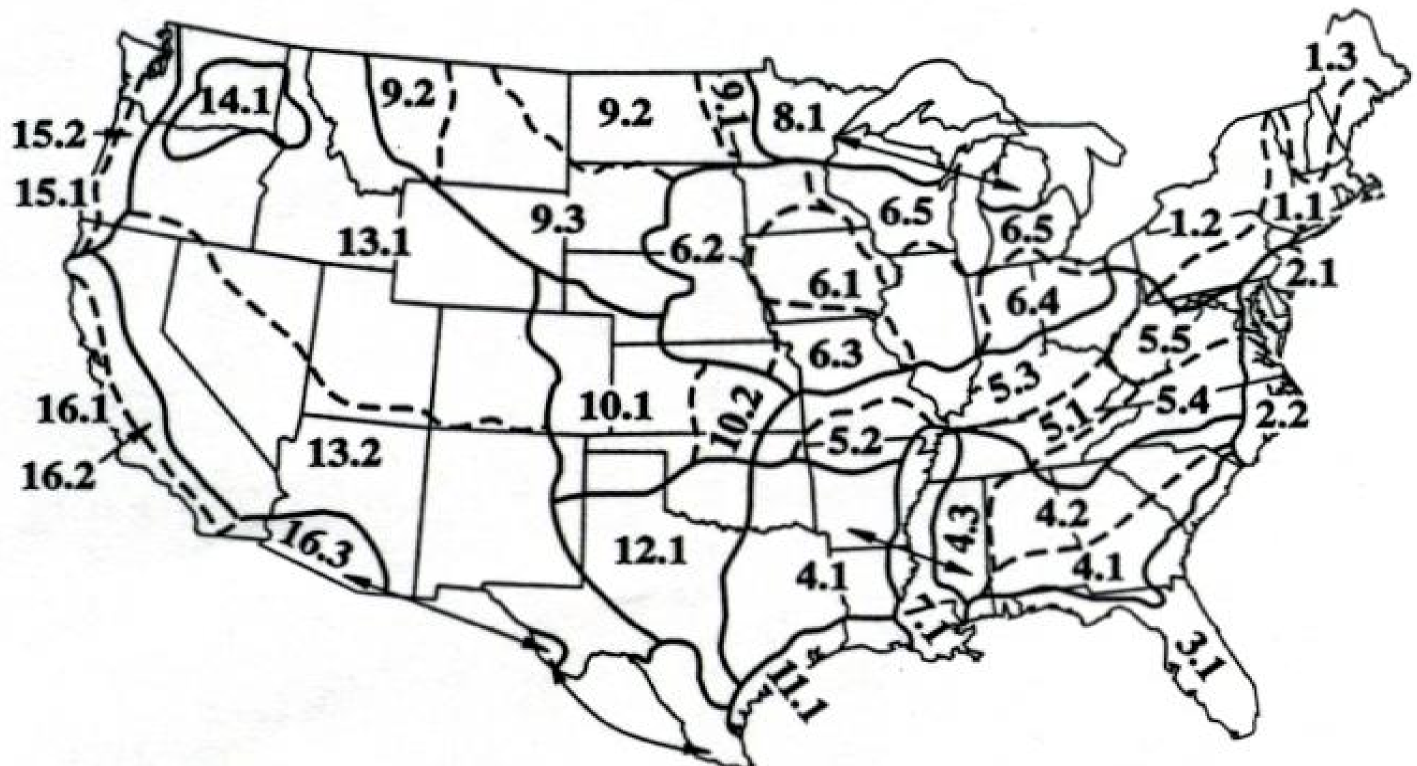
U.S. Total Real Public and Private Agricultural Research Expenditures, 1970-2009 (Billions 2006 dol.)



Source: Private agricultural research effort from Fuglie, et al. (2011). Public agricultural research effort from the authors.

Figure 2

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

Figure 3
Real Public Agricultural Research Expenditures, CA, IA, NC, and TX, 1970-2009 (millions of 2006 dol.)

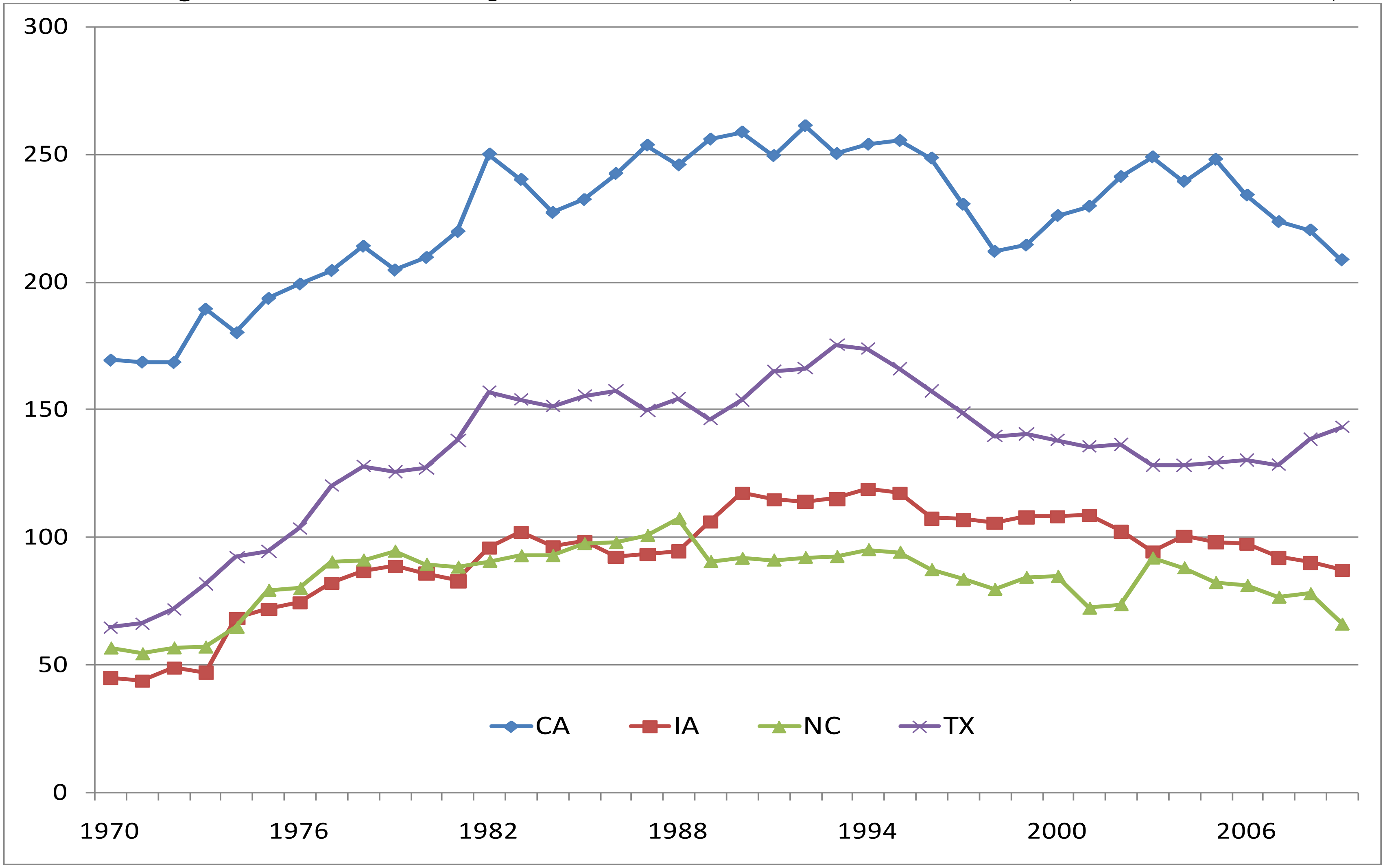


Figure 4

Real Public Agricultural Research Capital: CA, IA, NC, and TX, 1971-2012 (35-year lag)

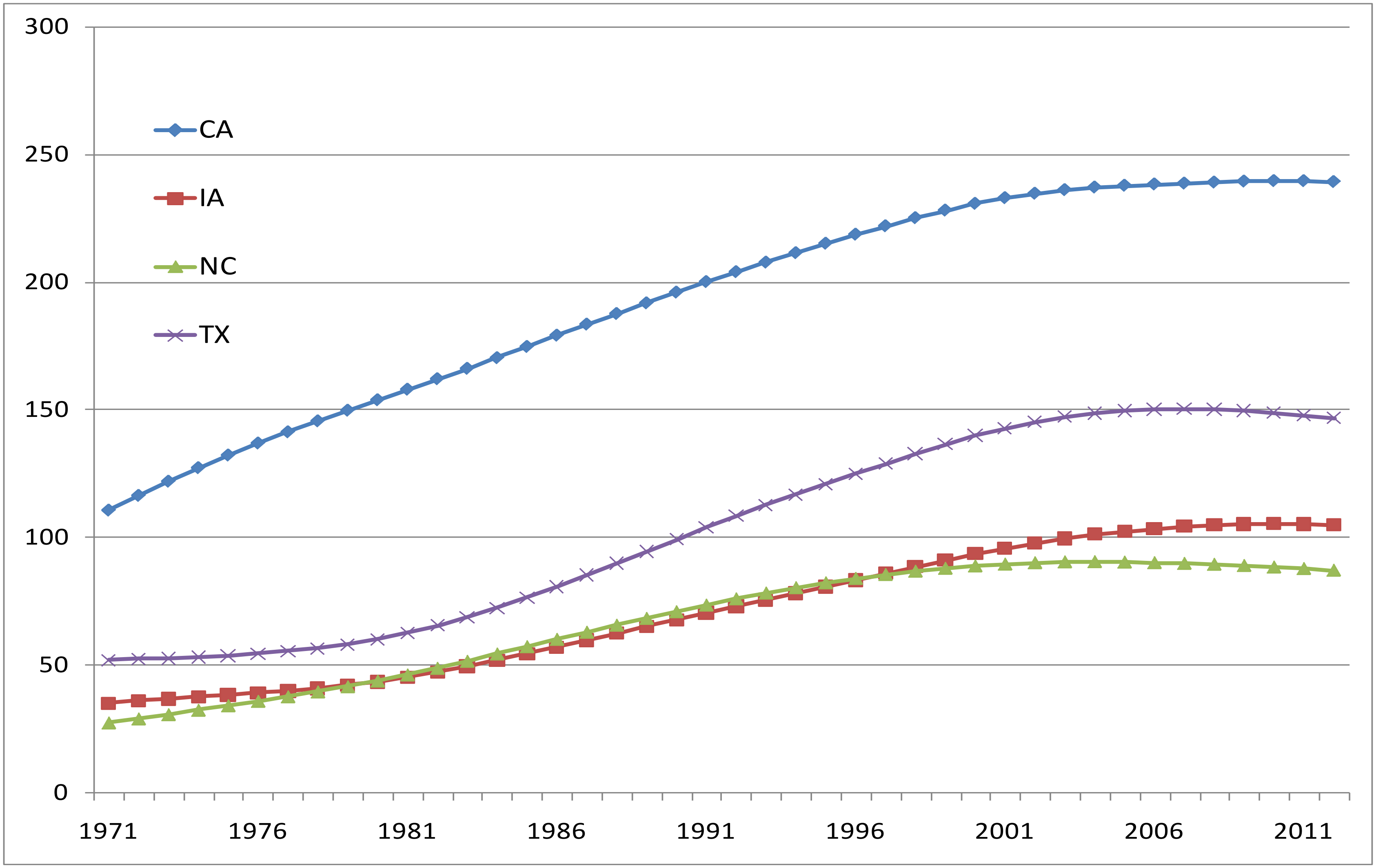


Figure 5

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

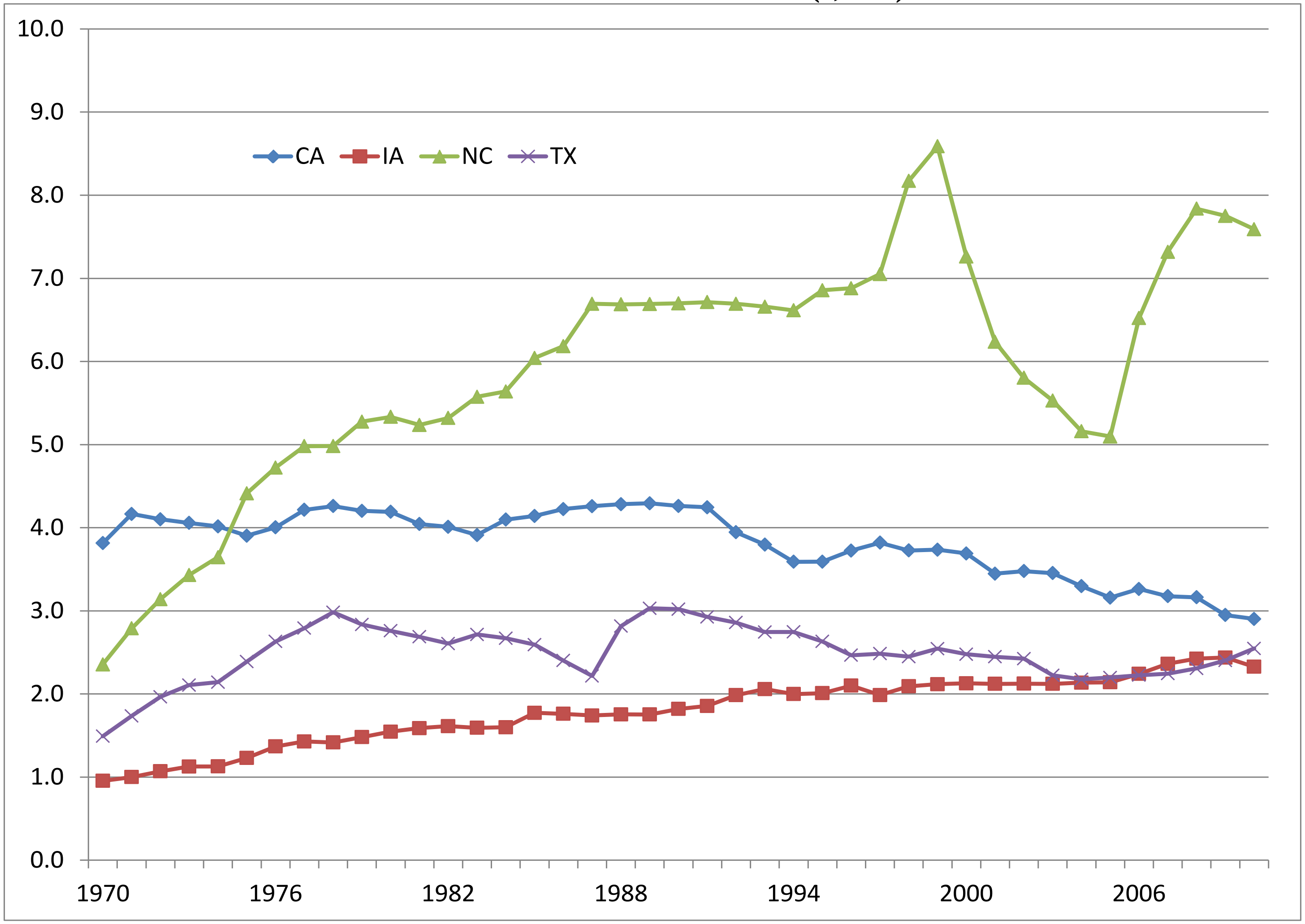


Figure 6

Public Agricultural Research Timing Weights, Lag Length and Shape

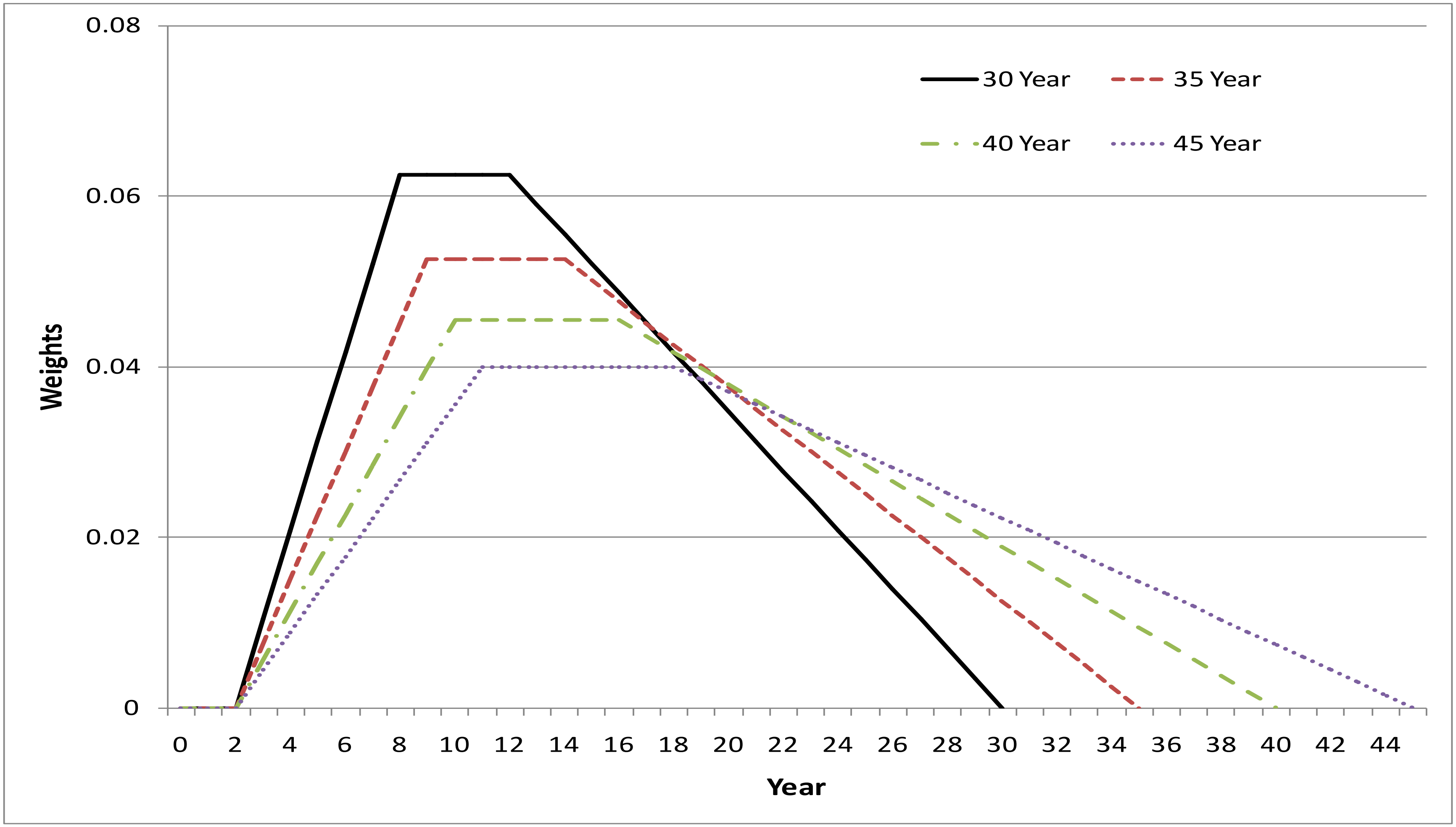


Figure 7

Performance (R-squared) of ln (TFP) Models by Paired Lag Length for Within-State and Spillin Agricultural Research Stocks

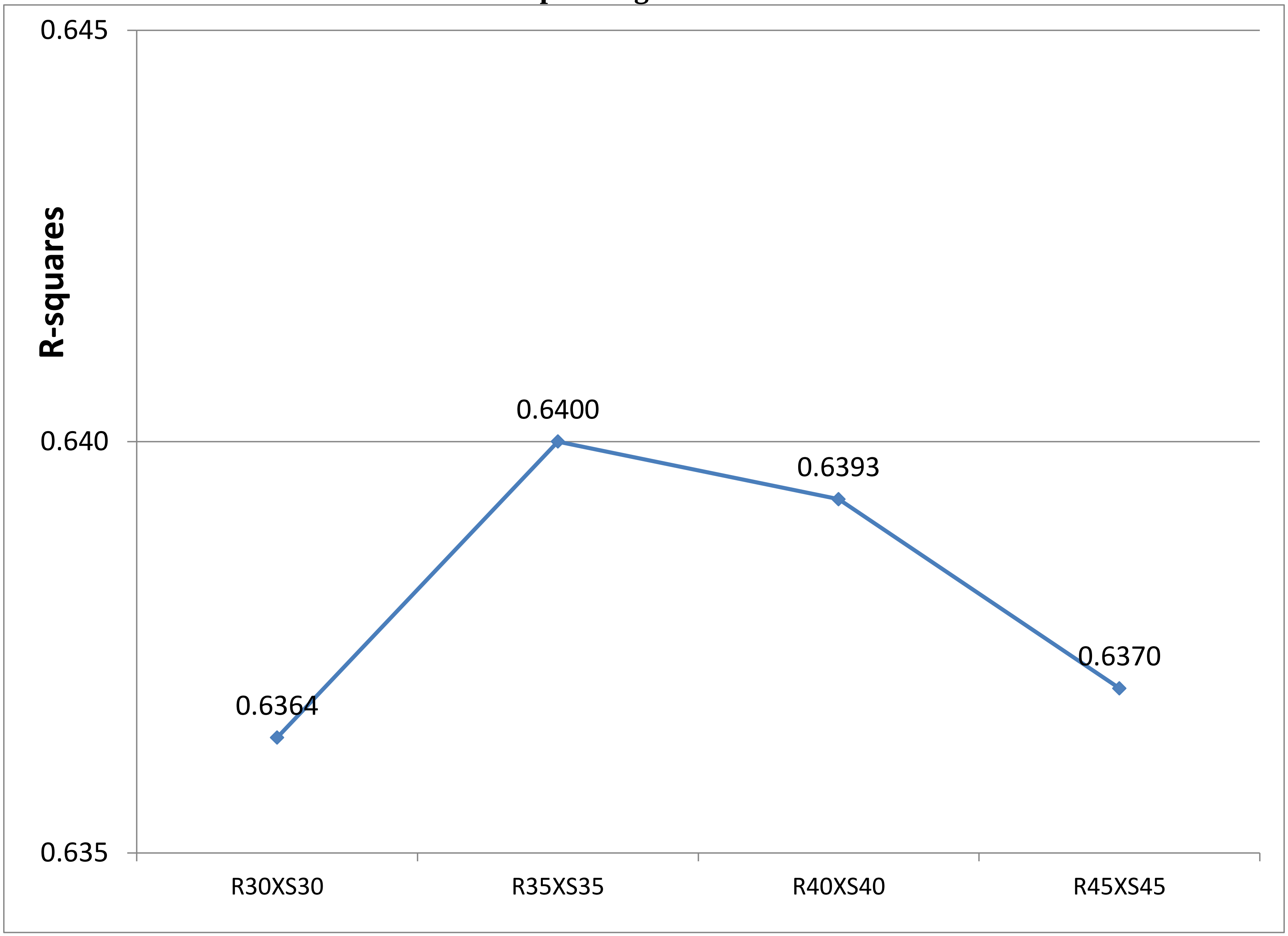


Figure 8. Actual ln(*TFP*), 1971-2004, and Predicted ln(*TFP*), 1971-2010, for 48 States

Figure 8, Cont.

Figure 9. Plots of Actual ln(*TFP*) and One-year Ahead Forecasts of ln(*TFP*) within Sample, 1971-2004, and Out-of-sample, 2005-2010, and 90% Confidence Interval for the Mean Forecast, 2005-2011 (Model 2 in Table 2 and Actual Public Agricultural Research Capital)

Panel A: California

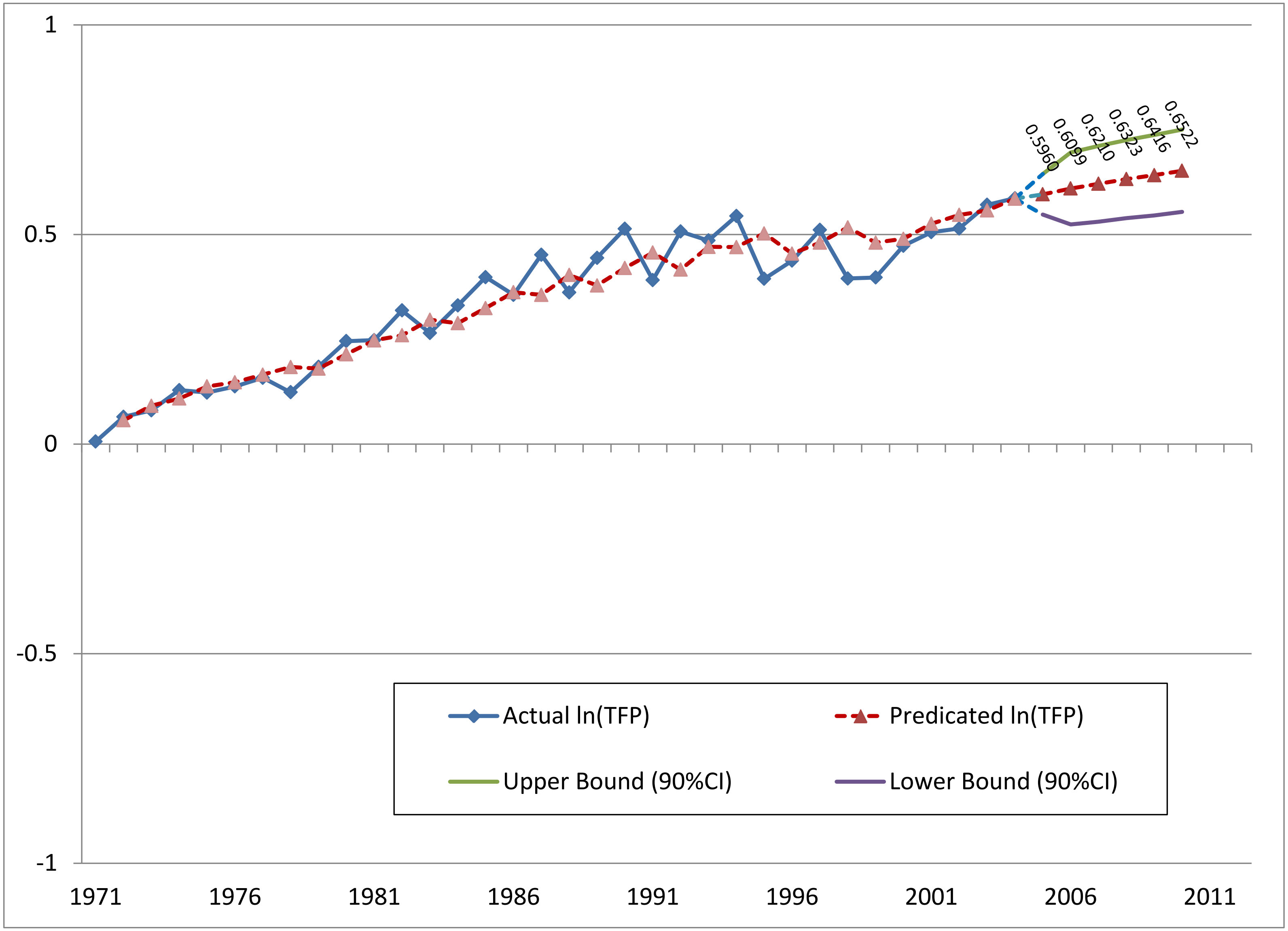


Figure 9, continued.

Panel B. Iowa

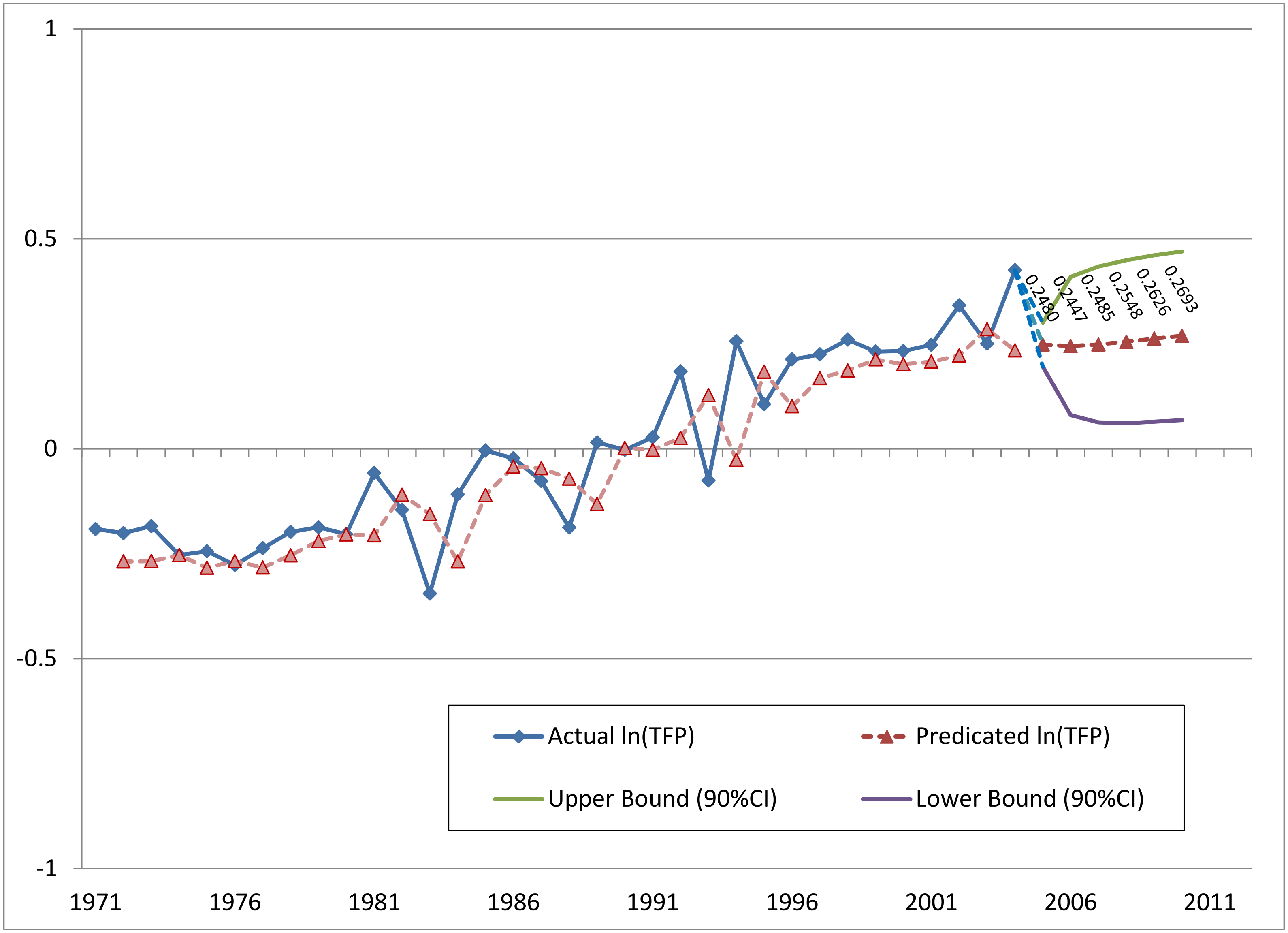


Figure 9, continued.

Panel C. North Carolina

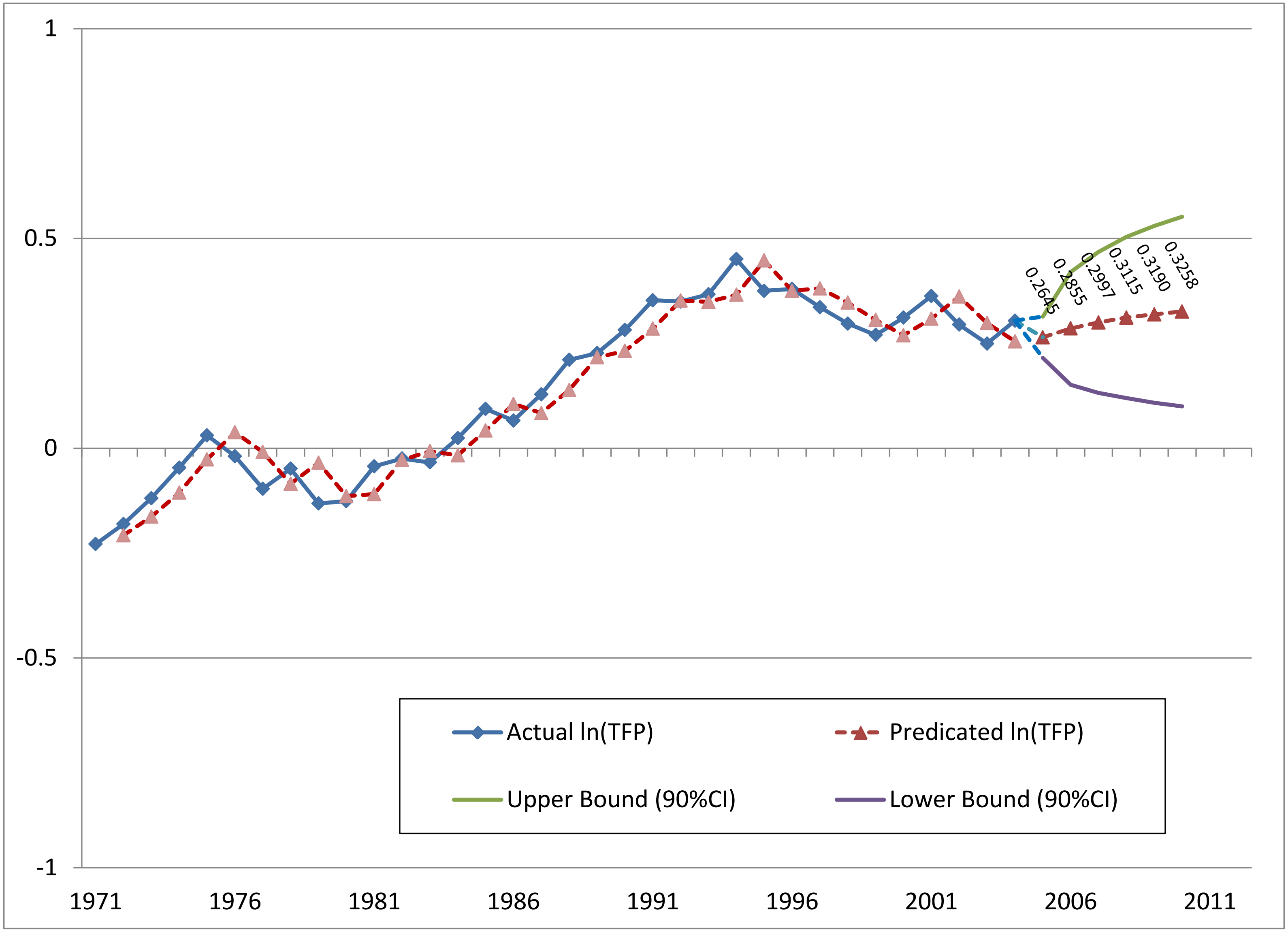


Figure 9, continued.

Panel D. Texas

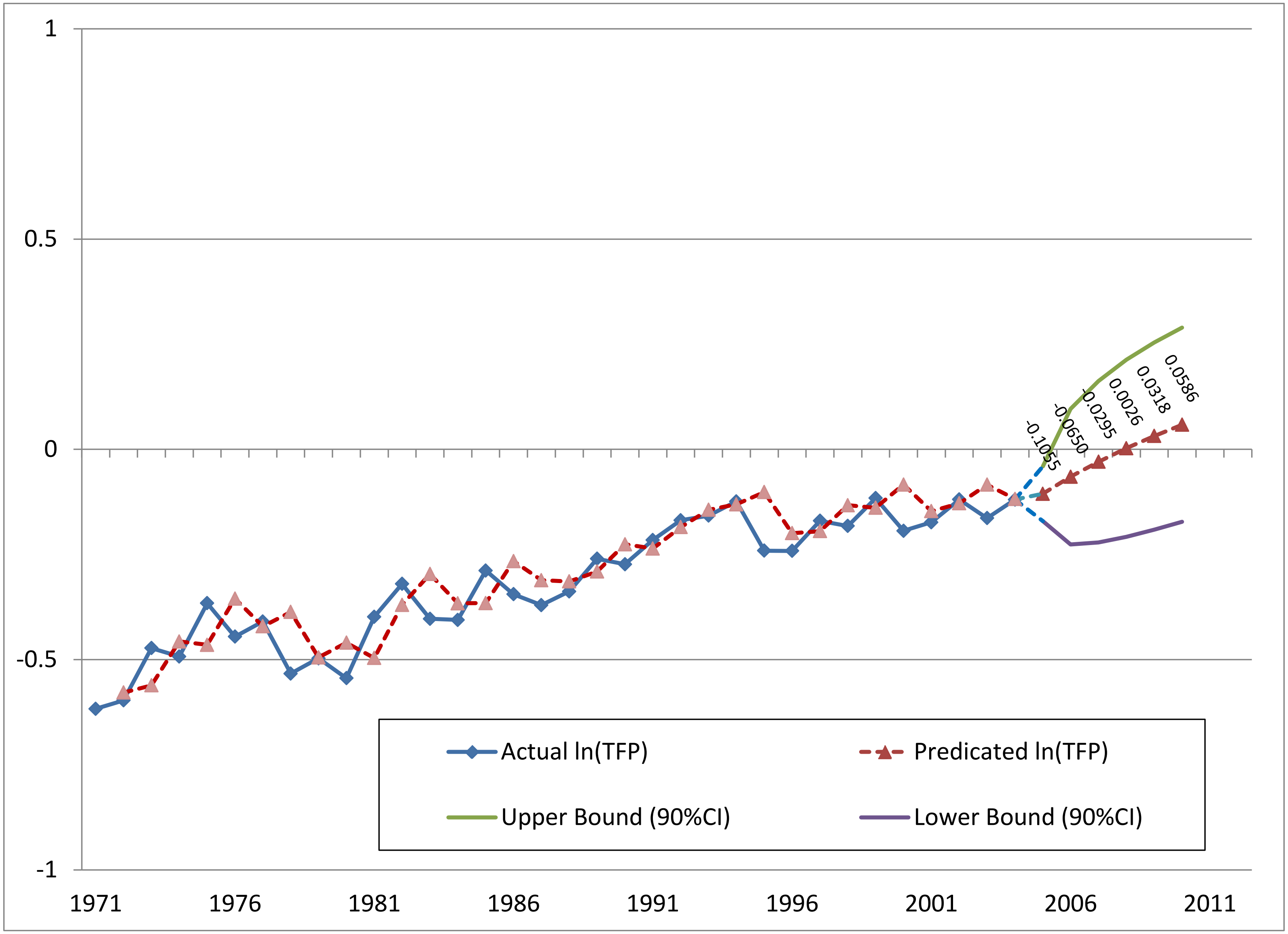


Table 1. Variable Names and Definitions for Annual

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 millions. See Figure 5.
Spillin Public Agri-Research Capital	*S*(35)	1.406 (0.493)	Spillin productivity-oriented public-agricultural-research capital in 10 millions. Trapezoidal shaped timing weights.
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.
Private Agricultural Capital	*P*(19)	6.077 (0.248)	Private agricultural research created from private sector patent data (Johnson and and Brown and Huffman and Evenson (2006).
Regional indicators	D_1		Dummy variable taking a 1 if state is the Northeast Region, excluding 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 x T = 48 x 34 = 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 ρ 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 ρ 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. See Appendix figure 1 for a plot of the $\widehat{\rho}$`s.

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 2).

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

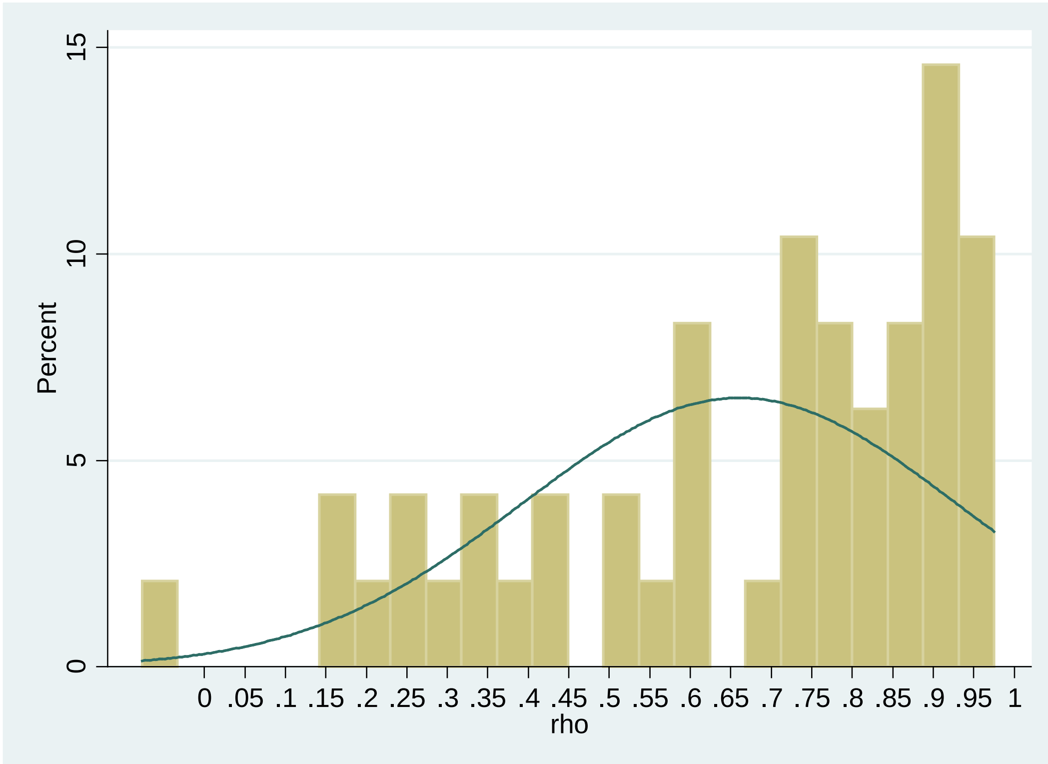
Table 4. Average Annual Rate of Agricultural *TFP* Growth, by State and Sub-periods

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

Table 3, Continued

Southeast		
South Carolina	1.469	0.720
Georgia	1.273	0.659
Florida	0.785	0.099
Alabama	1.267	0.067
Delta States		
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

Appendix Figure 1. Histogram of Estimates of ρ_i, the First-order Autocorrelation Coefficient, and the Normal Kernel Density Function for These Values



Appendix Table 1. Econometric Estimates of State Agricultural Productivity Equation: Contribution of Public Agricultural Research Capital and Other Factors, Forty-Eight U.S. States, 1971-2004 (N x T = 48 x 34 = 1,632)

	Regression (1)		Regression (2)	
Regressors	Coefficients	z-values[a]	Coefficients	z-values
Intercept	-18.805	5.67	-18.654	5.60
ln *R*(35)	0.177	7.14	0.442	1.31
ln *S*(35)	0.093	6.03	0.093	5.90
ln *EXT*(5)	0.078	5.76	0.075	5.59
ln *R*(35) x ln *EXT*(5)	-0.030	2.27	-0.033	2.27
ln *P*(19)	-0.021	0.23	-0.055	0.52
ln P(19) x ln R(35)	-	-	-0.043	0.08
Regional Indicators				
D_1	0.115	2.15	0.121	2.48
D_{2e}	0.062	2.38	0.059	2.21
D_{2w}	-0.069	2.47	0.066	2.26
D_{3w}	0.063	4.03	0.064	3.91
D_{4e}	-0.008	0.52	-0.025	0.72
D_{4w}	0.077	1.18	0.071	1.10
D_{4ca}	0.309	5.02	0.273	3.35
Trend	0.012	7.58	0.009	5.63
R^2	0.668		0.682	

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; *P* = the stock of private agricultural research. 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. Parameters are estimated using the Prais-Winsten estimator with each of the 48 states having its own estimate of ρ.

[a] 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.