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A NONPARAMETRIC ANALYSIS OF THE INFLUENCE OF
RESEARCH ON AGRICULTURAL PRODUCTIVITY

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ABSTRACT: Nonparametric productivity analysis is extended by endogenizing technical progress as a function of public and private research expenditures. Results indicate that 30 year-lags are required to fully capture the effects of public research expenditures on U.S. agricultural productivity. Compared to public research, private research has a stronger influence on farm productivity in the short term but a smaller influence in the longer term. The internal rate of return is found to be 0.41 for public research and 0.36 for private research.

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A NONPARAMETRIC ANALYSIS OF THE INFLUENCE OF RESEARCH
ON AGRICULTURAL PRODUCTIVITY

I) Introduction.

Since the pioneering study by Schultz and Griliches (1958, 1964), a large body of literature has focused on measuring and explaining changes in agricultural productivity. Of particular interest has been the influence of variables such as research on technical progress (Norton and Davis). Alternative approaches have been used in the empirical investigation of this issue. Variables measuring research activities can be incorporated in the estimation of production functions (e.g. Griliches, 1964; Evenson, 1967; Bredahl and Peterson), or of its dual cost or profit functions (e.g. Huffman and Evenson, 1989). However, with a few exceptions (e.g. Huffman and Evenson, 1989), most of the empirical research has relied on a Cobb-Douglas production specification which imposes strong restrictions on the nature of the production technology (by restricting the Allen elasticities of substitution between inputs to be equal to one). Alternatively, some studies have relied on a two-stage decomposition: in a first stage, a productivity index is estimated; in a second stage, the productivity index is regressed on research and other variables to explain technical progress (e.g. Knutson and Tweeten; Evenson, 1984). This implicitly assumes that a productivity index can be calculated independently of the nature of technical progress. However, the validity of productivity indices can be affected by the nature of technical change (see Diewert (1976) and Caves et al. (p. 77, footnote 2)).

In the analysis of the effects of research on technical progress, several issues remain unresolved. Although all researchers seem to agree about the existence of lags between research expenditures and the improvement

in productivity, the nature of these lags is somewhat unclear. For example, while most previous research assumes 10 to 20 year-lag lengths between research and farm productivity (e.g. Evenson, 1967; Knutson and Tweeten; White and Havlicek), there is empirical evidence that such lags are as long as 30 years (Pardey and Craig). Also, there is some disagreement about the actual shape of the lag distribution: either inverted-V (e.g. Evenson, 1967), second order polynomial (e.g. Knutson and Tweeten) or trapezoidal (Huffman and Evenson, 1989). Finally, the influence of private research on farm productivity is mostly unknown. Indeed, most previous studies have limited their focus to the effects of public research on agricultural productivity; a large rate of return on investments in public research has generally been found (e.g. Griliches; Evenson, 1964; Bredhal and Peterson). In contrast, Huffman and Evenson (1989) have considered the separate effects of private and public research. However, somewhat surprisingly, they found that the marginal return of private research is negative (Huffman and Evenson, 1989, p. 770). These results suggest a need for a more refined analysis of the effects of private research on agricultural productivity.

This paper proposes an alternative methodology to the analysis of technical change and its origins. It relies on a nonparametric approach to the investigation of the effects of research on productivity. Building on the nonparametric work of Hanoch and Rothschild, and Varian, technical progress is modelled as a function of lagged research expenditures. The proposed nonparametric approach appears attractive for several reasons. First, it requires no a priori restrictions on the substitution possibilities among inputs (e.g. via parametric functional form assumptions). Second, the method allows joint estimation of the production technology, technical change, and

the effects of research on technical progress using very disaggregate inputs. Third, the approach allows considerable flexibility in the investigation of the length and shape of the lag distribution between research and productivity. Fourth, the method is flexible enough to permit an investigation of the separate effects of private research and public research on technical progress. Finally, the approach is empirically tractable in the sense that it requires only a standard linear programming algorithm. The usefulness of the approach is demonstrated with an application to U.S. agriculture.

II) The Model.

Consider a production process involving a set of n -inputs $x = (x_1, \dots, x_n)'$ and an output y . Let the underlying technology be represented by the concave production frontier

$$Y = g(X) \tag{1}$$

where $Y = Y(y, A)$ denotes "effective output", $X = X(x, B) = \{X_i(x_i, B_i), i=1, \dots, n\}$, X_i denoting the i^{th} "effective input", and A and $B = (B_1, \dots, B_n)'$ are technology indices. We assume that Y is a strictly increasing function of y and that X_i is a strictly increasing function of x_i , $i=1, \dots, n$. This formulation of technology corresponds to the augmentation hypothesis where technical change (as reflected by changes in A and B) influences the transformation of actual inputs (or output) into effective inputs (or output). In this context, technical progress can be characterized by increasing the effectiveness of inputs in the production of output.

The representation (1) is fairly general. Although it implies that the

marginal rate of substitution between any x_i and B_i is independent of the values of all (x_j, B_j) , $j \neq i$, it imposes no a priori restriction on the functional form $g(X)$. Also, changing A while holding B constant corresponds to the hypothesis of Hicks neutral technical change where the marginal rate of substitution between any two inputs is independent of the technology index A . Alternatively, changing values of B imply a bias in technical change as the marginal rate of substitution between inputs is affected by the technology indices B .

Now, consider the maintained hypothesis of profit maximization under competition

$$\text{Max}_{x,y} \{py - r'x : Y(y,A) = g(X(x,B))\} \quad (2)$$

where p is output price and $r = (r_1, \dots, r_n)'$ is the price vector for the inputs x . Note that expression (2) can be alternatively expressed as

$$\text{Max}_{x,y} \{py(Y,A) - r'x(X,B) : Y = g(X)\} \quad (3)$$

where $y(Y,A)$ and $x_i(X_i, B_i)$ are the inverse functions of $Y(y,a)$ and $X_i(x_i, B_i)$, $i=1, \dots, n$. Let $X^*(p, r, A, B)$ and $Y^*(p, r, A, B)$ denote the profit maximizing input demand and output supply functions corresponding to (3).

Assume that T observations are made on the production decisions (x_t, y_t) under situation (p_t, r_t, A_t, B_t) , $t=1, \dots, T$. It is of interest here to investigate under what conditions are such decisions consistent with profit maximization as stated in (2) or (3). This can be done in the context of nonparametric tests as proposed by Hanoch and Rothschild, Varian, Chavas and Cox, or Cox and Chavas.

Let $X_t = X^*(p_t, r_t, A_t, B_t)$, and $Y_t = Y^*(p_t, r_t, A_t, B_t)$, $t=1, \dots, T$. By

definition of the maximization problem in (3), profit maximizing behavior must satisfy the following set of inequalities

$$p_t[y(Y_t, A_t) - y(Y_s, A_t)] - r_t'[x(X_t, B_t) - x(X_s, B_t)] \geq 0 \quad (4)$$

for all $s, t = 1, \dots, T$. Cox and Chavas have shown that the inequalities in (4) are in fact necessary and sufficient conditions for the consistency of production behavior with the profit maximization hypothesis (as stated above). Thus, expression (4) provides a basis for a nonparametric analysis of production decisions in the sense that no a priori specification of the functional form $g(X)$ is needed in the characterization of production technology. Note that (4) is a generalization of the Weak Axiom of Profit Maximization (see Varian) to allow for technical change in output and inputs.

Note that using the inequalities (4) in empirical work requires prior information about the functional forms $Y(y, A)$ and $X_i(x_i, B_i)$, $i=1, \dots, n$. In this paper, we will focus on additive linear specifications where $Y = y - A$ and $X_i = x_i + B_i$, $i=1, \dots, n$. Such a linear specification has been called "translating" in the literature (see Pollak and Wales). This implies that expression (4) takes the form

$$p_t[y_t - A_t - y_s + A_t] - r_t'[x_t + B_t - x_s - B_s] \geq 0 \quad (5)$$

which has the convenient characteristic of being linear in A and B . Since, $y = Y + A$, it is clear that higher values of A are associated with higher productivity.

Previous nonparametric analysis of U.S. agricultural productivity by Cox and Chavas using equation (5) found that: 1/ there is strong nonparametric evidence of technical change in U.S. agriculture over the last forty years;

and 2/ there is nonparametric evidence of bias in technical change as a Hicks neutral specification (where $B_s = B_t$ for all s and t in (5)) is found to be inconsistent with the data. Also, Cox and Chavas have proposed $[y(A_s, X_t)/y(A_t, X_t)]$ as a productivity index measuring the shift in the production function between time t and time s . Since $y(A_s, X_t)/y(A_t, X_t) = 1 + (A_s - A_t)/y_t$ under the translating hypothesis, it follows that $[1 + (A_s - A_t)/y_t]$ can be interpreted as a productivity index for situation s measuring the impact of technical change on production, using t as a reference point.

Many analysts have focused on the role of research in generating technical progress arguing that investment in research stimulates the development of new technologies that improve productivity (e.g. Evenson; Hayami and Ruttan; Huffman and Evenson). Lag relationships between research and productivity reflect the fact that the process of technical change takes time. In the present context, these arguments suggest making the technology index in (5) a function of past investments in research. Denote research investment made at time t by the vector R_t . Assume that the technology index A_t takes the following linear form

$$A_t = \sum_{i=1}^m a_i' R_{t-i} \quad (6)$$

where the parameter vector $a_i \geq 0$ measures the marginal impact of research conducted at time $t-i$ on the technology index A_t , $i=1, \dots, m$, m being the maximum number of lags between research and productivity. Expression (6) makes the technology index A_t endogenous¹. Together with expression (5), this provides a basis for analyzing the effects of research on technical progress.

It may be of interest to "smooth" the parameters a_i 's in equation (6) by

imposing some smoothing restrictions. Here, we will consider the case where the a_i 's in equation (6) are restricted to follow a linear spline function of i . This is done by dividing the space $\{0, 1, \dots, m, m+1\}$ into s subspaces: $\{k_0, \dots, k_1\}, \{k_1, \dots, k_2\}, \dots, \{k_{s-1}, \dots, k_s\}$, where $k_0 = 0$, $k_s = m+1$ and $k_{j-1} < k_j$, $j = 1, \dots, s$. Then defining $\Omega_j = \{k_{j-1}, \dots, k_j\}$, the a_i 's are restricted as follows

$$a_i = \alpha_j + \beta_j i, \quad i \in \Omega_j, \quad j = 1, \dots, s, \quad (7)$$

where $\alpha_1 = 0$, $\alpha_j + \beta_j k_j = \alpha_{j+1} + \beta_{j+1} k_j$, $j = 1, \dots, s-1$, and $\alpha_s + \beta_s k_s = 0$. This implies that the parameters a_i are restricted to be linear in i within each segment Ω_j and to be a continuous, piece-wise linear function of i over the interval $\{0, 1, \dots, m+1\}$. In addition, a_i is restricted to be equal to zero at $i = 0$ and $i = m+1$ (end-point restrictions). This procedure is fairly flexible in that it allows the a_i 's to vary from one segment to another while imposing some degree of smoothness. Note that "inverted-V" and trapezoidal lag structures are easily accommodated via this spline specification.

III) Empirical Implementation.

Expressions (5)-(7) involve the observable variables p , r , x , y and R . They also involve the A 's, a 's, α 's, β 's and B 's that are typically not directly observable. In this case, the nonparametric approach to production analysis under technical change consists in finding values for the A 's, a 's, α 's, β 's and B 's which would satisfy (5)-(7). Note that these unobservable variables enter expressions (5)-(7) in linear form. This linearity is particularly convenient for the empirical implementation of our approach. It implies that checking the existence of a solution to equations (5)-(7) for the

unobservable variables can be formulated as a linear programming problem as follows.

Let $q = (A_1, \dots, A_T; B_1^+, \dots, B_T^+; B_1^-, \dots, B_T^-; a_1, \dots, a_m; \alpha; \beta)$ be the vector of unobservable variables in (5)-(7), where $B = B^+ - B^-$, $B^+ \geq 0$, $B^- \geq 0$. Allowing for positive as well as negative B supports various forms of bias in technical change (see Cox and Chavas). Expressions (5)-(7) can be written as $D'q \geq c$, given appropriate definitions of the matrix D and the vector c . Then, consider the linear programming problem

$$\text{Min}_q \{ b'q : D'q \geq c, q \geq 0 \} \quad (8)$$

where b is chosen such that problem (8) is necessarily bounded. It follows that the inequalities $D'q \geq c$ have a solution for q if and only if problem (6) has a solution (e.g. Luenberger). In this context, checking the existence of a solution to the nonparametric inequalities is performed by evaluating the existence of a solution to the linear programming problem (8) (e.g. using the simplex method). Choosing appropriate values for the b 's can yield useful information concerning the source and nature of technical change (see Cox and Chavas)². The usefulness of this approach is illustrated next in the context of U.S. agriculture.

IV) Application to U.S. Agriculture.

Aggregate time series data for the U.S. agricultural sector for the years 1950-1982 are taken from Capalbo and Vo. The data analyzed include quantity indices (1967=1.00) and associated implicit price indices for U.S. agricultural output and 9 inputs: family labor, hired labor, land, structures, other capital, materials, energy, fertilizers, pesticides, and miscellaneous.

The input measurements reflect a number of quality adjustments (see Capalbo and Vo for a description of the data). In particular, labor inputs were adjusted for changes in education and composition of the labor force. As a result, no further attempt was made to account for the effects of education in our analysis.

The research expenditure data were obtained for the period 1920-1984 from Huffman and Evenson (1991). They include the U.S. agricultural research funds in constant 1984 prices for public research (RPUB) as well as private research (RPRI). As a result, we have $R_t = (RPUB_t, RPRI_t)'$ and $a_i = (aPUB_i, aPRI_i)'$ in equation (6). The results reported below correspond to specifications using 15 years as well as 30 years of lagged research expenditures. The choice of a 30 year-lag is based on the evidence presented by Pardey and Craig suggesting that the impact of research on agricultural productivity may persist for as long as 30 years. As discussed in section II, the smoothing restrictions³ (7) were specified choosing four segments ($s = 4$) with $k_1 = 7$, $k_2 = 15$, $k_3 = 23$ and $k_4 = 31$ for the 30 year-lag specification; and with $k_1 = 4$, $k_2 = 8$, $k_3 = 12$ and $k_4 = 16$ for the 15 year lag specification.

The estimates of the a_i 's obtained from the solution of the linear programming problem (8) are presented in Table 1, and Figures 1 through 4. They provide useful information on the lag relationship between public research and productivity. First, the results indicate that the choice of the lag length can have a substantial impact on the results. In particular, the estimates of the a_i 's are found to vary widely between the 30 year-lag specification (reported in Figures 1 and 2) and the 15 year-lag specification (reported in Figures 3 and 4). For example, while the 15 year specification finds no impact of private research after 8 years, the 30 year specification

shows that private research has its maximum marginal impact at the 15 year-lag. This demonstrates the importance of including a sufficient number of lags in the analysis of the effects of research on farm productivity.

Second, the results show that public research may impact agricultural output for as long as thirty years (see Figure 1). This is substantially longer than the ten to twenty years lag length commonly assumed in most previous research (e.g. Evenson, 1967; Knutson and Tweeten; White and Havlicek)⁴. Our results (suggesting longer term impacts of public agricultural research on productivity) are consistent with the time series results obtained by Pardey and Craig.

Third, previous studies have commonly assumed a lag structure between public research and agricultural production that is either inverted-V (e.g. Evenson, 1967), second order polynomial (e.g. Knutson and Tweeten; White and Havlicek) or trapezoidal (Huffman and Evenson, 1989). Such structures have typically been imposed to avoid collinearity and degrees-of-freedom problems in the econometric analysis. The results reported in Figures 1 and 2 indicate that such structures appear to be restrictive. In general, the lag relationship between public research and agricultural productivity is found to be longer and/or more complex than assumed in previous studies. This could raise questions about the validity of some previous estimates of the effects of research on agricultural productivity.

Fourth, our results give a separate estimate of the effects of private research versus public research. The estimates of the impact of research on agricultural productivity summarized in Figures 1 and 2 indicate that the stream of benefits is quite different for private research than for public research. Although both private research and public research tend to have a

positive influence on farm productivity, the results show that the peak effect occurs after 23 years for public research (Figure 1), but after only 15 years for private research (Figure 2). In both cases, there appears to be a considerable lag time to develop and implement a new technology. Also, it is found that public research has no effect in the short term (1-7 years) but a very large effect in the longer term (15-30 years). In contrast, private research has a stronger impact in the short term (5-20 years) but no effect beyond 23 years. This result can be interpreted in light of current property rights to private inventions. U.S. patents, granting inventors exclusive rights to their invention, are enforceable for 17 years. During this period, patented inventions are legally protected from infringements by competitors. However, there is little incentive for private investments in research with payoffs beyond the enforcement period. This appears to be consistent with our results indicating that the return from private research take place mostly within the first 20 years (see Figure 2).

Our results have interesting implications for the current decline in public research funding and the relative increase in private research. Figures 1 and 2 show that \$1 of public research has a stronger and longer term impact on farm productivity than \$1 of private research. This suggests that a substitution of \$1 of research from public funding to private funding would increase farm productivity in the short term (0-15 years), but would tend to reduce the rate of technical progress in the longer run (20 years and beyond). In other words, the sources of research funds (i.e. private versus public) can be expected to have some significant effects on technical change in U.S. agriculture.

The implications of our analysis for technical progress can be

summarized using the productivity index $[1 + (A_s - A_t)/y_t]$ which measures productivity at time s using period t as a reference point (see section II). Three productivity indices are reported in Figures 5 and 6. The "no lags" productivity index corresponds to the situation where the model (8) is solved without the restrictions (6) and (7), i.e. without imposing any structure on the nature or source of technical change⁵. The "30 year" (or "15 year") productivity index corresponds to the solution of model (8) including the restrictions (6) and (7) and using the 30 year (or 15 year) lag specification. All three productivity indices in Figures 5 and 6 reflect the strong evidence of technical progress in U.S. agriculture over the last 40 years. Figure 5 shows that imposing the restrictions (5) and (6) using the 30 year-lag specification does not affect much the estimates of productivity. This suggests that the "30 year" specification of the effects of research on technical change is not overly restrictive. Also a comparison of Figures 5 and 6 shows that equations (5) and (6) appear more restrictive in the context of the "15 year" specification than the "30 year" specification. In particular, the 15 year lag specification fails to allow sufficient time for the effects of research to fully manifest, hence results in some underestimate of total factor productivity (see Figure 6). This can be interpreted as additional empirical evidence in favor of including at least 30 years of lags in the analysis of the effects of research on agricultural productivity.

In order to further evaluate the return to research, internal rates of return were calculated as follows

$$\sum_{i=1}^m a_i (Y/R)/(1+IRR)^i = 1,$$

where Y is the real value of output in 1977, R is the real value of

agricultural research in 1977, and IRR is the internal rate of return (Bredahl and Peterson, p. 688). Using the estimates of the a_1 's for the 30 year lag specifications, the internal rate of return is found to be 0.41 for public research and 0.36 for private research. The high rate of return for public research is fairly similar to those found in previous studies (e.g. Griliches, 1958; Evenson, 1967; Bredhal and Peterson; Knutson and Tweeten). Thus, our findings on public research pay-off are fairly consistent with previous evidence. What is new here is a separate estimate of the rate of return for private research: although the pay-off from private research is in the shorter term (compared to public research), the internal rate of return from private research is also found to be fairly high⁶.

V) Summary and Concluding Remarks.

This paper presents a nonparametric analysis of the effect of research on productivity in U.S. agriculture. Previous research on the nonparametric analysis of productivity (Cox and Chavas) is extended by endogenizing technical change as a function of private and public research expenditures. The approach is fairly flexible: it does not require explicit assumptions about the form of the underlying production technology; it allows for biased technical change using fairly disaggregate inputs (nine inputs in the present application); and it allows for detailed lag specifications concerning the impacts of research on productivity. Assuming that effective inputs and output are affected by technical change in a linear fashion, the empirical implementation of the methodology requires only a linear programming algorithm. The application to U.S. agriculture provides estimates of the effects of private as well as public research on agricultural productivity.

The results indicate that at least thirty years of lags are necessary to capture the effects of public research on agricultural productivity. These lags are longer than those used in most previous studies. Returns from private research are found to be shorter term (0-23 years) while the returns from public research are larger and longer term (8-30 years). The estimated internal rates of return are 0.41 for public research and 0.36 for private research. The high rate of return for public research is consistent with those obtained in previous studies. The rate of return for private research appears to be new. The results provide additional evidence of the high productivity of both public research and private research in the U.S. agricultural sector.

The empirical results presented here illustrate the usefulness of the nonparametric approach in the analysis of production decisions and technical change. The nonparametric approach is not a panacea for the difficult measurement issues involved in the analysis of technical change (e.g. data quality remains crucial). One of the main limitations of the analysis is the lack of hypothesis testing, as the proposed method is not statistically-based. However, the results appear reasonable and often comparable with previous research. This suggests that, given its the empirical ease and flexibility, the nonparametric approach provides new analytical tools that complement nicely the more traditional analyses of technology and production decisions. Hopefully, our research will help stimulate further applications of the nonparametric approach to the analysis of economic behavior.

Table 1. Marginal Effects of Public ($aPUB_i$) and Private ($aPRI_i$) Research Expenditures on U.S. Agricultural Productivity: 30 and 15 Year Lag Specifications.

LAG	30 YEAR LAGS		15 YEAR LAGS	
	$aPUB_i$	$aPRI_i$	$aPUB_i$	$aPRI_i$
1	0	0.000142	0	0.011752
2	0	0.000283	0	0.023504
3	0	0.000425	0	0.035256
4	0	0.000567	0	0.047008
5	0	0.000709	0.001961	0.035256
6	0	0.000850	0.003922	0.023504
7	0	0.000992	0.005882	0.011752
8	0.000918	0.001579	0.007843	0
9	0.001836	0.002167	0.025049	0
10	0.002754	0.002754	0.042255	0
11	0.003672	0.003341	0.059461	0
12	0.004590	0.003929	0.076667	0
13	0.005508	0.004516	0.057504	0
14	0.006426	0.005103	0.038334	0
15	0.007344	0.005691	0.019167	0
16	0.026390	0.004979	0	0
17	0.045436	0.004268	0	0
18	0.064482	0.003557	0	0
19	0.083528	0.002845	0	0
20	0.102574	0.002134	0	0
21	0.121620	0.001423	0	0
22	0.140666	0.000711	0	0
23	0.159712	0	0	0
24	0.139748	0	0	0
25	0.119784	0	0	0
26	0.099820	0	0	0
27	0.079856	0	0	0
28	0.059892	0	0	0
29	0.039928	0	0	0
30	0.019964	0	0	0
31	0	0	0	0

SOURCE: Computations by the authors.

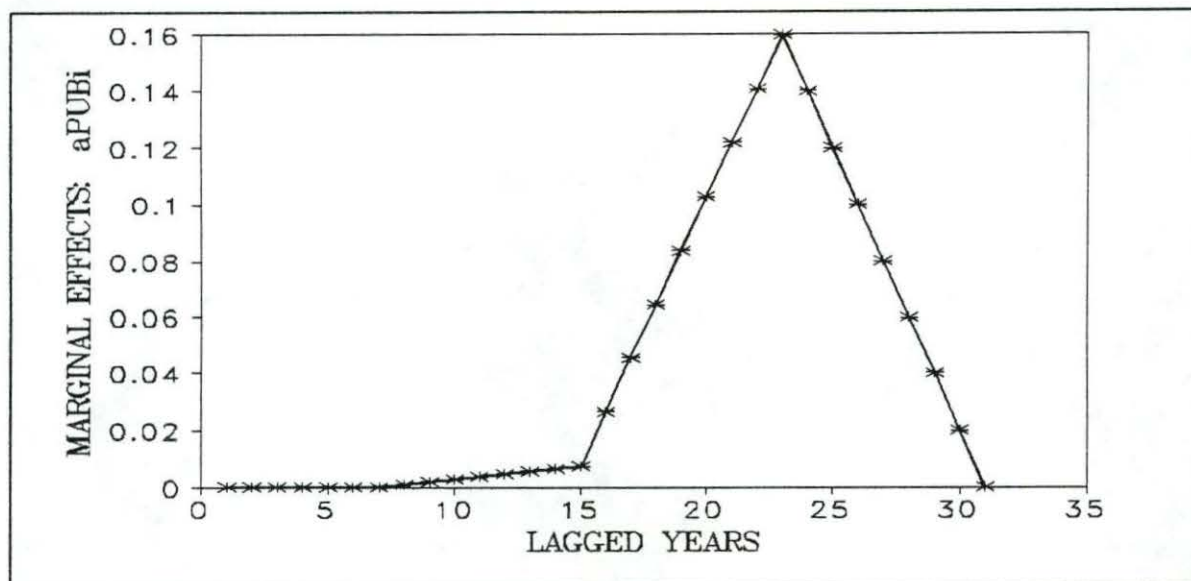


Figure 1. MARGINAL EFFECTS OF PUBLIC (aPUBi) RESEARCH EXPENDITURES ON U.S. AGRICULTURAL PRODUCTIVITY, 30 YEAR LAG SPECIFICATION.

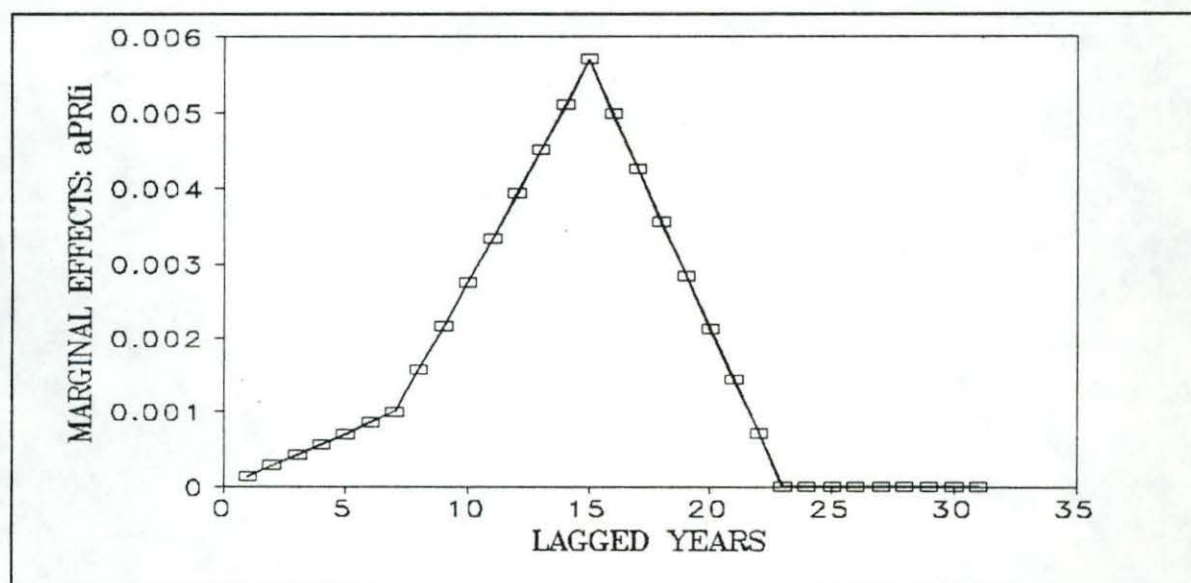


Figure 2. MARGINAL EFFECTS OF PRIVATE (aPRIi) RESEARCH EXPENDITURES ON U.S. AGRICULTURAL PRODUCTIVITY, 30 YEAR LAG SPECIFICATION.

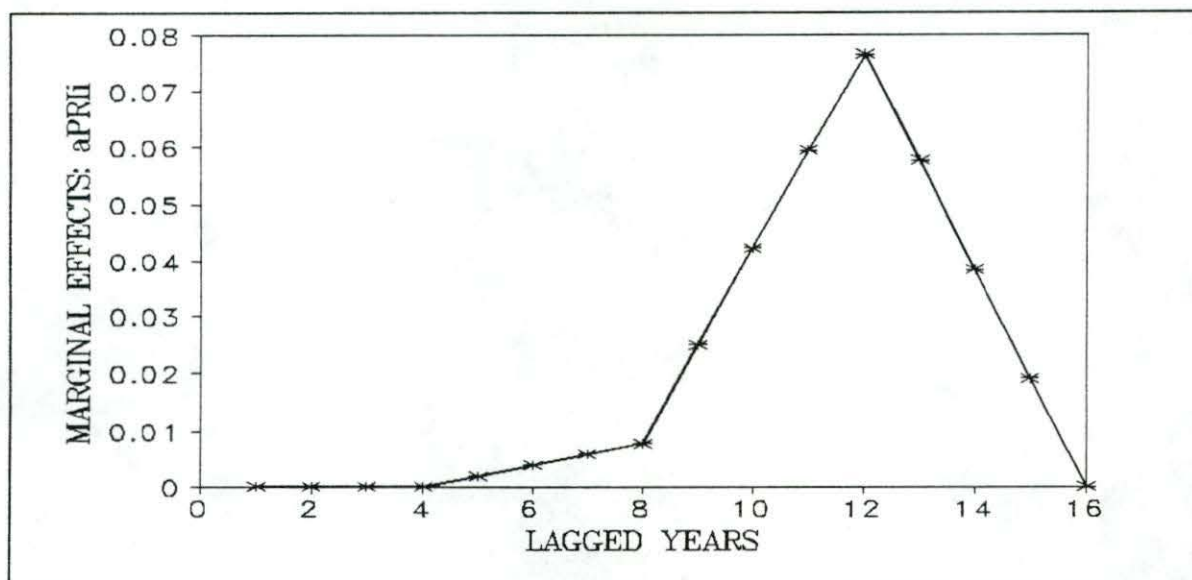


Figure 3. MARGINAL EFFECTS OF PUBLIC (aPUBi) RESEARCH EXPENDITURES ON U.S. AGRICULTURAL PRODUCTIVITY, 15 YEAR LAG SPECIFICATION.

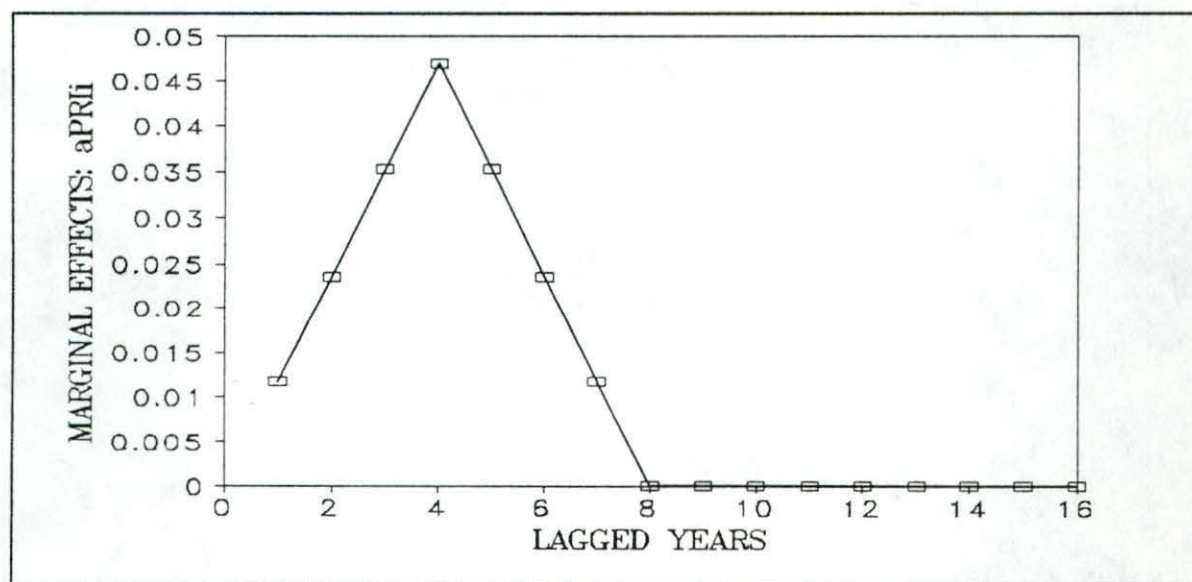


Figure 4. MARGINAL EFFECTS OF PRIVATE (aPRIi) RESEARCH EXPENDITURES ON U.S. AGRICULTURAL PRODUCTIVITY, 15 YEAR LAG SPECIFICATION.

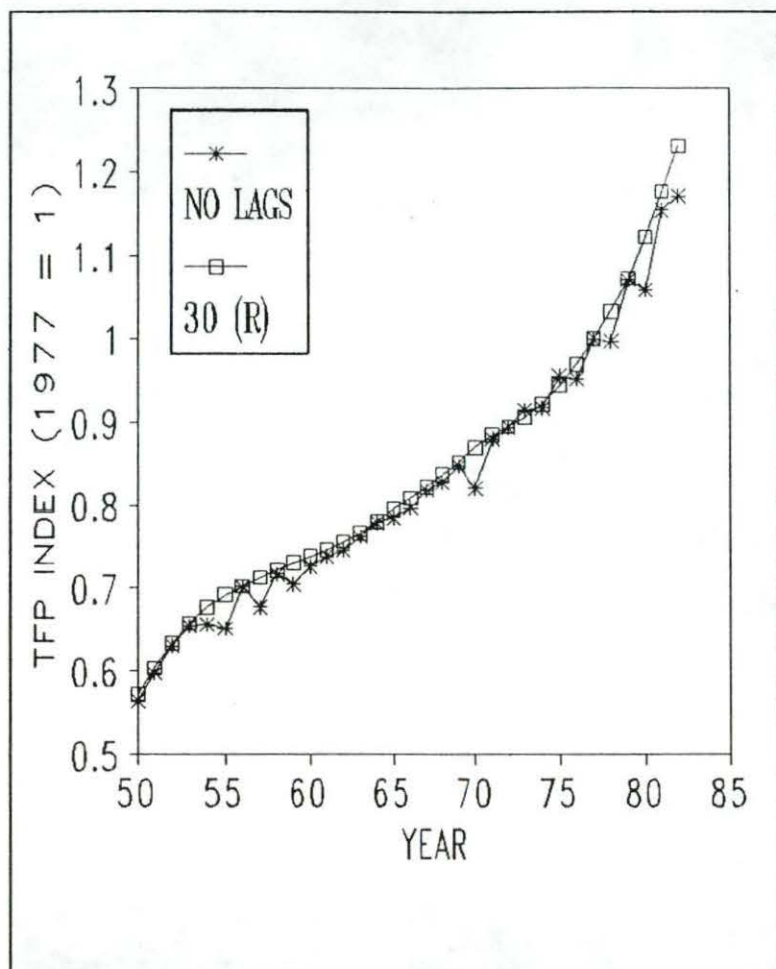


Figure 5. TOTAL FACTOR PRODUCTIVITY INDEXES FOR U.S. AGRICULTURE, 30 YEAR VERSUS NO LAG SPECIFICATION.

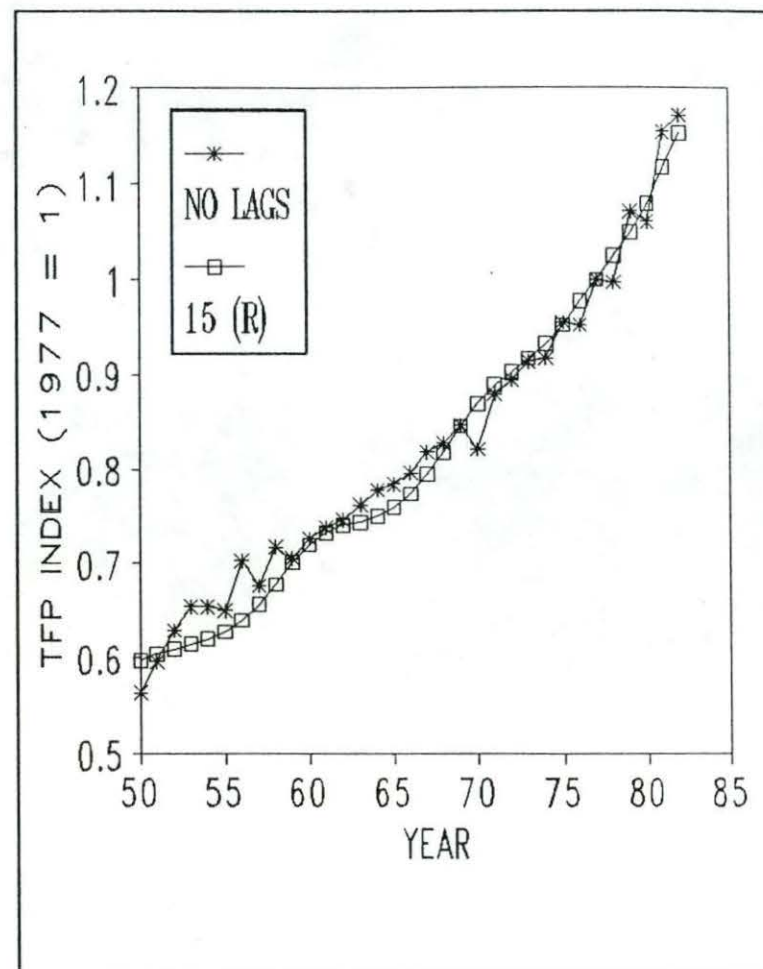


Figure 6. TOTAL FACTOR PRODUCTIVITY INDEXES FOR U.S. AGRICULTURE, 15 YEAR VERSUS NO LAG SPECIFICATION.

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Footnotes

1. Note that similar arguments could be made with respect to the indices B . This would allow endogenizing the nature of the bias in technical change by expressing B as a function of lagged research expenditures. This would permit an empirical investigation of the induced innovation hypothesis. However, this is not the focus of this paper. Such an investigation appears to be a good topic for further research.
2. As discussed in Cox and Chavas, the elements of the vector b in (8) can be chosen to be equal to k if they are coefficients of A , equal to k^2 if they are coefficients of b , and equal to zero otherwise, where k is a large positive scalar. Given this choice, the results of the linear programming problem (8) give the smallest possible biases in technical change and the smallest possible output augmentations (given the B 's) that are consistent with the data. The results presented below correspond to $k = 1000$ (see Cox and Chavas).
3. The model was also estimated without the smoothing restrictions (7). However, for both private and public research, the patterns of the unsmoothed a_i 's was found to be quite erratic. As a result, we focus here on the restricted case where the smoothing restrictions (8) are imposed.
4. Apparently, the only other studies that have considered at least 30 years of lag effects of research on farm productivity are the ones by Pardey and Craig, and by Huffman and Evenson (1989).
5. The "no lags" specification corresponds to the one reported in Cox and Chavas. Cox and Chavas have shown that the estimates of productivity indices obtained from the nonparametric method are similar to the ones obtained from more traditional methods.

6. This contrasts with the findings obtained by Huffman and Evenson (1989, p. 770) who found that private research has a negative value.