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A NONPARAMETRIC ANALYSIS OF THE SOURCE AND NATURE OF TECHNICAL CHANGE: THE CASE OF U.S. AGRICULTURE

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I- <u>Introduction</u>:

Much research has been done on technical change and its economic significance. The importance of technical change in economic growth is widely acknowledged (e.g., Solow, 1957). Yet, the process of technical change is quite complex and still poorly understood. It is often described as a dynamic two-stage process: 1/ the creation of new knowledge and technology; and 2/ the adoption of new technology by firms. For example, in his study of an innovation cycle, Griliches (1957) identified significant lags between the creation of new knowledge and the adoption of the associated new technology. The creation of new knowledge is stimulated by expenditures on research and development (R&D). Because of the cost of acquiring new knowledge and adapting it to local conditions, the adoption process for a new technology can be slow. The lags between R&D investment and its payoff can vary with each technology and each industry. However, as a rule, these lags are longer as the research is more basic, and shorter as the research is more applied.

A distinction often made in the literature concerns the source of funding for R&D, i.e., public versus private. When new knowledge has the characteristics of a public good, then public funding of research may be appropriate (e.g., Arrow, 1962). Alternatively, when property rights to technology can be privately assigned and enforced (e.g., through patents), then private institutions can have the proper incentive to invest in R&D. But because patent rights expire at the end of the patent life, private incentives to invest in basic research with longer term (and more uncertain) payoffs are weak. As a result, basic research tends to be funded publicly, and private R&D tends to focus on applied research with shorter term payoffs that can be appropriated during a patent life.

The linkage between technical change and resource scarcity has been the subject of much scrutiny. By definition, technical progress allows the production of greater outputs with the same amount of resources, or the use of fewer resources to produce the same outputs. Thus, it can help reduce resource scarcity. The feedback effect of resource scarcity on technical change is also of interest. It has been expressed in terms of "induced innovation". As first suggested by Hicks, the induced innovation hypothesis states that relative resource scarcity tends to guide the process of technical change:

> A change in relative prices of the factors of production is itself a sign to invention, and to invention of a particular kind -- directed to economising the use of a factor which has become relatively expensive (Hicks, 1932).

The induced innovation hypothesis is typically formulated in terms of the bias in technical change (e.g., see Binswanger and Ruttan, 1978). Roughly stated, technical change is said to be biased toward a particular factor (or <u>factor-using</u>) if it stimulates the relative use of this factor. Conversely, technical change is biased against a particular factor (or <u>factor-saving</u>) if it reduces the use of this factor relative to other factors. In this context, the induced innovation hypothesis predicts that technical change will be biased against a particular factor (i.e., factor-saving) when this factor's relative scarcity (e.g., its relative price) increases. Conversely, technical change will be biased in favor of a given factor (i.e., factor-using) when its relative price declines.

The induced innovation hypothesis has been subject to empirical testing. Binswanger

(1974) and Hayami and Ruttan (1985) found empirical evidence in support of the hypothesis, while Olmstead and Rhodes (1993) uncovered some historical evidence inconsistent with induced innovation. This research has typically measured the bias in technical change and compared its direction with changes in relative prices. The linkage between this bias and the nature of invention has often not been made explicit. This is unfortunate, since Hicks's original formulation of the induced innovation hypothesis explicitly mentions inventive activities. This suggests a need to explore jointly the economics of R&D investments and induced innovations. Given the dynamics of R&D effects, this indicates that induced innovations should also be investigated in a dynamic setting.

The objective of this paper is to analyze the process of technical change with a joint focus on the effects of R&D investments and on the induced innovation hypothesis. This is done relying on nonparametric methods developed by Afriat (1972), Hanoch and Rothschild (1972) and Varian (1984) (section II). The nonparametric approach to production analysis consists in analyzing a finite body of data without ad hoc specification of functional forms for production function, supply-demand functions, cost or profit function. In a multi-input multi-output framework, we extend the Afriat-Varian methodology by introducing technical change in the form of "netput augmentation", which transforms actual netputs into "effective netputs" (section III). Given a nonparametric representation of the "effective technology", netput augmentations then provide a complete characterization of technical change. By specifying a dynamic relationship between netput augmentations and R&D investments, we develop a formal model of the innovation process. We also allow relative prices to influence the nature of innovations. This provides a dynamic framework for the joint investigation of R&D effects and the induced innovation hypothesis for both inputs and outputs (section IV). This appears to be novel in the literature. The methodology is illustrated in an application to U.S. agriculture (section V). By distinguishing between private and public R&D investments, the analysis provides useful insights in the source and dynamic nature of technical progress.

II- <u>The Nonparametric Approach</u>:

Consider a competitive firm choosing a (n×1) vector of netputs $x = (x_1, ..., x_n)'$. The vector x can be partitioned as $x = (x_O, x_I)$ where $x_O \geq 0$ is the vector of outputs (defined to be positive), and $x_I \leq 0$ is the vector of inputs (defined to be negative). Let N = {1, ..., n} denote the set of netputs, where $N = \{N_I, N_O\}$, $N_O = \{i: x_i \geq 0; i \in N\}$ being the set of outputs, and $N_I = \{i: x_i \leq 0; i \in N\}$ being the set of inputs. The underlying technology is represented by the feasible set $F \subset \mathbb{R}^n$, where feasible netput choices satisfy $x \in F$. This allows for a general multi-factor multi-product joint technology. We will assume throughout the paper that the feasible set F is non-empty, convex[1/] and negative monotonic[2/].

Assume that the firm behaves in a way consistent with the profit maximization hypothesis. Let $p = (p_1, ..., p_n)' > 0$ denote the (n×1) vector of market prices for the netput vector x. Then, profit is denoted by (p' x) and the firm's production decisions are made as follows:

$$\pi(p) = \max_x \{p'\, x: x \in F\}, \qquad (1)$$

where $\pi(p)$ is the indirect profit function. The solution to (1) gives the profit maximizing output supplies and input demand correspondences denoted by $x^*(p)$.

Suppose that the firm is observed making production decisions τ times. Let T be the set of these observations: $T = \{1, 2, ..., \tau\}$. The t-th observation on input-output decisions is denoted by $x_t = (x_{1t}, ..., x_{nt})'$ with corresponding prices $p_t = (p_{1t}, ..., p_{nt})'$, $t \in T$. We define economic rationality for production decisions in terms of profit maximizing behavior as stated in equation (1). We will say that a technology F rationalizes the data $\{(x_t, p_t): t \in T\}$ if $x_t = x^*(p_t)$ for all $t \in T$. A key linkage between observable behavior and production theory (as given by (1)) is presented in the following proposition.

Proposition 1: (Afriat, 1972; Varian, 1984)

The following conditions are equivalent:

a) The data satisfy the Weak Axiom of Profit Maximization (WAPM):

$$p_t' x_t \geq p_t' x_s, \tag{2}$$

for all $s, t \in T$.

b) There exists a negative monotonic, convex production possibility set that rationalizes the data in T according to (1), and that can be represented by:

$$F_T = \{x: p_t' x \leq p_t' x_t, t \in T; x_i \geq 0 \text{ for } i \in N_O; x_i \leq 0 \text{ for } i \in N_I\} \tag{3}$$

The Afriat-Varian results stated in Proposition 1 establish conditions for the existence of a production possibility set that can rationalize observable production behavior. Equation (2) states that the t-th profit ($p_t' x_t$) is at least as large as the profit that could have been obtained using any other observed production decision ($p_t' x_s$), $s \in T$. It gives necessary and sufficient conditions for the data $\{(x_t, p_t): t \in T\}$ to be consistent with profit maximization (1).

This is useful as a means of testing the relevance of production theory in particular situations. Perhaps more importantly, equation (3) provides a basis for recovering a representation F_T of the underlying technology that is consistent with the data in T. This is particularly useful when all observations in T are associated with the same technology. This is the implicit assumption made by Afriat (1972) or Varian (1984) in their nonparametric approach to the analysis of production behavior.

III- Technical Change:

What if the underlying technology is not the same across all observations in T? This could happen under technical change, with each observation being possibly associated with a different technology. In this section, we consider the case of time series observations where technical progress can shift the production possibility set across observations. We propose an extension to the Afriat-Varian approach that allows for technical change.

In the presence of technical change, we distinguish between actual netputs $x_t = (x_{1t}, ..., x_{nt})'$ and "effective netputs" denoted by $X_t = (X_{1t}, ..., X_{nt})'$. This can be done through an "augmentation hypothesis". Following Chavas and Cox (1990), assume that actual netputs and effective netputs are related through the functional relationship:

$$X_{it} = X(x_{it}, A_{it}),\ i \in N;\ t \in T, \tag{4}$$

where X(x, .) is a one-to-one increasing function, and A_{it} is a technology index associated with the i-th netput and the t-th observation. Intuitively, (4) states that the technology index A_{it} can "augment" the actual quantities into effective quantities. Using (4), assume that problem (1) takes the form:

$$\pi(p_t, A_t) = \max_x [p_t' x: X(x, A_t) \in F^e], \quad (5)$$

for $t \in T$, where $A_t = (A_{1t}, ..., A_{nt})'$ is a $(n\times1)$ parameter vector. The production technology $F^e \subset \mathbb{R}^n$ in (5) is an "effective technology" expressed in terms of the effective netputs: $X_t \in F^e$, $X_t = (X_{1t}, ..., X_{nt})'$ being a $(n\times1)$ vector of effective netputs for the t-th observation with $X_{it} \equiv X(x_{it}, A_{it})$. In this context, technical change (as measured by changes in the A's) influence the transformation of actual netputs into effective netputs. More specifically, technical progress can be characterized by increasing the effectiveness of inputs in the production of outputs.

Note the generality of the representation of technology in (5). Although it implies that the marginal rate of substitution between any x_i and A_i is independent of the values of all (x_j, A_j), $i \neq j$, it imposes no a priori restriction on the effective technology F^e. Also, changes in the A's can be interpreted in terms of bias in technical change since the marginal rate of substitution between netputs is in general affected by the technology indexes A (see below).

The function in (4), being one-to-one, can be inverted and expressed equivalently as: $x_{it} = x(X_{it}, A_{it})$, $i \in N$, $t \in T$. Many specifications for the function $x(X, A)$ are possible. Two of these specifications appear particularly appealing:[3/]

- the scaling hypothesis corresponding to the multiplicative specification $x_i = X_i A_i$,[4/]

- and the translating hypothesis corresponding to the additive specification $x_i = X_i + A_i$.

For simplicity, we will focus here on the translating hypothesis.[5/] Under translating, equation (5) can be written as:

$$\pi(p_t, A_t) = \max_X [p_t' (X+A_t): X \in F^e]$$

$$= p_t'A_t + \max_X [p_t' X: X \in F^e], \quad (6)$$

for $t \in T$. Equation (6) is a standard profit maximizing problem similar to (1), except that it involves the effective netputs X. The associated Weak Axiom of Profit Maximization (WAPM, corresponding to (2)) is:

$$p_t' X_t \geq p_t' X_s, \ s, t \in T, \quad (7)$$

or

$$p_t' [x_t-A_t] \geq p_t' [x_s-A_s], \ s, t \in T. \quad (7')$$

Next, consider some values for the A's that satisfy equation (7') for a given data set T. Using these values, we can obtain the corresponding effective netputs: $X_t = x_t - A_t$. These effective netputs necessarily satisfy the WAPM condition (7) for all s, $t \in T$. It is then clear from (6) and (7) that all the results related to actual netputs x and presented in proposition 1 apply as well to these effective netputs X. In particular, after substituting X for x, equation (3) gives a representation of the underlying effective technology given by

$$F_T^e = \{X: p_t' X \leq p_t' X_t, t \in T; X_i \geq 0 \text{ for } i \in N_O; X_i \leq 0 \text{ for } i \in N_I\}. \quad (8)$$

As we will see below, using equation (8) as a representation of the effective technology will prove useful in the empirical evaluation of technical change.

Finally, under translating, note that any change in the technology parameters A across observations has a simple interpretation in terms of the bias in technical change. First consider the case of inputs, $x_i \leq 0$ for $i \in N_I$. Given $X_i = x_i - A_i$, finding $A_{it'} \leq A_{it}$ means that technical change from t to t' is i^th-input using: ceteris paribus, a lower value of A_i implies that producing the same effective netputs X requires more of the i^th input ($-x_i \geq 0$). Alternatively, finding $A_{it'} \geq A_{it}$ means that technical change from t to t' is i^th-input saving: ceteris paribus, a higher value of A_i implies that producing the same effective netputs X can be produced with less of the i^th input ($-x_i \geq 0$). Second, consider the case of outputs, $x_i \geq 0$ for $i \in N_O$. Given $X_i = x_i - A_i$, finding $A_{it'} \leq A_{it}$ means that technical change from t to t' is i^th-output reducing: ceteris paribus, a lower value of A_i implies that less of the i^th output can be produced with the same effective netputs X. Alternatively, finding $A_{it'} \geq A_{it}$ means that technical change from t to t' is i^th-output augmenting: ceteris paribus, a higher value of A_i implies that more of the i^th output can be produced with the same effective netputs X. Finally, a technical change from A_t to $A_{t'}$ that satisfies $A_{it} = A_{it'}$ can be interpreted as being neutral toward the i^th netput since producing the effective netputs X can be done using the same quantity of the i^th netput x_i, ceteris paribus. This specification can thus provide a basis for analyzing technical change bias (and the induced innovation hypothesis) on the input side as well as the output side. This indicates that the nonparametric approach to production analysis can provide considerable flexibility in the analysis of technology and technical change.

IV- Model Specification:

In this section, we develop a nonparametric method that can be used in the investigation of the source and nature of technical change. While we have just argued that technology indexes A that satisfy (7') can provide valuable information, it would be useful to obtain more specific insights as to the factors influencing technical progress. This can be done by developing specific hypotheses about the determinants of the A's.

Much research has focused on the role of research in generating technical progress. Investment in R&D is expected to stimulate the development of new technologies that can improve productivity. However, the process of technical change takes time, suggesting the existence of lag relationships between research and productivity. This indicates that the technology indexes A can be modeled as a function of past R&D investments. Also, the induced innovation hypothesis indicates that innovative activities tend to be guided by relative resource scarcity. This suggests that the marginal impact of R&D depends on relative prices. On that basis, we propose the following model specification for the A's:

$$A_{it} = \alpha_{it} + \sum_{j=0}^{m} \{[\beta_{ij} + (P_{i,t-j} - 1)\gamma_{ij}] R_{t-j}\},\ i \in N,\ t \in T, \tag{9}$$

where:

$R_{t\text{-}j}$ is a (k×1) vector of R&D investments made at time t-j. In the analysis presented below, we will distinguish between public and private R&D investments. This corresponds to k = 2 and R = (Rpub, Rpri).

$P_{i,t\text{-}j}$ is a relative price index for the i-th netput at time t-j.

α_{it} is an intercept reflecting the value taken by A_{it} in the absence of R&D investments.

m is the maximum number of lags between R&D investment and its impact on productivity.

β_{ij} is a $(1\times k)$ parameter vector measuring the marginal effect of R_{t-j} on A_{it} when relative prices are constant (corresponding to $P_{i,t-j} = 1$).

γ_{ij} is a $(1\times k)$ parameter vector measuring the interaction effect of $P_{i,t-j}$ and R_{t-j} on A_{it}.

Note that setting $\gamma_{ij} = 0$ would imply that relative prices play no role in guiding the effects of R&D. And assuming $\partial A_{it}/\partial R_{t-j} > 0$, the induced innovation hypothesis suggests that $\gamma_{ij} > 0$. To see that, note that an increase in the relative price $P_{i,t-j}$ tends to increase the marginal impact of R&D on A_{it}, thus increasing A_{it}. On the input side ($x_i \leq 0$ for $i \in N_I$), with $X_i = x_i - A_i$, a higher A_{it} corresponds to <u>biased technical change</u> in the direction of decreasing the use of the i^th input ($-x_i \geq 0$). This is Hicks' induced innovation hypothesis: a rise (decline) in the i^{th} input cost tends to stimulate i^{th} input-saving (i^{th} input-using) technical change. On the output side ($x_i \geq 0$ for $i \in N_O$), with $X_i = x_i - A_i$, a rise in A_{it} corresponds to <u>biased technical change</u> in the direction of increasing output x_i. This is the multi-output version of the induced innovation hypothesis: a rise (decline) in the i^{th} output price increases (decreases) the profitability of the i^{th} output, which tends to stimulate innovations and generate i^{th} output-augmenting (i^{th} output-reducing) technical change. Thus, throughout the rest of the paper, we will interpret $\gamma_{ij} > 0$ in (9) as being consistent with the induced innovation hypothesis. Alternatively, finding $\gamma_{ij} \leq 0$ would be inconsistent with this hypothesis. Note that this is a dynamic version of the induced innovation hypothesis since it considers the guiding role of prices in the <u>lagged effects</u> of R&D investments. It is fairly general since it allows γ_{ij} to change magnitude (and possibly sign) with the lags j. In other words, for each netput i, this specification allows the presence and strength of the induced innovation hypothesis to vary through an innovation cycle.

Equation (6) provides a basis for analyzing the source and dynamic nature of technical change. However, given the large number of parameters included in (6), it may be of interest to "smooth" some of these parameters. Here, we consider a number of smoothing restrictions applied to the parameters A, α, β, and γ in (9). First, we impose a form of nonregressive technical change with respect to the technology indexes A_{it} corresponding to outputs:

$$A_{it} \geq \frac{\sum_{j=1}^{r} A_{i,t-j}}{r}, \quad i \in N_O. \tag{10a}$$

Second, we restrict the parameters α_{it}, β_{ij} and γ_{ij} such that the corresponding lag structures in (9) follow a spline specification. These spline restrictions can be written as:

$$\alpha_{it} = f_{\alpha i}(t), \;\; t \in T, \tag{10b}$$

$$\beta_{ij} = f_{\beta i}(j), \;\; j \in [0, m], \tag{10c}$$

$$\gamma_{ij} = f_{\gamma i}(j), \;\; j \in [0, m], \tag{10d}$$

where f(t) and f(j) denote piece-wise linear continuous functions in their respective domains of definition. Third, we impose the restriction that the marginal impact of R&D on the technology indexes A is nonnegative:

$$\partial A_{it}/\partial R_{t-j} = \beta_{ij} + (P_{i,t-j}-1)\, \gamma_{ij} \geq 0. \tag{10e}$$

This restriction simply states that R&D investments cannot generate regressive technical change.

Finally, while equation (9) can provide useful insights in the process of technical change, it does not make explicit the relationship between R&D and productivity. To examine this linkage, it is necessary to estimate a productivity index that is consistent with equation (9). Assume that all observations are technically efficient, i.e., that each observation is on the boundary of the feasible set representing the technology available when each observation is made. Following Caves et al. (1982), consider the input-based productivity index: $Q(x) = \min_k \{k: (x_O, -k\, x_I) \in F, k \in \mathbb{R}^+\}$. For a given $x = (x_O, x_I)$, Q is the smallest rescaling of all inputs x_I that remains feasible in the production of outputs x_O under technology F. An index Q > 1 (< 1) means that the netput vector $x = (x_O, x_I)$ uses a better technology (an inferior technology) compared to the technology represented by F. In this context, if Q < 1 (Q > 1), then (1 - Q) can be interpreted as the percentage cost reduction (cost increase) that is achieved by shifting from the current technology to technology F. Using the effective technology F_T^e in (8), we can then define the following productivity index associated with the observation x:

$$Q(x, A) = \min_k \{k: p_{Ot}'\, x_O + p_{It}'\, (k\, x_I) \leq p_t\, X_t\, ;\, X_t = x_t - A_t;\, t \in T;\, k \in \mathbb{R}^+\}, \qquad (11)$$

The productivity index Q(x, A) in (11) provides a simple radial measure of the distance between observation x and the technology F_T^e. But F_T^e depends on the technology indexes A, which in turn depend on R&D investments through equation (9). It follows that the index Q(x,A) in (11), along with equation (9), can provide a basis for measuring the dynamic impact of R&D investments on productivity. The usefulness of these results is illustrated next in the context of an application to U.S. agriculture.

V- <u>An Application to U.S. Agriculture</u>:

We consider the analysis of technical change in U.S. agriculture between 1951 and 1983. The data used in the analysis consists of annual observations on quantity and price indexes for six categories of outputs and ten categories of inputs from 1920 to 1983. The price and quantity indexes from 1950 to 1983 are obtained from Capalbo and Vo. For the period 1920-1950, the price and quantity indexes are calculated from U.S. Department of Agriculture published data, following the Capalbo-Vo method as closely as possible.[6/] All price indexes are implicit price indexes defined such that price times quantity equals expenditure. The output categories are: 1/ small grains; 2/ coarse grains; 3/ other field crops; 4/ fruits; 5/ vegetables; and 6/ animal products. The input categories include: 1/ family labor; 2/ hired labor; 3/ land; 4/ structures; 5/ other capital; 6/ energy; 7/ fertilizer; 8/ pesticides; 9/ feed and seed; and 10/ other inputs. The data provide a basis for evaluating technical change in U.S. agriculture over the last few decades. We also analyze the effects of both public and private agricultural R&D on technical progress. The agricultural R&D data (both private and public) are taken from Huffman and Evenson.

Based on the discussion presented in previous sections, we consider the following optimization problem:

$$\min_{A,\alpha,\beta,\gamma} [\textstyle\sum_{i\in N} \{\sum_{t\in T} w_1\alpha_{it}^2 + \sum_j (w_2\beta_{ij}^2+w_3\gamma_{ij}^2)\}\text{: equations (7'), (9) and (10);}$$

$$x_{it}-A_{it} \geq 0,\ i \in N_O;\ x_{it}-A_{it} \leq 0,\ i \in N_I\ ;\ t \in T], \tag{12}$$

where (w_1, w_2, w_3) are positive weights.[7/] Note that the solution to (12) for the A's is necessarily consistent with the WAPM conditions (7) or (7'). Obtaining this solution is straightforward since (12) can be formulated as a standard optimization problem. Using the solution from (12) for the A's, we can obtain the corresponding effective netputs: $X_t = x_t - A_t$. These effective netputs necessarily satisfy the WAPM condition (7) for <u>all</u> s, t $\in$ T. Equation (8) gives a representation of the underlying effective technology F_T^e. Since equation (12) searches for the smallest absolute values of the α's, β's and γ's (and thus the A's) that are consistent with profit maximization, F_T^e in (8) can be interpreted as the technology that is "as close to the data as possible" while satisfying WAPM in (6) for all data points. Finally, the solution to equation (12) provides estimates of the parameters α, β and γ which characterize the dynamic effects of R&D and the associated innovation process.

In the empirical implementation of (12) in the context of U.S. agriculture, the following assumptions are made. The maximum number of lags m in equation (9) is set equal to 28 years. This is consistent with the empirical evidence presented by Pardey and Craig (1989), who identify a maximum lag between agricultural R&D and productivity of about 30 years. Thus the values of α_{it}, β_{ij}, and γ_{ij} in (9) need to be estimated for i $\in$ N and $0 \leq j \leq 28$.

The relative price P_i in (9) is calculated as the ratio of the price index for the i^{th} input (output), divided by the Tornqvist aggregate price index for all inputs (all outputs).[8/] The value of r in (10a) is set equal to 5 years, implying nonregressive technical change of the A_{it}'s with respect to their previous five-year moving averages. The restrictions in (10b) are imposed only for inputs, i.e., for i $\in N_I$.[9/] The spline restrictions for (10b) involve continuous linear segments for the periods 1951-61, 1961-72 and 1972-82. And the spline restrictions (10c) and (10d) are imposed using four continuous linear segments: 0-7 years, 7-14 years, 14-21 years, and 21-28 years. End-point restrictions (at 0 years and 28 years) are imposed, forcing the functions to be equal to zero at these points. Finally, while the β_{ij}'s and the γ_{ij}'s are allowed to be non-zero for public R&D for $0 < j < 28$, these parameters are further restricted for private R&D. This is motivated by current U.S. patent laws, which grant private inventors exclusive rights to their inventions for a period of 17 years. During this period, patents are legally protected from infringement by competitors. However, there is little incentive for private investment in research with payoffs much beyond the enforcement period. Therefore, the β_{ij}'s and the γ_{ij}'s for private R&D are restricted to be equal to zero for $21 \leq j \leq 28$.

The only issue left then is the choice of the weights (w_1, w_2, w_3) in the objective function (12). In the empirical results presented below, we chose these weights such that, at 1967 values, the relative marginal impacts of α, β and γ in problem (12) are the same. This can be interpreted to mean that, in our approach, we assume no a priori bias about the relative importance of the three terms in equation (9).

Selected results on the estimates of the A's obtained from the solution to (12) are presented in Figure 1. The A's associated with outputs tend to increase over time. This is consistent with technical progress. Selected estimates of the β's and γ's are presented in Figures 2a, 2b and 2c for both public and private R&D.

On the input side ($i \in N_I$), the results presented in Figures 2a and 2b are somewhat mixed concerning the induced innovation hypothesis. The results for labor are inconsistent with the hypothesis (see Figure 2a). The estimates of the γ's for land and structure are either zero or close to zero, suggesting that relative prices do not play a major role in influencing the bias of technical change for these inputs. In contrast, the estimates of the γ's for energy, fertilizer, and pesticides provide rather strong evidence in favor of the induced innovation hypothesis ($\gamma_{ij} > 0$) (see Figure 2b). These findings are consistent with previous research (e.g., Binswanger; Hayami and Ruttan). Thus, in general, our findings provide some support for the induced innovation hypothesis with respect to inputs that are more actively traded (e.g., energy, fertilizer, pesticides). However, we do not find any evidence in favor of induced innovation for inputs that are less actively traded (e.g., land, farm labor). This suggests that the lack of active markets may undermine the economic intuition that motivates the induced innovation hypothesis. In such situations, it may well be that nonmarket forces play a more significant role in determining the bias in technical change.

On the output side ($i \in N_O$), the results in Figure 2c are consistent with the induced innovation hypothesis ($\gamma_{ij} > 0$). This indicates that changes in relative output prices tend to guide the innovation process and generate biased technical change in favor (against) outputs that are becoming more (less) profitable. However, some significant differences appear to exist between private and public R&D effects. In general, the values of the β's and γ's for private R&D are positive for lags between 0 and 15 years, but zero for lags beyond 15 years. In contrast, the values of the β's and γ's for public R&D are either small or zero in the short term, but tend to become positive and larger in the longer term (lags between 15 and 28 years). This suggests that public R&D (private R&D) has a more important effect on productivity in the longer-term (shorter-term). This result will be further illustrated below.

Given the solution obtained in (12), the importance of technical change and productivity gains in U.S. agriculture was evaluated using equation (11). The nonparametric productivity index Q obtained from (11) is presented in Figure 3, along with the Christensen-

Jorgenson Divisia productivity index commonly used in the literature (e.g., Ball, 1985). These indexes indicate that the U.S. agricultural sector has been the subject of significant technical progress over the last few decades. This is consistent with previous research done on this topic (e.g., Jorgenson and Gollop, 1992; Chavas and Cox, 1992). In general, the Christensen-Jorgenson Divisia productivity index tends to rise faster than our nonparametric productivity index (see Figure 3). This difference suggests that our nonparametric representation of the effective technology does not approximate the parametric restrictions needed to justify the Christensen-Jorgenson productivity index.[10/]

The marginal impact of R&D on productivity was also evaluated numerically by solving equation (11) for different levels of both public and private R&D. The results are presented in Figure 4. They indicate that both public and private R&D have a large and positive effect on productivity. Figure 4 also shows important differences in the dynamic impacts of private versus public R&D. Private R&D has a strong short-term effect on productivity (after 5 to 10 years) and basically little longer-term effect. This is consistent with current patent rights applicable to private institutions, which grant inventors exclusive rights to their invention for a period of 17 years (thus providing little incentive for private investment in research with longer-term payoffs). In contrast, public R&D has a small short-term impact on productivity, but a larger positive impact in the longer-term (after 15 to 22 years).

Our results have interesting implications concerning the current shift in R&D funding from public to private. Figure 4 shows that private R&D generates larger benefits in the short-run compared to public R&D. It also shows that public research has a strong but longer-term impact on productivity. This suggests that a substitution of current R&D funding from public to private would increase productivity in the short-term (after 0-10 years), but would tend to reduce the rate of technical progress in the longer-term (beyond 15 years).

Finally, the marginal impacts of R&D on productivity presented in Figure 4 can be used to estimate the internal rate of return to public and private research. Interpreting the productivity index as a measure of the cost savings generated by technical progress, we calculate the benefits of an additional $100 million of R&D investment in terms of the associated reduction in production costs. We then evaluate the associated internal rate of return for public as well as private research. The estimated rates of return are 0.27 for public R&D, and 0.46 for private R&D. These results are fairly similar to those found in previous studies (e.g., Griliches, 1958; Evenson, 1967; Bredhal and Peterson, 1976; Knutson and Tweeten, 1979; Chavas and Cox, 1992). Thus, these findings are consistent with previous evidence: in general, the internal rates of return to private as well as public research are fairly high.

VI- Conclusion:

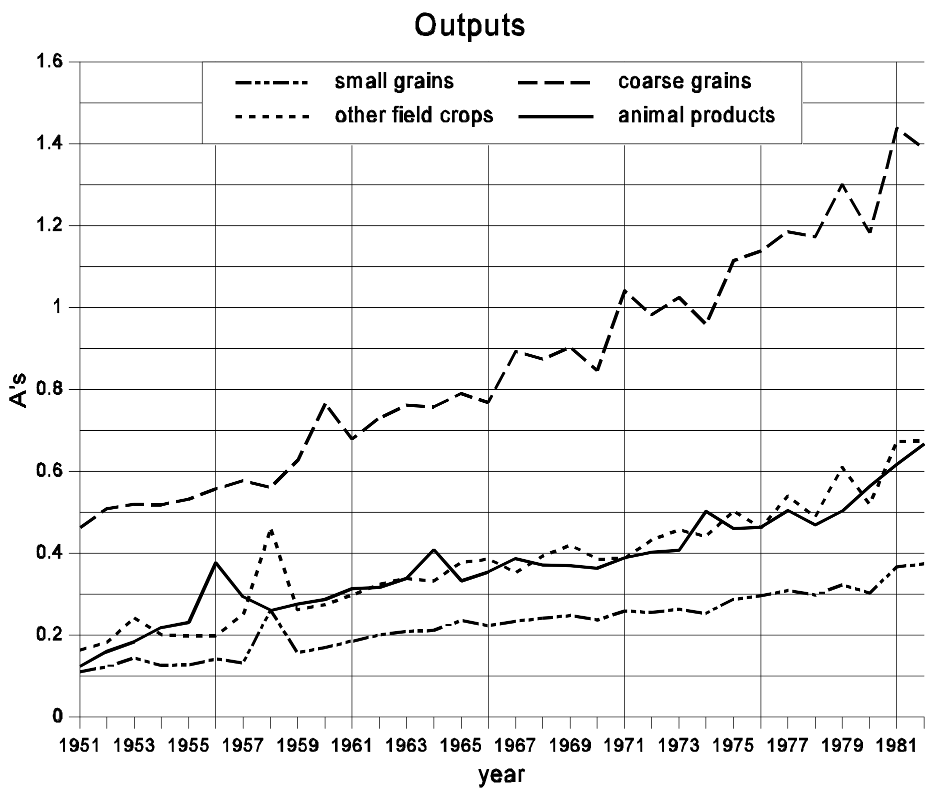
This paper presents a nonparametric methodology to investigate the nature of technical change, with a special focus on the effects of both private and public R&D on productivity. The method is illustrated in an application to U.S. agriculture. The approach is fairly flexible: it does not require explicit assumptions about the form of the underlying production technology; it allows for biased technical change using disaggregate inputs and outputs (ten inputs and six outputs in our case); and it allows for refined lag specifications between R&D,

relative prices, and technology indexes. The application to U.S. agriculture provides useful information on the source and nature of technical change.

The dynamic effects of private and public R&D on technical change differ. The effects of private research are larger in the short-term (5 to 15 years) but small in the longer-term. In contrast, the returns from public research are small in the short-term, but larger in the longer-term (15-25 years). However, the internal rates of return from both private and public R&D are found to be fairly large. This provides additional evidence of the high productivity of both private and public research in the U.S. agricultural sector. The results also give some empirical support in favor of the induced innovation hypothesis for the netputs that are actively traded: for these netputs, market signals tend to guide the direction of the bias in technical change. However, our results do not support the induced innovation hypothesis for the inputs that are less actively traded: land and farm labor. This suggests that, for these inputs, non-market forces may play a more significant role in guiding the innovation process.

The empirical results presented here illustrate the usefulness of the nonparametric approach in the analysis of production and technical change. The nonparametric method, however, has its limitations. First, it remains subject to measurement problems typically involved in the investigation of technical change. Second, its main limitation may be the absence of hypothesis testing, as the method is not statistically based. Nevertheless, the empirical results presented here appear reasonable and often comparable with those obtained from previous research. As such, the proposed methodology appears to be a useful complement to more traditional parametric methods in the economic analysis of production issues and technical change.

Figure 1: Technology Indexes for Selected Netputs



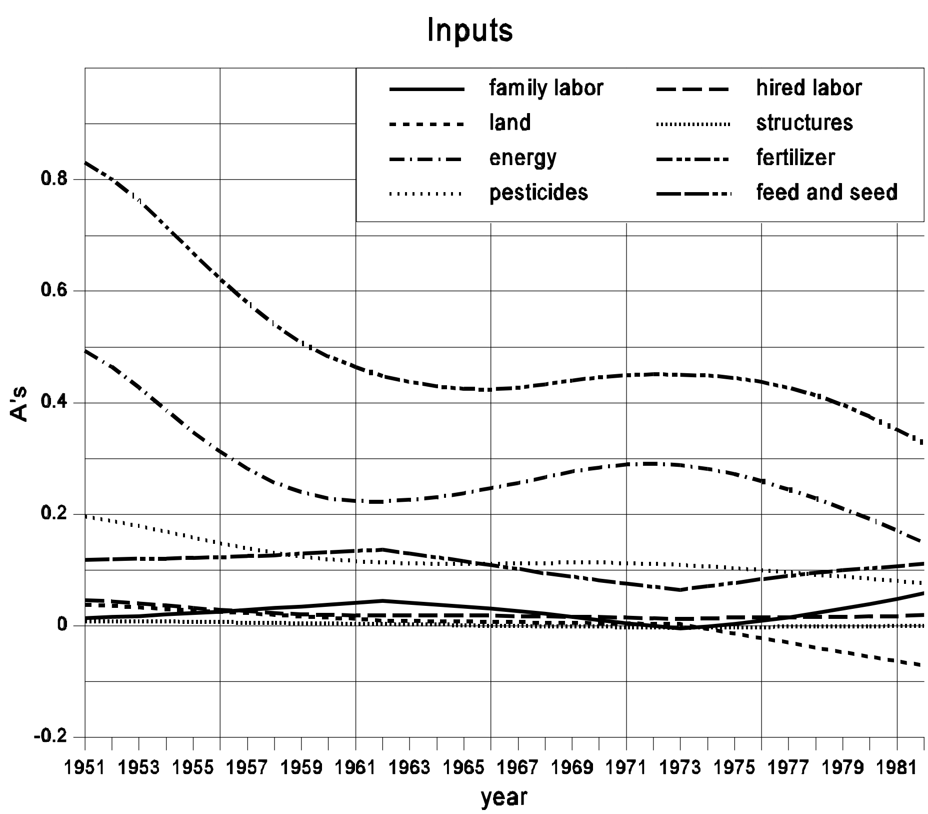


Figure 2a: Selected Estimates of the β's and γ's

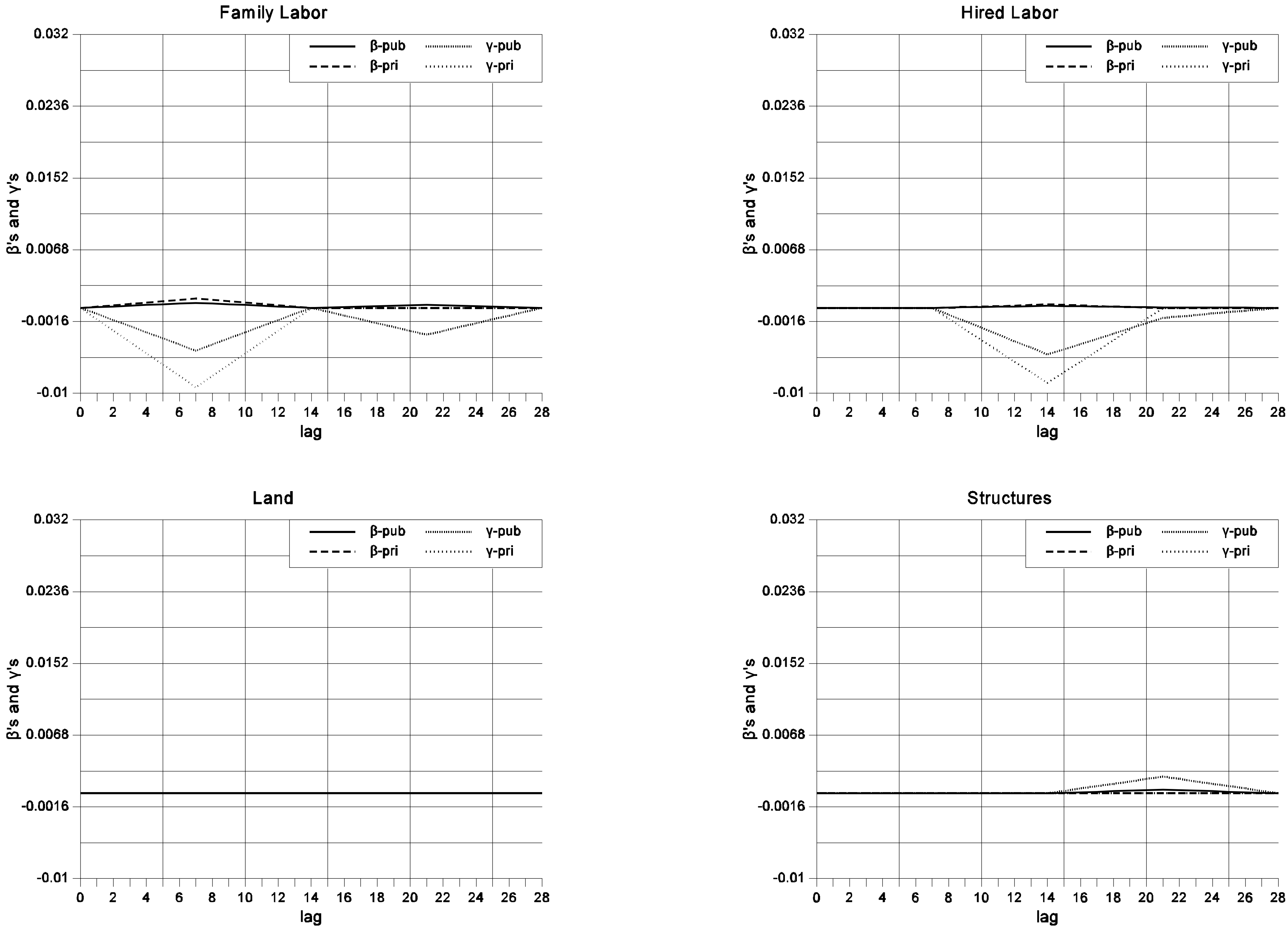


Figure 2b: Selected Estimates of the β's and γ's (continued)

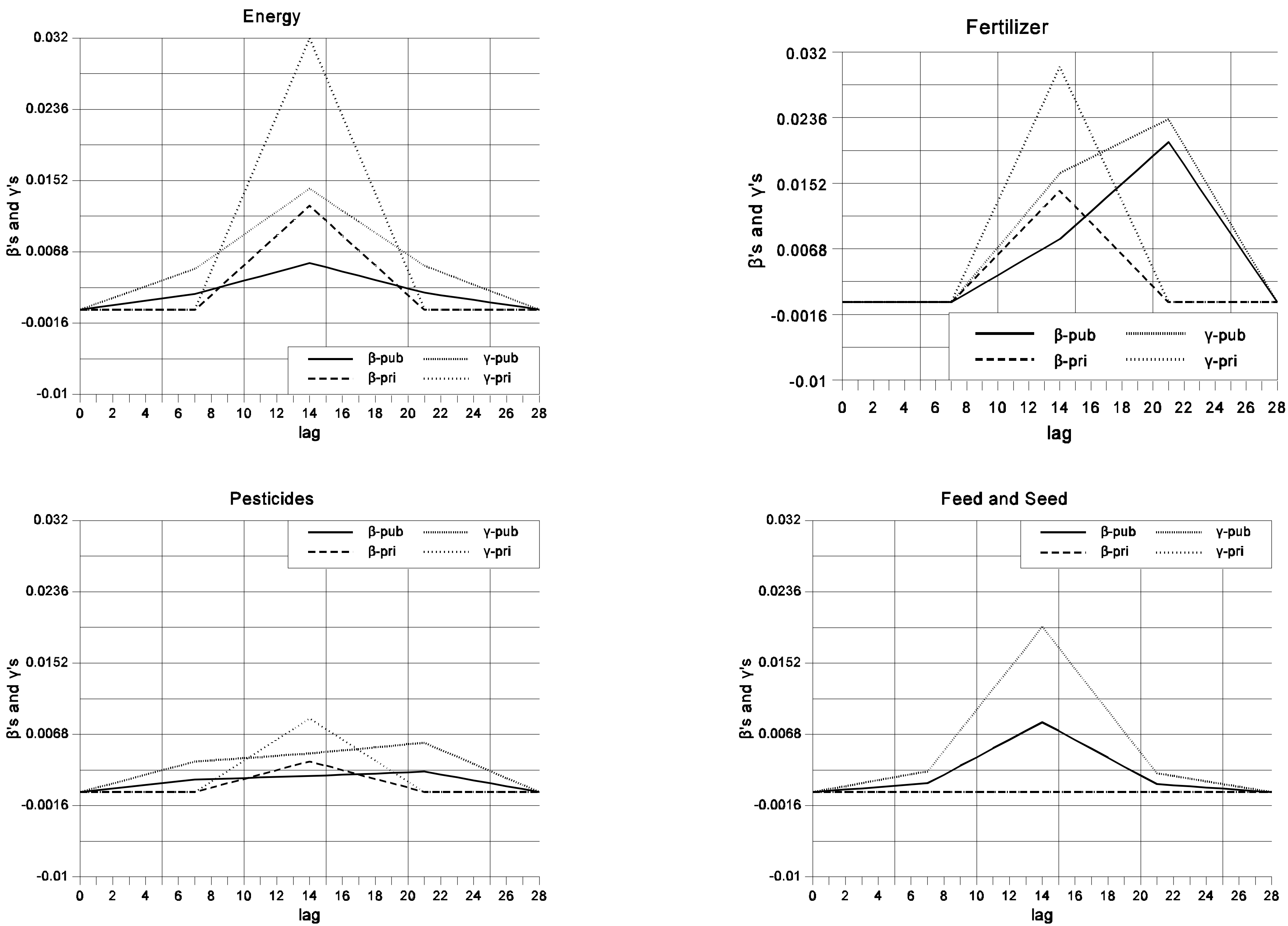


Figure 2c: Selected Estimates of the β's and γ's (continued)

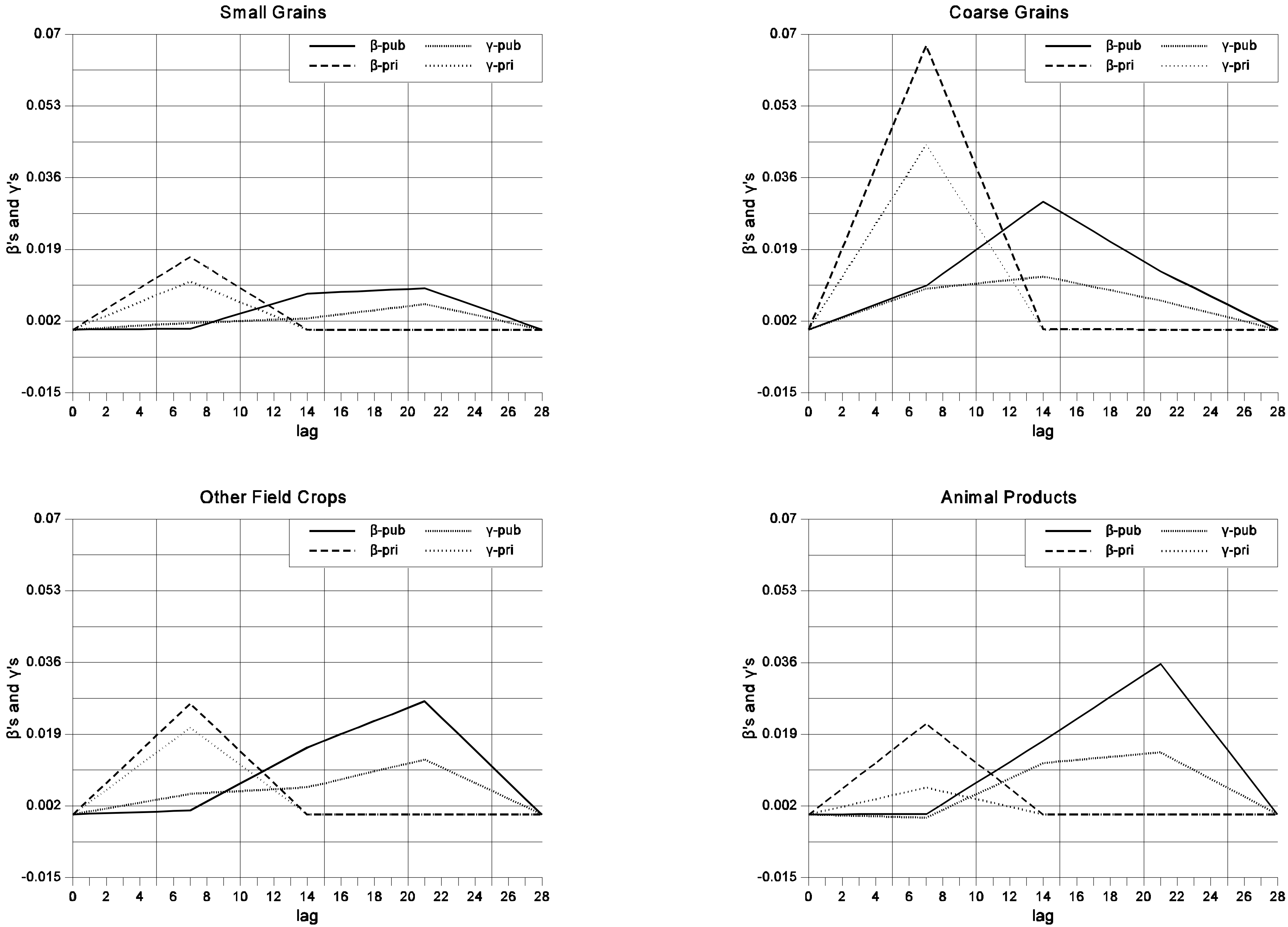


Figure 3: Total Factor Productivity (TFP) Measures

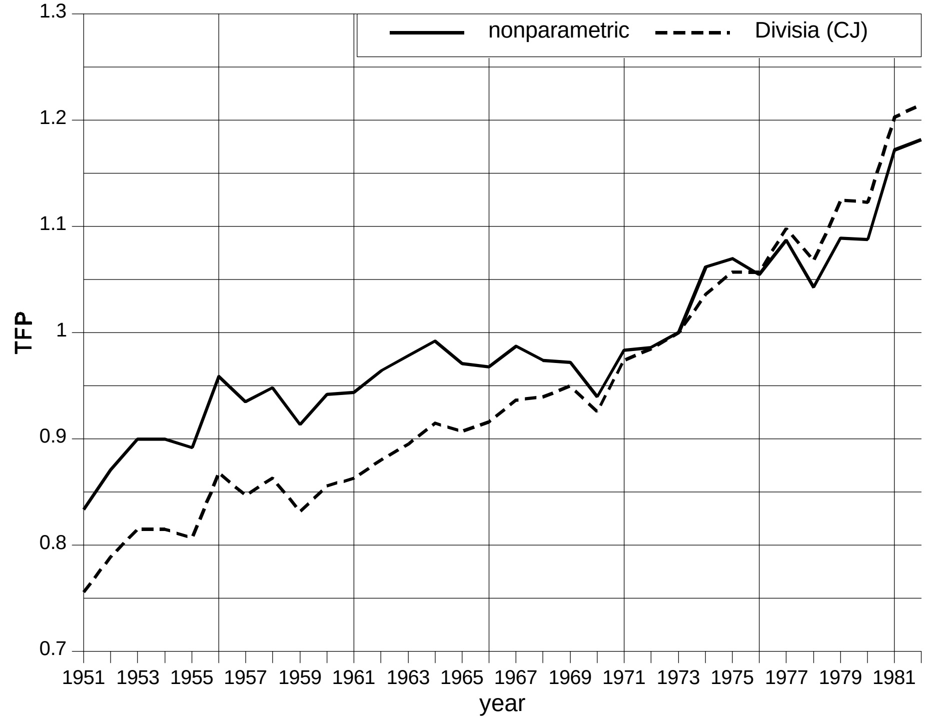
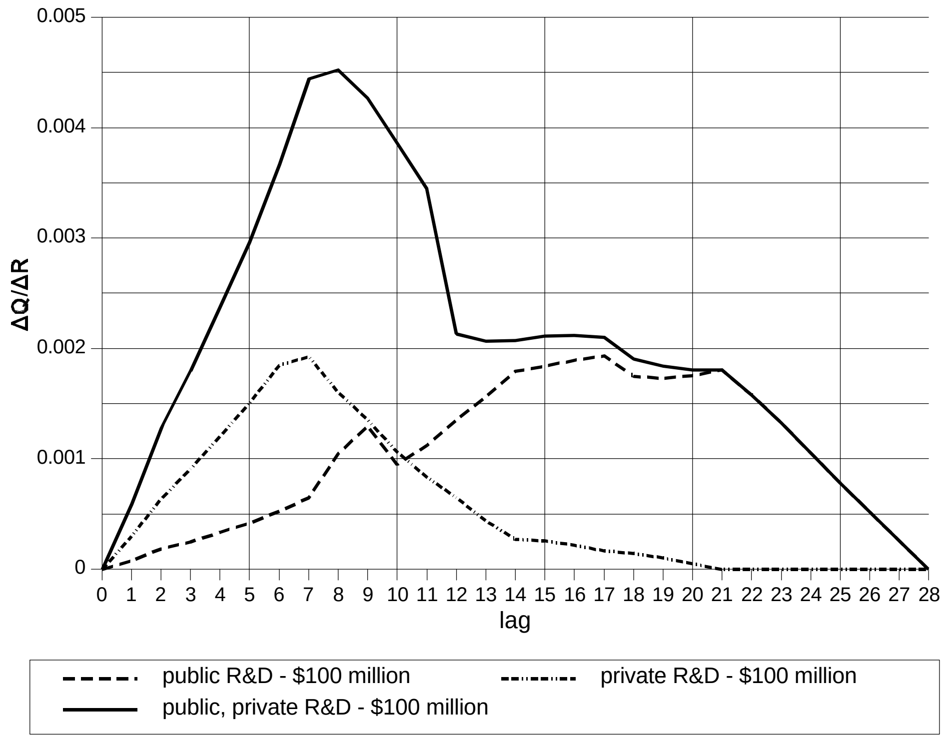


Figure 4: Marginal Impact of Public and Private R&D



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Footnotes

1. The convexity of F means that, for any $x^a \in F$ and $x^b \in F$, then $[\lambda x^a + (1-\lambda) x^b] \in F$ for any λ, $0 < \lambda < 1$. This corresponds to the standard assumption of "non-increasing marginal productivity" commonly made in economics.

2. Negative monotonicity of F means that for any $x^a \in F$ and $x^b \leq x^a$, then $x^b \in F$. This is sometimes called the "free disposal" assumption.

3. For example, see Pollak and Wales for the use of scaling and translating hypotheses in the context of consumer demand.

4. Note that the use of scaling in the analysis of technical change has been proposed and discussed by Solow (1967).

5. In the context of scaling, equation (5) becomes

$$\pi(p_t, A_t) = \max_X [p_t' (X A_t): X \in F^e]$$

for $t \in T$. The associated Axiom of Profit Maximization is:

$$p_t' x_t \geq p_t' [y_s A_s/A_t], \quad s, t \in T.$$

Note that, in contrast with (7'), the above expression is nonlinear in A. This nonlinearity makes the scaling hypothesis more difficult than the translating hypothesis to use empirically.

6. Quantity indexes calculated from disaggregate information are obtained using Tornqvist indexes. Service prices for all capital assets are calculated according to the method outlined by Christensen and Jorgenson. Pre-1940 data for land and structures are estimated from Tostlebe. Note that, for some of the pre-1950 data, it was not possible to follow exactly the Capalbo-Vo method. For example, in the absence of a reliable source of information, we assumed the same unit price before 1950 for family labor and hired labor. Also, we did not quality-adjust the pre-1950 labor data.

7. The choice of these weights is discussed below.

8. The relative price indexes are all normalized to be equal to 1 in 1967. As a result, (P_i-1) in equation (9) can be interpreted as the percentage change in the relative price of the i^{th} netput compared to the 1967 situation.

9. As a result, the α_{it} are "unsmoothed" for outputs, i.e., for $i \in N_O$. This was done to account for possible weather shocks that can affect outputs from one year to the next.

10. As shown by Caves et al. (1992), the Christensen-Jorgenson productivity index is appropriate if the frontier technology can be represented by a linear homogenous translog function with constant second-order coefficients. The difference between the two productivity indexes reported in Figure 3 can thus be interpreted to mean that our nonparametric representation of the technology does not approximate these parametric restrictions.