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Nonparametric Measures of the Impacts of Public Research Expenditures on Australian Broadacre Agriculture: Preliminary Results

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NONPARAMETRIC MEASURES OF THE IMPACTS OF PUBLIC RESEARCH EXPENDITURES ON AUSTRALIAN BROADACRE AGRICULTURE

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Abstract: *Nonparametric methods are used to measure the impacts of public research expenditures on Australian broadacre agriculture over the 1953-94 period. The data and methods used were unable to recover separate impacts due to extension under several alternative specifications. Preliminary results using both unrestricted and 30 year lagged specifications of the research impacts on productivity suggest that while certain aspects of the recovered multi-input/output technologies are quite robust to alternative specifications (in particular, the associated Malmquist total factor productivity indexes), other aspects are less stable (in particular, the indexes on input (and to a lesser extent, output) biased technical change).*

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INTRODUCTION

Until a recent study by Mullen and Cox (1995), discussion of whether Australia was under investing in public research in agriculture was qualitative in nature (Harris and Lloyd, 1991; Industry Commission, 1995). Empirical analysis of returns to public investments in agricultural research at an aggregate level in Australia had not been possible because research expenditure data were unavailable. Using a unique data set described in Mullen, Lee and Wrigley (1996), Mullen and Cox (1995) concluded that the returns to research in broadacre agriculture in Australia may have been in the order of fifteen to forty percent over the 1953 - 1988 period. They employed a two stage estimation procedure in which a measure of productivity was derived in the first stage and then regressed against explanatory variables including research, in the second stage. The productivity measures they used are described in Mullen and Cox (1996). Data limitations and the econometric techniques used were insufficient to resolve some important issues such as the length and shape of the research lag profile and the separate contributions of research and extension to productivity growth. While this two stage procedure in estimating the returns to research is the most widely applied in studies of returns to research, it does impose separability restrictions on the nature of technology, the most obvious one being neutral technical change, that may bias estimates of returns to research.

The work of Mullen and Cox (1995) has been extended in this paper in several important respects.[1/] First, new data from 1989 to 1994, assembled as part of a study of the financing of rural research in Australia by Alston, Harris, Mullen and Pardey (1995) have been used. More importantly, this paper uses nonparametric methods to measure the impacts of research and extension expenditures on total factor productivity (TFP) in Australian broadacre agriculture. The use of nonparametric techniques allows for analysis of the research and extension impacts on productivity in a multiple input/output production context while imposing minimal *a priori* structure on the underlying production technology. We use nonparametric methods proposed by Afriat (1972), Diewert and Parkan (1983), Hanoch and Rothschild (1972), and Varian (1984) as elaborated on and further developed in Chavas and Cox (1992, 1993, 1994, 1995).[2/] In particular, we follow the procedures in Chavas and Cox (1992) and Chavas, Aliber and Cox (1996) in assessing the impacts of research and extension expenditures on total factor productivity.

The basic intuitions behind the Afriat/Varian nonparametric approach are straightforward. If one believes that a behavioral premise such as profit and/or preference maximization (or cost minimization) can be adequately characterized by sufficient "structure" (regularity conditions) so that the solution to the associated optimization problem can be characterized by a saddle point (Takayama, 1993), then there will exist restatements of this saddle point characterization in the form of generalized axioms of revealed technology (preference). These results take the form of inequality statements which must be satisfied if the underlying behavioral premise (and the requisite regularity conditions) are consistent with the observed data. Varian's Generalized Axiom of Revealed Preference (GARP) and the Weak Axiom of Profit Maximization (WAPM) are special cases of these very general saddle point characterizations (Chavas and Cox, 1993).

One beauty of the saddle point perspective on these GARPs is the strong linkage between saddle points and concave programming (Sposito, 1975; Takayama, 1993). This insight is seminal to programming based nonparametric methods first proposed by Diewert and Parkan (1983) as it provides a convenient means for recovering empirically tractable representations of fairly general technologies (preferences) while imposing minimal functional structure not implied by the theory. Much econometric estimation of primal and/or dual models of behavior using flexible functional forms is plagued with a disturbing failure of the estimated technology (preferences) to satisfy the assumed regularity conditions (see Mullen and Cox, 1995). In contrast to econometric estimation, the technologies recovered with the nonparametric methods used here are, by construction, theoretically consistent at every data point. This is very attractive for applied analysis of welfare and technical change. Unfortunately, part of the price of recovering these globally consistent and quite general technologies (preferences) with nonparmetric methods is that standard goodness of fit measures and statistical hypothesis testing procedures are lacking.

The programming approach to obtaining solutions to these saddle point based inequalities allows the recovery of parameters that can be used to characterize the nature of technical change, productivity, and input and output supply response. The "augmentation hypothesis" which distinguishes observed from effective netputs, is particularly useful in this respect (Chavas and

Cox: 1992, 1994). In turn, by making these augments functions of shift factors such as research expenditures (Chavas and Cox, (1992)) and relative prices (Chavas, Aliber, and Cox (1996)), one can assess the impacts of alternative lag and functional specifications of these factors on induced innovation, TFP, and internal rates of return (IRR).

The outline of the paper is as follows. First, we assume a generalized, augmented technology with sufficient functional structure to guarantee the existence of a saddle point. Assuming profit maximization as the maintained behavioral premise, this generalized technology generates an augmented form of the WAPM which is empirically tractable with additional assumptions on the nature of technical change. We use a translating augmentation to generate non-radial measures of technical change that are time period and netput specific. The nonparametric/saddle point characterization allows solution of the augmented WAPM conditions for the augmentation parameters as a standard concave programming problem. Using the WAPM consistent, augmented netputs which summarize this technology, we then compute Malmquist TFP measures using input and output distance functions. We compare the netput augments and associated TFP measures across several alternative specifications to assess the robustness of these recovered technologies.

Given this reference technology, we next assess the impacts of research and extension expenditures on the augmentation parameters, and hence, on TFP under several lag specifications. Again, using the WAPM consistent, augmented netputs which characterize these technologies, we compute Malmquist measures of TFP. We summarize and compare the netput augments, research/productivity lag structures, and TFPs across alternative specifications. Summary and conclusions as to the strengths and weakness of this approach and our results are then provided.

THE NONPARAMETRIC APPROACH

Afriat/Varian WAPM

Assume a general multi-factor multi-product joint technology is represented by the feasible set F $\subset \mathbb{R}^n$, where the $(n\times1)$ vector of feasible netputs $x = (x_1, ..., x_n)'$ satisfies $x \in F$. In order to guarantee the existence of a saddle point characterization, we assume the feasible set F is nonempty, closed, convex[3/] and negative monotonic[4/]. Partition the netput vector as $x = (x_O, x_I)$ where $x_O \geq 0$ is the vector of outputs, and $x_I \leq 0$ is the vector of inputs. Denote the set of netputs $N = \{1, ..., n\} = \{N_I, N_O\}$, where $N_O = \{I: x_i \geq 0; I \in N\}$ is the set of outputs and $N_I = \{I: x_i \leq 0; I \in N\}$ is the set of inputs. The (nx1) vector of market prices associated with x is denoted by $p = (p_1, ..., p_n)' > 0$. Assuming the behavior of a competitive firm is consistent with the maintained hypothesis of profit maximization subject to this general production technology, then firm level decisions can be characterized by

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

where $\pi(p)$ is the profit function, profits are $(p' x)$, and the optimal netput supply and demand correspondences, the solutions to (1), are denoted by $x^*(p)$.

Since the nonparmetric methods we employ are variations on the saddle point characterization associated with (1), we need to derive the special cases of what are essentially generalized axioms of revealed technology. In this case, we assume the technology is revealed by the firm's observed production decisions where $T = \{1, 2, ..., \tau\}$ is the set of these τ decisions, and the t^{th} observed netput decisions is denoted by $x_t = (x_{1t}, ..., x_{nt})'$ with corresponding prices $p_t = (p_{1t}, ..., p_{nt})'$, $t \in T$. We want to recover a technology F that rationalizes the data $\{(x_t, p_t): t \in T\}$ in the sense that $x_t = x^*(p_t)$ for all $t \in T$ (i.e., such that the observed data solve (1)). Note that such a technology is theory consistent at each observed data point.

The following Afriat/Varian proposition provides the seminal revealed technology linkage between observable behavior and production theory as given by (1).

<u>Proposition 1</u>: (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:

$$F_T = \{x: p_t' x \le p_t' x_t,\ t \in T;\ x_i \ge 0 \text{ for } I \in N_O;\ x_i \le 0 \text{ for } I \in N_I\}. \tag{3}$$

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 ($p_t' x_s$), $s \in T$; these are necessary and sufficient conditions for the data $\{(x_t, p_t): t \in T\}$ to be consistent with profit maximization (1). 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. Lastly, note the generality of (3) in that it provides a characterization for **any netput vector x**, given the technology embodied in the T observations.

Augmented WAPM

Next, following Chavas and Cox (1992), we allow for technical change through an augmentation hypothesis that defines the functional relationship between actual netputs $x_t = (x_{1t}, ..., x_{nt})'$ and "effective netputs" $X_t = (X_{1t}, ..., X_{nt})'$ as

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

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. Basically, the technology indexes A_{it} in (4) "augment" the actual quantities into effective quantities. In this context, the behavioral hypothesis in (1) can be restated as:

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

for $t \in T$, where $A_t = (A_{1t}, ..., A_{nt})'$ is a (n×1) 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×1) vector of effective netputs for the t-th observation with $X_{it} \equiv X(x_{it}, A_{it})$. Note the generality of the representation of technology in (5) in that it does not *impose a priori* restriction on the effective technology F^e. As well, changes in the A's can be interpreted in terms of biased technical change since the marginal rate of substitution between netputs is in general affected by the technology indexes A (see below). This will allow us to characterize the impacts of research and extension expenditures on input and output biased technical change.

The "augmented" profit maximization formulation in (5) is the basis for the saddle point characterization that yields augmented WAPM conditions and provides empirical measures of technical change by solving (5) for the A's. This requires additional structure on the nature of technical change through a functional specification of the augmentation functions in (4). While there are a variety of potential specifications, we follow Chavas and Cox (1992) and specify an additive or translating specification primarily for it's empirical tractability. Noting that the functions in (4), being one-to-one, can be inverted and expressed equivalently as $x_{it} = x(X_{it}, A_{it})$, $I \in N$, $t \in T$, the additive (translating) specification of (4) yields $X_i = x_i - A_i$, or equivalently, $x_i = X_i + A_i$. Under translating, the augmented profit maximization problem in (5), now denominated in effective (versus actual) netputs becomes:

$$\begin{aligned} \pi(p_t, A_t) &= \max_X [p_t' (X+A_t): X \in F^e] \\ &= p_t'A_t + \max_X [p_t' X: X \in F^e], \end{aligned} \tag{6}$$

for $t \in T$. Associated with (6) is an empirically tractable, augmented Weak Axiom of Profit Maximization (i.e., the augmented counterpart to the WAPM inequalities in (2)):

$$p_t' X_t \geq p_t' X_s, \text{ for all } s, t \in T, \tag{7}$$

or

$$p_t' [x_t-A_t] \geq p_t' [x_s-A_s], \text{ for all } s, t \in T. \tag{7'}$$

Augmentation parameters, the A's, that satisfy equation (7') for a given data set T yield the corresponding effective netputs, $X_t = x_t - A_t$, which necessarily satisfy the WAPM condition (7) for <u>all</u> s, t $\in$ T. From (6) and (7), all the results in proposition 1 (which refer to actual netputs x) hold as well for these effective netputs X. Substituting X for x in equation (3) yields an empirical representation of the underlying augmented technology

$$F_T^e = \{X: p_t' X \le p_t' X_t, t \in T; X_i \ge 0 \text{ for } I \in N_O; X_i \le 0 \text{ for } I \in N_I\}. \tag{8}$$

As with (3), note that this recovered technology must hold for **any effective netput**. This provides the empirical basis for estimating technical change under the maintained behavioral and technology assumptions.

Interpretation of the technology parameters, A, as measures of bias in technical change is straight forward. In the case of inputs (i.e., $x_i \le 0$ for $I \in N_I$ and $X_i = x_i - A_i$), finding $A_{is} - A_{it} < 0$ (> 0) implies input using (saving) technical change in the i^{th}-input from time period t to s: *ceteris paribus*,[5/] a lower (higher) value of A_i implies that producing the same effective netputs X requires more (less) of the i^{th} input ($-x_i \ge 0$). In the case of outputs (i.e., $x_i \ge 0$ for $I \in N_O$ and $X_i = x_i - A_i$), finding $A_{is} - A_{it} < 0$ (> 0) implies that technical change from t to s is output reducing (enhancing) for the i^{th} output: *ceteris paribus*, a lower (higher) value of A_i implies that less (more) of the i^{th} output can be produced with the same effective netputs X. Lastly, finding $A_{it} = A_{is}$ can be interpreted as technical change which is neutral toward the i^{th} netput since producing the i^{th} effective netput X_i can be done using the same quantity of the i^{th} actual netput x_i.

Augmentation as a Function of Exogenous Shift Factors (Research and Extension)

In order to evaluate the impacts of research and extension on the technical change, we follow Chavas and Cox (1992) and Chavas, Aliber and Cox (1996) and specify the augmentation parameters from (7') as lagged functions research (RD) and extension (EXT). In this paper we evaluate the following specifications:

$$A_{ti} = \alpha_{ti} + \sum_{k}^{30} \beta_{ki} * RD_{t-k} \tag{9}$$

$$A_{ti} \; = \; \alpha_{ti} \; + \; \sum_{k}^{30} \; \beta_{ki} * RD_{t-k} \; + \; \sum_{j}^{10} \; \delta_{ji} * EXT_{t-j} \tag{10}$$

$$A_{ti} \; = \; \alpha_{ti} \; + \; \sum_{k}^{30} \; \beta_{ki} * RD_{t-k} \; + \; \sum_{j}^{10} \; \delta_{ji} * EXT_{t} * RD_{t-j}. \tag{11}$$

where β_{ki} measures the direct effect of lagged research expenditures (RD_{t-k}) on the i^{th} netput augment in the t^{th} time period, δ_{ji} measures the direct (10) or interaction (11) impacts of lagged (current) extension expenditures on netput augmentation, and the α_{ti} measure all other netput and year specific augmentations such as those induced by weather and other exogenous shocks. Following Pardey and Craig (1989), we allow for 30 years of lagged impacts with respect to research expenditures. There is some evidence that extension lag effects are considerably shorter than in research effects and that extension likely reinforces the impacts of research; however, the empirical evidence on extension impacts is somewhat thin (Davis (1979); Thirtle and Bottomley (1989); and Huffman and Evenson (1993)). Here we allow for 10 years of lagged extension expenditures to directly impact the augmentations (10) as well as allow current period extension expenditures to impact 10 years of lagged research expenditures (11).

Given that the augments in (7') and the augmentation functions in (9)-(11) generate potentially large numbers of parameters, we evaluate a number of "smoothing" restrictions. We impose a form of non-regressive technical change by restricting the output augments (i.e., A_{it} for $I \in N_O$) to be greater than or equal to a 5 year moving average of previous output augments. We also restrict the lagged impacts of research (β_{ki}) and extension (δ_{ji}) to follow continuous, piece-wise linear spline specifications that allow for inverted-V (Evenson, 1967) and trapezoidal lag structures (Huffman and Evenson 1989). We restrict the β_{ki} splines to zero at year 0 and 31 (δ_{ji} spline functions to zero at year 0 and 11). Last, we restrict the β_{ki}, the direct research impacts on netput augments, to be non-negative (non-positive) for outputs (inputs) implying that research cannot generate negative technical change in netputs.

We solve (6) and the additional "smoothing" constraints (e.g., (9)-(11)) by minimizing the sum of $(X_{it} - x_{it})^2$ across netputs and time periods. Noting the $A_{it} = X_{it} - x_{it}$, this quadratic objective function yields augmented netputs that are as close to the actual data as possible. This basically chooses the minimal technical change required to satisfy the augmented WAPM in (6) using a least squares criterion. As the “smoothing” constraints we use are linear, the resulting optimization is a standard quadratic program which we solve using GAMS/MINOS software.

Nonparametric Total Factor Productivity Measures

Given the representation of the augmented technologies in (8), we can use the associated WAPM consistent effective netputs to generate Malmquist radial measures of TFP by computing the corresponding input and output distance functions. As noted by Banker and Maindiratta (1988) and Chavas and Cox (1994, 1995), these radial TFP measures are associated with the dual, tightest outer bound on the production possibility set T. In the this context, the dual, input based radial TFP index associated with observation x is defined as

$$Q_I(x, A) = \min_k \{k: p_{Ot}' x_O + p_{It}' (k\, x_I) \leq p_t X_t ; X_t = x_t - A_t; t \in T; k \in \mathbb{R}^+\}, \tag{12}$$

where Q_I is the smallest proportional rescaling of all inputs, x_I, that remains feasible in the production of outputs, x_O, under the effective technology F_T^e in (8). An index $Q_I > 1$ (< 1) means that the netput vector $x = (x_O, x_I)$ uses a better technology (an inferior technology) compared to the reference technology represented by F_T^e. Thus, if $Q_I < 1$ ($Q_I > 1$), then $(1 - Q_I)$ can be interpreted as the percentage cost reduction (cost increase) that is achieved by shifting from the current technology to technology F_T^e (Caves et al., 1982).

Similarly, the dual, output based radial TFP index associated with observation x is defined as

$$1/Q_O(x, A) = \max_k \{k: p_{Ot}' (k\, x_O) + p_{It}' x_I \leq p_t X_t ; X_t = x_t - A_t; t \in T; k \in \mathbb{R}^+\}, \tag{13}$$

where Q_O is the largest proportional rescaling of all outputs, x_O, that remains feasible using the inputs, x_I, under the effective technology F_T^e in (8). An index $Q_O > 1$ (< 1) means that the netput vector $x = (x_O, x_I)$ uses a better technology (an inferior technology) compared to the reference technology represented by F_T^e. Thus, if $Q_O < 1$ ($Q_O > 1$), then ($1 - Q_O$) can be interpreted as the percentage revenue increase (revenue decrease) that is achieved by shifting from the current technology to technology F_T^e.

Since $Q_I = Q_O$ only under constant returns to scale, we use the geometric means of these two productivity measures in our results below. Note, that (12) and (13) are functions of the technology parameters, A_t, which in turn are functions of the arguments in (9), (10), and (11). This provides a basis for measuring the dynamic impacts of research and/or extension expenditures on total factor productivity.[6/]

DATA

The data used in this study cover the 1953-94 period and were obtained from the Australian Bureau of Agricultural and Resource Economics (ABARE). ABARE has been collecting farm survey data since 1952-53. In that time the target population for the surveys has been broadened from the Australian sheep industry, defined to include all farms carrying at least 200 sheep, to those engaged in broadacre agriculture in Australia, as covered by the Australian Agricultural and Grazing Industries Survey. More information about the extent of the surveys, the methodology used and the definition of variables can be found in several papers by ABARE staff (Paul (1984); Beck, Moir, Fraser and Paul (1985); and Knopke (1988)). Our sample was drawn from those who had more than 200 sheep to enable us to use a sample extending back to the original sheep industry surveys. One implication of defining the survey population in this way is that our sample does not include specialist crop farmers.[7/] The number of producers in the sample ranged from 600 to 700. The outputs were crop, livestock sales, wool and other outputs. The inputs were contracts, services, materials, labor, livestock purchases, use of livestock capital, use of land capital, and use of plant and structures. There were series for the value, price and quantity of these inputs and outputs.[8/] As with all of the previous Chavas and Cox work, we also normalize the quantity data to equal one in the chosen base period (in this case, the first period of the data, 1953). Note, this effectively normalizes expenditures using the base period prices as the numeraire, a procedure also suggested by Chalfant and Zhang.[9/]

The research data set used here and the methods by which it was assembled are described in Mullen, Lee and Wrigley (1996). Research and extension expenditure data for the 1953-94 period were collected from publicly available financial reports. Research and extension nominal expenditures were both deflated. As we needed research and extension data back to 1923 to estimate 30 year lag structures starting from 1953, we “backcasted” from the deflated 1952-75 data series.[10/] This “missing data” procedure and the difficulty to cleanly disentangle research and extension expenditures in these data (Mullen and Cox, 1995) suggest that due caution be exercised in the interpretation of the results.

CSIRO is the largest single agricultural research body in Australia. As a group, the State Departments of Agriculture account for the largest share of expenditure on agricultural research, and the expenditure by Departments has grown steadily relative to the GVP of agriculture since 1953. Universities make a relatively small contribution to agricultural research and rely heavily on external grants for funding. In nominal dollars, total expenditure on agricultural research by State Departments, CSIRO and Universities rose from $9m in 1953 to $530m in 1994. Relative to the value of GDP in agriculture, this is an increase from 0.6 percent in 1953 to 4.4 percent in 1994. Research as a percentage of farm GDP was as high as 5.2 percent in 1978 . Alston, Chalfant and Pardey (1993, p14) note that of OECD countries, Australia was second only to Canada in the level of its research intensity (defined as the ratio of research expenditure to agricultural GDP) in 1985.[11/] Nominal expenditure on broadacre research in Australia rose from $6.4m in 1953 to $312m in 1994. In real dollars, expenditure on broadacre research grew from $84m in 1953 to $312m in 1994. It has drifted downwards since the early 1980s.

RESULTS

We summarize results for 5 alternative specifications: (S1) NO R&D, Unrestricted; (S2) NO R&D with Smoothing Restrictions; (S3) R&D, No Spline, Unrestricted; (S4) R&D, No Spline with Smoothing Restrictions; (S5) R&D, 3 Spline with Smoothing Restrictions. Specifications S1 and S2 minimize the sum of squared augmentations subject to the augmented WAPM constraints from equation (7'). S2 normalizes the base period (1953) augments to zero and restricts the output augments to be greater than or equal to the moving average of the augments for the 5 prior years, a form of non-regressive technical change. Thus, comparison of S1 and S2 provides an indication of the impacts of these smoothing priors on the recovered technology and associated technical change and productivity measures. S3-S5 follow equation (9) and restrict the augmentation parameters as functions of 30 years of lagged research expenditures. S3 minimizes the sum of squared augmentations subject to (7') and (9) without additional restrictions; hence, comparison of S1 and S3 indicates the impacts of introducing research expenditures into an unsmoothed, augmentation specification. S4 adds smoothing priors similar to S2 (plus restricts the lagged impacts of research on output (input) augments to be non-negative (non-positive)); hence comparison of S2 and S4 provides an indication of impacts of introducing research expenditures into a smoothed augments specification. Lastly, S5 adds spline restrictions to the specification in S4. This specification restricts the lagged research impacts to follow a spline specification with 3 segments of 10 years each, allowing for inverted-V as well as trapezoidal lag structures. These splines are restricted to zero at lags 0 and 31 (endpoint restrictions) and are restricted to be equal at the overlapping lag points (i.e., lagged years 10 and 20) to provide a continuous lag structure. S5 provides a research/productivity specification similar to that used by Chavas and Cox (1992) and Chavas, Aliber and Cox (1996).[12/]

Extension expenditure specifications similar to S5 but using (10) and (11) rather than (9) were also estimated. These specifications generated results that were virtually identical to S5 (i.e., the δ_{ji} = 0 for all i,j), indicating that the data and nonparametric procedures used here were unable to distinguish separate research and extension impacts, a common finding in the literature. While additional specification and exploration of these extension impacts is clearly warranted, our preliminary results with these data are not promising.

Total Factor Productivity Measures

One of the striking results of this nonparametric estimation exercise is the robustness of the Malmquist TFP measures (TFPs) computed from (12) and (13) across the alternative specifications. Table 1 summarizes the dual Malmquist TFPs computed from (12) and (13) and their geometric means for S5 and S1 (geometric mean only), the most extreme comparison between these scenarios (i.e., no R&D/unrestricted versus R&D/restricted with spline functions). The input (Q_I) and output (Q_O) TFPs and their respective geometric means from S5 have correlations of 0.91, 0.95 and 0.93 with the S1 geometric mean measure. The input based TFPs (Q_I) associated with S5 generate TFP measures considerably higher than the output based TFPs, Q_O . Since $Q_I \neq Q_{O,}$ these results indicate that Australian broadacre agriculture over the 1953-94 period was not characterized by constant returns to scale, contrary to common assumption in the computation of TFP indexes. The geometric mean TFP for S5 is considerably higher than for S1, indicating that imposing the non-regressive technical change smoothing priors on the output augments generates higher TFP measures in these data. The geometric mean TFPs for specifications S2-S5 are virtually identical (e.g., correlation coefficients 1.000, see Table 2), and display virtually identical relationships to S1 as were found for S5.

In order to assess their “reasonableness”, Figure 1 compares the “smoothed” geometric mean TFPs from S5 and S1 with more conventional TFP measures obtained by Mullen and Cox (1996) using these same data. Table 3 provides the associated correlations across these alternative TFP measures. The Fisher Ideal (Diewert, 1992) and CCD No Scale Adjustment (Caves, Christensen and Diewert 1982) TFP measures are both superlative indexes (i.e., they are exact indexes for the associated implicit functional form (quadratic mean of order 2 and unit translog cost function, respectively), Diewert, 1967) which assume constant returns to scale. The CCD Scale Adjusted (Caves, Christensen and Diewert, 1982) and Translog Cost (Mullen and Cox, 1996) TFP measures allow for non-constant (decreasing) returns to scale. As noted in Mullen and Cox (1996), the estimated translog cost function was not particularly “well behaved” in terms of consistency with theoretical priors. In contrast, the technologies used to generate the S1 and S5 TFP measures are theory consistent at every data point.

As can be seen from Figure 1, the unrestricted nonparametric TFP measure associated with S1 is considerably lower than all other measures while the S5 measure indicates slightly higher productivity gains than all other measures. Chavas and Cox (1994) found similar S5 results (i.e., smoothed nonparametric TFP measures were larger than divisia type TFP indexes) while Mullen and Cox (1995) found similar S1 results (i.e., unsmoothed nonparametric TFP measures were smaller than divisia type TFP indexes). In general, all TFP measures except for S1, are quite similar (with S5 showing slightly higher productivity gains). Table 3 indicates that the correlations among all TFP measures are greater than 0.90 and, except for the Translog Cost and nonparametric S1 measures, higher that 0.99.

These results suggest that the augmentation hypothesis and smoothing priors associated with the nonparametric TFP measure in S5 are certainly plausible in that they generate results similar to a variety of alternative measures derived using quite different methodologies and functional structure assumptions. We interpret these results as evidence that these smoothing priors are as reasonable as those required by conventional TFP measures. However, these results also suggest that such smoothing can generate higher productivity measures (e.g., Figure 1). Lastly, these results suggest that the measurement of TFP in Australian broadacre agriculture using these data for the 1953-94 period is moderately robust to a variety of quite diverse estimation procedures.

Output Augments

While the evidence of robustness in aggregate TFP measurement is encouraging, there is considerable interest in more disaggregate, netput level productivity and technical change measurement. The nonparametric estimation used here generates netput specific augmentations for each year. As indicated earlier, these measures can be interpreted as productivity and bias in technical change measures. Perhaps not surprisingly, the evidence as to robustness is more varied in these netput level results. Due to space limitations, we focus our discussion here on two specifications S2 and S5 (results for S3 and S4 are available on request).

Figures 2 and 3 summarize the output augments from S2 and S5, which both contain the same smoothing restrictions with the exception that the augments in S5 are spline functions of 30 years of lagged research expenditures. Hence, comparison of these results indicates the impacts of introducing R&D spline functions into the additive augmentations, holding all other smoothing priors constant. Recall that these augments are normalized with respect to the base period (1953) augments equal to zero. Hence, augments greater (less) than zero indicate how much more (less) output could be produced under the new technology using the base level effective netputs. As with most technical change measures, the somewhat “non-smooth” nature of these measures reflects the impacts of other shift factors such as weather, as it does in all of the TFP measures in Figure 1 (e.g., the 1983 drought impacts on “productivity” in Figure 1).

On average over the 1953-94 period, the ranking of broadacre outputs with respect to revenue shares was: wool (38%), livestock (31%), crops (28%) and other (3%). With the exception of crop outputs, Figures 2 and 3 indicate that the augments generated by these specifications are quite similar: little or no productivity growth in other outputs; higher productivity growth in wool versus livestock outputs, both with productivity gains around 100-200 percent relative to the 1953 reference technology. Both specifications indicate that the technical change in crop outputs has, in general, been much greater than in livestock, wool and other outputs. Similar results were found by Knopke *et al* with respect to cropping and livestock specialists. While incorporating research effects through S5 generated higher crop productivity gains, S2 generated slightly larger gains to wool and livestock outputs than the S5 specification. These results provide nonparametric evidence of significant technical change in Australian broadacre agriculture over the 1953-94 period and provide measures of the differential impacts across crop, wool, livestock and other outputs.

Input Augments

Above we argue that the netput level technical change measures are under identified. As a result, the associated additive netput augments tend to be somewhat "noisy". To provide a clearer picture of the underlying trends in technical change recovered by the nonparametric methods used here, 5 year moving averages at 5 year intervals are presented and discussed. Recall that for inputs, finding $A_{is} - A_{it} < 0$ (> 0) implies input using (saving) technical change in the i^{th}-input from time period t to s: *ceteris paribus*, a lower (higher) value of A_i implies that producing the same effective netputs X requires more (less) of the i^{th} input ($-x_i \geq 0$). We summarize these input technical change results in Figures 4-7. Again, due to space limitations, we focus on contrasts between specifications S2 and S5 which reflect the impacts of the research expenditure spline functions on the these measures of technical change, holding the other smoothing priors constant.

Figures 4 and 5 summarize the additive augments for the labor, materials, land and plant and equipment inputs for S2 and S5. On average, these inputs account for 75% of total input costs (27%, 23%, 11% and 15%, respectively). Note that the magnitude of the input augments for Figure 4 (S2) is considerably larger than for Figure 5 (S5), indicating that making the augments a function of lagged research expenditures generated considerably smaller measures of technical change for these inputs. The S5 specification generally indicates that factor saving technical change (negative slopes) characterized these inputs with the following exceptions: materials (1960-65, 1970-75, 1985-94), plant and equipment (1970-75), and labor (1975-80). The S2 specification also indicates factor saving technical change for land and plant and equipment (except for the 1970-75 and 90-94 periods). Note that the shape of the land and plant and equipment input bias is quite similar across these specifications. Both S2 and S5 indicate several periods of materials using technical change (positive slopes). While S5 generally indicates labor saving, S2 shows a considerable period (1975-90) of labor using technical change.

Figures 6 and 7 summarize the 5 year average augments for services, livestock purchase, livestock usage, and contracts comprising, on average, 25% of total input costs (9%, 12%, 2%, and 2%, respectively). As with Figures 4 and 5, the S2 specification generates input augments that are considerably larger than for S5. Both specifications indicate relatively little biased technical change in livestock use and contracts. Both S2 and S5 indicate considerably larger, and generally factor using, technical change in livestock purchases with a similar pattern over time. Services are generally found to be input saving in S2 with little evidence of technical change in S5.

While these input bias measures are quite varied, the following generalization can be noted: making the input augments a function of research expenditures generates considerably smaller augments; both specifications generally indicate factor saving technical change in land, and plant and equipment; both specifications generally indicate factor using technical change in materials, livestock purchases; both specifications generally indicate neural technical change in contract; and lastly, quite mixed results were found for labor, services, and livestock usage. These results indicate that there can be considerable variation in measures of input biased technical change among the infinity of technologies that are consistent with the data and the maintained augmented WAPM maintained hypothesis. This is another manifestation of the fundamental under identification of these types of technical change measures.

Lagged Research Impacts

Figures 8-10 summarize the marginal impacts of research expenditures on the netput augments estimated from specification S5. Similar to Chavas and Cox, we find considerable evidence of lagged research impacts on productivity change out as far as 30 years. The 3 spline specification used allows for either inverted-V or trapezoidal lag structure with peaks at either 10 or 20 years. Figure 8 indicates that inverted-V lag structures with peaks at 20 years were found for crops, livestock and wool outputs. Note that the lagged, marginal impacts of research on crops productivity are considerably larger than for the livestock and wool outputs. This results is not too surprising given that the rate of productivity growth in crops was found to be 5-6 times larger than for wool and livestock in this specification (see Figure 3). However, these research induced productivity changes take some time to occur (after 10 years), build quite sharply to year 20, and then decline along the inverted-V lag structure.

Livestock and wool are found to have similar lagged, marginal impacts of research on productivity. Like crops, research impacts on livestock productivity are found to occur only after 10 years. In contrast, the research impacts on wool productivity start immediately. Both impacts peak at year 20 with inverted V lagged structures. This specification generated zero lagged research impacts on the productivity of other outputs.

Figures 9 and 10 summarize the lagged marginal impacts of research expenditures on the input technical change measures. With the exception of land, research impacts on inputs are generally found to be somewhat shorter run (20 years) than the results for output (30 years). As well, the magnitude of the R&D impacts on input augments are considerably smaller than the R&D impacts on output augments (i.e., note the scale differences in Figures 8, 9, and 10). This also reflects the differences in magnitudes in the actual netputs. In general, research impacts on input augments are found to peak at 10 years and to be fully dissipated by year 20 (with the exception of land plant and equipment). The impacts on land are similar but delay 10 years before manifesting R&D impacts and peak at year 20 before declining. As with the output results, inverted-V research lag structures predominate in these results.

Lagged R&D Impacts on TFP Measures

In order to assess the aggregate lagged effects of R&D on productivity, we compute the marginal changes in TFP due to shocking R&D expenditures sequentially through 30 years using 1973 as the reference point.[13/] Table 4 and Figure 11 summarize the lagged marginal effects on 1973 TFPs from specification S5 due to a 25% shock in 1973 R&D expenditures.[14/] The shape of these marginal R&D impacts (Figure 11) are clearly dominated by the marginal R&D effects on the output augments (Figure 8). While the marginal R&D impacts on inputs (Figures 9 and 10) suggest shorter term impacts with peaks at 10 years, the relative magnitude of these impacts is quite small compared to the output effects. Thus, while there are marginal R&D impacts on the TFPs up through year 10 (see Table 4), they are quite small. These results are similar to the public R&D impacts by Chavas and Cox (1972) and Chavas, Aliber, and Cox (1996).

SUMMARY AND CONCLUSIONS

This paper uses nonparametric methods to assess the impacts of research expenditures on technical change in Australian broadacre agriculture for the 1953-94 period. If one is willing to assume sufficient structure such that a maintained behavioral premise has an optimum and can be characterized by a saddle point, then there will exist a broad set of generalized axioms of revealed technologies (preferences) such as the augmented WAPM used here. The empirical methodology based on these saddle point characterizations is quite general, easily handles multiple outputs, allows considerable flexibility in modeling the technical change impacts of exogenous shift factors (such as research expenditures), and imposes minimal structure on the implicit production technology (beyond the regularity conditions impled by the associated behavioral premise). Perhaps more importantly, these nonparametric techniques recover representations of the underlying technology that are theory consistent at every data point. This is very attractive for applied economic and welfare analysis. Empirical implementation of these techniques requires the solution of standard concave programming problems.

The augmentation hypothesis provides a powerful framework for generating technologies with a variety of technical change characteristics. The linear augmentation (translating) hypothesis used here generates netput specific technical change parameters for each time period, hence allows for considerable (perhaps too much) flexibility in modeling technical change. Restrictions on these augments are used to provide some “smoothing” on the estimated technical change parameters. Unfortunately, as is the case in virtually all estimation of implicit technologies (or preferences), there exist an infinity of technologies (in this case, linear augments) that are consistent with the specific data and the maintained behavioral premise (in this case, augmented WAPM). As a result, these technical change parameters are fundamentally under identified. This under identification is not unique to the nonparametric methods used here; e.g., consider the choice of flexible functional forms in econometric estimation. The analyst must choose from amongst this infinity of theory consistent technologies by choosing specific augmentation hypotheses, smoothing priors, data normalizations, functional forms, etc.

A unique aspect of the nonparametric techniques used here is that they provide a relatively easy means for empirically recovering specific representations from this infinity of theory consistent, augmented technologies. As well, these methods force you to realize that you are explicitly choosing a representative technology from amongst the feasible set. In our application key choices determining the specific technology we recover include the additive augmentation specification, the use of alternative smoothing priors, and specification of the reference technology by normalizing all netput quantity indexes to equal one in the base period (1953, the first year of the data) which generates technical change parameters relative to base period augments. This data normalization is somewhat akin to choosing an expansion point for Taylor approximations to arbitrary technologies or preferences.

Given that technical change parameters are fundamentally under identified, an empirical issue arises as to the robustness of certain aspects of these theory consistent technologies recovered using nonparametric methods. Our results focus on the robustness of the associated TFP measures, netput technical change biases, and lagged impacts of exogenous shift factors (research expenditures) on productivity measures. Our application to Australian broadacre agriculture over the 1953-94 period, indicates that the TFP measures tend to be quite robust to a variety of alternative “smoothing” specifications. More importantly, our results suggest that imposing moderate non-regressive technical change on the output augments generates results quite similar to more traditional index based TFP measures. Conversely, specifications with relatively unrestricted (non-smoothed) augmentations generated TFP measures that were considerably lower, suggesting that smoothing priors generate may upward impacts on TFP measures.

Comparison of netput augments from two specifications (S2 and S5) provides nonparametric evidence of differential technical change across netput categories as well as the impacts of endogenizing augments as a function of research expenditures. With respect to outputs, our results indicate: that technical change in crop outputs has, in general, been greater than in livestock, wool and other outputs; that wool is characterized by higher productivity growth than livestock outputs (both with 100-200% productivity gains relative to the 1953 reference technology); and, little or no productivity growth in other outputs (which, on average, accounts for 3% for total revenues). Input specific biased technical change measures were found to be much less robust though general trends were apparent. Our results suggest that making the input augments a function of research expenditures generates considerably smaller augments. The two specifications summarized generally indicated factor saving technical change (land and plant and equipment), factor using technical change (materials and livestock purchases), neutral technical change (contracts) and quite mixed results for labor, services, and livestock usage. These results indicate that there can be considerable variation in measures of input biased technical change among the infinity of technologies that are consistent with these data and the maintained augmented WAPM maintained hypothesis.

Our attempts to model technical change as a function of exogenous shift factors such as research and extension expenditures met with limited success. The method used allows for a simultaneous estimation of netput and time period specific technical change and the marginal impacts of exogenous shift factors on these technical change parameters. One virtue of this approach is that it easily handles multi-output/input specifications and allows considerable flexibility in specifying the augmentation functions. The 3 spline specification used allows for either inverted-V or trapezoidal lag structure with peaks at either 10 or 20 years. While we were unable to identify separate extension expenditure impacts, our results provide nonparametric evidence of lagged research impacts on productivity in Australian broadacre agriculture out as far as 30 years. Inverted-V lag structures with 20 year peaks were found for crops, livestock and wool outputs with considerably larger marginal impacts of research on crops productivity are than for the livestock and wool. For crops and livestock, these impacts were found to be primarily longer run in nature as they occurred only after 10 years. With respect to all inputs (except labor) our results suggest that the lagged impacts of research peak at 10 years and are fully dissipated by year 20. Clearly, further research on alternative augmentation functions and smoothing priors is required in order to more fully evaluate the range and reasonableness of the research induced technical change estimates that can be generated from the infinity of technologies that are consistent with the data and the maintained augmented WAPM maintained hypothesis.

In conclusion, we are encouraged by the theoretical foundations, modeling flexibility, and ease of empirical implementation of the nonparametric methods used here. Clearly, these are heuristic tools that complement our more traditional estimation methods by allowing us to recover fairly flexible, joint multi-output/multi-input production technologies while imposing a minimum of functional structure not implied by the theory. While the under identification of key aspects of these theory and data consistent technologies (in particular the bias in technical change measures) can be disturbing, our results suggest that other aspects of these technologies (in particular, the Malmquist TFP measures) may be quite robust. These are exactly the kinds of empirical foundations required to better understand the strengths and shortcomings of our alternative methodologies and the applied policy inferences that derive from them.

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Table 1. Summary of Dual Malmquist Total Factor Productivity Measures From Specification S5 (Augments = f(R&D), 3 Splines with Smoothing Restrictions) and S1 (No R&D, Unrestricted).

YEAR	INPUT (Qi): S5	OUTPUT (Qo): S5	GEOM MEANS: S5	GEOM MEANS: S1
1953	1.000	1.000	1.000	1.000
1954	0.986	0.983	0.984	0.952
1955	0.985	0.986	0.985	0.968
1956	1.141	1.092	1.116	1.038
1957	1.155	1.102	1.128	1.014
1958	1.008	1.005	1.006	0.859
1959	1.319	1.213	1.265	0.972
1960	1.322	1.218	1.269	0.973
1961	1.396	1.271	1.332	0.985
1962	1.446	1.306	1.374	0.997
1963	1.494	1.344	1.417	0.986
1964	1.567	1.399	1.480	0.986
1965	1.498	1.357	1.426	0.935
1966	1.228	1.163	1.195	0.861
1967	1.645	1.458	1.548	0.952
1968	1.454	1.323	1.387	0.859
1969	1.877	1.641	1.755	1.006
1970	1.784	1.572	1.675	0.982
1971	1.814	1.586	1.696	1.045
1972	1.863	1.635	1.745	1.077
1973	1.517	1.381	1.448	0.911
1974	1.757	1.564	1.658	0.957
1975	2.149	1.793	1.963	1.174
1976	2.157	1.812	1.977	1.163
1977	1.824	1.604	1.710	1.013
1978	1.971	1.721	1.842	1.085
1979	2.358	2.003	2.173	1.341
1980	2.358	2.020	2.182	1.380
1981	1.920	1.688	1.800	1.047
1982	2.250	1.939	2.089	1.298
1983	1.802	1.613	1.705	1.005
1984	2.660	2.241	2.442	1.588
1985	2.698	2.275	2.478	1.630
1986	2.770	2.313	2.531	1.642
1987	2.837	2.371	2.594	1.713
1988	2.473	2.107	2.283	1.468
1989	2.535	2.178	2.349	1.578
1990	2.715	2.315	2.507	1.712
1991	3.064	2.536	2.788	1.867
1992	2.838	2.382	2.600	1.737
1993	3.230	2.654	2.928	2.004
1994	3.524	2.898	3.196	2.294

Table 2. Correlation Between Dual Nonparametric Total Factor Productivity Measures Across Specifications S1-S5.

	S1	S2	S3	S4	S5
S1	1.0000				
S2	0.9322	1.0000			
S3	0.9321	1.0000	1.0000		
S4	0.9320	1.0000	1.0000	1.0000	
S5	0.9321	1.0000	1.0000	1.0000	1.0000

Figure 1. Comparison of Total Factor Productivity Measures From Mullen and Cox (1996) with Specifications S1 and S5.

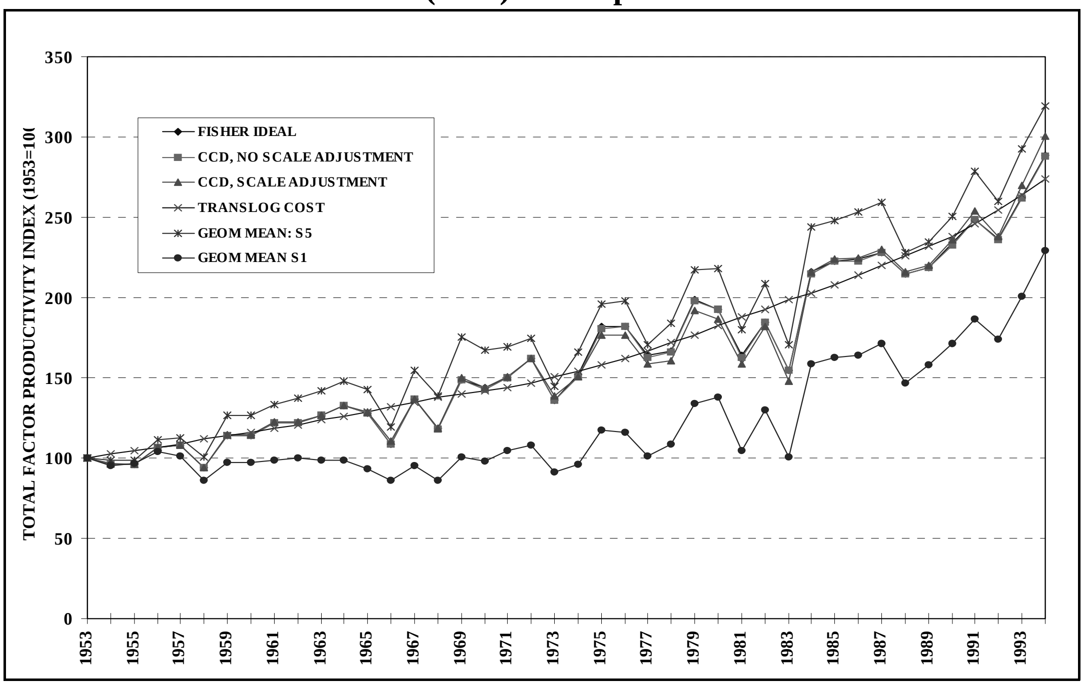


Table 3. Correlations Between the Alternative TFP Measures in Figure 1.

	FISHER	CCD	CCD-ADJ	TL COST	S5	S1
FISHER	1.000					
CCD	1.000	1.000				
CCD-ADJ	0.998	0.998	1.000			
TL COST	0.965	0.965	0.963	1.000		
S5	0.996	0.996	0.994	0.958	1.000	
S1	0.940	0.940	0.953	0.903	0.932	1.000

Figure 2. Output Augments for Specification S2: No R&D with Smoothing Restrictions.

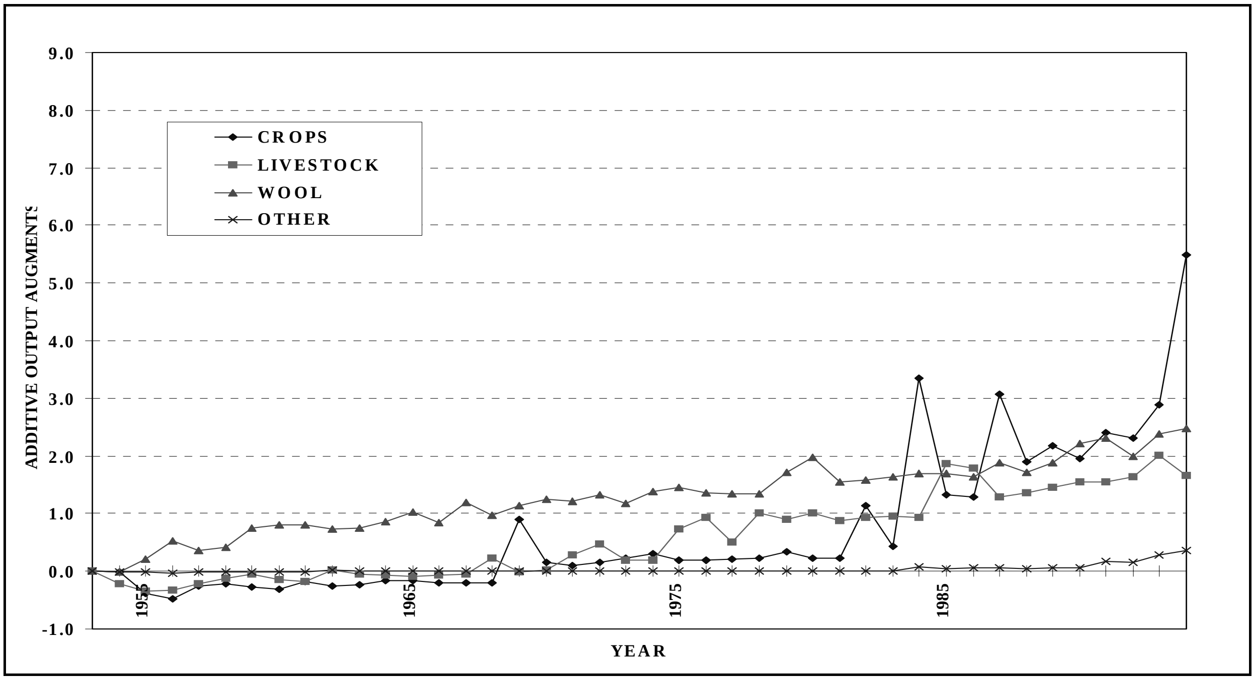


Figure 3. Output Augments for Specification S5: Augments = f(R&D), 3 Splines with Smoothing Restrictions.

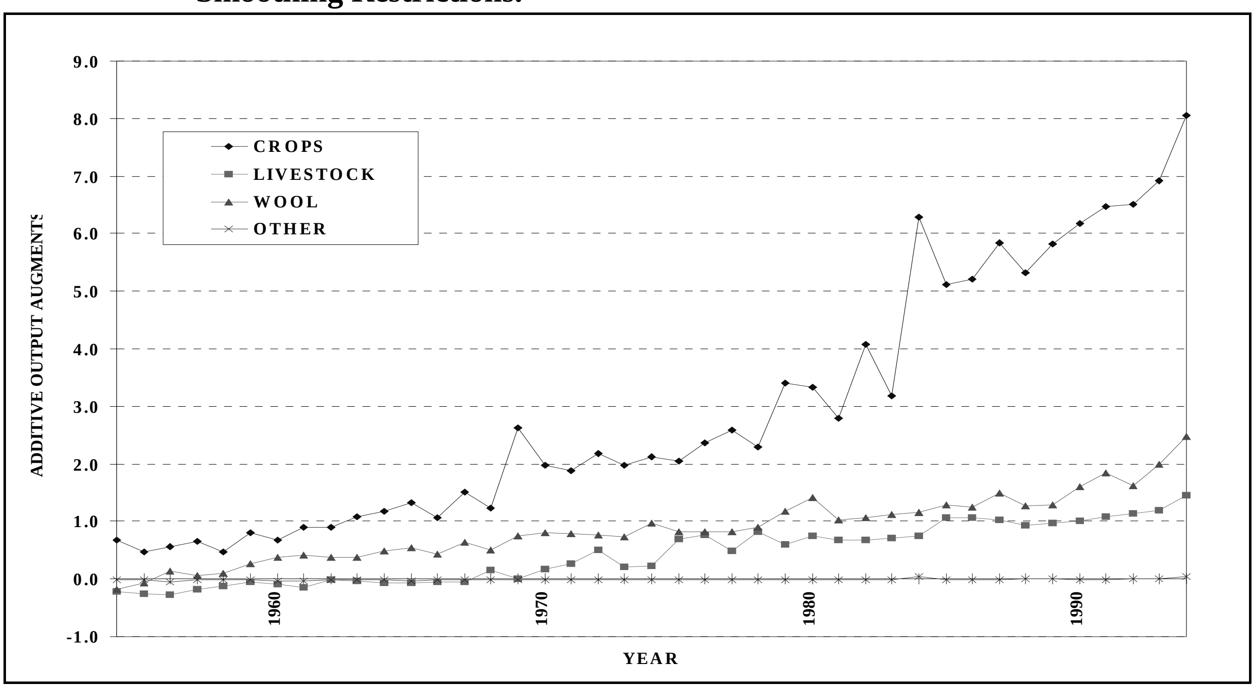


Figure 4. Input Augments for Specification S2: No R&D with Smoothing Restrictions.

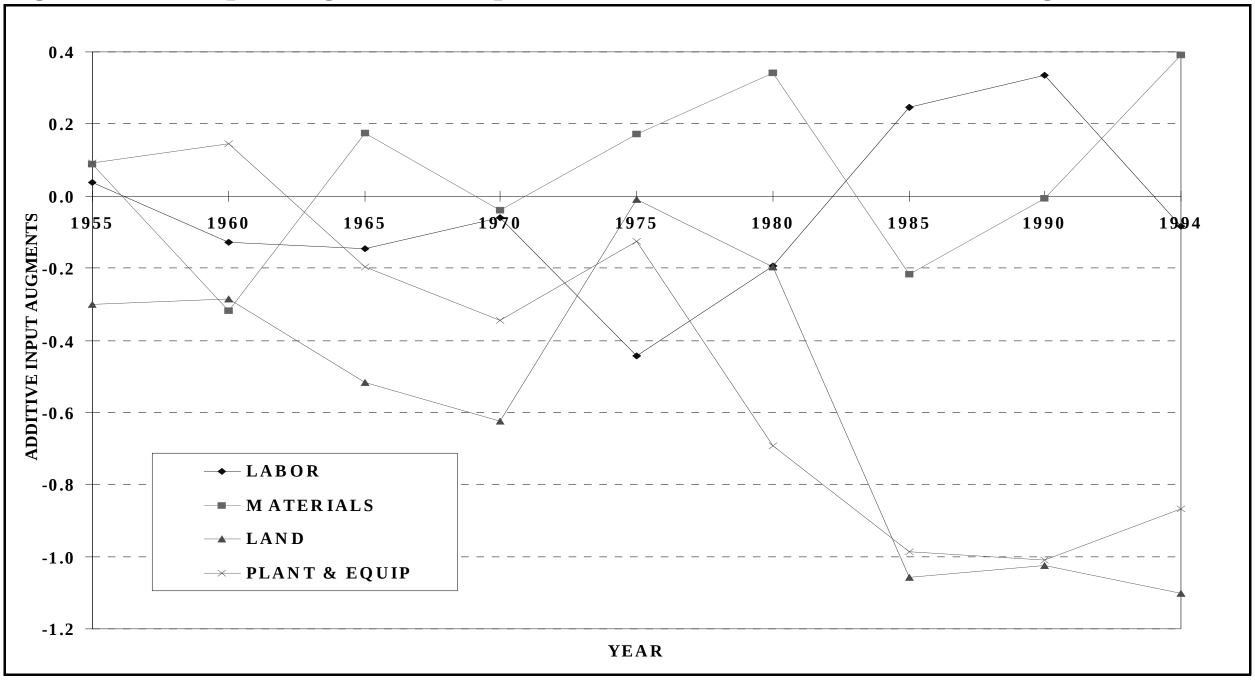


Figure 5. Input Augments for Specification S5: Augments = f(R&D), 3 Splines with Smoothing Restrictions.

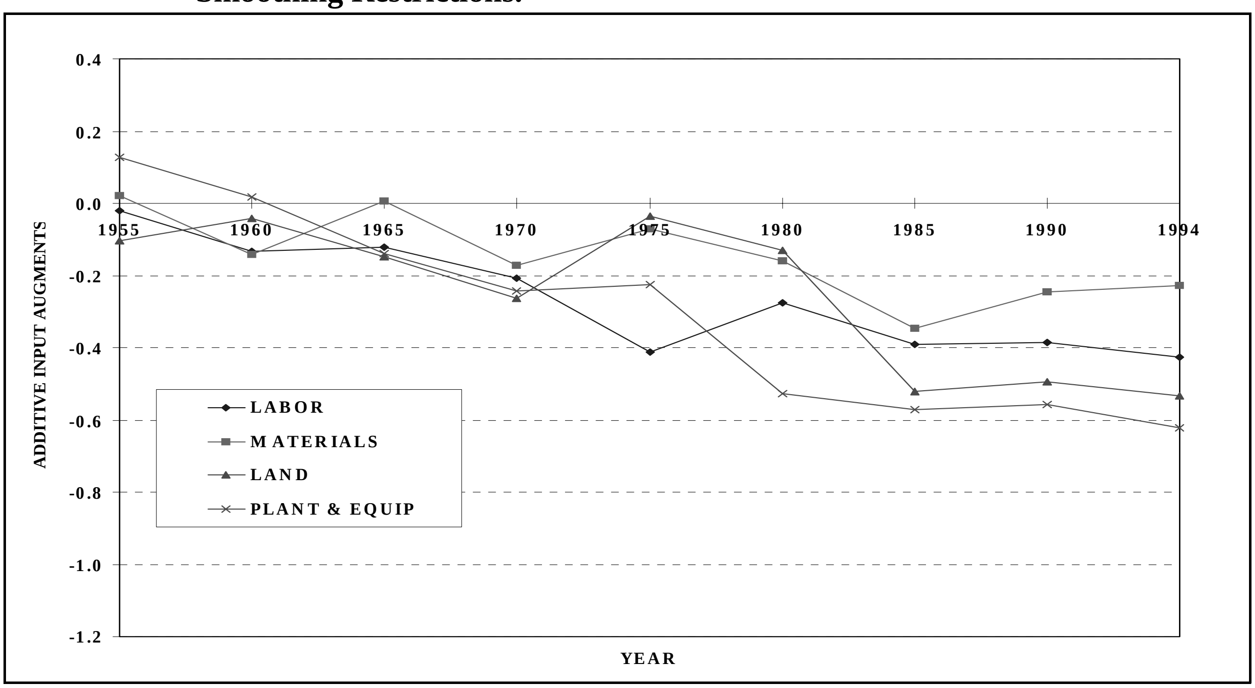


Figure 6. Input Augments for Specification S2: No R&D with Smoothing Restrictions.

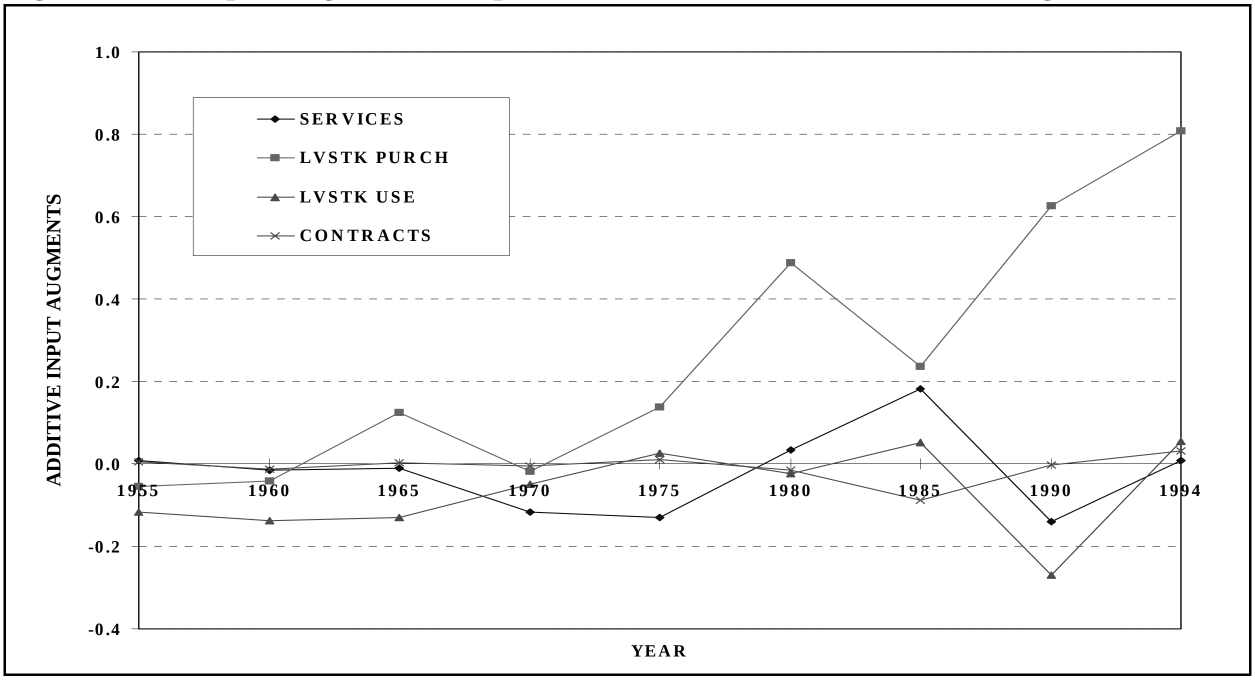


Figure 7. Input Augments for Specification S5: Augments = f(R&D), 3 Splines with Smoothing Restrictions.

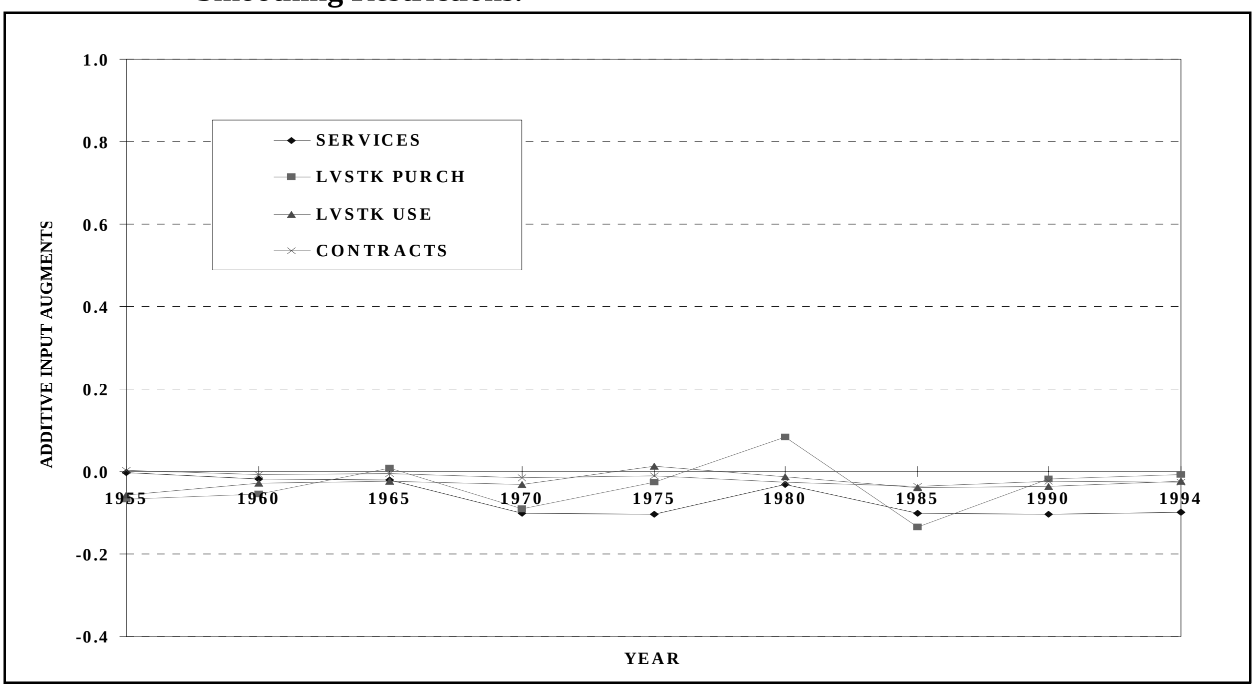


Figure 8. Lagged, Marginal Impacts of Research Expenditures on Output Augments for Specification S5: Augments = f(R&D), 3 Splines with Smoothing Restrictions.

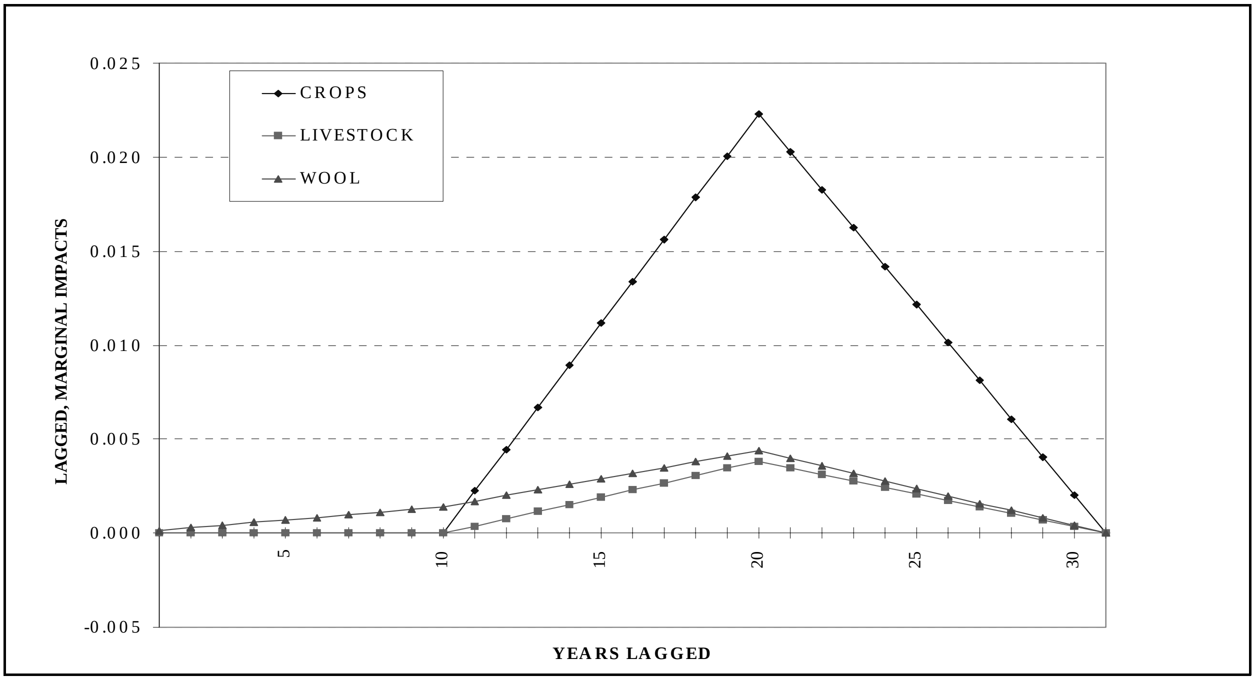


Figure 9. Lagged, Marginal Impacts of Research Expenditure on Input Augments for Specification S5: Augments = f(R&D), 3 Splines with Smoothing Restrictions.

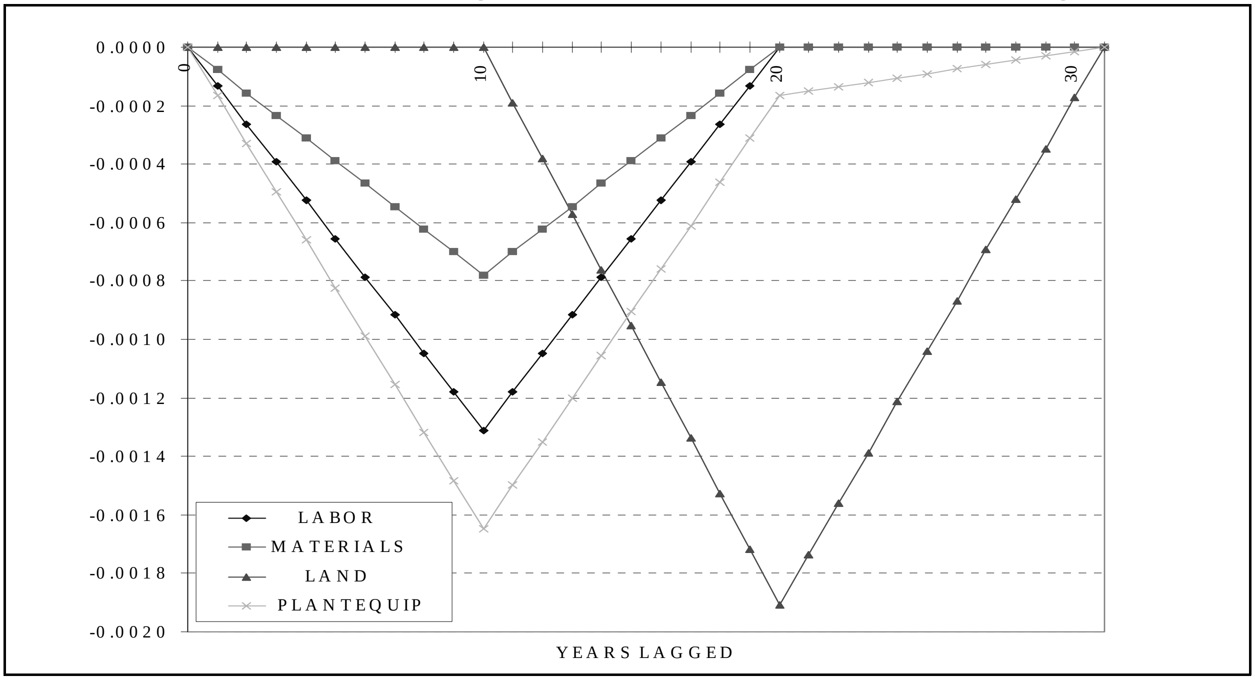


Figure 10. Lagged, Marginal Impacts of Research Expenditures on Input Augments for Specification S5: Augments = f(R&D), 3 Splines with Smoothing Restrictions.

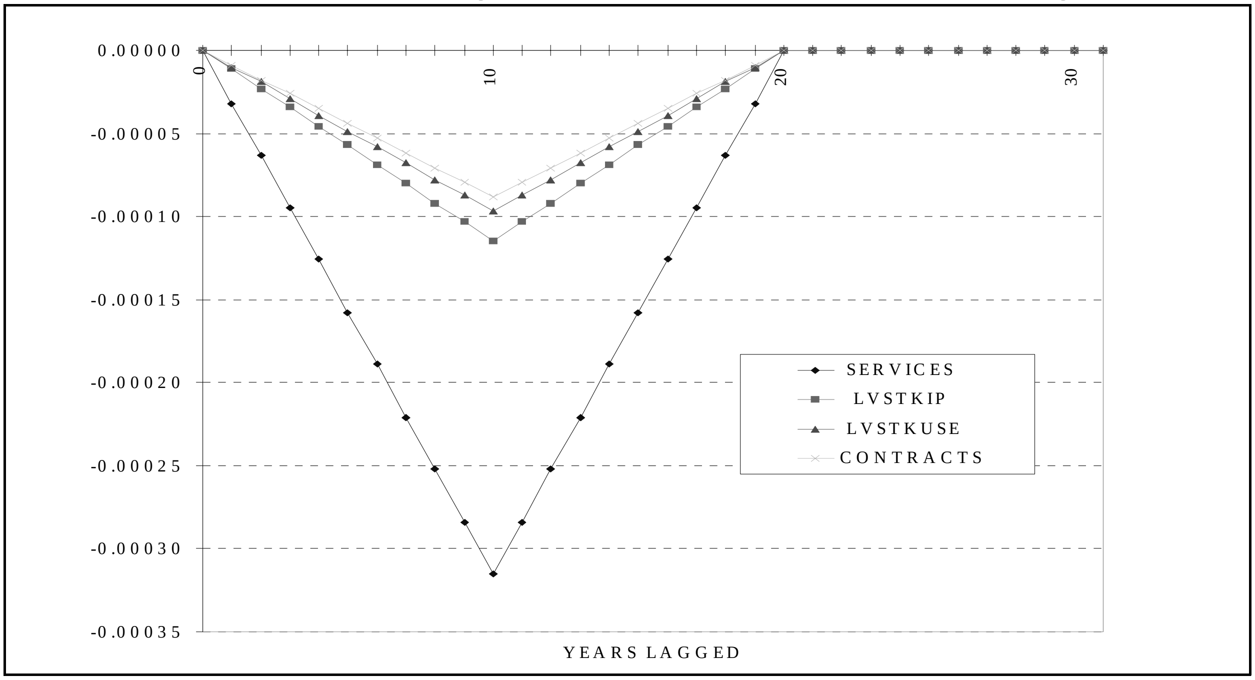
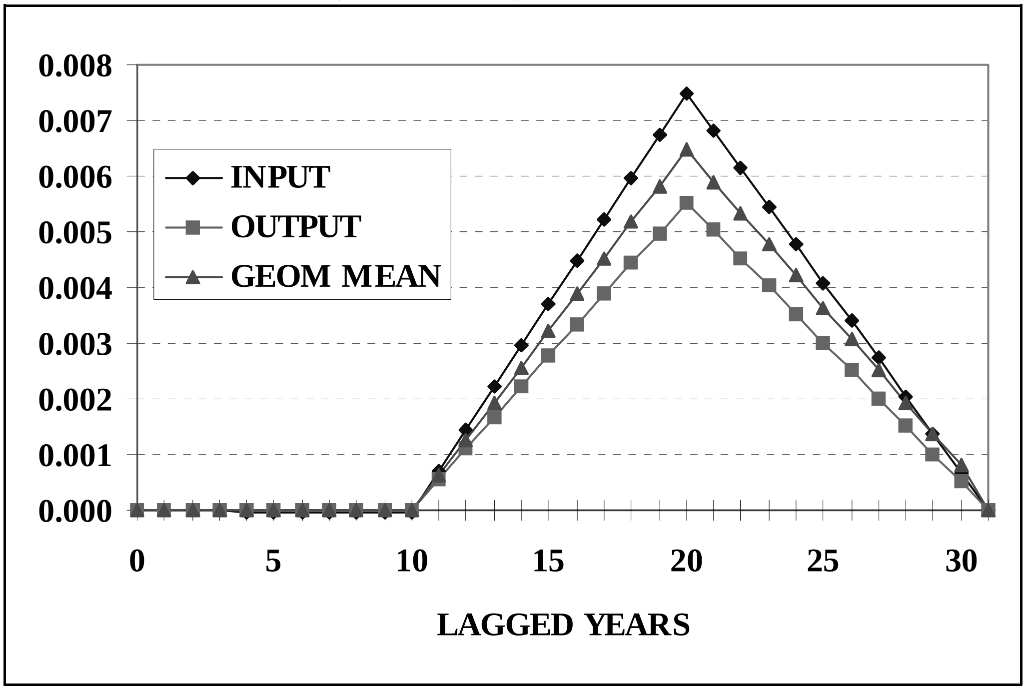


Table 4. Summary of Lagged Marginal Impacts if R&D Expenditures on TFP Measures: Specification S5, 1973 Base reference.

LAGGED YEARS	INPUT	OUTPUT	GEOM MEAN
0	0.000000	0.000000	0.000000
	-0.000005	0.000002	-0.000002
	-0.000011	0.000003	-0.000004
	-0.000016	0.000005	-0.000005
	-0.000021	0.000006	-0.000007
5	-0.000027	0.000008	-0.000009
	-0.000032	0.000009	-0.000011
	-0.000037	0.000011	-0.000012
	-0.000043	0.000012	-0.000014
	-0.000048	0.000014	-0.000016
10	-0.000053	0.000015	-0.000018
	0.000699	0.000565	0.000630
	0.001451	0.001116	0.001277
	0.002204	0.001667	0.001925
	0.002958	0.002218	0.002573
15	0.003712	0.002770	0.003222
	0.004467	0.003321	0.003871
	0.005223	0.003874	0.004521
	0.005979	0.004426	0.005171
	0.006735	0.004979	0.005821
20	0.007493	0.005532	0.006472
	0.006812	0.005029	0.005906
	0.006131	0.004526	0.005339
	0.005450	0.004023	0.004772
	0.004768	0.003521	0.004205
25	0.004087	0.003018	0.003637
	0.003406	0.002515	0.003070
	0.002725	0.002012	0.002502
	0.002044	0.001509	0.001934
	0.001363	0.001006	0.001366
30	0.000681	0.000503	0.000798
	0.000000	0.000000	0.000000

Figure 11. Lagged Marginal Impacts of R&D Expenditures of Total Factor Productivity Measures: Specification S5, 1973 Base Reference.



ENDNOTES

1. In a companion paper, Mullen and Strappazzon (1996) focus on the time series properties of the relationship between productivity and variables such as research expenditure, weather, education and terms of trade using these same data.

2. It is worth noting that the nonparametric methods we refer to are not “statistical” nonparametric (kernel or method of moment) estimation methods. Rather, the methods we employ here are referred to as “deterministic” nonparametric methods.

3. 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.

4. 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.

5. Here, *ceteris paribus* means that all other augmentation factors (besides A_{it}) are assumed held constant. Although this assumption is not likely to be satisfied empirically, it does provide a simple and intuitive interpretation of the analysis.

6. We accomplish this by shocking expenditures sequentially back over the hypothesized lag length to simulate the impacts on the current period TFP. This provides a simulated lag structure of expenditures on the TFP indexes.

7. Knopke et al. (1995) found that cropping specialists had higher rates of productivity growth over their sample period than did livestock specialists.

8. Value data were always available. For inputs, quantity series were derived using ABARE price series. For outputs, in some cases quantity data were directly available and in other cases they were derived from the value and price series. In constructing indices a standard approach of deriving quantity data from value and price series was used to ensure the price times quantity gave value. The data procedures and definitions we use are discussed more fully in Mullen and Cox (1996).

9. Note that this normalization procedure basically defines the “reference technology” for the augmentation parameters in (6) and (7') and is essentially arbitrary. In some regards, this is similar to choosing an expansion point for a flexible functional form.

10. Several specifications and time periods were evaluated for these backcasts. While we use the results of the exponential forecasts ($yhat = Ae^{B*t}$, where A and B are estimated parameters and t is the time index) for the 1953-75 period, the results were moderately robust to alternative specifications. Additional details are available on request.

11. Mullen, Lee and Wrigley (1995) noted that the increase in research intensity in real terms was much smaller.

12. We also evaluated 4 segment spline specifications similar to S5. These results are not presented due to space limitations but are available on request.

13. We shock R&D expenditures 25% of the 1973 levels, recompute the augments (via equation (9)) and then, holding 1973 effective netputs constant, rescale the "actual" 1993 netputs via the additive specification of equation (4). This allows us to hold the augmented WAPM consistent, effective technology constant as our base of reference for assess in the productivity impacts of lagged changes in R&D expenditures via equations 12 (input distance function under augmented WAPM) and 13 (output distance function under augmented WAPM). Note that 1- Q_I (1- Q_O) are interpreted as the percentage change in costs (revenues) due to the change in R&D expenditures.

14. We also evaluated shocked ranging from 10%-50% and reference bases for 1963 and 1983. Results due to larger (smaller) R&D shocks are virtually identical. Choice of base reference is more crucial. We chose 1973 as it is roughly the midpoint of the 1954-1994 data.