

# **Nonparametric measures of the impact of public research expenditures on Australian broadacre agriculture**

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Nonparametric methods are used to measure the impact of public research expenditures on Australian broadacre agriculture over the 1953–94 period. Results using both unrestricted and 30-year lagged specifications of the research impacts on productivity suggest that while certain aspects of the nonparametric 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). Internal rates of return to research expenditures on Australian broadacre agriculture are estimated to be in the 12 per cent to 20 per cent range.

## **1. 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 15 to 40 per cent over the 1953–88 period. They employed a two-stage estimation procedure in which a measure of productivity was derived in the first stage, then regressed against explanatory variables (including research expenditures) 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.

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While this two-stage procedure is widely applied in studies of returns to research, it does impose separability restrictions on the nature of technology, the most obvious being neutral technical change, that may bias estimates of returns to research.

The work of Mullen and Cox (1995) has been extended in this article in several important respects. First, new research and extension expenditures 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 included in the analysis. In addition, nonparametric methods are used 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 further developed in Chavas and Cox (1992, 1993, 1994, 1995).<sup>1</sup> 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 TFP.

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

The programming-based methods first proposed by Diewert and Parkan (1983) provide a convenient means for recovering empirically tractable, nonparametric representations of fairly general technologies while imposing minimal functional structure not implied by the theory. Much econometric estimation of primal and/or dual models using flexible

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<sup>1</sup>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.

functional forms is plagued with a disturbing failure of the estimated technology to satisfy the assumed regularity conditions (see Mullen and Cox 1995) as well as the possibility of obtaining biased results as a result of an incorrect and/or overly restrictive functional form. In contrast to econometric estimation, the technologies recovered with the nonparametric methods used here are, by construction, theoretically consistent at every data point and impose a minimal *a priori* functional structure. 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) using nonparametric methods is that standard goodness of fit measures and statistical hypothesis testing procedures are lacking.

The programming approach to solving the nonparametric GARP and WAPM type inequalities allows the recovery of parameters that can be used to characterise 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 specifying these augmentations as 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 to research/extension investments (IRR).

The outline of the article is as follows. First, we assume a generalised, augmented technology which is sufficiently well behaved to guarantee the existence of an optimal solution. Assuming profit maximisation, this generalised technology generates an augmented form of the WAPM which is empirically tractable with additional assumptions on the nature of technical change. We use an additive augmentation to generate non-radial measures of technical change that are both time period and netput specific. We then solve these augmented WAPM conditions for the augmentation parameters as a standard quadratic programming problem. Using the WAPM consistent, augmented netputs which summarise this technology, we then compute Malmquist TFP measures using input and output distance functions. Netput augments and associated TFP measures are compared 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 characterise the reference technology, we compute Malmquist measures of TFP. We summarise and compare the netput

augmentations, research/productivity lag structures, and TFPs across alternative specifications. Finally, we simulate the marginal lagged impacts of research expenditures on TFP and compute the associated IRRs. Summary and conclusions as to the strengths and weakness of this approach and our results are then provided.

## 2. 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  $(n \times 1)$  vector of feasible netputs  $x = (x_1, \dots, x_n)'$  satisfies  $x \in F$ . To guarantee the existence of an optimum to the profit maximisation framework, we assume the feasible set  $F$  is 'well behaved'.<sup>2</sup> 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. As the discussion that follows requires a set notation for outputs and inputs, denote the set of netputs  $N = \{1, \dots, n\} = \{N_I, N_o\}$ , where the partition  $N_o = \{I : x_i \geq 0; I \in N\}$  is the set of outputs and  $N_I = \{I : x_i \leq 0; I \in N\}$  is the set of inputs. The  $(n \times 1)$  vector of market prices associated with  $x$  is denoted by  $p = (p_1, \dots, p_n)' > 0$ . Assuming the behaviour of a competitive firm is consistent with the maintained hypothesis of profit maximisation subject to this general production technology, then firm level decisions can be characterised by:

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

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  $x^*(p)$ .

Next, we need to derive the special cases of what are essentially generalised axioms of revealed technology associated with (1). In this case, we assume the technology is revealed by the firm's observed production decisions where  $T = \{1, 2, \dots, \tau\}$  is the set of these  $\tau$  decisions, and the  $t$ th observed netput decision is denoted by  $x_t = (x_{1t}, \dots, x_{nt})'$  with corresponding prices  $p_t = (p_{1t}, \dots, p_{nt})'$ ,  $t \in T$ . We want to recover a technology  $F$  that rationalises the data  $\{(x_t, p_t) : t \in T\}$  in the sense that  $x_t = x^*(p_t)$  for all  $t \in T$  (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

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<sup>2</sup>'Well behaved' in this context means that the feasible set is nonempty, closed, convex ('non-increasing marginal productivity' assumption) and negative monotonic ('free disposal' assumption); see Sposito (1975) and Takayama (1993).

technology link between observable behaviour and production theory as given by (1).

*Proposition 1* (Afriat 1972; Varian 1984)

The following conditions are equivalent:

(a) The data satisfy the WAPM:

$$p'_t x_t \geq p'_t x_s, \quad (2)$$

for all  $s, t \in T$ .

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

$$F_T = \{x : p'_t x \leq p'_t x_t, t \in T; x_i \geq 0 \text{ for } I \in N_o; x_i \leq 0 \text{ for } I \in N_l\}. \quad (3)$$

The Afriat/Varian results stated in proposition 1 establish conditions for the existence of a production possibility set that can rationalise observable production behaviour. 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 ( $p'_t x_s$ ),  $s \in T$ . Note that these are necessary and sufficient conditions for the data  $\{(x_t, p_t) : t \in T\}$  to be consistent with profit maximisation (1). This is a key intuition from the nonparametric approach. Perhaps more importantly (and apparently somewhat less well appreciated), equation (3) also 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 behaviour. Finally, note the generality of (3) in that it provides a characterisation for *any netput vector*  $x$ , given the technology embodied in the actual  $T$  observations.

## 2.1 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  $x_t = (x_{1t}, \dots, x_{nt})'$  and 'effective netputs'  $X_t = (X_{1t}, \dots, X_{nt})'$  as:

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

where  $X(x, \cdot)$  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 profit maximisation hypothesis in (1) can be restated as:

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

for  $t \in T$  (for all observed data points), where  $A_t = (A_{1t}, \dots, A_{nt})'$  is a  $(n \times 1)$  parameter vector. The production technology  $F^e \subset \mathbb{R}^n$  in (5) is an 'effective technology' expressed in terms of the effective netputs:  $X_t \in F^e$ ,  $X_t = (X_{1t}, \dots, X_{nt})'$  being a  $(n \times 1)$  vector of effective netputs for the  $t$ -th observation with  $X_{it} \equiv X(x_{it}, A_{it})$ . Note the generality of the technology represented in (5): in particular, it does not *impose a priori* restrictions on the effective technology  $F^e$ . As well, changes in the  $A$ 's can be interpreted in terms of biased technical change because the marginal rate of substitution between netputs is, in general, affected by the technology indexes  $A$  (see below). This will allow us to characterise the impacts of research and extension expenditures on input and output biased technical change.

The 'augmented' profit maximisation formulation in (5) is the basis for the augmented WAPM conditions and provides empirical measures of technical change by solving (5) for the  $A$ 's. This requires additional assumptions 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 its 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 maximisation problem in (5), now denominated in effective (versus actual) netputs becomes:

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

for  $t \in T$  (for all observed data points). Associated with (6) is an empirically tractable, augmented form of the WAPM (the augmented counterpart to the WAPM inequalities in (2)):

$$p'_t X_t \geq p'_t X_s, \text{ for all } s, t \in T, \quad (7)$$

or

$$p'_t [x_t - A_t] \geq p'_t [x_s - A_s], \text{ for all } s, t \in T. \quad (7')$$

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 all  $s, t \in T$ . From (6) and (7), all of 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 as:

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

This result basically states that the production possibility set for the augmented profit maximisation problem in (5) must satisfy augmented WAPM conditions similar to (7) or (7'). As with (3), note that the technology in (8) must hold for *any effective netput* ( $X$ ), not just the set of observed netputs ( $X_s$ ) as in (7). This provides an empirical basis for estimating technical change under the maintained behavioural and technology assumptions. Below we use (8) to solve for the radial productivity measures associated with input and output distance functions as the basis for estimating Malmquist total factor productivity indexes.

Interpretation of the technology parameters,  $A$ , as measures of bias in technical change is straightforward. In the case of inputs ( $x_i \leq 0$  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*,<sup>3</sup> a lower (higher) value of  $A_i$  implies that producing the same effective netputs  $X$  requires more (less) of the  $i$ th input ( $-x_i \geq 0$ ). In the case of outputs ( $x_i \geq 0$  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  $X$ . Finally, finding  $A_{it} = A_{is}$  can be interpreted as neutral technical change with respect to the  $i$ th netput because producing the  $i$ th effective netput  $X_i$  can be done using the same quantity of the  $i$ th actual netput  $x_i$ .

## 2.2 Augmentation as a function of exogenous shift factors (research and extension)

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 article we evaluate the following specifications:

<sup>3</sup> 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.

$$A_{it} = \alpha_{it} + \sum_k^{30} \beta_{ki} * RD_{tk} \quad (9)$$

$$A_{it} = \alpha_{it} + \sum_k^{30} \beta_{ki} * RD_{tk} + \sum_j^{10} \delta_{ji} * EXT_{tj} \quad (10)$$

$$A_{it} = \alpha_{it} + \sum_k^{30} \beta_{ki} * RD_{tk} + \sum_j^{10} \delta_{ji} * EXT_t * RD_{tj} \quad (11)$$

where  $\beta_{ki}$  measures the direct effect of lagged research expenditures ( $RD_{t-k}$ ) on the  $i$ th netput augment in the  $t$ th time period,  $\delta_{ji}$  measures the direct (10) or interaction (11) impacts of lagged (current) extension expenditures on netput augmentation, and the  $\alpha_{it}$  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 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 a potentially large number of parameters, we evaluate several 'smoothing' restrictions. We impose a form of non-regressive technical change by restricting the output augments ( $A_{it}$  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 ( $\beta_{ki}$ ) and extension ( $\delta_{ji}$ ) 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  $\beta_{ki}$  splines to zero at year 0 and 31 ( $\delta_{ji}$  spline functions to zero at year 0 and 11). Last, we restrict the  $\beta_{ki}$  (the direct research impacts on netput augments) to be non-negative for outputs and non-positive for inputs, implying that research cannot generate negative netput technical change.

We solve (6) and the additional 'smoothing' constraints (9)–(11) by minimising 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 optimisation is a standard quadratic program which we solve using GAMS/MINOS software.

### 2.3 Nonparametric TFP measures

After solving (6) for the augments ( $A_t$ ) as described above, we have solutions for the WAPM consistent effective netputs  $X_t$  at each observed time period. This enables us to empirically specify the augmented technology in (8). Given this empirical representation of the augmented technology 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 this context, the dual, input-based radial TFP index associated with observation  $x$  is defined as:

$$Q_I(x, A) = \min_k \{k : p'_{O_t}x_O + p'_{I_t}(kx_I) \leq p_t X_t; X_t = x_t - A_t; t \in T; k \in \mathbb{R}^+\}, \quad (12)$$

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). In particular, we solve (12) to radially rescale each observed input bundle ( $x_{I_s}$ ) to attain the efficiency frontier specified by the effective netputs ( $X_t$ ). Noting that (12) is a standard linear programming (LP) problem, this procedure provides us with an index  $k = Q_I(x, A)$  at each time period. An index  $Q_I > 1 (< 1)$  means that the netput vector  $x = (x_O, x_I)$  uses a better technology (an inferior technology) compared with 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, Christensen and Diewert 1982).

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

$$1/Q_O(x, A) = \max_k \{k : p'_{O_t}(kx_O) + p'_{I_t}x_I \leq p_t X_t; X_t = x_t - A_t; t \in T; k \in \mathbb{R}^+\}, \quad (13)$$

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). We solve (13) in a similar fashion as (12), but radially rescaling actual outputs ( $x_{O_s}$ ) rather than actual inputs ( $x_{I_s}$ ). An index  $Q_O > 1 (< 1)$  means that the netput vector  $x = (x_O, x_I)$  uses a better technology (an inferior technology)

compared with 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 and computing the associated IRRs.<sup>4</sup>

### 3. 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 et al. (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.<sup>5</sup> 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, labour, 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

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<sup>4</sup>One way to accomplish this is by shocking expenditures sequentially back over the hypothesised lag length to simulate the impacts on the current period TFP. This provides a simulated lag structure of the marginal effects of research/extension expenditures on the TFP indexes. The marginal impacts are then monetised as changes in total costs (via (12)) or total revenues (via (13)) per unit of research/extension investment. Associated IRR computations are straightforward.

<sup>5</sup>Knopke *et al.* (1995) found that cropping specialists had higher rates of productivity growth over their sample period than did livestock specialists.

Direct quantity indexes (1953 = 100)

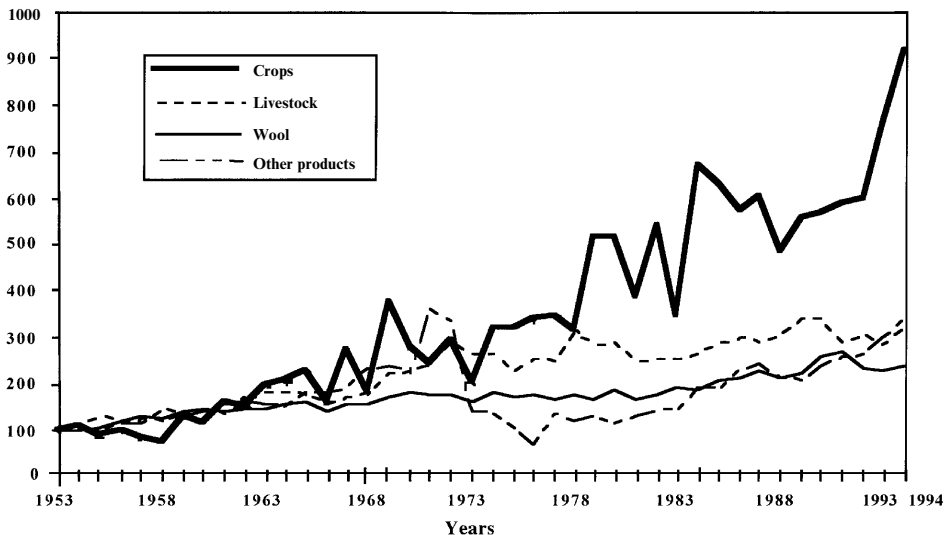


Figure 1 Output quantity indexes, Australian broadacre agriculture, 1953–94

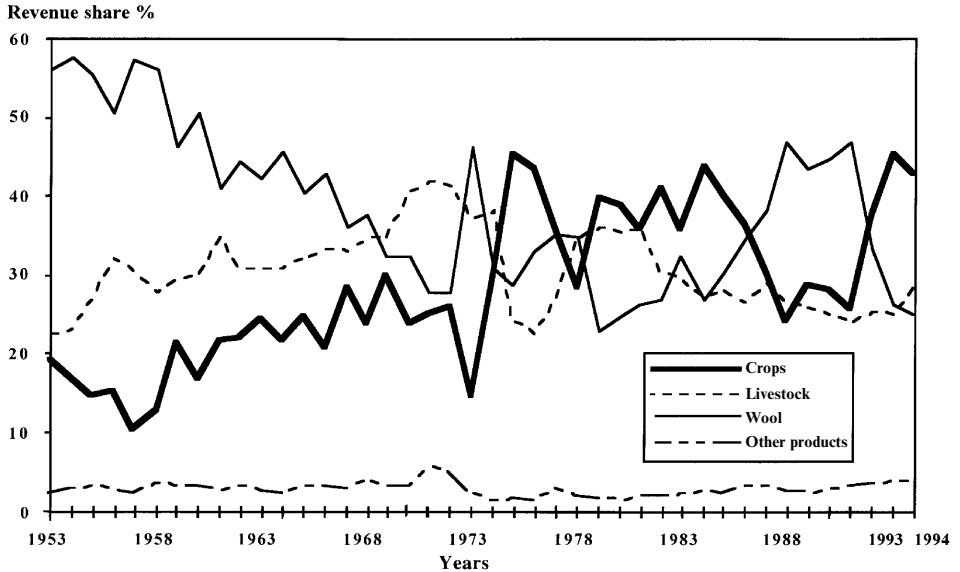
outputs.<sup>6</sup> We normalise the quantity data to equal one in the chosen base period (in this case, the first period of the data, 1953).<sup>7</sup>

Figures 1 and 2 summarise the output quantity indexes and revenue shares from these data for the 1953–94 period. Figure 1 indicates that crops output has increased ninefold over 1953 levels while other outputs (especially wool and livestock) have generally increased 2–3 times. Crops output indicates somewhat more variability than wool and livestock outputs, likely due to weather (rainfall) conditions.

On average over the 1953–94 period, the ranking of broadacre outputs with respect to revenue shares was: wool (38 per cent), livestock (31 per cent), crops (28 per cent) and other (3 per cent). Figure 2 indicates that while wool was clearly the dominant revenue source up through the late 1960s

<sup>6</sup> 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).

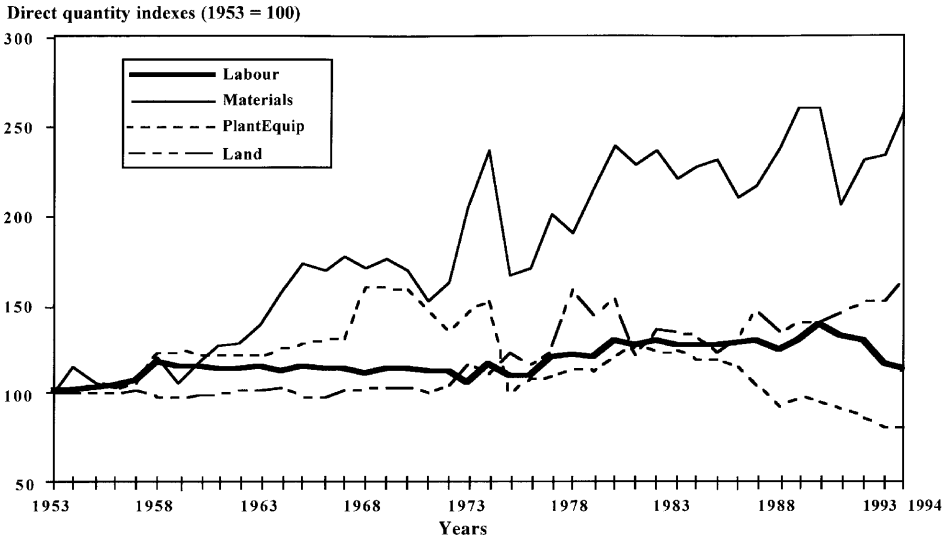
<sup>7</sup> Note, this effectively normalises expenditures using the base period prices as the numeraire. This normalisation basically defines the 'reference technology' for the augmentation parameters in (7') and is essentially arbitrary. Given the quadratic objective function ( $\text{MIN} \sum (X - x)$ ) which is used to recover the  $A$ 's from (7'), this procedure is fully consistent with the those suggested by Chalfant and Zhang (1994).



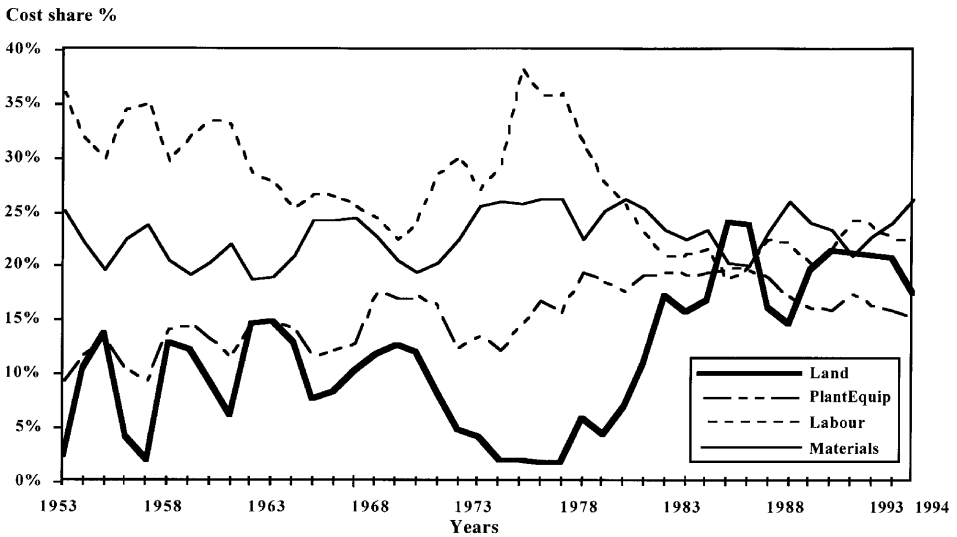
**Figure 2** Revenue shares, Australian broadacre agriculture, 1953–94

(over 40 per cent of revenues), this dominance has been steadily offset by the rise in livestock outputs (up through the early 1970s) and crop outputs (with notable exceptions during 1973 and the mid to late 1980s). Since the early 1980s, crops has accounted for slightly less than 40 per cent of total revenues while wool and livestock each accounted for roughly 30 per cent. In contrast, wool averaged more than 50 per cent of total revenues followed by livestock (roughly 30 per cent) and crops (roughly 20 per cent) early in this data period (prior to 1960). Clearly, crops have grown in importance in the output mix of Australian broadacre agriculture over this period, particularly when rainfall has been favourable. The potential role of research and extension in affecting these output trends is raised as an interesting issue amenable to a multi-product productivity analysis.

Figures 3 and 4 summarise the quantity indexes and cost shares of 4 major inputs (labour, materials, plant/equipment, and land) which accounted for 75 per cent of total costs, on average, over the 1953–94 period. Figure 3 indicates that the largest input changes relative to the 1953 base period occurred in materials usage. Use of plant and equipment rose through the early 1970s, then declined since the early 1980s. Land usage held somewhat constant through the early 1970s and then increased somewhat steadily through the end of the period, up 50 per cent over 1953 levels in 1994. Labour usage, in contrast, appears relatively constant through much of the time period with a slight rise and then decline through the late 1970s. Labour



**Figure 3** Quantity indexes for major inputs, Australian broadacre agriculture, 1953–94



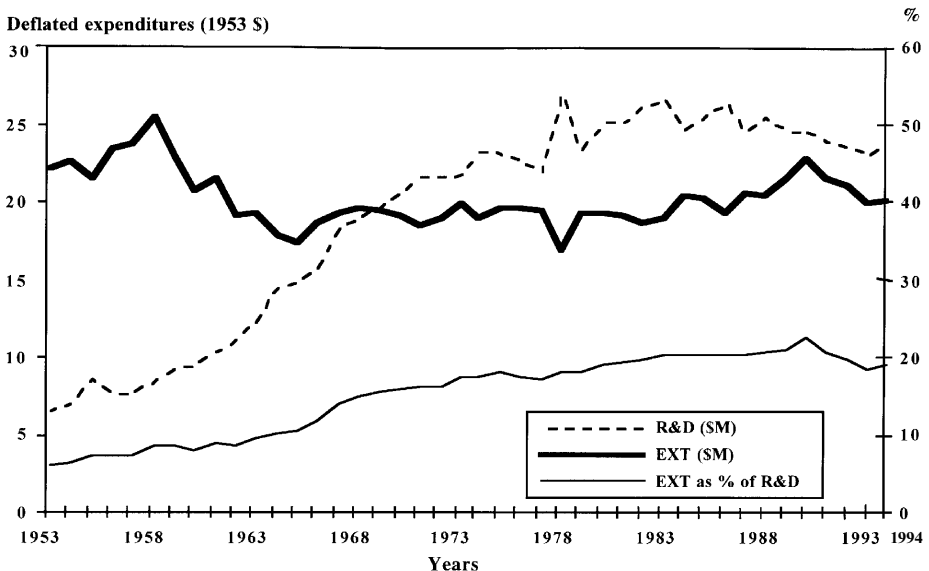
**Figure 4** Cost shares for major inputs, Australian broadacre agriculture, 1953–94

has been the dominant cost share (27 per cent, on average) through much of the 1953–94 period, followed by materials (23 per cent) and plant/

equipment (15 per cent). Labour and materials averaged between 20 and 25 per cent of total costs since the early 1980s, with land costs around 20 per cent, and with plant/equipment cost less than 15 to 20 per cent (and trending downward) during this period.

Figures 1 and 3 suggest that there have been significant changes in the netput mix characterising Australian broadacre agriculture, especially since the early to mid-1970s. In particular, the rise in relative importance of crops at the expense of livestock outputs (and, to a lesser extent, wool) and the sharp increase in materials input usage (first in the late 1950s, and again in the mid-1970s) figure prominently in these trends. If research and extension expenditures were to have the hypothesised lagged impact on productivity, we might expect to see sharp rises in these expenditures 10–30 years prior to the start of these netput trend changes. Figure 5 summarises the research and extension expenditures evidence at hand.

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. 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 GDP of agriculture since 1953. Universities make a relatively small contribution to



**Figure 5** Comparison of research and extension expenditures on Australian broadacre agriculture

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 per cent in 1953 to 4.4 per cent in 1994. Research as a percentage of farm GDP was as high as 5.2 per cent in 1978. Alston, Chalfant and Pardey (1993, p.14) 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.<sup>8</sup>

The research and extension nominal expenditures are both deflated and since research and extension data back to 1923 are required to estimate 30-year lag structures starting from 1953, we 'backcasted' from the deflated 1952–75 data series.<sup>9</sup> Figure 5 summarises the deflated (1953 dollars) research and extension expenditures 1953–94 values and percentage that extension expenditures were relative to research. This figure indicates that research expenditures grew quite rapidly from \$6.4m in 1953 to a maximum of \$26.7m in 1978, somewhat levelled off around \$25m during the late 1970s and early 1980s, and have declined somewhat since the mid to late 1980s. These R&D expenditure trends are visually consistent with the hypothesis that their relatively rapid growth through the 1950s–60s contributed to the rise in crops output and materials input usage that characterised Australian broadacre agriculture over this period. It remains to be seen what nonparametric evidence we can find to support this intuitive visualisation. Note, however, the 'missing data' procedures we were forced to employ and the difficulty in cleanly disentangling research and extension expenditures in these data (see Mullen and Cox 1995) suggest that due caution be exercised in the interpretation of the results.

#### 4. Results

We summarise results for five 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

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<sup>8</sup> Mullen, Lee and Wrigley (1995) noted that the increase in research intensity in real terms was much smaller.

<sup>9</sup> Several specifications and time periods were evaluated for these backcasts. While we use the results of the exponential forecasts ( $\hat{y} = Ae^{Bst}$ , 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.

minimise the sum of squared augmentations subject to the augmented WAPM constraints from equation (7'). S2 normalises 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 minimises 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 augments to be non-negative), hence comparison of S2 and S4 provides an indication 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 (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).

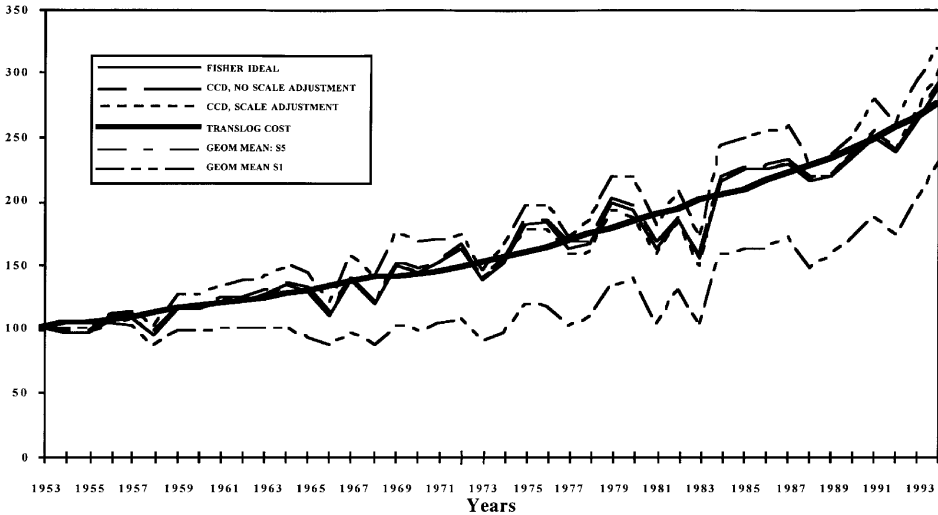
Extension expenditure specifications similar to S5 but using (10) and (11) rather than (9) were also estimated. These specifications generated results that were virtually identical to S5 (the  $\delta_{ji} = 0$  for all  $i, j$ ), indicating that the data and nonparametric procedures used here were unable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

#### 4.1 TFP measures

One of the striking results of this nonparametric estimation exercise is the robustness of the Malmquist TFP measures computed from (12) and (13) across the alternative specifications S2–S5. The input ( $Q_I$ ) and output ( $Q_O$ ) TFPs (and their respective geometric means) are virtually identical for S2–S5 (correlation coefficients 1.000) while the correlation of these TFPs with S1 is 0.91, 0.95 and 0.93, respectively. 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



Total Factor Productivity index (1953 = 100)



**Figure 6** Comparison of TFP measures from Mullen and Cox (1996) with specifications S1 and S5

agriculture over the 1953–94 period was not characterised 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 non-regressive technical change (through the use of smoothing priors) on the output augments generates higher TFP measures in these data.

In order to visually assess their ‘reasonableness’, figure 6 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. The Fisher Ideal (Diewert 1992) and CCD No Scale Adjustment (Caves, Christensen and Diewert 1982) TFP measures are both superlative indexes which assume constant returns to scale.<sup>10</sup> 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 and should be somewhat preferred on theoretical grounds.

<sup>10</sup> They are exact indexes for the associated implicit functional form (quadratic mean of order 2 and unit translog cost function, respectively). See Diewert (1976).

As can be seen from figure 6, 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 (smoothed nonparametric TFP measures were larger than Divisia type TFP indexes) while Mullen and Cox (1995) found similar S1 results (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). The correlations among all TFP measures (except for the Translog Cost and nonparametric S1) are greater than 0.99.

These results suggest that the augmentation hypothesis and smoothing priors associated with the nonparametric TFP measure in S5 are certainly plausible and 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 reasonable. However, these results also suggest that such commonly employed smoothing can generate higher productivity measures. Finally, 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.

## 4.2 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. This is a particular strength of the nonparametric approach used here in so far as it generates netput specific augmentations for each year. As indicated earlier, these measures can be interpreted as productivity and bias in technical change measures. Not surprisingly, the evidence as to robustness is more varied in these netput level results.

Figures 7 and 8 summarise 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. Recall that these augments are normalised 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 and TFP measures, the somewhat ‘non-smooth’ nature of these measures reflects the impacts of other shift factors such as weather (consider the 1983 drought impacts on ‘productivity’ in figure 6).

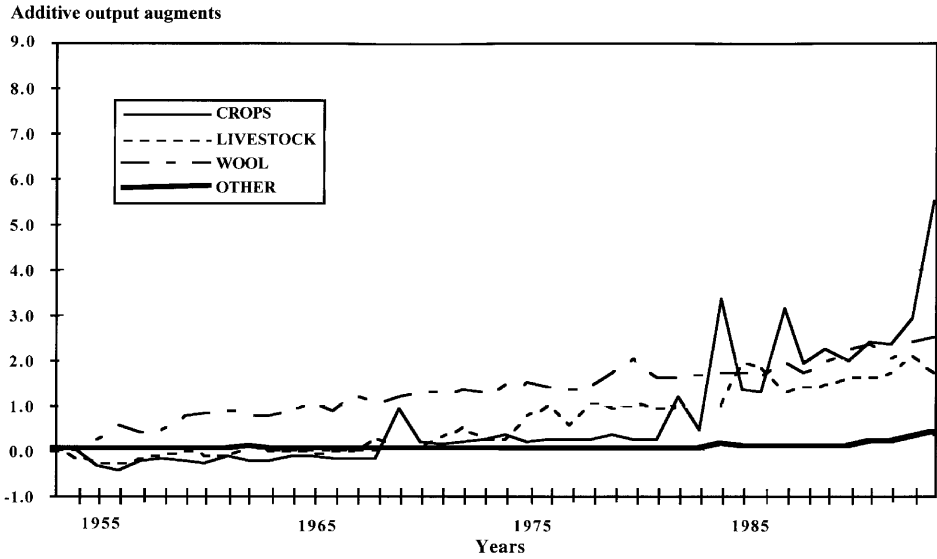


Figure 7 Output augments for specification S2: no R&D with smoothing restrictions

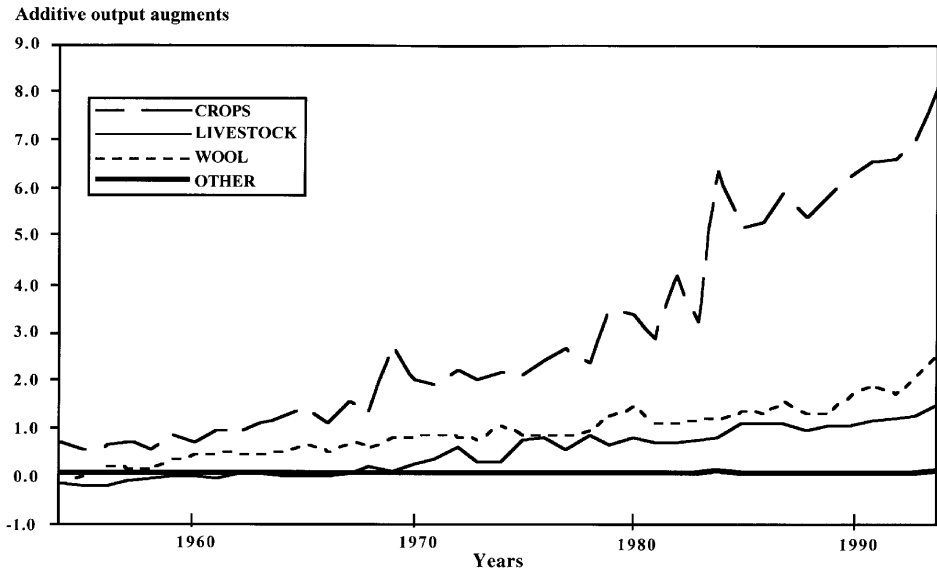


Figure 8 Output augments for specification S5: augments = f(R&D), 3 splines with smoothing restrictions

With the exception of crop outputs, figures 7 and 8 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 per cent relative to the 1953 reference technology. Both specifications indicate that the technical change in crop outputs has, in general, been greater than in livestock, wool and other outputs. These results provide nonparametric evidence of significant output 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 over time. These results are consistent with the output trends discussed in figures 1 and 2. Estimates of this type of differential impacts (for crops versus livestock) of research and extension on productivity are a key advantage of the nonparametric methods used here.

### 4.3 Input augments

The additive netput augments for all 5 specifications tend to be somewhat ‘noisy’ reflecting their fundamental under-identification (Chavas and Cox 1995). 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 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 focus on specification S5 which reflects the impacts of the research expenditure spline functions on these measures of technical change, holding the other smoothing priors constant.<sup>11</sup>

The scale of the input augments is considerably smaller than those for the output augments in figures 7 and 8. This partially reflects the difference in quantity magnitudes (see figures 1 (outputs) and 2 (major inputs)) but also indicates most of the technical change is being captured by the output augmentations in these results. Factor-using technical change (negative slopes) generally characterised these inputs with the following factor-saving exceptions: materials (1960–65, 1970–75, 1985–94), plant and equipment (1970–75), and labour (1975–80). The input augments associated with services, livestock purchases and use, and contracts are relatively small but do provide some evidence of factor-saving technical change for livestock

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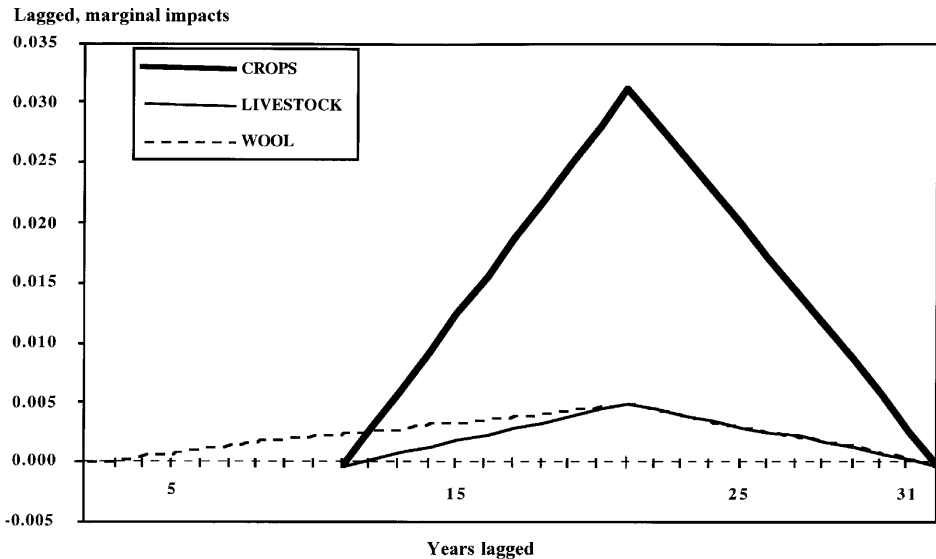
<sup>11</sup> A table of these input augment results for the 5 specifications is available on request from the authors.

purchases (1955–65, 1970–80, and 1985–94) and services (1975–80). Input bias with respect to livestock use and contracts is minimal.

#### 4.4 Lagged research impacts

Figure 9 summarises the marginal impacts of research and extension expenditures on the output 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 9 indicates that inverted-V lag structures with 20-year peaks were found for crops, livestock and wool outputs. Note that the lagged, marginal impacts of research and extension on crops productivity are considerably larger than for the livestock and wool outputs. This result 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 8). 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 effects of research on output productivity. Like crops, research impacts on livestock



**Figure 9** Lagged marginal impacts of research and extension expenditures on output augments for specification S5: augments =  $F(R\&D)$ , 3 splines with smoothing restrictions

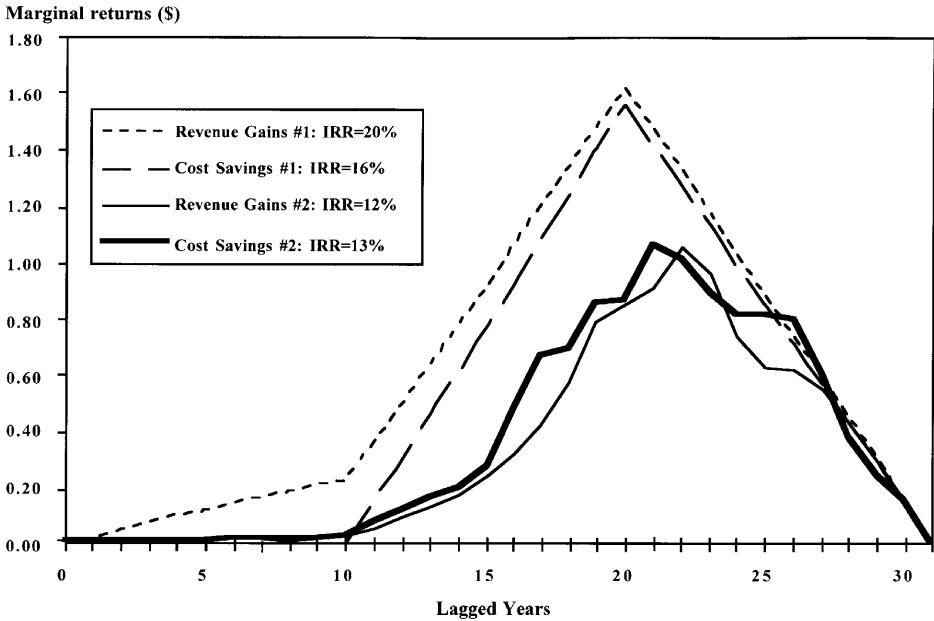
productivity are found to occur only after 10 years. In contrast, these results suggest the impacts of research on wool productivity start immediately. Both impacts peak at year 20 with inverted-V lagged structures. This specification generated zero lagged research impacts on the productivity of other outputs.

With the exception of labour, research is found to induce factor-saving technical change for the first 10 years, factor-using technical change for the next 10 years, and the factor-neutral technical change for the last 10 years. The impacts on labour are found to be just the opposite. Similar results are noted in Chavas, Aliber, and Cox (1996). The magnitude of marginal R&D impacts are quite small relative to the associated input augments in suggesting that the R&D impacts associated with these input augments will be similarly small. Comparison of these magnitudes with the marginal research expenditure impacts on output augments reinforces this point – most of the impacts on productivity are likely to occur through the output augmentations in these results. The simulations used to generate the IRR estimates presented next bear these intuitions out.

#### **4.5 Internal rates of return to research and extension expenditures**

Following (8) we simulate the dynamic impacts of the research and extension expenditures on total factor productivity under two scenarios. In the first, holding the augmented technology constant, we shock research expenditures sequentially through 30 years to generate the lagged impacts of these expenditures on TFP. Recall that the TFP indexes associated with (12) and (13) can be interpreted as measuring the cost savings (via the input distance function in (12)) or revenue gains (via the output distance function via (13)) generated by the productivity change. Hence, we monetise the marginal impacts of research on productivity following (12) and (13) by measuring the change in costs or revenues associated in year 0 (the base year for the simulation). Note that this procedure holds the simulation base period prices, as well as the reference technology, constant. The second experiment performs only one shock, 30 years prior to the simulation base, and measures the impacts on cost and revenues at each time period up to and including the base. Note, in contrast, this procedure does not hold prices constant as cost and revenues are evaluated at multiple years.

We evaluated a number of expenditure shocks and base simulation periods. Results are very robust to the expenditure shocks but do vary slightly with the choice of the base period for the simulation. In the results below, we use 1994 as the base and with expenditure shocks equal to 25 per cent of 1973 real research and extension expenditures (\$4.5m). Standard internal rates of return are computed from the flow of cost savings or



**Figure 10** Comparison of simulated marginal effects of investing \$1 of research and extension expenditures on Australian broadacre agriculture with associated internal rates of return (IRR)

revenue enhancements generated by the research/extension expenditure shock. Figure 10 summarises the results of these simulations where the dominance of lagged effects of research and extension on the output augments is clearly manifest (compare figures 9 and 10). Note, however, that figure 10 represents multifactor productivity impacts while figure 9 reflects individual netput level impacts. Similar to figure 9, these results indicate the multifactor productivity impacts of R&D generally take about 10 years to manifest, and thereafter follow an inverted-V shape. Chavas, Aliber and Cox (1996) found similar multifactor productivity lag structures. The associated IRRs range from 12 per cent to 20 per cent and are quite similar to those found by Mullen and Cox (1995).

### 5. Conclusions

This article uses nonparametric methods to assess the impacts of research expenditures on technical change in Australian broadacre agriculture over the 1953–94 period. If one is willing to assume sufficient structure such that a maintained behavioural premise has an optimum that can be characterised by a saddle point, then there will exist a broad set of generalised axioms of

revealed preference (technologies) such as the augmented WAPM used here. This is the seminal intuition of Afriat/Varian nonparametric approach to production analysis. The empirical nonparametric methodology used here is quite general, easily handles multiple outputs, allows considerable flexibility in modelling the technical change impacts of exogenous shift factors (such as research and extension expenditures), and imposes minimal structure on the implicit production technology (beyond the regularity conditions implied by the associated behavioural 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 quadratic and linear 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 flexibility in modelling 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 exists an infinity of technologies (in this case, linear augments) that are consistent with the specific data and the maintained behavioural 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, but rather is a key characteristic of technical change when the underlying production technology is unknown. The analyst must choose from amongst this infinity of theory-consistent technologies by choosing specific augmentation hypotheses, smoothing priors, data normalisations, functional forms, etc.

A unique aspect of the nonparametric techniques used here is that they provide a relatively easy means of empirically recovering specific representations from this infinity of theory-consistent, augmented technologies. As well, these methods force one to realise 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 normalising 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.

Given that technical change is 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 commonly used smoothing priors may generate upward bias in TFP measurement.

Comparison of netput augments from two specifications provides nonparametric evidence of differential technical change across netput categories as well as the impacts of endogenising augments as a function of research expenditures. With respect to outputs, our results suggest several conclusions: (1) that technical change in crop outputs has, in general, been greater than in livestock, wool and other outputs; (2) that wool is characterised by higher productivity growth than livestock outputs (both with 100–200 per cent productivity gains relative to the 1953 reference technology); and (3) that little or no productivity growth was evident in other outputs (which, on average, accounts for 3 per cent for total revenues). This latter result may, in part, reflect that cropping specialists were not included in the data. 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 specification with lagged research effects generally indicated factor-using technical change in land and plant and equipment, factor-saving technical change in materials and livestock purchases, neutral technical change in contracts and quite mixed results for labour, services and livestock usage.

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 and extension 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 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 labour) our results suggest that the lagged impacts of research induce input-saving technical change for 10 years, followed by 10 years of input using technical change. This suggests longer-term factor adjustments that reverse the bias in technical change are induced by such research. 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 augmented WAPM maintained hypothesis. Finally, our simulations of the marginal impacts of research and extension expenditures on total factor productivity and the computed IRRs associated with these simulations generated returns on the order of 12 per cent to 20 per cent. These compare favourably to previous estimates generated using quite different estimation procedures and assumptions concerning the technology underlying Australian broadacre agriculture over the 1953–94 period.

In conclusion, we are encouraged by the theoretical foundations, modelling flexibility and ease of empirical implementation of the non-parametric 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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