MEASURING PRODUCTIVITY GROWTH IN AUSTRALIAN BROADACRE AGRICULTURE

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Introduction

Australian primary producers pay levies to fund investments in on- and off-farm research and development (R&D), and promotion. Little is known about the returns being earned by these alternative investments and hence it is difficult to judge the relative profitability of the present portfolio of investments. Scobie, Mullen and Alston (1992) speculated that the return to investment in on-farm R&D in the wool industry may be of the order of nine percent to Australian taxpayers and 25 percent to Australian woolgrowers. To arrive at this estimate they assumed that productivity growth in the industry attributable to R&D has been about 1.5 percent per year. (This estimate also depended on assumptions about lags in the development and adoption of new technology and about demand and supply elasticities.)

The final objective of our research is to measure the nature and extent of the contribution of R&D to productivity growth and to estimate the returns from this investment to Australian primary producers and taxpayers. Because much of Australian agriculture is characterised by jointness in production and in the supply of R&D services, the focus of this project has been broadened from the wool industry to broadacre agriculture encompassing the wool, cattle and cropping industries.

The purpose of this paper is to raise for discussion three issues that we have encountered in choosing how best to measure productivity growth using the data set from ABARE's survey of broadacre agriculture. The first issue concerns the extent to which outputs and inputs can be aggregated. A widely used approach, the index number or growth accounting approach (Lawrence, 1980; Lawrence and McKay, 1980; Paul, 1984; Paul, Abbey and Ockwell, 1984; and Beck, Moir, Fraser and Paul, 1985), estimates productivity growth as the difference in the rates of growth in aggregate measures of outputs and inputs. Used less often has been the econometric approach based on cost or profit functions (McKay, Lawrence and Vlastuin, 1982; Fisher and Wall, 1990). Both approaches usually make strong assumptions about the separability of inputs and outputs using a particular functional form to represent technology. In this paper a non-parametric approach is used to assess which alternative ways of aggregating inputs and outputs are consistent with profit maximisation.

The second issue that follows from the aggregation question is how to measure productivity growth. We compared estimates of productivity growth from a translog cost function with the traditional discrete Divisia TFP index and with several non-parametric measures which while independent of functional form, represent different views of the nature of technical change and of returns to scale in agriculture.

The third issue concerns the appropriate way of incorporating the impact of weather when measuring productivity growth and technical change. Clearly weather affects the supply of agricultural products and hence is an appropriate explanatory variable in supply, production and profit functions. However the extent to which weather influences producers' input demand decisions and hence enters input demand and cost functions as an explanatory variable is unclear and has not been discussed in production economics literature.

Data

ABARE has been conducting a survey of broadacre agricultural industries in Australia since 1952–53. More information about the extent of the survey, 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). The number of producers in the sample, who had to have at least 200 sheep, ranged from 600 to 700 and the sample can be stratified by three climatic zones known as the high rainfall, wheat–sheep and pastoral zones.

The four outputs were crop, livestock sales, wool and other outputs. The eight inputs were contracts, services, materials, labour, livestock purchases, use of livestock capital, use of land capital, and use of plant and structures. Divisia indices of aggregate output, aggregate inputs and total factor productivity were also available. Other data series available included an index for pasture growth.

The most disconcerting feature of the data is the number of years in which total expenditure exceeds total revenue. Prior to 1981 there were nine years in which costs exceeded revenue. However since 1981 costs have exceeded revenue in every year. Drought and unexpected price falls may explain occasional years of loss but eight consecutive years of loss does not appear to be consistent with profit maximisation. This issue is raised again briefly later in the paper.

Apart from costs exceeding revenue for the last eight years, the other notable feature of the data is the marked upward trend in prices since the early seventies. This prompts questions about whether the nature of technical change and the rate of productivity growth have been different under these two price regimes. This issue has not yet been pursued.

Aggregation of Outputs and Inputs

Following Varian (p. 588), a nonparametric test for weak separability of the implicit production technology under the behavioral assumption of profit maximization is given by the $T^2 - T$ inequalities:

(1) $$h_t - h_s + \gamma_t p_t'(x_t - x_s) \geq 0, \quad \gamma_t > 0, \quad s,t, = 1,\ldots,T$$

where T is the total number of observations, x_t represents a vector of a subset of netputs (following the negative inputs convention) with associated netput price vector p_t, and $\gamma_t = 1/\lambda_t$, the inverse of marginal cost. The existence of a solution (h_t, γ_t) to these nonparametric inequalities is a necessary and sufficient condition for the observed behavior $X = \{x_1,\ldots,x_t\}$ to be consistent with the maintained hypothesis, weak separability under profit maximization in this case. If the vector x is a subset of the netputs, then this allows nonparametric testing of whether there is an aggregator, h, of the subset of netputs under consideration. If, in contrast, the vector x includes all netputs, then a nonparametric test of Hicks-neutral technical change in its most general form results (see Chavas and Cox (1988), p. 304–6).

We tested for the existence of solutions to (1) using linear programming (LP) with GAMS/MINOS software. If the corresponding LP problem was infeasible, then the data were considered to be inconsistent with the particular functional form being tested, and hence provided nonparametric evidence against the existence of the implied aggregator function via weak separability. In particular, we tested for the existence of the following aggregators:

a) **Hicks neutral technical change**: All netputs.
b) **Aggregate output**: Crop, livestock sales, wool and other outputs.
c) **Crop/other output**: Crop and other outputs.
d) **Wool/livestock output**: Wool and livestock sales.
e) **Aggregate input**: Contracts, services, materials, labour, livestock purchases, use of livestock capital, use of land capital, and use of plant and structures.
f) **Plant/structures and land input**: Use of plant and structures and use of land capital.
g) **Livestock input**: Livestock purchases and use of livestock capital.
h) **Contracts/services/materials**: Contracts, services, and materials.

All functional structure, weak separability hypotheses except for (h) were found to generate infeasible solutions to the nonparametric inequalities in (1). Hence, these data were only found to be consistent with the existence of a contracts/services/materials input aggregator over the time period analyzed.

Parametric Measures of Productivity Growth

We used a translog cost function to estimate the extent and nature of productivity growth in broadacre agriculture. The most general form of a multi-product, multi-input translog cost function is given by:

$$
\begin{aligned}
lnC = {} & \alpha_0 + \sum_i \alpha_i lnW_i + \frac{1}{2}\sum_i\sum_j \gamma_{ij} lnW_i lnW_j + \sum_k \beta_k lnQ_k \\
& + \frac{1}{2}\sum_k\sum_l \beta_{kl} lnQ_k lnQ_l + \sum_i\sum_k \rho_{ik} lnW_i lnQ_k + \sum_i \theta_i T_i \\
& + \frac{1}{2}\sum_i\sum_j \theta_{ij} T_i T_j + \sum_i\sum_j \phi_{ij} lnW_i T_j + \sum_i\sum_j \psi_{ij} lnQ_i T_j \\
& + \sum_i \delta_i lnZ_i + \frac{1}{2}\sum_i\sum_j \delta_{ij} lnZ_i lnZ_j + \sum_i\sum_j \epsilon_{ij} lnZ_i lnW_j \\
& + \sum_l\sum_k \eta_{lk} lnZ_l lnQ_k + \sum_i\sum_l \kappa_{il} lnZ_i T_l
\end{aligned}
$$

where products are represented by the Q_k terms, prices of variable inputs by the W_i terms, quantities of fixed inputs by the Z_i terms and the technical change and weather terms by T_1 and T_2. Differentiating this cost function with respect to input prices gives a series of input demand equations where the dependent variable is the share of total cost, S_i, accounted for by an input. These demand equations take the form:

$$S_i=\alpha_i+\sum_j\gamma_{ij}lnW_j+\sum_k\rho_{ik}lnQ_k+\sum_j\phi_{ij}T_j+\sum_l\epsilon_{il}lnZ_l$$

Differentiating the total cost function with respect to output quantities gives a series of revenue share equations where the dependent variable is the ratio of revenue from products to total cost, R_i. These revenue share equations take the form:

$$R_i=\beta_k+\sum_l\beta_{kl}lnQ_l+\sum_i\rho_{ik}lnW_i+\sum_j\psi_{ij}T_j+\sum_l\eta_{ik}lnZ_l$$

The properties of cost functions are discussed in general terms in Chambers (1988) and in terms specific to the translog functional form in Antle and Capalbo (1988).

Referencing Ohta, Ball and Chambers define the rate of technical progress as:

$$\begin{aligned}\epsilon_t &= -\partial lnC/\partial t\\ &= -(\theta_1+\sum_j\theta_{1j}T_j+\sum_i\phi_{1i}lnW_i+\sum_i\psi_{1i}lnQ_i\end{aligned}$$

This can be calculated at every data point but at the point of expansion reduces to θ_1.

Following the results of the non-parametric investigation of alternative ways of aggregating inputs and outputs, the base parametric model consists of four outputs, six variable inputs, one of which is an aggregate of contracts, services and materials; and trend and weather variables. A system of equations consisting of the cost function and input and output cost share equations were estimated using a maximum likelihood estimator. The weather and technical change variables entered the cost function interactively with the output and input price variables and hence also appeared in the input and output share equations allowing for a biased impact of these variables on outputs and inputs. Input cost shares must sum to one. To avoid a singular residual covariance matrix, the cost share equation for the use value of plant and structures was omitted during estimation and its parameters derived from the restrictions applied. The properties of symmetry and homogeneity in input prices were imposed.

This base model was compared with a model in which contracts, services and materials were not aggregated, a four output – eight input model and a model in which all outputs were aggregated, a single output – eight input model. The models were compared on the basis of how well they met some of the conditions required of a cost function that were discussed above and in terms of the nature of the impact of technical change and weather.

Four output six input model

Parameter estimates for the base four output – six input model are presented in Table 1 in the left hand columns headed weather to indicate that weather has been included in all equations. The numbering system used to identify inputs and outputs can be found in Table 3. Monotonicity in input prices and outputs requires first, that cost and revenue shares be positive. This condition was met at the point of expansion because all α_i and β_i were positive and significantly different from zero. This condition was met at most data points except for the use value from livestock capital and land which were negative for the four years from 1974 until 1977. The share of crop output was negative in 1958 although very small.

A necessary condition for concavity in prices is that own price elasticities of input substitution be negative. All elasticities of input substitution were negative at the point of expansion although the elasticity for labour was not statistically significant. Concavity in prices has not been checked for all data points.

A necessary condition for convexity in outputs is that the β_{ii} terms, the inverse of the elasticity of product transformation, be positive. The function was not convex in outputs. The elasticity for crop output was negative and statistically significant (t = –2.07). The elasticity for livestock output was positive and significant but the elasticities for wool and other output were both insignificant.

Many of the interaction terms were significant. Thirteen of 21 γ_{ij} terms and nine of ten β_{ij} terms were significant suggesting that the supply of one product is influenced by the supply of other products. Hence it seems unlikely that the cost function is non–joint in inputs allowing total cost to be estimated as the sum of individual cost functions for each product. The log of the likelihood function for this model was 1066.

The rate of cost reduction was 1.7 percent at the point of expansion which means that there has been a neutral component to technical change such that the cost function has drifted down through time at a rate of 1.7 percent per year, which is lower than the rate suggested by studies using an index number approach such as Lawrence and McKay (1980) and by Beck et. al. (1985). However it should be noted that the rate of cost reduction is only equivalent to a TFP index lunder constant returns to scale. Technical change reduced the share of revenue from livestock and wool. It was saving of labour and livestock and was biased towards the use of land (but not plant and structures). These findings can be contrasted with those of McKay et al. (1982) who found that technical change was land saving and biased in favour of crop production. Weather was a significant explanatory variable in the cost function itself and interacted significantly with three inputs but not with any of the outputs.

Four output eight input model

Parameter estimates for alternative models can be found in Table 2. Because inputs and outputs have been aggregated differently, their numbering is different but is described in Table 3. In one alternative model the contracts, services and materials inputs were not aggregated. This model required the estimation of another 27 parameters and increased the likelihood that some parameters would not be precisely estimated because of collinearity between input prices. The log of the likelihood function was 1434.

The eight input model did not meet the condition of concavity in input prices. The own price elasticity of input substitution for services was significantly positive and the elasticities for contracts and for labour were not significantly different from zero although both were negative. The requirement for convexity in outputs, that the elasticity of product transformation be positive, held for livestock output but did not hold for the crop product category. The elasticities for wool and for other products were not statistically significant.

Monotonicity in input prices and outputs was met at the point of expansion because all α_i and β_i were positive and significantly different from zero. This condition was met at most data points except for the use value from livestock capital and land which were negative for the four years from 1974 until 1977. Of the 36 γ_{ij} terms 20 had t-statistics greater than 1.8 despite very high correlations between many of these variables.

The direct effects on the cost function of both technical change and weather were significant and negative. In the case of technical change, the cost function has drifted down through time at a rate of 1.7 percent per year. Several of the interaction terms between technical change and input prices and outputs were also significant suggesting that technical change has been saving of labour and livestock purchases and bised towards the use of materials and land. Technical change has reduced the revenue share from livestock.

Single output model

Past studies of productivity growth in the Australian sheep industry have often used a single aggregate output measure. For this model, reported in Table 2, the log of the likelihood function was 977. It was monotonic in input prices and output at the point of expansion. The α_i were all positive and significant and all γ_{ii} terms except for that associated with contract services were significant and positive. Again 20 of the γ_{ij} terms were significant. The direct output term, β_5, was not significant and β_{55} was significant but negative.

As for the multiple output model, own price elasticities of substitution at the point of expansion were negative, as required for concavity in prices, except for services. Nor does this cost function appear to be convex in output as τ_{55}, which should be positive, was −106 at the point of expansion.

The effect of technical change on the cost function is to add to costs at the rate of 1.2 percent per year although with a t-stat of 1.6, this effect is probably not significant. Technical change is biased towards the use of materials and land and away from the use of livestock purchases and plant and structures. The interaction term between ouput and technology, ψ_{15}, is positive and significant. The direct effect of weather is also insignificant but many of its interaction terms are significant.

Modelling the impact of weather

As mentioned above there is some uncertainty about the appropriate way to incorporate the impact of weather. In the models above weather has been treated as a fixed input following Weaver (1983) and it serves as an explanatory variable in all equations. An alternative view is that while weather certainly has an impact on realized levels of output, it does not enter the ex ante decisions of farmers about input use and hence it should not enter as an explanatory variable in cost and input demand functions. Against this, it can be argued that for products with long production cycles, farmers can adjust input use to some degree in response to changes in weather. A further issue is that realized levels of outputs have been used as explanatory variables but these have clearly been affected by weather and hence are not exogenous to input decisions in the same sense that planned levels of output are.

When the weather variables were removed from the cost and input demand functions but not the output functions in the base model, nine fewer parameters were estimated. The log of the likelihood function fell by 20 to 1046 which means that the null hypothesis that weather does not enter the cost or input demand equations can be accepted at the 99 percent significance level. There appeared to be little change in the degree to which other conditions for a cost function were met.

The rate of cost reducjtion estimated from this model was slightly higher at 1.9 percent. It was biased towards the use of land and away from the use of labour and livestock. It reduced the share of revenue from livestock and wool. In three of the four output equations, crop, livestock and wool, the weather term was positive and statistically significant.

The log of the likelihood function for the four output – eight input model in which weather only appeared in the output functions was 1407, a decline of 26, or a log likelihood test statistic of 52. The critical value of the χ^2 statistic for eleven degrees of freedom at the 99 percent level of significance is 24.73, hence the null hypothesis that weather only enters through output functions is rejected. Three of the four weather terms in the output equations were significant and the fourth had a t – value of 1.67.

Other properties of this reduced model were similar to those of the full model. There were still problems with convexity in both inputs and outputs and the cost shares of land and plant and structures were negative in some years. The estimated rate of productivity growth was 1.8 percent. Technical change reduced the revenue shares of crop and livestock output, was saving of labour and operating livestock and using of land.

Negative Profits

An area of concern, mentioned above, is that from 1981 until 1988 expenditure on inputs has exceeded revenue in every year. Such a long run of negative profits is not consistent with profit maximising behaviour nor can it be explained by unexpected price and weather conditions.

This situation has arisen in part because the use values of assets such as land and plant and structures, which have been calculated using a real rate of interest and a market valuation of capital assets, were large and rose significantly in these years. The real rate of interest has fluctuated markedly. It was greater than five percent in six years since 1981 and reached 9.24 percent in 1985. This raises the issue of the return producers are prepared to accept from investments in inputs such as land and consequently whether such inputs are best treated as fixed inputs. It is likely that many farm families would accept a lower rate of return on these assets.

One solution to this problem is to treat land and plant and structures as being fixed factors that earn a residual rather than a market rate of return. To do this requires adjustments to some of the input categories. We have not yet been able to make these adjustments in a way that is consistent with the rest of the input series and hence have not reported the fixed input models in any detail. However some general comments can be made from these fixed input models. In particular the estimated rate of neutral technical change is much larger at about 3.1 percent. The important implication of this is that estimation of the rate of cost reduction is sensitive to the way in which technolgy is modelled. Given the qualification about the data, the fixed input model is not concave in either input prices nor convex in outputs and the log of the likelihood function is 1031.

Nonparametric Total Factor Productivity Measures

Cox and Chavas (ERAE, 1990) showed that the existence of a solution to the following $T^2 - T$ inequalities is necessary and sufficient for the data to be consistent with profit maximization under the input and output additive augmentation (translating) hypothesis:

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

where y_t denotes output with associated price p_t, x_t denotes inputs with associated prices r_t, A_t denote output augments (higher values of A denote higher productivity) and B_t denotes input augments (where $B > 0$ ($B < 0$) implies factor saving (using) input bias). Furthermore, if such a solution exists, then $[y(A_s,x_t)/y(A_t,x_t)]$ can be viewed as a productivity index measuring the shift in the production function between time t and time s. Since $y(A_s,x_t)/y(A_t,x_t) = 1 + (A_s - A_t)/y_t$ under the translating hypothesis, it follows that $[1 + (A_s - A_t)/y_t]$ can be interpreted as a productivity index for situation s measuring the impact of technical change on production, using t as a reference point. Note, however, that this formulation holds for a single output while these data were shown above to be inconsistent with the existence of such an output aggregator. This suggests that a multiple–output productivity index is likely to be more appropriate for these data.

We computed this output based TFP index as suggested by Cox and Chavas for an aggregate output and disaggregate input (AODI) specification and refer to it as AODI/IOT (input/output translating) O/P (i.e., an output versus input based productivity measure) in the results that follow. Note however, that potential aggregation bias may contaminate these productivity measures given the nonparametric evidence above that these data are not consistent with the existence of an output aggregator. We contrasted this index with the more traditional discrete divisia TFP index suggested by Christensen and Jorgensen (CJ), which is the method used by ABARE in the past. Caves, et.al. (1982a) have showed this index to be superlative and exact for constant returns to scale, translog transformation functions with constant second order coefficients (across time and/or across firms To the extent that these maintained hypotheses are not supported by the data, the CJ TFP index is likewise potentially biased.

Given the questionable a priori functional structure required to fully rationalize the AODI/IOT and CJ productivity indices, more general, multiple output total factor productivity measures are desirable. Caves, et.al. (1982b) succinctly summarize the relationship between distance functions as developed by Shephard and productivity indices. Afriat, Banker and Maindiratta, and Chavas and Cox (1992) show that these distance functions can be readily computed with standard nonparametric techniques.

For the underlying technology implied by the production possibility set T, where $(y, -x) \in T$ (and the set T is non–empty, closed, convex and negative monotonic), Shephard (p. 64–78) defines the input distance function as:

$$(3) \qquad D_T(y, x) = \sup\{\delta: (y, -x/\delta) \in T\}.$$

The input distance function yields the input requirement set $IR_T(y) = \{x: D_T(y, x) \geq 1\}$ as well as the frontier isoquant of a production set $IS_T(y) = \{x: D_T(y, x) = 1)\}$ (Shephard, p. 67). Hence, the input distance function completely characterizes the technology T and measures the proportional (or radial) reduction in all inputs x that would bring the firm to the frontier isoquant $IS_T(y)$.

Similarly, the output distance function is defined by Shephard (p. 206–212) as:

$$(4) \qquad F_T(y, x) = \inf\{\delta: (y/\delta, -x) \in T\}.$$

The output distance function yields the production correspondence $PC_T(x) = \{y: F_T(y, x) \leq 1\}$ and the frontier correspondence $FC_T(x) = \{y: F_T(y, x) = 1\}$ (Shephard, p. 209). Hence, as with the input distance function, the output distance function provides a complete characterization of the underlying technology where $1/F_T(y, x)$ measures the proportional rescaling of all outputs, y, that would bring the firm to the frontier production correspondence $FC_T(x)$.

Caves et al. (1982b) propose the input based productivity index:

(5) $IP = 1/D_T(y, x)$

which measures the radial inflation factor for all inputs such that the inflated inputs $(IP\ x) = x/D_T(y, x)$ lie on the frontier isoquant $IR_T(y)$ generated by technology T (Caves et al., p. 1407). In this context, a firm choosing (y, x) has a higher (lower) productivity than the reference technology T if IP > 1 (< 1). Caves et al. (1982b) also propose the output based productivity index:

(6) $OP = F_T(y,x)$

which measures the radial deflation factor for all outputs by which the deflated outputs $(y/OP) = y/F_T(y, x)$ lie on the frontier correspondence $FC_T(x)$ generated by technology T (Caves et al., p. 1402). Thus, a firm choosing (y, x) has a higher (lower) productivity than the reference technology T if OP > 1 (< 1).

Under constant returns to scale, the input and output distance functions are reciprocal to each other (Shephard, p. 207–208). Hence, the input based and output based productivity measures in (5) and (6), respectively, will be identical under constant returns to scale (Caves, et.al., p. 1408). Therefore, empirical evidence that these measures are different indicates the existence of variable versus constant returns to scale.

Following Banker and Maindiratta, Chavas and Cox (1992) show that the dual input distance function $D_L(y, x)$ in (3) can be obtained from the solution of the linear programming problem:

(7) $$1/D_L(y_j, x_j) = \min_\delta[\delta\colon p_i'y_j - r_i'x_j\delta \le p_i'y_i - r_i'x_i,\ i \in E].$$

Similarly, the dual output distance function $F_S(y, x)$ in (4) can be obtained from the solution of the linear programming problem:

(8) $$1/F_L(y_j, x_j) = \max_\delta[\delta\colon p_i'y_j\delta - r_i'x_j \le p_i'y_i - r_i'x_i,\ i \in E].$$

The dual nonparametric results from (7) and (8) can be used to obtain the input based, radial productivity measures $IP = 1/D_T(y, x)$ as well as the output based, radial productivity measures $OP = F_T(y, x)$. We computed these input and output based productivity measures for both the AODI as well as disaggregate output/disaggregate input (DODI) specifications. This allowed us to evaluate the likely magnitude of the aggregation bias induced by incorrectly assuming the existence of an output aggregator (as in the AODI/IOT index). As well, comparison of the input and output productivity measures allowed us to evaluate the existence of constant returns to scale.

Table 4 and Figures 1–4 summarize these alternative TFP measures for the data from the survey of Australian broadacre agriculture, 1953–88. Figure 1 compares the Chavas and Cox (1992) input and output based, dual nonparametric productivity measures for both the AODI and DODI specifications. The AODI input and output measures are higher than the corresponding DODI measures. This difference between the AODI and DODI measures give some indication of potential aggregation bias attributable to incorrectly assuming the existence of an output aggregator. In this case, the assumption of AODI overestimates the productivity growth in Australian agriculture relative to DODI.

The divergence between the input and output based measures in Figure 1, holding the level of aggregation constant, provides nonparametric evidence of non-constant returns to scale in Australian agriculture over the period analyzed. This also implies that the more traditional C&J TFP index, which is an exact index under the CRTS assumptions noted above, may be biased as well. Figures 2 and 3 lend further support to these inferences.

Figure 2 compares the alternative, nonparametric output based productivity measures with the C&J TFP. Note that the C&J and IOT/AODI measures are quite similar up through 1974, then diverge. Similarly, the CC/AODI and CC/DODI measures are quite similar up through mid- to late 1960's. Both of these distance function based measures suggest the C&J and IOT/AODI measures are overstated up through the early to mid-1970's. After this period, the alternative nonparametric, aggregate output based measures (IOT/AODI and CC/AODI) are roughly parallel and suggest that the C&J TFP is overstated. In contrast, the CC/DODI output measure suggests that both of these aggregate output based as well as the C&J measures are likely overstated due to incorrect functional structure assumptions. Figure 3 reveals a similar story with respect to the nonparametric, input based versus the C&J TFP measures. The CC/AODI is consistently higher than the CC/DODI index (except in 1958 and 1972), again suggesting potential aggregation bias due to incorrect assumption of aggregate output. In contrast, the CC/DODI and C&J measures are quite similar from 1974- 1988.

At this point the we have several alternative TFP measures to choose from. In some respects, the nonparametric indices based on the DODI specification are the least restrictive, hence most supported by these data. But, as the previous discussion suggests, different conclusions arise from use of the input versus output based measures under variable returns to scale. One solution is to use geometric means of the input and output measures to generate a "composite". Table 4 compares these composite measures for the CC/AODI and CC/DODI indexes (they are re-normalized to 100 in the base year, 1953), the IOT/AODI and the C&J TFP measures.

Note that the composite CC/AODI and C&J measures in Figure 4 are quite similar over most of the period analyzed. Previous results/discussion suggests that these measures are likely overstated due to the incorrect assumptions of CRTS (C&J) or output aggregation (CC/AODI). The IOT/AODI and composite CC/DODI measures in figure 4 are also very similar over the period analyzed. Aside from the different aggregation assumptions of these two measures, they are slightly different representations of technical change. On the one hand, the CC index is a composite radial measure (i.e., a proportional rescaling of inputs or outputs) derived from the underlying distance functions. In contrast the IOT index is more of a mixed specification allowing for the rescaling a single output (in a sense a radial measure) and non-radial input bias measures (the Bt of equation (2)). This latter specification allows for differential versus proportional rates of technical change (bias) in each input. Further work on the differences and relative benefits/costs of these alternative productivity measures is clearly warranted.

Average annual rates of productivity growth from each of these measures, noted at the bottom of Table 4, were estimated by dividing the change in each index from 1953 until 1988 by the number years, 36. They varied from 1.4 percent for the CC/DODI output based measure to 4.3 percent for the CC/AODI input based measure. The average rate of growth from the C&J measure, the approach used by ABARE, was 3.5 percent.

Conclusions

Parametric and non-parametric methodologies have been applied to data from the ABARE survey of broadacre agriculture in Australia for the period 1953-88 to examine the extent and nature of productivity growth.

The ABARE data set consisted of price and quantity indices for four outputs and eight inputs. Nonparametric separability tests suggested that only the aggregation of the contracts, services and materials inputs was consistent with profit maximisation. In particular the data do not seem to support the aggregation of all outputs, which has been a common practice.

Our parametric approach to analysing productivity growth using a translog cost function has not been wholly successful to date. None of the models estimated so far fully comply with properties expected of a well behaved cost function. Nevertheless the econometric approach used here has provided an estimate of the average rate of cost reduction in agriculture of about 1.7 percent which is lower than past estimates of the rate of productivity growth from index number approaches which have been about 2.7 percent (Beck et. al. p.8).

Perhaps stronger evidence for this finding comes from the nonparametric analysis of productivity growth, which suggested a rate of growth of about 2.3 percent. To the extent that one accepts the appropriateness of radial productivity measures and the nonparametric functional structure tests employed in these results, the CC/DODI measures suggest previous TFP measurement for Australian agriculture are likely to be overstated due to the imposition of CRTS and aggregation structures not supported by the data.

Areas for further research include investigating the properties of alternative nonparametric productivity measures; estimating the use value of assets and the problem of negative profits; and the appropriate way of modelling the impact of weather. It is also our intention to attempt to isolate the contribution of R&D to productivity growth when data on R&D expenditure in agriculture are finally assembled.

Table 1: Four Output, Six Input Cost Functions

	Weather		No Weather	
	Coefficient	t – stat	Coeff.	t – stat
α_0	10.686	730.06	10.683	657.27
α_1	0.238	50.31	0.240	48.11
α_2	0.261	52.11	0.262	53.35
α_3	0.138	17.70	0.122	17.18
α_4	0.028	17.51	0.031	19.05
α_5	0.110	20.69	0.110	19.94
α_6	0.224	42.38	0.234	45.80
γ_{11}	0.098	4.16	0.106	4.65
γ_{12}	–0.082	–3.98	–0.087	–4.41
γ_{13}	0.014	2.20	0.386E02	0.61
γ_{14}	–0.029	–5.02	–0.025	–4.20
γ_{15}	–0.570E02	–1.01	–0.849E02	–1.49
γ_{16}	0.484E02	0.35	0.011	0.80
γ_{22}	0.168	6.82	0.174	7.29
γ_{23}	–0.055	–8.36	–0.055	–8.44
γ_{24}	0.151E02	0.27	–0.202E02	–0.36
γ_{25}	–0.038	–6.62	–0.032	–5.68
γ_{26}	0.443E02	0.29	0.177E02	0.12
γ_{33}	0.054	6.99	0.079	10.44
γ_{34}	–0.825E02	–3.83	–0.013	–5.88
γ_{35}	–0.345E02	–0.87	0.303E02	0.85
γ_{36}	–0.150E02	–0.23	–0.018	–2.68
γ_{44}	0.015	5.79	0.016	5.73
γ_{45}	–0.104E02	–0.44	–0.222E02	–0.90
γ_{46}	0.022	4.87	0.027	5.75
γ_{55}	0.069	19.42	0.066	17.60
γ_{56}	–0.021	–4.59	–0.026	–5.61
γ_{66}	–0.879E02	–0.54	0.445E02	0.28
β_1	0.275	18.94	0.286	17.92
β_2	0.314	25.96	0.303	26.09
β_3	0.345	11.13	0.346	10.94
β_4	0.023	20.26	0.023	19.74
β_{11}	0.128	7.90	0.133	7.66
β_{12}	–0.034	–2.64	–0.050	–3.85
β_{13}	–0.088	–2.55	–0.094	–2.62
β_{14}	–0.406E02	–3.58	–0.447E02	–3.94
β_{22}	0.419	14.29	0.426	14.50
β_{23}	–0.655E02	–0.14	–0.023	–0.48
β_{24}	0.013	3.84	0.014	4.13

Table 1: Four Output, Six Input Cost Functions				
	Weather		No Weather	
	Coefficient	t – stat	Coeff.	t – stat
β_{33}	0.265	2.07	0.311	2.38
β_{34}	–0.023	–4.48	–0.022	–4.44
β_{44}	0.026	19.49	0.025	18.88
ρ_{11}	–0.010	–2.15	–0.858E02	–1.76
ρ_{12}	–0.449E03	–0.09	–0.896E03	–0.19
ρ_{13}	0.846E02	1.03	–0.699E02	–0.93
ρ_{14}	–0.883E02	–6.10	–0.673E02	–4.65
ρ_{15}	–0.030	–5.52	–0.027	–4.75
ρ_{16}	0.041	8.22	0.051	10.87
ρ_{21}	–0.027	–1.86	–0.027	–1.94
ρ_{22}	–0.074	–4.94	–0.077	–5.38
ρ_{23}	0.172	14.84	0.177	15.84
ρ_{24}	0.505E02	1.29	0.662E02	1.65
ρ_{25}	–0.036	–5.48	–0.035	–5.32
ρ_{26}	–0.040	–3.06	–0.044	–3.48
ρ_{31}	0.106	5.43	0.102	5.38
ρ_{32}	0.012	0.61	0.018	0.92
ρ_{33}	–0.844E02	–0.36	–0.030	–1.28
ρ_{34}	–0.478E02	–0.85	–0.191E02	–0.32
ρ_{35}	–0.076	–5.52	–0.076	–5.41
ρ_{36}	–0.030	–1.39	–0.012	–0.57
ρ_{41}	0.019	4.59	0.020	4.99
ρ_{42}	0.165E02	0.41	0.481E03	0.12
ρ_{43}	–0.663E02	–4.26	–0.579E02	–3.64
ρ_{44}	0.274E02	2.14	0.287E02	2.16
ρ_{45}	–0.473E02	–3.84	–0.493E02	–3.90
ρ_{46}	–0.012	–3.19	–0.012	–3.41
θ_1	–0.017	–10.31	–0.019	–9.87
θ_2	–0.141E02	–3.41		
θ_{11}	0.203E03	0.68	0.494E03	1.50
θ_{12}	–0.739E04	–2.59		
θ_{22}	0.982E05	0.72		
ϕ_{11}	0.106E02	1.38	0.746E03	0.93
ϕ_{12}	–0.175E02	–2.05	–0.186E02	–2.21
ϕ_{13}	–0.892E02	–8.18	–0.596E02	–5.89
ϕ_{14}	0.283E03	1.11	–0.247E03	–0.94
ϕ_{15}	0.801E02	10.66	0.794E02	9.53
ϕ_{16}	0.132E02	1.46	–0.622	–0.70
ϕ_{21}	–0.299E03	–4.05		

Table 1: Four Output, Six Input Cost Functions				
	Weather		No Weather	
	Coefficient	t – stat	Coeff.	t – stat
ϕ_{22}	−0.664E04	−0.85		
ϕ_{23}	0.150E03	0.91		
ϕ_{24}	−0.506E05	−0.18		
ϕ_{25}	0.388E03	3.36		
ϕ_{26}	−0.168E03	−2.01		
ψ_{11}	−0.280E02	−1.45	−0.340E02	−1.59
ψ_{12}	−0.010	−5.48	−0.796E02	−4.26
ψ_{13}	−0.830E02	−1.76	−0.862E02	−1.73
ψ_{14}	0.534E05	0.03	0.694E04	0.35
ψ_{21}	0.183E03	0.50	0.100E02	4.89
ψ_{22}	0.434E03	1.67	0.401E03	2.61
ψ_{23}	0.849E03	1.35	0.849E03	1.83
ψ_{24}	0.161E04	0.89	−0.188E04	−1.27

Table 2: Multiple and Single Output Cost Functions				
	Multiple Output		Single Output	
	Coefficient	t – stat	Coeff.	t – stat
α_0	10.700	780.00	10.700	642.0
α_1	0.021	7.18	0.018	6.79
α_2	0.084	21.1	0.071	16.7
α_3	0.127	33.5	0.141	31.2
α_4	0.268	55.8	0.254	42.2
α_5	0.135	17.3	0.119	14.3
α_6	0.031	18.5	0.029	16.8
α_7	0.111	21.3	0.130	26.2
α_8	0.223	43.3	0.239	40.4
γ_{11}	−0.018	−0.77	−0.278E02	−0.14
γ_{12}	−0.016	−1.01	−0.020	−1.24
γ_{13}	0.700E02	1.11	0.894E02	1.57
γ_{14}	0.012	1.16	0.356E02	0.39
γ_{15}	0.013	5.15	0.182E02	0.711
γ_{16}	−0.537E02	−1.54	0.315E02	1.07
γ_{17}	0.305E02	0.90	−0.538E02	−1.89
γ_{18}	0.383E02	0.76	0.011	2.26
γ_{22}	0.199	9.70	0.122	4.91
γ_{23}	−0.666E02	−0.69	−0.621E03	−0.045
γ_{24}	−0.112	−8.32	−0.990E02	−0.45
γ_{25}	−0.036	−9.35	−0.019	−3.23
γ_{26}	−0.225	−0.48	0.779E02	1.35
γ_{27}	−0.615E02	−1.43	−0.013	−2.31
γ_{28}	−0.021	−2.29	−0.068	−5.66
γ_{33}	0.010	0.76	0.062	3.10
γ_{34}	−0.024	−2.11	−0.083	−4.81
γ_{35}	0.044	8.45	0.040	5.39
γ_{36}	−0.017	−4.15	−0.022	−4.57
γ_{37}	−0.823E03	−0.20	0.373E02	0.74
γ_{38}	−0.012	−1.13	−0.852E02	−0.60
γ_{44}	0.174	10.20	0.147	4.96
γ_{45}	−0.053	−8.84	−0.036	−3.40
γ_{46}	−0.805E02	−1.72	−0.758E03	−0.12
γ_{47}	−0.034	−7.22	−0.033	−4.99
γ_{48}	0.045	3.74	0.012	0.73
γ_{55}	0.049	6.03	0.063	4.40
γ_{56}	−0.744E02	−3.46	−0.933E02	−3.76
γ_{57}	−0.625E02	−1.57	−0.238E02	−0.52
γ_{58}	−0.332E02	−0.50	−0.038	−4.26

Table 2: Multiple and Single Output Cost Functions				
	Multiple Output		Single Output	
	Coefficient	t – stat	Coeff.	t – stat
γ_{66}	0.013	4.92	0.023	8.00
γ_{67}	0.670E03	0.29	–0.735E02	–2.79
γ_{68}	0.027	6.01	0.631E02	1.51
γ_{77}	0.068	19.7	0.070	18.8
γ_{78}	–0.024	–5.39	–0.014	–2.98
γ_{88}	–0.015	–0.92	0.098	6.29
β_1	0.281	20.7		
β_2	0.307	27.7		
β_3	0.327	11.0		
β_4	0.023	19.1		
β_5			0.184	1.40
β_{11}	0.133	9.20		
β_{12}	–0.039	–3.25		
β_{13}	–0.107	–3.19		
β_{14}	–0.398E02	–3.34		
β_{22}	0.394	15.20		
β_{23}	–0.809E02	–0.19		
β_{24}	0.012	3.60		
β_{33}	0.268	2.16		
β_{34}	–0.019	–3.73		
β_{44}	0.027	18.10		
β_{55}			–3.44	–4.15
ρ_{11}	0.592E02	4.58		
ρ_{12}	0.515E02	0.00		
ρ_{13}	–0.022	–5.74		
ρ_{14}	0.113E02	0.24		
ρ_{15}	0.760E02	0.93		
ρ_{16}	–0.845E02	–5.99		
ρ_{17}	–0.027	–5.23		
ρ_{18}	0.043	8.88		
ρ_{21}	0.122E02	0.25		
ρ_{22}	0.173E02	0.22		
ρ_{23}	–0.049	–4.23		
ρ_{24}	–0.056	–4.56		
ρ_{25}	0.184	16.4		
ρ_{26}	0.798E02	2.10		
ρ_{27}	–0.038	–6.19		
ρ_{28}	–0.051	–4.16		
ρ_{31}	0.499E02	0.79		

Table 2: Multiple and Single Output Cost Functions

	Multiple Output		Single Output	
	Coefficient	t – stat	Coeff.	t – stat
ρ_{32}	−0.010	−0.94		
ρ_{33}	0.067	4.07		
ρ_{34}	0.030	1.58		
ρ_{35}	0.014	0.57		
ρ_{36}	−0.682E02	−1.21		
ρ_{37}	−0.079	−5.97		
ρ_{38}	−0.019	−0.92		
ρ_{41}	−0.738E03	−0.46		
ρ_{42}	−0.441E02	−1.53		
ρ_{43}	0.013	4.20		
ρ_{44}	0.013	3.78		
ρ_{45}	−0.654E02	−4.01		
ρ_{46}	0.264E02	1.96		
ρ_{47}	−0.463E02	−3.65		
ρ_{48}	−0.012	−3.11		
ρ_{51}			0.020	3.33
ρ_{52}			−0.592E02	−0.39
ρ_{53}			−0.018	−0.93
ρ_{54}			−0.113	−4.58
ρ_{55}			0.079	2.17
ρ_{56}			−0.012	−1.78
ρ_{57}			−0.071	−2.93
ρ_{58}			0.120	4.79
θ_1	−0.017	−10.70	0.012	1.61
θ_2	−0.172E02	−4.35	0.148E02	2.54
θ_{11}	0.222E03	0.84	−0.672E02	−4.48
θ_{12}	−0.598E04	−2.70	−0.906E03	−5.25
θ_{22}	0.430E04	4.18	0.837E05	0.68
ϕ_{11}	−0.630E03	−1.37	−0.671E03	−1.52
ϕ_{12}	−0.492E03	−0.82	0.136E02	1.58
ϕ_{13}	0.420E02	6.68	0.256E02	2.51
ϕ_{14}	−0.325E02	−4.11	0.126E02	0.913
ϕ_{15}	−0.901E02	−8.37	−0.456E02	−2.22
ϕ_{16}	−0.380E04	−0.15	0.303E03	0.822
ϕ_{17}	0.781E02	10.8	0.445E02	3.43
ϕ_{18}	0.140E02	1.61	−0.471E02	−3.35
ϕ_{21}	−0.385E04	−1.94	−0.356E04	−1.46
ϕ_{22}	0.262E04	0.41	0.535E04	0.91
ϕ_{23}	−0.274E03	−4.64	−0.297E03	−3.90

Table 2: Multiple and Single Output Cost Functions				
	Multiple Output		Single Output	
	Coefficient	t – stat	Coeff.	t – stat
ϕ_{24}	–0.814E04	–1.05	0.932E04	0.91
ϕ_{25}	0.162E03	1.01	–0.114E03	–0.68
ϕ_{26}	–0.103E04	–0.38	0.501E06	0.02
ϕ_{27}	0.381E03	3.60	0.450E03	4.16
ϕ_{28}	–0.165E03	–1.98	–0.151E03	–1.34
ψ_{11}	–0.319E02	–1.88		
ψ_{12}	–0.837E02	–5.08		
ψ_{13}	–0.522E02	–1.15		
ψ_{14}	–0.832E05	–0.04		
ψ_{15}			0.151	4.15
ψ_{21}	0.190E03	0.53		
ψ_{22}	0.432E03	1.82		
ψ_{23}	0.798E03	1.35		
ψ_{24}	0.162E04	0.87		
ψ_{25}			0.017	5.18

TABLE 3: NUMBERING OF INPUTS AND OUTPUTS IN TABLES 1 & 2.

	Numbering in Table 1	Numbering in Table 2
Inputs		
Contracts	1	1
Services	1	2
Materials	1	3
Labour	2	4
Livestock purchases	3	5
Livestock use	4	6
Land use	5	7
Plant, structures use	6	8
Outputs		
Crop	1	1
Livestock	2	2
Wool	3	3
Others	4	4

TABLE 4: NONPARAMETRIC TFP MEASUREMENT (ASSUMING PROFIT MAXIMIZATION) FOR THE 1953–88 AGGREGATE AUSTRALIAN BROADACRE INDUSTRIES SURVEY DATA.

YEAR	AOAI CI	AODI IOT OP	AODI CC OP	DODI [illegible]	[illegible]	DODI CC IP	GEOMETRIC MEANS CC AODI	GEOMETRIC MEANS CC DODI
53	100.0	100.0	100.0	[illegible]	100.0	100.0	100.0	100.0
54	98.0	99.4	88.7	87.2	96.6	96.0	92.7	91.7
55	99.0	101.1	88.1	85.8	96.7	95.8	92.5	90.9
56	107.6	107.1	99.6	97.2	105.9	103.9	102.8	100.6
57	108.3	107.4	104.1	100.9	[illegible]	112.2	109.3	106.7
58	95.0	103.8	84.5	84.9	108.7	109.2	97.3	97.8
59	113.7	117.3	90.1	88.9	117.8	114.5	104.9	102.5
60	115.0	117.0	[illegible]	93.6	125.2	122.2	111.0	108.8
61	121.1	121.5	97.1	93.7	129.9	122.8	114.7	109.2
62	124.2	122.6	97.8	96.1	131.0	127.0	115.6	112.6
63	128.1	125.5	102.8	96.9	138.1	128.6	121.7	113.9
64	132.8	127.8	108.3	103.0	146.6	137.5	128.9	121.5
65	127.3	128.1	107.6	100.5	144.0	132.9	127.1	117.8
66	107.9	114.4	105.0	99.7	140.2	132.2	123.8	117.1
67	134.6	133.2	113.3	107.0	153.1	144.2	134.7	127.0
68	119.7	124.6	109.0	99.6	144.7	134.3	128.1	118.2
69	151.7	150.1	136.6	124.1	184.8	170.5	162.5	149.1
70	145.3	145.2	130.4	118.1	175.6	161.6	154.7	141.5
71	150.3	144.8	134.2	118.7	181.7	163.0	159.7	142.6
72	128.5	130.4	113.5	123.4	150.4	169.3	133.2	148.1
73	148.3	143.3	130.7	104.6	175.7	140.9	154.8	124.1
74	163.6	155.1	145.3	119.8	196.8	163.6	173.0	143.4
75	206.0	162.9	178.1	145.7	253.0	208.3	218.8	179.8
76	206.6	166.0	176.4	144.3	248.3	204.5	215.4	177.0
77	184.6	160.5	153.5	124.5	210.1	171.5	184.0	149.8
78	186.5	173.[illegible]	158.1	128.9	215.3	177.1	188.9	154.9
79	217.4	184.7	183.9	150.3	253.6	209.4	221.5	182.3
80	208.2	183.2	177.6	148.5	242.9	205.7	212.8	179.4
81	175.8	160.3	149.2	122.4	201.3	166.7	177.2	146.2
82	200.7	179.5	171.3	142.5	233.4	196.5	204.7	171.6
83	170.1	156.9	140.8	118.5	187.9	159.9	166.0	140.7
84	232.2	194.1	196.7	165.8	271.2	231.7	236.9	201.4
85	241.5	196.6	199.6	167.4	274.8	233.7	240.2	203.3
86	237.9	198.4	203.2	169.8	281.7	238.5	245.6	207.0
87	243.4	204.0	204.8	171.2	282.6	239.6	246.8	208.2
88	226.5	184.7	184.0	149.2	253.0	207.3	221.2	180.6
Av.	3.5	2.4	2.3	1.4	4.3	3.0	3.4	2.2

INDEXES LEGEND:

CJ: Christensen and Jorgenson TFP Index.
IOT: Cox/Chavas (ERAE, 1991) TFP Index (assuming input and output translating).
CC: Chavas/ Cox Dual, Radial Nonparametric TFP Index.

MODEL SPECIFICATION LEGEND:

AODI: Aggregate Output, 8 Disaggregate Inputs
DODI: 4 Disaggregate Outputs, 8 Disaggregate Inputs

PRODUCTIVITY INDEX LEGEND:

OP: Output Based Productivity Measure.
IP: Input Based Productivity Measure.

FIGURE 1: COMPARISON OF NONPARAMETRIC TFP MEASURES FOR AUSTRALIAN AGRICULTURE

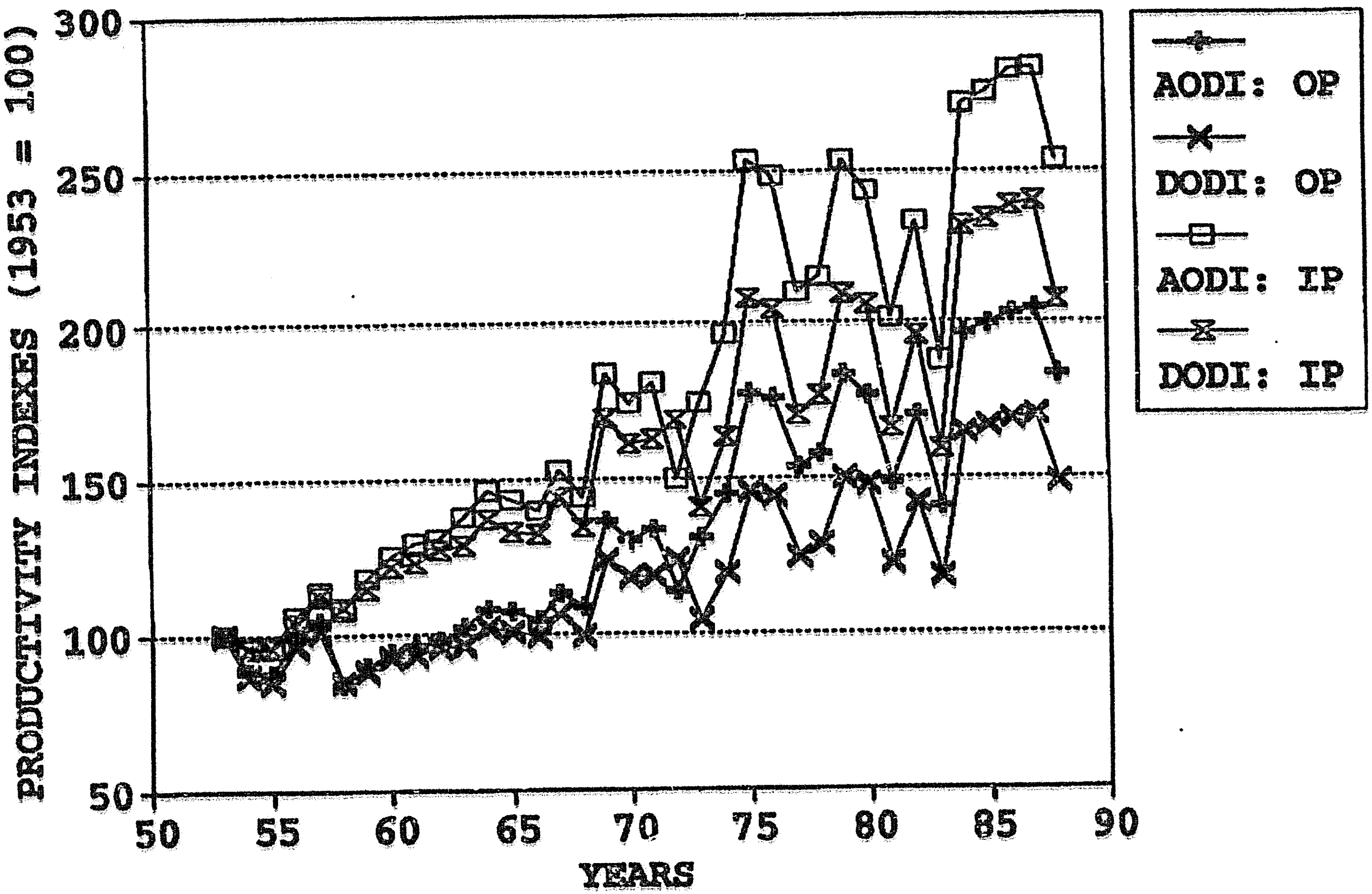


FIGURE 2: COMPARISON OF NONPARAMETRIC OUTPUT BASED VERSUS C&J TFP MEASURES

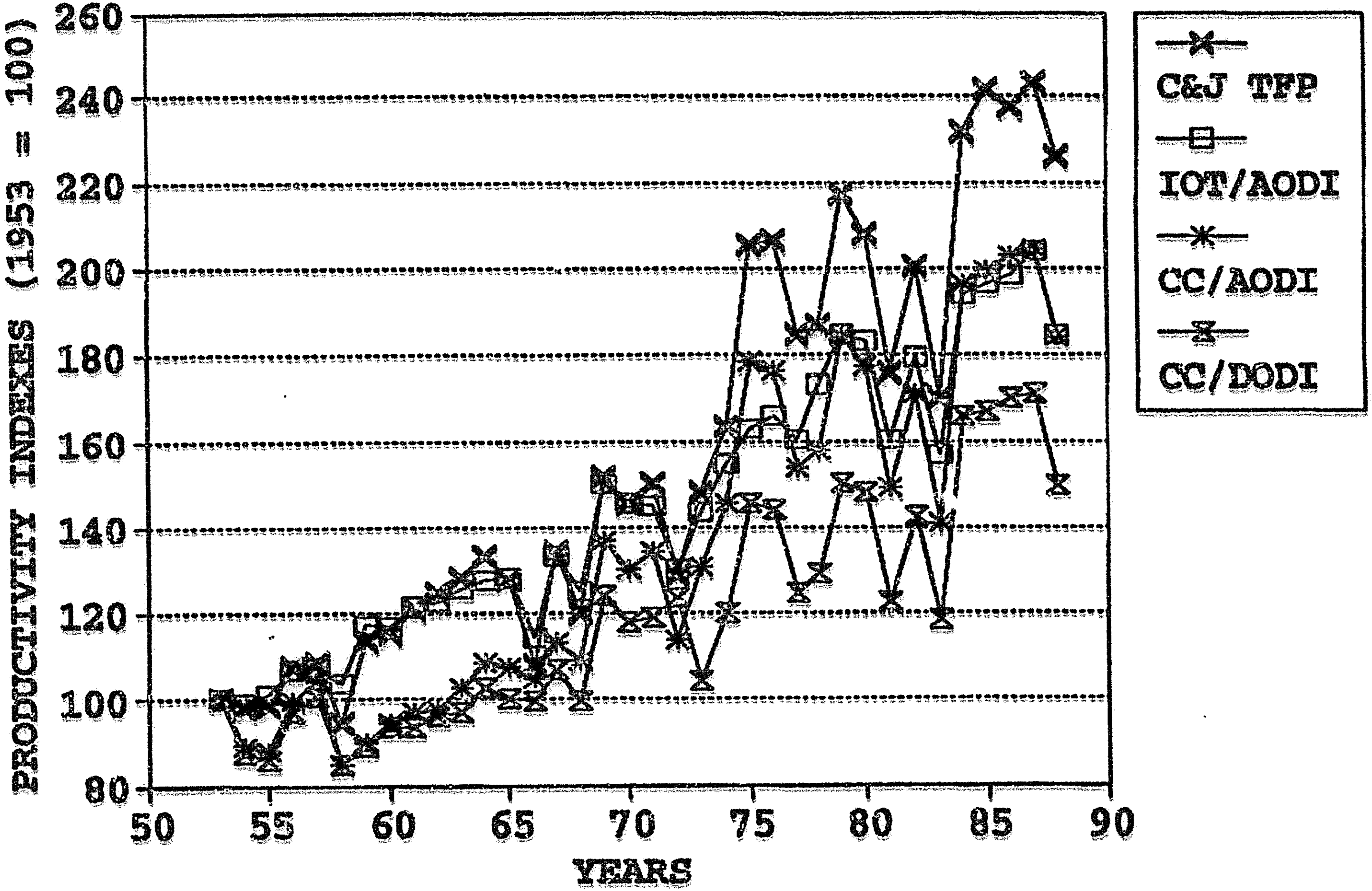


FIGURE 3: COMPARISON OF NONPARAMETRIC INPUT BASED VERSUS C&J TFP MEASURES

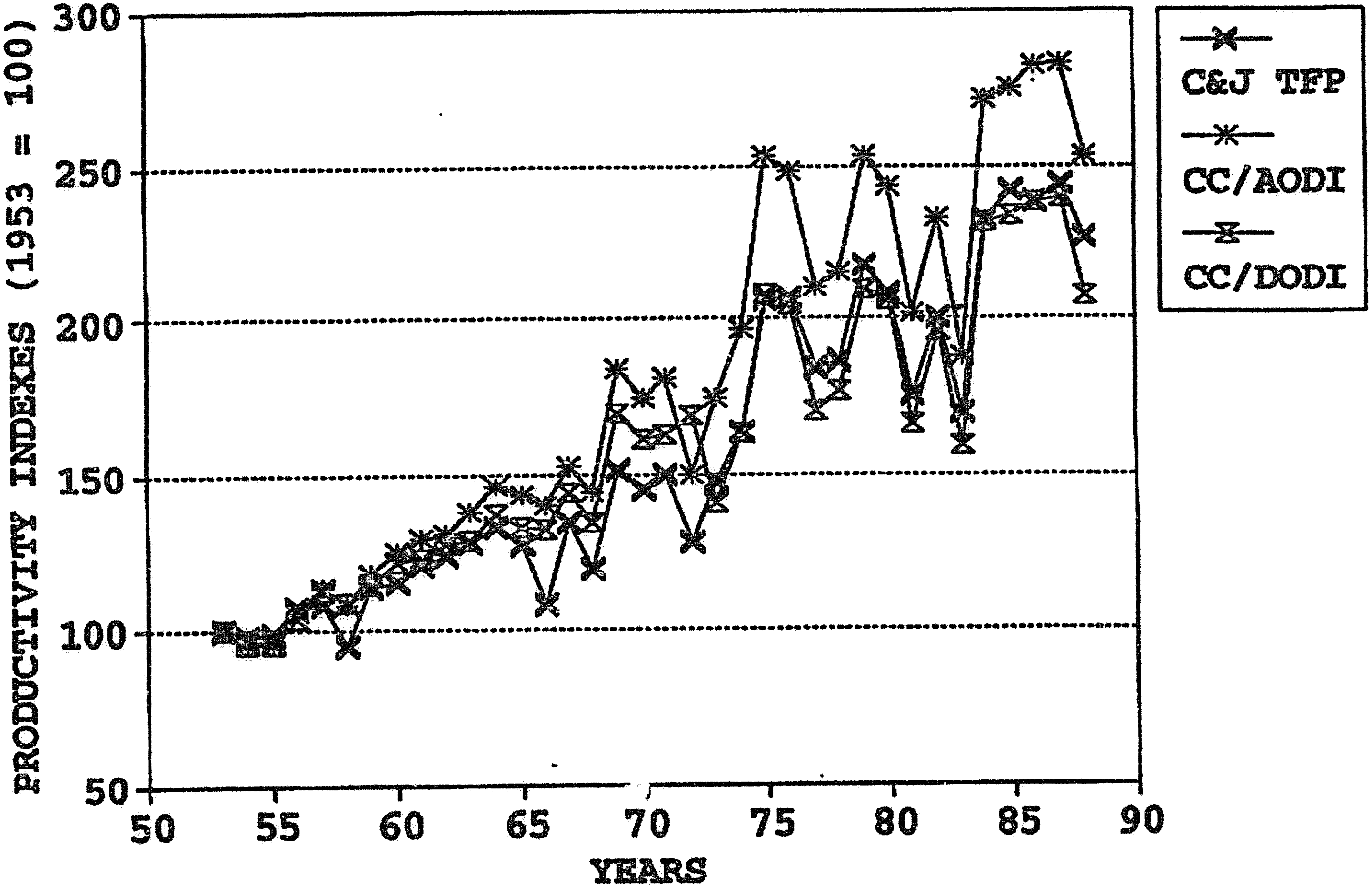
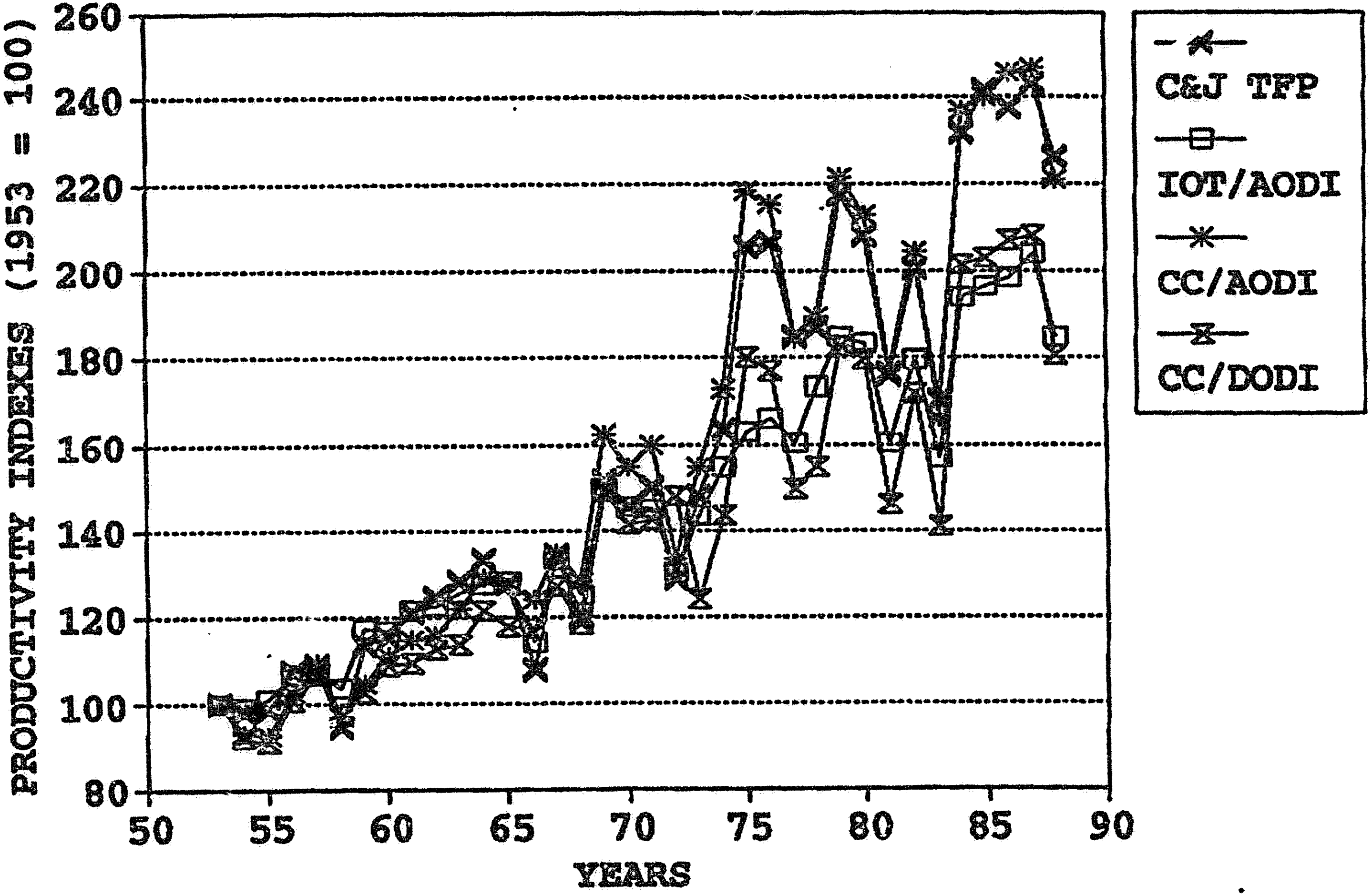


FIGURE 4: COMPARISON OF C&J, IOT/AODI, AND CC (GEOMETRIC MEANS) TFP MEASURES



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