An Application of the Stochastic Latent Variable Approach to the Correction of Sector level TFP Calculations in the Face of Biased Technological Change

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Contributed paper selected for presentation at the 25th International Conference of Agricultural Economists, August 16-22, 2003, Durban, South Africa

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Abstract:*The measurement of the impact of technical change has received significant attention within the economics literature. One popular method of quantifying the impact of technical change is the use of growth accounting index numbers. However, in a recent article Nelson and Pack (1999) criticise the use of such index numbers in situations where technical change is likely to be biased in favour of one or other inputs. In particular they criticise the common approach of applying observed cost shares, as proxies for partial output elasticities, to weight the change in quantities which they claim is only valid under Hicks neutrality. Recent advances in the measurement of product and factor biases of technical change developed by Balcombe et al (2000) provide a relatively straight-forward means of correcting product and factor shares in the face of biased technical progress. This paper demonstrates the correction of both revenue and cost shares used in the construction of a TFP index for UK agriculture over the period 1953 to 2000 using both revenue and cost function share equations appended with stochastic latent variables to capture the bias effect. Technical progress is shown to be biased between both individual input and output groups. Output and input quantity aggregates are then constructed using both observed and corrected share weights and the resulting TFPs are compared. There does appear to be some significant bias in TFP if the effect of biased technical progress is not taken into account when constructing the weights.*

KEY WORDS: Biased Technological Change; Latent Variables, TFP.

1. INTRODUCTION

Increased productivity in agriculture has a number of important effects (Ahearn et al, 1998). First, it releases resources that can be used by other sectors thereby generating economic growth. Second, higher levels of agricultural productivity result in lower food prices that increase consumers' welfare. And third, in the context of an open economy, productivity growth improves the competitive position of a country's agricultural sector. Against this background, it is clear that productivity measures provide a key indicator of the performance of a country's agricultural sector. This has long been recognised and there now exists a vast literature on agricultural productivity measurement. The aims of most productivity studies are to monitor the performance of the agricultural sector, to make performance comparisons across industries and countries, and finally to help policymakers to design optimal policies to enhance productivity.

In particular, productivity growth can be largely attributed to public research and development (R&D) expenditure so that productivity measurement is a first step to establish whether the investments made in agricultural research represent an appropriate use of public funds.

It is therefore clear that the implications of inaccurate measurement of productivity are far reaching. The most popular method of productivity measurement is the index number approach[1], which is practical but makes a number of restrictive assumptions, in particular that technological change is Hicks neutral (Hsieh, 2000). The implications of that assumption have recently been the focus of attention by growth economists interested in evaluating the relative contributions of capital accumulation and technological progress in the growth of the East-Asian Tigers (Nelson and Pack, 1999; Felipe and McCombie, 2000; Rodrick, 1997; Hsieh, 2000). In agriculture, Murgai (2001) represents the only attempt to address the issue. The conclusion that is reached by all the authors is invariably that if technological change is biased, then conventional TFP growth is not a satisfactory measure of productivity growth and can lead to erroneous policy conclusions. However, this literature does not provide a satisfactory alternative to the conventional TFP index. Our aim in this paper is to suggest a new TFP index that can be used when technological change is biased. This index is computed from UK data and it is shown that it departs substantially from the conventional index.

The paper is organised as follows. Section two discusses the theoretical problem, highlights the potential for measurement bias when technical progress in not Hicks-neutral and discusses the dual and latent-variable framework that is used to correct the TFP index. Section three describes the data and summarises the results, paying particular attention to the direction and magnitude of any difference between the two indices. Finally section four draws conclusions.

2. THEORETICAL FRAMEWORK

The limits of conventional TFP growth as a measure of technological change

Consider that the technology is described by a time-varying production function $Y=F(X, t)$, where Y denotes output, X a vector of n inputs X_i and t is a time index. Under the standard

[1] For instance, as mentioned by Ahearn et al (1998), all the major estimates of agricultural productivity in the USA use an index number approach.

assumptions of profit maximisation and constant returns to scale, the Divisia TFP index is defined as:

$$\gamma_{TFP} = \gamma_Y - \sum_{i=1}^{n} \alpha_i(X,t)\gamma_{X_i} \quad (1)$$

where γ denotes the growth rate of the variable used as subscript, and $\alpha_i(X,t)$ denotes the cost share of input *i*. This procedure makes an implicit adjustment for the relative productivity of each input in the aggregation of input growth since it uses the cost shares as weights. If the existence of technical inefficiencies is ruled out, TFP growth is equal to the rate of technical change. The exact index of TFP is then obtained by integrating equation (1) forward to produce:

$$\ln\left(\frac{TFP_t}{TFP_0}\right) = \ln(Y_t / Y_o) - \int_{X_0,t_0}^{X,t} \left(\sum_{i=1}^{n} \alpha_i(X,t)\frac{dX_i}{X_i}\right) \quad (2)$$

This expression is usually approximated by the Tornqvist-Theil index:

$$\ln\left(\frac{TFP_t}{TFP_0}\right) = \ln\left(\frac{Y_t}{Y_o}\right) - \sum_{i=1}^{n} \frac{1}{2}[\alpha_i(X_t,t) + \alpha_i(X_0,0)]\ln\left(\frac{X_{it}}{X_{i0}}\right) \quad (3)$$

A fundamental problem with the Divisia TFP index and its discreet-time approximations that has been largely ignored in the literature arises from the observation that the factor shares $\alpha_i(X,t)$ that are used to weigh each individual input in the computation of TFP depend in general on the state of the technology at a particular time and hence on the cumulative effect of the process of technological change. This makes the interpretation of standard productivity studies problematic as we will now attempt to clarify. The conclusion that is reached, as in Murgai (1999), Hsieh (2000) and Felipe and McCombie (2001), states that the input index derived from observed cost shares conflates the contribution of factor accumulation to output growth with that of technological change. As a result, the corresponding TFP growth rate does not reflect only changes in technology and its interpretation becomes ambiguous.

For simplicity of exposure and to be consistent with the existing literature, consider that there are only two inputs in production, labour *L* and an aggregate of all other inputs referred to as capital K[2]. Following Ferguson (1968, 1969), the evolution of the capital share α_k over time is expressed as:

$$\gamma_{\alpha_K} = (1-\alpha_k)[B + (1-1/\sigma)(\gamma_K - \gamma_L)] \qquad (4)$$

where B is the technological change bias and σ denotes the elasticity of substitution[3]. This expression shows clearly that in the most general case, changes in factor shares will depend on the bias of technological change, and that this result holds irrespective of the value of the elasticity of substitution. If technological change takes a purely factor augmenting form, i.e. $F(K, L, t)=G(A_K(t)K, A_L(t)L)$ where $A_K(t)$ and $A_L(t)L$ denote the factor-augmenting functions, equation (4) becomes:

$$\gamma_{a_K} = (1-\alpha_k)(1-1/\sigma)(\gamma_K + \gamma_{A_K} - \gamma_L - \gamma_{A_L})] \qquad (5)$$

This expression shows that for factor-augmenting technological progress, if the elasticity of substitution differs from unity and the factor-augmenting functions grow at different rates for the two inputs, the factor shares will change over time as a result of the process of technological change.

The conclusion that the factor shares used to build the TFP index depend on the cumulative process of technological change raises a fundamental problem. What is equation (1), which defines the growth in conventional TFP, really measuring? It is expressed as the residual between output growth and input growth ***given the current state of technology*** since it is the observed shares $\alpha_i(X,t)$ that are used in the weighting procedure. Therefore, if biased technological progress takes place between the base period and time t in a way that increases the relative productivity of a particular input X_i, the effect is incorporated in the contribution of that input to output growth and not attributed to its technological change component.

Whether this is a problem or not depends on our objective in measuring TFP. Our view, which is essentially in line with that presented by Solow (1957) in his seminal article and that

[2] The results presented here in the two-input case were generalised by the authors to any finite number of inputs by using a dual framework based on a cost function. The generalisation is not presented due to the space constraint.

has been expressed recently by Hsieh (2000), is that the goal of productivity measurement is to isolate the share of output growth that is due to technological change or, in other words, to infer what the rate of growth over an extended period of time would have been if inputs had grown at the observed rate but there had been no technological progress. But the previous analysis shows that in the general case, the input Divisia index unfortunately conflates the effect of factor accumulation and that of biased technological change so that the standard TFP index is inappropriate to draw conclusions about the relative importance of technological change in the process of growth. This is true unless technological change is Hicks neutral (equation (4)) or if the process of technological progress is purely factor-augmenting and the technology has a unitary elasticity of substitution equal to unity (equation (5)).

Adjusting the conventional TFP index when technological change is biased

The previous deficiency can be remedied by proposing, as suggested by Rodrik (1997), that the rate of TFP growth be defined as the difference between actual output growth γ_Y and the output growth that would have resulted in the absence of technical change γ_{Y*}:

$$\gamma_{TFP*} = \gamma_Y - \gamma_Y^* \qquad (6)$$

where output in the absence of technical change $Y*$ is equal to $F(X,0)$. Differentiating this expression with respect to time produces the growth rate of the new index of total factor productivity $TFP*$:

$$\gamma_{TFP*} = \gamma_Y - \sum_{i=1}^{n} \alpha_i(X,0)\gamma_{X_i} \qquad (7)$$

Hence, this new definition of total factor productivity growth is very similar to the original one, presented in equation (1), except that input growth rates are now weighted not by the observed cost shares $\alpha_i(X,t)$ but by the shares that would result from the use of the base period technology in year t, $\alpha_i(X,0)$, referred to as the constant-technology shares. The difference between the two rates, which represents the bias of the conventional TFP growth rate, is equal to:

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[3] More precisely, $B = \frac{F_{Kt}}{F_K} - \frac{F_{Lt}}{F_L}$ and $\sigma = \frac{F_K F_L}{F F_{KL}}$.

$$\gamma_{TFP} - \gamma_{TFP*} = \sum_{i=1}^{n} [\alpha_i(X,0) - \alpha_i(X,t)]\gamma_{X_i} \quad (8)$$

Suppose that technological change between the base period and time t is biased in favour of input i, meaning that $\alpha_i(X,t) > \alpha_i(X,0)$. Equation (8) shows that if factor i accumulates at time t ($\gamma_{Xi} > 0$) the standard TFP growth rate will be negatively biased. This is explained by the fact that the Divisia input index assigns a weight to γ_{Xi} that is too high in the sense that only through biased technological change has the productivity of that particular input been maintained, hence preventing a further decrease in its cost share. The message emerging from this analysis is therefore that if technological progress is biased in favour of the factors accumulating rapidly, the conventional TFP growth rate clearly underestimates the contribution of technological progress to output growth. The reverse is true when the bias of technological progress plays against the quickly accumulating factors. This mechanism is used by Murgai (2000) to explain the apparent productivity paradox that the period of the Green revolution in the Indian Punjab is characterised by relatively slow TFP growth.

Deriving the modified TFP index requires integrating equation (8) and the result can be approximated by the following discreet-time Tornqvist-Theil index:

$$\ln\left(\frac{TFP_t}{TFP_0}\right) = \ln\left(\frac{Y_t}{Y_o}\right) - \sum_{i=1}^{n} \frac{1}{2}[\alpha_i(X_t,0) + \alpha_i(X_0,0)]\ln\left(\frac{X_{it}}{X_{i0}}\right) \quad (9)$$

Although the previous TFP index appears theoretically sound, it unfortunately cannot be computed directly since the constant technology shares $\alpha_i(X,0)$ are not directly observable. A logical idea to infer their values consists in integrating equation (4) forward from the base period to time t in the absence of technological progress (implying $B=0$) but this strategy requires knowledge of the elasticity of substitution σ. However, Diamond et al. (1978) have established that the elasticity of substitution and the bias of technological change are not identifiable[4], meaning that for any arbitrarily chosen path for parameter σ, it is possible to build a path for the bias B that will ensure consistency with the data. Hence, since an infinite number

[4] Diamond et al. (1978), Theorem 1, page 133.

of production structures are consistent with the data, it is impossible to determine the true technological relationships from which the observations have been generated.

The above ‘impossibility theorem’ does imply that computation of equation (9) certainly requires the imposition of more structure to the model. In doing so, our objective consists in choosing a structure that imposes as few a priori restrictions as possible but that solves the identification problem. In that respect, however, the existing literature (Felipe and McCombie (2001), Murgai (2001) and Hsieh (2000)) seems rather unsatisfactory in that a constant elasticity of substitution is assumed and arbitrarily chosen by the researcher. Although the approach is useful in illustrating the possible shortcomings of the conventional TFP measures, it is flawed since it relies on the selection of a limited range of values for the elasticity of substitution, when the impossibility theorem of Diamond et al. (1978) tells us that any value of parameter σ can be deemed ‘reasonable’. Further, the previous methodology can only be applied at a high level of aggregation, which makes its value for the analysis of agricultural productivity rather limited.

In the next section, we propose an alternative approach to produce estimates of the adjusted TFP index (9). The identification problem outlined above is circumvented by the parametric estimation of the constant-technology shares, but the structure that is implied on the production function and the pattern of technological change is much less restrictive than in the existing literature. Furthermore, our approach can accommodate a large number of inputs and is therefore suitable for the analysis of TFP growth in the agricultural sector.

Duality, Share Equations and Technology Biases

The method used here to remove the effect of technical change from Divisia weights described above involves the estimation of the share equation systems of both cost and revenue functions separately where technology is modelled explicitly within each equation. Constant technology cost and revenue shares are subsequently constructed by removing the estimated share biases from the observed shares for use as weights in the Tornqvist-Theil input and output indices.

The model used to estimate cost and revenue biases is based on the revenue function and the single output long-run cost function applying strict input output separability:

$$R = H\left(X, P, \mu(t)\right), \qquad C = G\left(Y, W, \mu(t)\right) \quad (10)$$

where R is revenue, *P* is a vector of output prices, *C* is cost and *W* is a vector of input prices, $\mu(t)$ represents a vector of 'technological states' and *H(.)* and *G(.)* are the functions which are dependent on the nature of the underlying technology of the production process. Provided that

$$R = \exp\left(H^*\left(x, p, \mu(t)\right)\right), \quad C = \exp\left(G^*\left(y, w, \mu(t)\right)\right) \qquad (11)$$

can approximate the long-run revenue and cost functions respectively (where the lower case letters denote the natural logarithms of the variables), the application of the Samuelson-McFadden Lemma to the revenue function gives

$$\frac{\partial H^*}{\partial p_i} = s_i\left(x, p, \mu(t)\right), \qquad (12a)$$

the share of revenue derived from the production of output *i*, the *n* output revenue share equations, and by Shephard's Lemma from the cost function yields:

$$\frac{\partial G^*}{\partial w_k} = s_k\left(y, w, \mu(t)\right), \qquad (12b)$$

the share of costs derived from the use of input *k*, the *m* input cost share equations.

The conditions

$$\frac{\partial s_i}{\partial t} = 0, \quad \text{for all } i \quad \text{and} \quad \frac{\partial s_k}{\partial t} = 0 \quad \text{for all } k,$$

that these shares, s_i s_k, are invariant to changes in technology, has commonly been defined as unbiased technical change. This definition is not the same as Hicks neutral technical change, and might be called output or input share neutrality (Chambers 1988, p.219).

The specification of both revenue and cost functions as translog (including $\mu(t)$) leads to linear share equations

$$s_i = \sum_j \theta_{ij} p_j + \beta_i x + \mu_i(t) + e_i, \quad \text{and} \quad s_k = \sum_l \theta_{kl} w_l + \beta_k y + \mu_k(t) + e_k \qquad (13)$$

The usual adding up conditions, homogeneity and symmetry apply in each case (Clark and Youngblood, 1992). In addition there is the requirement that $\Sigma\ \mu_i(t)=0$ and $\Sigma\ \mu_k(t)=0$, but there are no additional rank restrictions as implied by Lambert and Shonkwiler (1995).

Model Specification and Estimation

If $\mu(t)$, is modelled as a random walk with drift then from (13) the system of cost shares can be modelled as

$$\begin{aligned} s_{kt} &= \sum_l \theta_{kl} w_{lt} + \beta_k y_t + \psi_k T_t + \tau_{kt} + e_{kt} \\ \tau_{kt} &= \tau_{kt-1} + \upsilon_{kt} \end{aligned} \qquad (14)$$

where T is a simple deterministic time trend. v_{it}, e_{it} and v_{kt}, e_{kt} are assumed to be independently and identically distributed innovations. These are the standard type of revenue and cost share equations with the exception that they include an unobserved random walk τ_{it} and τ_{kt}. Under Var(υ_{it})=0 (or Var(υ_{kt})=0 in the case of inputs) then $\tau_{it} = \tau$ ($\tau_{kt} = \tau$), a constant intercept. This general framework allows for a wide class of models, which encompasses both cointegrated and non-cointegrated systems. The technical change biases are then measured by first estimating the models and subsequently constructing

$$\hat{\mu}_{kt} = \hat{\psi}_k + \hat{\mu}_{kt-1} + \hat{\upsilon}_{kt} \qquad (15)$$

which is the technological path for the kth cost share equation. The same treatment is applied to the revenue share equations by substituting the subscript i for k in equations (14) and (15). Unlike the simple linear trend model, this approach allows for periods when technical change may be saving a given input (or replacing a given output), and periods when technical change favours the increased usage of that input (or production of a given output).

There exist several approaches to estimation of the system in equation (14). The approach to estimation we use here is a generalization of the methods discussed by Maddala and Kim, p.470 (1998). Details of both the estimation and inference procedures applied here are described fully in Balcombe et al (2002).

3 DATA AND RESULTS

The data used in this paper record the annual aggregate activity of the agricultural sector of the United Kingdom over the period 1953 to 2000. These data, derived from series collected by DEFRA, the Scottish Executive Rural Affairs Department, the National Assembly for Wales and the Department of Agriculture and Rural Affairs Northern Ireland, are those reported by Holding and Thirtle (2002) within which a full description of the data and their construction can be found. The variables used here include the annual cost shares of livestock related inputs (feed, veterinary inputs, and livestock capital formation), crop material inputs (seeds, fertilisers, pesticides and miscellaneous crop inputs), power and machinery, buildings and land improvements, labour and land, some six inputs. Annual revenue shares of field crops (all arable products), horticultural products, livestock and livestock products (milk eggs etc), some four output groups in all. Price indices for each input and output for each year are also included as are standard Tornqvist-Theil indices of aggregate physical output and input.

This covers the endogenous and exogenous variables in the two systems of cost and revenue share equations defined in equations (14). From this set of equations, that for livestock products and that for land were dropped prior to estimation to avoid singularity.

Summary of Results

For the purposes of the arguments presented in this paper, a full discussion of the estimation results, in particular the estimated parameters, price elasticities and their associated standard errors is not of great intrinsic interest. At this stage we simply need to reassure ourselves that the estimated equation systems conform, broadly, to theoretical requirements. The interested reader can find a full set of parameter estimates and price elasticities in the Annex 1 and 2 respectively. At this point we simply report that a significant proportion of the estimated parameters appear to be significantly different from zero, the signs of the price elasticities conform to theory and that both systems account for a very large proportion of the variation in the shares. In addition, symmetry and homogeneity assumptions appear to hold for the revenue system but marginally fail in the case of the cost share system. On the whole, both systems of equations appear to perform well. While the cost shares do appear to be relatively unresponsive to changes in relative prices, the estimated price elasticities are not dissimilar from those reported elsewhere.

Table 1 presents the results of the two formal tests used to detect both the presence and nature of technology biases in the estimated systems. First, the Wald statistic is calculated for the joint removal of the random walk components from the two systems of estimated equations. In both cases, the Wald statistic exceeds the value of the bootstrapped critical value of the test and suggests that the random walk components should be retained at greater than a 99% level of confidence. Second, each system of estimating equations is formally tested for cointegration using the McCabe-Leybourne statistic. In each case, the McCabe-Leybourne statistic exceeds the value of the bootstrapped critical value and thus suggests that we reject the possibility that either system is cointegrated at a high (>95%) level of confidence.

Table 1. Tests for the Presence of Technical Change Bias

Function	Test	Statistic	Critical Value
Revenue	Wald	743.9	170.14
	McCabe-Leybourne	0.185	0.15
Cost	Wald	1931.52	276.93
	McCabe-Leybourne	0.20	0.189

Thus, both of these tests suggest that the null hypotheses, that the random walk latent variables provide no additional information and that the system is cointegrated, must be rejected at greater than a 95% level of confidence. The implication of these results is that technical change appears to be biased and these biases do appear to take on a stochastic rather than deterministic form.

Removing the Biases of Technological Change from Observed Share

In order to investigate the extent to which biased technical change alters the estimated accounting TFP we first need to adjust the observed cost and revenue shares. The time paths of the random walk components, $\mu_i(t)$, from equation (15), for each of the six cost and four revenue elements of the two systems of share equations form the appropriate adjustment to observed shares, to form estimates of $\alpha_i(X,0)$ (and $\alpha_k(X,0)$,), used to construct the output (and input) quantity indices in equation (9). One important point to note with regard to these time paths is that they inevitably capture all systematic impacts on cost and revenue shares which are not accounted for by price induced movements of and around unit isoquants, production possibility frontiers and aggregate, non-homothetic, scale shifts in cost or revenue, shares. As such, they will not only capture the impact of biases of technical progress but will also include any impact of non-price policy change on shares. Any such policy induced biases should be treated in the same way as technology biases since they too would conflate the Tornqvist-Theil index weights. Furthermore, the technology time paths will also capture any impact of farm level scale economies, caused by structural change in the sector, which, on face value, should be excluded from our adjustment. However, we consider that much of the structural change in the sector is likely to have been made possible by farm scale biases in technical progress that legitimately should be included and so we make no attempt to condition this effect out. For the current purpose we examine the revenue and cost share biases in time *t* proportional to the observed shares in time *t* in Figures 1 and 2 respectively. As such, the graphs depict the proportional adjustment required to convert observed revenue and cost shares into estimates of what Nelson and Pack (1999) have termed as "constant technology" shares.

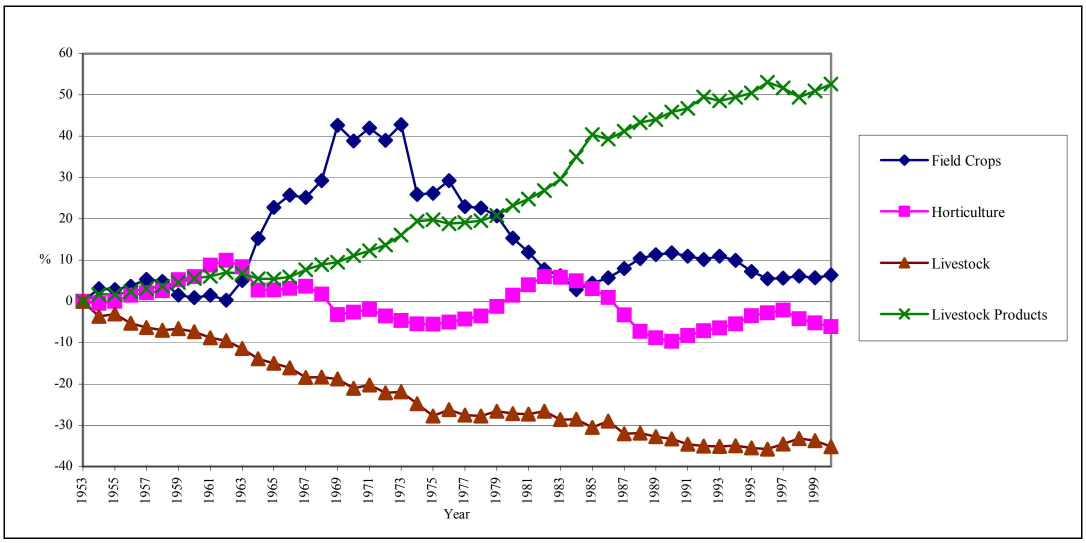

Figure 1. Proportional Adjustments to Observed Shares Required by Based Technical Progress: Revenue Shares

As the series presented in Figure 1 clearly show, the estimated share bias time-paths suggest that the observed revenue share of livestock products must, in the terminal period, be increased by 53% to restore it to the level which would have prevailed if technical change had been Hicks neutral over the entire period. Conversely, technical progress appears to have been biased in favour of an increased revenue share from livestock and this product's revenue share must be reduced by 35%. Technical progress does, however, appear to have had little impact on the share of horticulture in total revenue and the revenue share of this output requires very little, never more than ±10%, adjustment throughout the period. The advantage of representing technical change bias in a stochastic way is well illustrated in the case of field crops. Technical change appears to have been moving against this output from the late 1950s until 1973. Following 1973 a period of rapidly growing output promoting bias is observed which stabilised from the early 1980s but never quite returning to the 1953 level.

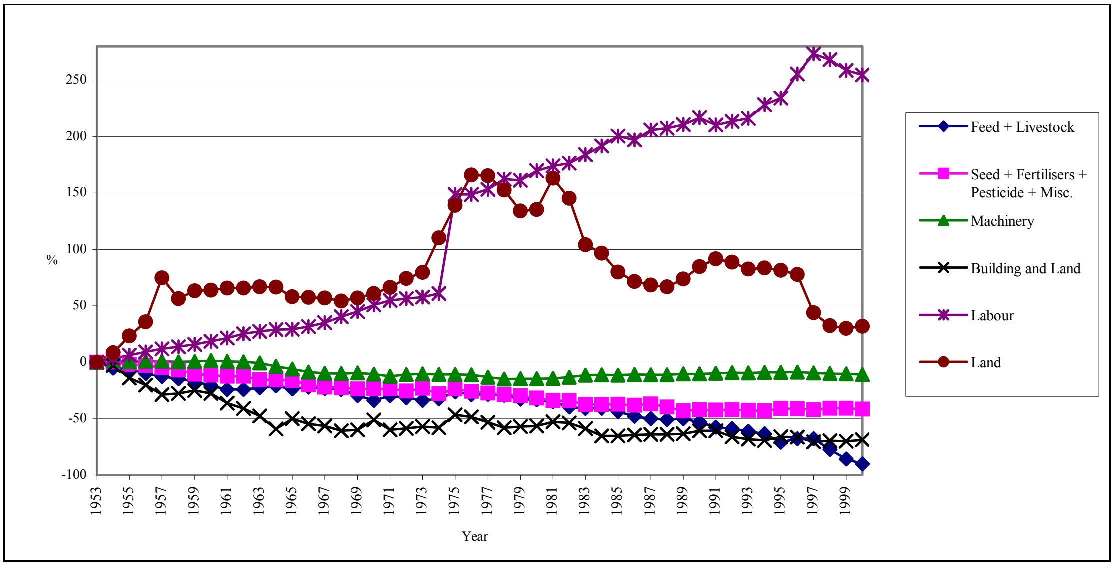

Figure 2. Proportional Adjustments to Observed Shares Required by Based Technical Progress: Cost Shares

On the input side of the account, Figure 2 reports that technical progress appears to have been cost share saving on both land and labour inputs and share using for all other factors. This result confirms the results of previous studies of factor biases, both in the UK (Khatri et al 1998) and in other countries (Townsend et al 1998, Balcombe et al 2000), and lends some tentative credence to the induced innovation hypothesis first discussed by Hicks (1932). Overall, the adjustment required to restore observed input shares into "constant technology" shares is much greater than that found for revenue shares and suggests that biased technical progress has had a much more profound effect on the input side of the UK agricultural account.

Bias in Conventional Divisia TFP

Figure 3 presents the TFP series constructed using conventional observed revenue and cost shares as weights in the Divisia aggregate output and input indices and the bias corrected or "constant technology" TFP constructed using our estimated constant technology shares. As can clearly be seen from the figure, the effect of simply assuming that technical progress conforms to the assumption of Hicks neutrality, in this case, results in a significant underestimation of real TFP growth. That is, by ignoring the technology biases within observed revenue and, more importantly in this case, cost shares, a large proportion of the TFP residual is conflated into the "accumulation" of outputs and inputs in particular.

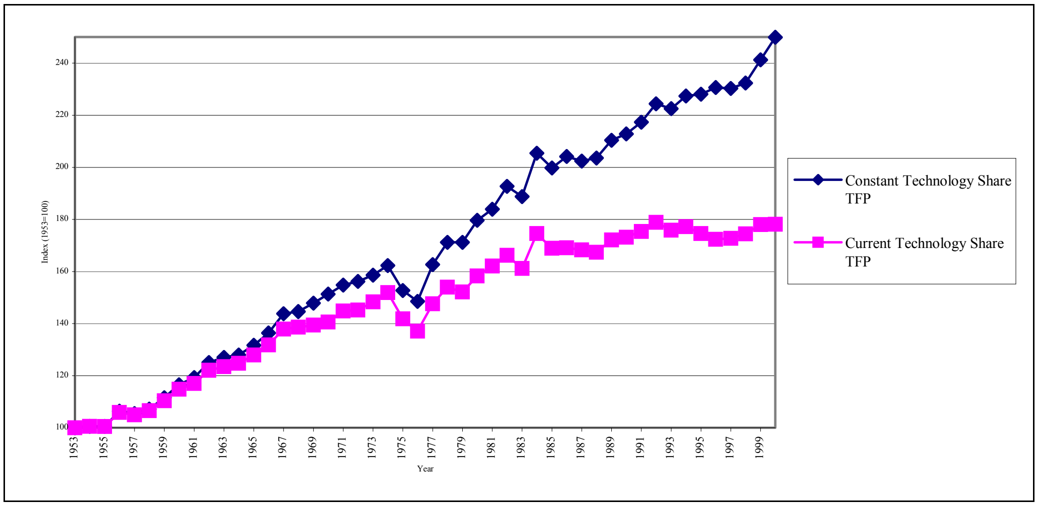

Figure 3. Conventional and Technology Bias Consistent TFP for UK Agriculture

The conflation of technology biases into the Divisia input and output quantity indices does appear to be most profound during the later part of the study period, from 1977 onward. This can be seen clearly in the results reported in Table 2. The conventional Divisia TFP suggests that the rate of TFP growth has reduced considerably over the sample period from relatively high rates, of over 2% per year in the 1950's and 1960's to just over a quarter of one percent in the 1990's. However, the use of our bias consistent indices suggests that the TFP growth rate achieved in the UK has been much more stable.

Table 2. Growth Rate lost by Conflation of Technical Change Bias in Conventional Divisia TFP Measures

Period	Average Annual Conventional TFP Growth	Average Annual Constant Technology TFP Growth	% Annual Average Conflated Growth
1991-2000	0.295%	1.632%	1.337%
1981-1990	0.952%	1.760%	0.808%
1971-1980	1.269%	1.810%	0.541%
1961-1970	2.061%	2.658%	0.597%
1954-1960	2.009%	2.235%	0.226%

The final column in Table 2 presents the additional average annual rate of Divisia TFP growth that is uncovered once technology biases are removed from factor shares. Data reported here suggests that the importance of recognising and compensating for the effect of biased technical change within the share weights used in the Divisia indices has grown through time.

An investigation of annual growth series for both the conventional and our TFP reveals that we do not have a monotonic effect. In some years the correction of bias in the share weights leads to an overestimation by the conventional TFP.

4 SUMMARY AND CONCLUSIONS

This paper examined the extent to which the assumption of Hicks neutrality in technical progress biases the estimates of the Divisia TFP residual when technical change is not Hicks neutral. The case of UK agriculture, over the period 1953 to 2000, is used for illustration. We review the theory underpinning the use of the Tornqvist-Theil discreet approximation to the Divisia index, and discuss the possible ways in which these measures can be modified to accommodate possibly biased technical progress. Previous work in this area, in particular the work of Nelson and Pack (1999), Felipe and McCombie (2000) and Murgai (2001) is found wanting since their approach to the approximation of constant technology Divisia weights requires estimates of the unobserved elasticity of substitution between inputs. Moreover, their methodology appears to be practical only when working from a very high degree of aggregation and when one is prepared to accept that technology biases are themselves fully separable. To counter these criticisms, we adopt a different approach to the estimation of constant technology share weights that both allows the practitioner to relax the assumption of Hicks neutrality at a low level of aggregation and avoids the need to guess the value of the various elasticities of substitution.

Translog revenue and cost share equations, including stochastic latent variables to model technological change, are used to detect and quantify the share biases. There is strong evidence that the latent variable representation of technical change is appropriate, that technical change occurred in a stochastic manner and that this technical change is itself biased. The results also suggest that the representation of technology as a smooth deterministic function of time is a severe mis-representation of the data. Technical change appears to explain a significantly large amount of the variation in cost shares.

The use of constant technology cost and revenue shares in the construction of Divisia input and output indices for use in TFP calculation does, in the case of UK agriculture, appear to significantly increase the value of the estimated TFP residual, over that of the conventional measure, in the majority of years. The incorrect use of a conventional, observed share weighted, Divisia TFP would, in this case, result in an 82% underestimation of the value of the the average annual TFP growth rate in the terminal decade. Moreover, the conventional TFP results would, erroneously suggest that the UK should invest considerable less in R&D directed toward agriculture in future years since a significant proportion of the benefit gained by technical progress, in the form of technology biases, has been misallocated to the input index.

We recognise that there is a degree of circularity in the arguments presented in this paper. Clearly, a measure of the Solow residual can be calculated directly from the cost or profit function without resort to index numbers. However, our proposed method for the correction of the Divisia weights only involves the estimation of the two systems of share equations from the revenue and cost functions, from which a Solow residual cannot be calculated. We also recognise that the separate estimation of revenue and cost shares is not ideal and does impose strong separability between outputs and inputs that may bias the results presented here. However, this methodology does provide a means of illustrating the degree of under (or over) estimation of the conventional accounting TFP. Moreover, this technique is relatively simple and inexpensive to apply in empirical studies.

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Annex 1. Parameter Estimates From Revenue and Cost Share Systems.

Of the seventy-two parameters estimated (for which standard errors are calculated) within both the system of revenue and cost share equations reported in Table A1 and A2, forty-eight are significantly different from zero at the 90% level of confidence. In addition, both estimated systems appear to account for a significantly large proportion of the variation in the shares as reported by the rather high values of the systems R^2 statistic in Tables A1 and A2.

Table A1. Revenue Share Equation Parameters*

	Field Crops	Horticulture	Livestock	Livestock Products
Field Crops	0.1025	-0.0252	-0.0266	-0.0507
	8.319	*-4.759*	*-2.740*	-6.013
Horticulture	-0.0252	0.0592	-0.0090	-0.0250
	-4.759	*9.224*	*-1.151*	-3.217
Livestock	-0.0266	-0.0090	0.0831	-0.0475
	-2.740	*-1.151*	*4.738*	-3.003
Livestock Products	-0.0507	-0.0250	-0.0475	0.1232
	-6.013	*-3.217*	*-3.003*	
Input Quantity	-0.0397	0.0139	0.0439	-0.0182
	-2.125	*1.707*	*2.947*	
Time Trend	-0.0004	0.0002	0.0028	-0.0026
	-0.340	*0.325*	*3.172*	
Systems R^2	*0.9994*			

*Figures in italic script are respective parameter *t*-ratios.

A joint Wald test for the hypotheses that both symmetry and homogeneity are present in the data was performed. For the revenue function, this test statistic has a value of 15.94, against a critical value of 27.14 at the 95% confidence level. However, in the case of the cost function, the corresponding Wald statistic has a value of 69.94 against a critical value of 41.46, again at the 95% confidence level. Thus, the assumptions of symmetry and homogeneity appear to be consistent with the revenue data but not with that of costs.

Table A2. Cost Share Equation Parameters*

	Feed & Livestock	Seeds, Fertilisers, Pesticide & Misc.	Machinery	Building & Land improve-ments	Labour	Land
Feed & Livestock	0.1851	-0.0396	-0.0432	-0.0224	-0.0702	-0.0096
	17.031	*-6.486*	*-7.809*	*-6.062*	*-13.248*	*-2.552*
Seeds, Fertilisers, Pesticide & Misc.	-0.0396	0.0642	-0.0066	0.0048	-0.0268	0.0040
	-6.486	*5.554*	*-0.739*	*0.789*	*-6.383*	*1.071*
Machinery	-0.0432	-0.0066	0.1219	-0.0372	-0.0287	-0.0062
	-7.809	*-0.739*	*10.913*	*-6.512*	*-7.102*	*-1.871*
Building & Land improvements	-0.0224	0.0048	-0.0372	0.0826	-0.0154	-0.0123
	-6.062	*0.789*	*-6.512*	*15.189*	*-6.002*	*-5.516*
Labour	-0.0702	-0.0268	-0.0287	-0.0154	0.1501	-0.0091
	-13.248	*-6.383*	*-7.102*	*-6.002*	*35.992*	*-3.291*
Land	-0.0096	0.0040	-0.0062	-0.0123	-0.0091	0.0334
	-2.552	*1.071*	*-1.871*	*-5.516*	*-3.291*	
Output Quantity	0.0339	0.0035	0.0071	-0.0021	-0.0261	-0.0163
	2.286	*0.440*	*0.928*	*-0.415*	*-3.035*	
Time Trend	0.0039	0.0018	0.0005	0.0022	-0.0078	-0.0006
	3.469	*3.797*	*0.985*	*6.844*	*-12.552*	
Systems R^2	0.9998					

*Figures in italic script are respective parameter *t*-ratios.

Annex 2. Estimated Hicksian Price Elasticities.

The estimated price elasticities of both supply and derived demand, which are reported in Table A3 and A4, are broadly consistent with a priori expectations. The figures on the principal diagonal in each case show that the own price elasticities of the output supply equations are all positive, and those of the input demands are negative. All of these own price elasticities appear to be of quite plausible magnitudes and suggest that the supply of each output is relatively inelastic and are not dissimilar to those found by Khatri and Thirtle (1996) using a similar data set. The reported t ratios, again constructed using a stationary bootstrap, confirm that the estimated own price elasticities of output supply are significantly different from zero in all cases.

Table A3. Hicksian Price Elasticities of Output Supply*

	Field Crops	Horticulture	Livestock	Livestock Products
Field Crops	**0.3109**	0.0088	-0.2603	-0.0594
	4.598	*0.322*	*-4.698*	*-1.386*
Horticulture	0.0179	**0.3404**	-0.2987	-0.0596
	0.322	*5.790*	*-4.400*	*-0.898*
Livestock	-0.1478	-0.0837	**0.4001**	-0.1686
	-4.698	*-4.400*	*8.154*	*-4.231*
#Livestock Products	-0.0441	-0.0218	-0.2204	**0.2863**
	-1.386	*-0.898*	*-4.231*	*4.480*

*Figures in italic script are respective parameter *t*-ratios constructed using a stationary bootstrap.

Five of the estimated cross price elasticities of supply reported in Table A3 appear to be significantly different from zero. All of these suggest some degree of substitution exists The only cross price elasticities that suggest a complementory relation between output groups might exist, for field crops and horticulture, appears to be insignificantly different from zero. In contrast, Khatri and Thirtle (1996) found no significant cross price elasticities from their long or short-run profit functions.

Table A4. Hicksian Price Elasticities of Derived Demand*

	Feed & Livestock	**Seeds, Fertilisers, Pesticide & Misc.**	**Machinery**	**Building & Land improve-ments**	**Labour**	**Land**
Feed & Livestock	**-0.0522**	0.0312	0.0391	0.0124	-0.0345	0.0040
	-0.999	*1.264*	*1.506*	*0.725*	*-1.236*	*0.233*
Seeds, Fertilisers, Pesticide & Misc.	0.0489	**-0.4583**	0.1586	0.1211	0.0678	0.0618
	1.264	*-5.145*	*2.301*	*2.896*	*1.461*	*2.118*
Machinery	0.0548	0.1415	**-0.1825**	-0.0958	0.0745	0.0074
	1.506	*2.301*	*-2.242*	*-2.421*	*1.450*	*0.308*
Building & Land improvements	0.0363	0.2259	-0.2001	**-0.0267**	0.0571	-0.0924
	0.725	*2.896*	*-2.421*	*-0.337*	*0.956*	*-2.677*
Labour	-0.0430	0.0539	0.0663	0.0243	**-0.0991**	-0.0024
	-1.236	*1.461*	*1.450*	*0.956*	*-1.790*	*-0.136*
Land	0.0284	0.2771	0.0370	-0.2220	-0.0133	**-0.1071**
	0.233	*2.118*	*0.308*	*-2.677*	*-0.136*	*-0.980*

*Figures in italic script are respective parameter *t*-ratios constructed using a stationary bootstrap.

In general the magnitude, and the level of significance, of the reported Hicksian price elasticities of derived demand in Table A4 is low. To some degree, the level of inelasticity reported in Table A4 can be attributed to the restrictive behavioural assumption of cost minimisation required here, a point noted in Khatri and Thirtle (1996 p348). To this extent the elasticities reported in Table A4 are similar to their counterparts in Khatri (1994) and Khatri et al (1998) who report elasticities estimated using a variable cost function on an earlier version of this data. Furthermore, the representation of technology bias in the specification used here is more general than that seen in previous studies. If technical change bias really is the dominant force effecting factor ratios, and our specification captures it's full effect, then price elasticities will be small.