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STOCHASTIC BIASES IN TECHNICAL CHANGE IN SOUTH AFRICAN AGRICULTURE

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This paper examines biased technical change in South African agriculture using a system of share equations with unobserved components. Developing on the work of Lambert and Shonkwiler (1995), this paper generalises previous work by introducing independent unobserved components into each model using a regression-based approach. We find evidence of stochastic technical change, which is itself biased between the four factors of production: machinery, land, labour and fertiliser, and which closely reflects distinct phases of South African agricultural policy and development.

1 INTRODUCTION

Technical change, or technological adoption is a critical element in the determination of factor productivity and factor rewards. However, while the importance of technical change and its associated biases has generally been recognised, its causes, measurement, and even definition, have been debated.

In common with Clark and Youngblood (1992) and Lambert and Shonkwiler (1995) we adopt a share equation approach, which is principally aimed at examining factor cost share biases in technical change rather than reconstructing the parameters, which determine the production technology itself. However, along with Lambert and Shonkwiler we treat technical change as a stochastic unobserved variable, and in doing so allow for the modelling of equations, which encompass both cointegrated and non-cointegrated systems.

The impetus for our approach is the view that modelling of technical change as a smooth deterministic function of time is likely to misrepresent the nature of technical change. The innovations themselves and the rate of technological adoption might not cause a smooth increase in the productivity of inputs.

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Arguably both the innovations themselves, the rate of adoption, and their impact are likely to be largely unpredictable, rather than deterministic. One avenue which would overcome the problem of treating technology in a deterministic way was developed by Townsend *et al* (1998). Their approach captured stochastic components by assuming a dependence of the technical change on those variables, which explain cost shares. Our approach is similar to that of Lambert and Shonkwiler (1995), which treats technology as a latent variable. However it differs in two ways. First, we use a regression approach to estimation, and secondly we allow for linearly independent unobserved components in each equation.

The paper is organised as follows. Section 2.1 discusses the theoretical framework of duality and technology within which this research is set, Section 2.2 considers model specification, estimation and inference of our cost function latent variable representation of technical change Section 3 describes the data and summarises the results and finally Section 4 draws conclusions.

2. THEORETICAL FRAMEWORK

2.1 Duality, share equations and technology

We focus on an indirect cost function:

$$C = H\,(P, Y, \mu(t)) \tag{1}$$

where

Y is a measure of outputs, and $\mu(t)$ represents a vector of 'technological states', C is cost, P is a vector of input prices and $H(.)$ is a function which is dependent on the nature of the underlying technology of the production process. Providing

$$C - \exp\,(H^*(p, y, \mu(t))) \tag{2}$$

(lower case letters denoting the natural log of a variable) can approximate the indirect cost function, the application of Shephard's Lemma gives

$$\frac{\partial H^*}{\partial P_i} = s_i\,(p, y, (t))$$

The condition that

$$\frac{\partial s_i}{\partial t} = 0 \quad \text{for all } i \tag{3}$$

has commonly been defined as unbiased technical change. This definition is not the same Hicks neutral technical change, and might be called input share neutrality (Chambers, 1988:219).

The specification of the indirect translog cost function as (including $\mu(t)$) leads to the a linear share equation

$$s_i = \sum_j \theta_{ij} p_j + \beta_i y + \mu_i(t) + e_i \tag{4}$$

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

2.2 Model specification and estimation

2.2.1 Specification

If $\mu(t)$, is modelled as a random walk with drift, then from [4]

$$\begin{aligned} s_{it} &= \sum_j \theta_{ij} p_{jt} + \beta_{i1} y_t + \lambda_i \cdot t + \tau_{it} + e_{it} \\ \tau_{it} &= \tau_{it-1} + \upsilon_{it} \end{aligned} \tag{5}$$

where v_{it} and e_{it} are assumed to be independently and identically distributed innovations. This is the standard type of share equation with the exception that it includes an unobserved random walk τ_{it}. Under Var(υ_{it})=0 then $\tau_{it} = \tau$ (a constant intercept). This general framework allows for a wide class of models, which encompasses both cointegrated and non-cointegrated systems. Technical change is measured by estimating the model and constructing

$$\hat{\mu}_{it} = \hat{\lambda}_i + \hat{\mu}_{it-1} + \hat{\upsilon}_{it} \tag{6}$$

which is the technological path of for the *i*th equation. Unlike the simple linear trend model, this allows for periods when technical change was moving in favour of a given input, and periods when it was moving against.

2.2.2 *Estimation and inference*

There are several avenues which one could pursue for estimation of the system above. The model is simply a special case of a random walk parameter model in which all parameters except the intercept have been constrained to have a zero variance. The estimation of these models can be approached via maximum likelihood using the Kalman Filter (or related filters) or spectral approaches (see Harvey, 1985). Alternatively a regression based approach (see for instance Maddala & Kim, 1989:470) can be used. The Kalman Filter has been the most popular method for the estimation of these models. However, Snyder (1990) argues the Regression based approach is at least as good. Moreover, since applied economists are likely to be more comfortable with the regression-based approach (which avoids both the detail of the Kalman Filter but also the unfamiliar specification in state space form), it is this avenue which we pursue here. The details of the estimation process are not covered in this paper, but are available on request.

3. EMPIRICAL SECTION

3.1 Data

The data employed in this paper record the annual aggregate activity of the commercial agricultural sector of the Republic of South Africa over the period 1947 to 1992. These data were first used by Thirtle *et al*. (1993), in which the data construction and definitions are fully described. Only a subset of the variables used in the Thirtle *et al*. study are used here, these include: the annual cost shares of all labour, land, fertiliser and machinery inputs, in addition to price indices for each of these inputs and an aggregate agricultural output index for each year. It is these data which form the endogenous and exogenous variables respectively in our system of 4 cost share equations.

3.2 Summary of results

The results of the model can conceptually be considered in two parts, the estimated cost share system itself and then the estimated technical change biases. Of the 18 parameter estimates of the cost share equation system presented in Table 1, six display a significant difference from zero at the 95%, and 10 at the 90% level of confidence. The data does not reject the assumptions of symmetry and homogeneity, the joint Wald test statistic for these hypotheses is presented in Table 2.

Table 1:

	Estimated parameters Cost shares		
Parameter	**Machinery**	**Labour**	**Land**
θ_{mj}	0.1103 (0.02201)	-0.00097 (0.004282)	-0.02014 (0.01281)
θ_{lj}	-0.00097 (0.004282)	0.0051 (0.005328)	0.001909 (0.005227)
θ_{aj}	-0.02014 (0.01281)	0.001909 (0.005227)	-0.02354 (0.01441)
θ_{fj}	-0.08917 (0.01699)	-0.00604 (0.004057)	0.04176 (0.01027)
β_I *(Output)*	-0.0278 (0.0191)	-0.04742 (0.02314)	0.01236 (0.02363)
λ_i *(Time trend)*	0.000833 (0.001188)	-0.00426 (0.001319)	0.002985 (0.001368)

System R^2 0.9951
Figures in parenthesis are standard errors.
Where m indexes Machinery, l indexes Labour, a indexes Land & f indexes Fertiliser.

Table 2:

Joint test for symmetry and homogeneity		
Wald statistic	**df.**	**Probability**
5.72	6	0.4555

The second part of the estimation investigates the effect of technical change. The Wald statistic presented in Table 3 relates to the joint test for the removal of the three random walk components from our system of estimated equations. This statistic suggests that the random walk components should be retained and as such our set of share equations cannot be characterised as a cointegrated system. The implication being that technical change is biased in a stochastic manner.

Table 3:

Joint test for the removal of 4 Random Walks	
Wald statistic	**Probability**
2702	<0.001

The price elasticities reported in Table 4 are broadly consistent with a priori expectations. The own price elasticities are all negative and less than unity, although the own price elasticity for land seems rather high (-0.9895). This may be due to the incomplete coverage of total farmland within the commercial sector and could indicate trade in land between the commercial and other subsectors of South African agriculture. All but one pair of cross price elasticities suggest a reasonable degree of factor substitution. The exception to this is that of fertiliser - machinery where a complementary relationship exists. This is in line with the complementary relationship found by Townsend *et al* (1998) and is not unexpected since the yield increase resulting from increased use of fertiliser is likely to increase the demand for machinery particularly at harvest. Table 5 presents the Allen Partial Elasticities of Substitution for completeness, however the conclusions remain the same.

Table 4:

	Price elasticities			
	Machinery price	**Labour price**	**Land price**	**Fertiliser price**
Machinery	-0.3273	0.3927	0.08761	-0.153
Labour	0.2806	-0.591	0.1636	0.1469
Land	0.1562	0.4081	-0.9895	0.4252
Fertiliser	-0.2669	0.3588	0.4163	-0.5082

Table 5:

	Allen partial elasticities of substitution			
	Machinery	**Labour**	**Land**	**Fertiliser**
Machinery	-1.157	0.9914	0.5518	-0.9433
Labour		-1.492	1.03	0.9059
Land			-6.233	2.622
Fertiliser				-3.134

Figure 1 presents the normalised estimated series constructed from the random walk components for each of our estimated cost share equations (where that for fertiliser is calculated residually). They show the change in cost share that cannot be explained by movements around the constant technology isoquant. As such, they can be interpreted as cost share biases in technical change.

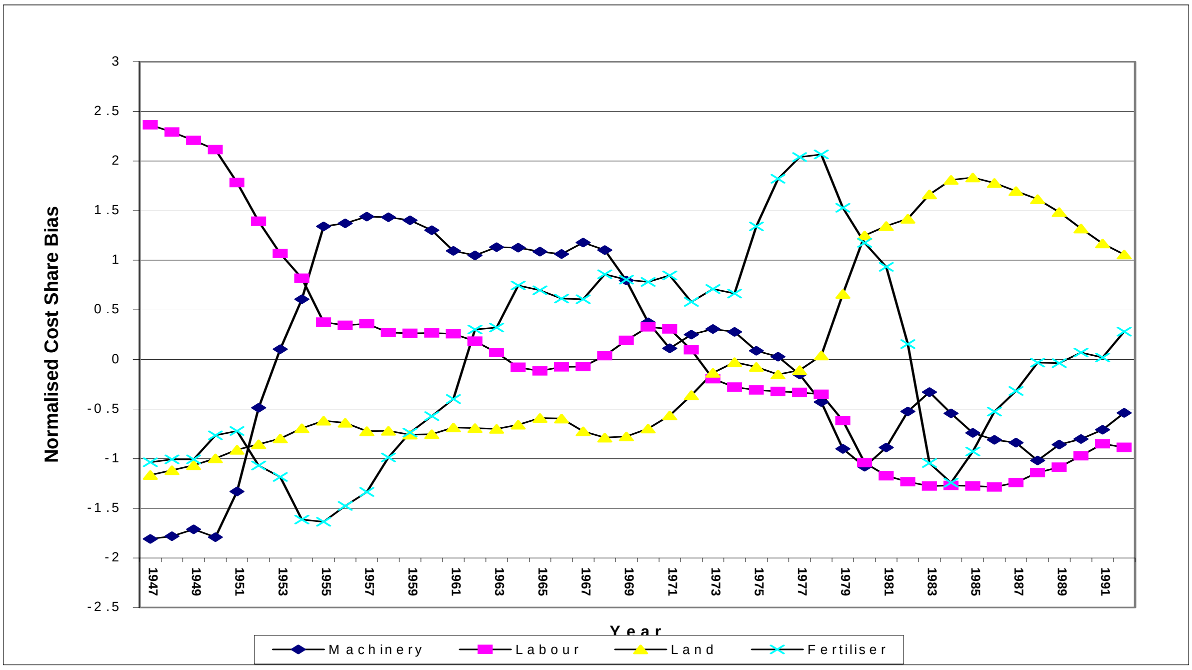

Figure 1: Technical change components

The trends in the technical change components depicted in Figure 1 reflect distinct changes in post war agricultural policy in South Africa. Between 1948 and the early 1980s, the commercial farming sector was transformed into one characterised by a dramatically reduced dependence on labour to one initially dependant on machinery and later more reliant on other inputs at the expense of labour. Pearce (1996) has suggested that the decline in the use of employed labour and its substitution by machinery has, to a large extent, been a reflection of the political rather than the economic environment. Townsend *et al* (1998) also find a large machinery using bias, however their results differ from those presented in this paper in that this occurs at a later stage and is not associated with a labour saving bias. The initial stages of the graph in Figure 1 (1947 - 57) depict a strong labour saving, machinery using bias in technical change. From 1955 there was a clear increase in the use of fertiliser that can not be explained by changing relative prices, but is perhaps explained by the wider commercial availability of improved chemical fertilisers. From the mid 1960s to mid 1970s there was a period of stability, with a small degree of re-substitution away from machines towards labour, possibly due to import supply difficulties.

From the late 1970's, several factors led to significant policy reform in the sector. These included the escalation of the budgetary cost of policies and increased isolation from world markets. These factors resulted in a reduction in subsidy levels and wider deregulation of financial and agricultural input and output markets. Van Rooyen *et al* (undated) suggest that in the late 1970s, producer prices rose by only 9% whilst costs rose 15%. Consequently, farmer's debt levels increased and by 1978 the sector's net income was only 62% of the total debt. This suggests that the price of capital and purchased inputs did not reflect their true scarcity to the farmer. This appears to be borne out in Figure 1 with a switch away from fertiliser and machinery towards a less intensive use of land. This might to some extent also be caused by an increased marginal productivity of land resulting from the use of improved crop varieties (an omitted variable in this study) from the mid 1970s onwards. In this respect, our results differ from those presented in Townsend *et al* (1998) who treat land as a fixed input.

4. SUMMARY AND CONCLUSIONS

This paper employed latent variables to detect and quantify cost biases in technical change in South African Agriculture. We found strong evidence for both stochastic technical change and that this technical change is itself biased between the cost shares of the four factors of production: machinery, land, labour and fertiliser. The results suggested that technical changes switched from factor saving to factor using (or *visa versa*) over time and that the representation of technology as a smooth deterministic function of time is a severe misrepresentation of the data. We also found that our estimated cost share biases correspond to distinct phases of South African agricultural policy and development. Future work in this field could generalise and encompass the approaches pursued in this paper and that followed in Townsend *et al* (1998). Such approaches could also be used to separate out induced and non-induced components

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