The Impact of Technology Accumulation on Technical Efficiency: an Analysis of the Sri Lankan Clothing and Agricultural Machinery Industries.

SONALI DERANIYAGALA[1]

ABSTRACT This paper examines the effects of technology accumulation on firm-level technical efficiency in the Sri Lankan clothing and agricultural machinery industries, using cross-section survey data. Econometric analysis of the economic effects of technology development in developing countries is limited and this paper seeks to address this gap in the literature. The analysis shows simple adaptive technical change to have a significant and positive effect on efficiency in both industries. In addition, variables relating to technological skills and training also emerge as significant determinants of firm-level efficiency.

1. Introduction

In recent years there has been increased interest in the issue of technology accumulation in developing countries. Empirical research has drawn attention to two aspects of technology accumulation; technical change and the acquisition of technological capabilities (Lall, 1993; Evenson and Westphal, 1995). The fact that technology accumulation by developing country firms who do not innovate at the global technology frontier is largely incremental and adaptive has been emphasised (Bell and Pavitt, 1993).

This recent literature has implications for analysing the economic performance of firms in developing countries. Recent theoretical models, in particular those in the evolutionary tradition, have demonstrated that incremental technology accumulation can have a positive impact on firm-level efficiency and productivity. Empirical research on this issue, however, is limited. While micro-econometric research on industrialised countries has shown technology accumulation involving formal Research and Development (R&D) to promote efficiency at the firm level (Hanusch and Hierl, 1992; Caves and Barton, 1990), these methodologies have rarely been used to investigate the economic impact of informal technology accumulation in developing countries. Some qualitative case studies of individual

[1] Sonali Deraniyagala, Department of Economics, SOAS, Thornhaugh Street, Russell Square, London WC1H OXG, UK. The author wishes to thank Frances Stewart, Sanjaya Lall and Martin Bell for comments on earlier versions of the paper.

firms in developing countries have shown technology accumulation to be positively related to firm performance (Katz, 1987; Dahlman and Fonseca 1987), but wider generalization from these studies is limited.

This paper addresses this gap in the literature by investigating the effects of technology accumulation on technical efficiency among clothing and agricultural machinery producers in Sri Lanka. Cross-section survey data is used to test the hypothesis that the two aspects of technology accumulation – technical change and technological capability acquisition – have a positive impact on technical efficiency. The clothing and agricultural machinery industries were chosen for two reasons. Firstly, given that clothing is an important entry level export industry for most developing countries, and light engineering sectors such as agricultural machinery produce generic skills and other externalities, testing the technology-efficiency link in these industries can have wider general implications. Secondly, both industries use relatively simple technologies and the proposed analysis provides a useful counterpoint to earlier qualitative research which focused on technologically advanced industries such as precision engineering, steel and cement.

The paper is organised as follows. Section 2 deals with data and definitions. Section 3 estimates firm-specific technical efficiency using a stochastic frontier model. Section 4 sets out the hypotheses relating to the determinants of technical efficiency and undertakes the econometric analysis of these hypotheses. Section 5 provides conclusions.

2. Data and Definitions

We focus on two aspects of technology accumulation: incremental technical change and technological capability acquisition. Incremental technical change is defined as minor change undertaken to adapt and improve a given 'core' technology- i.e. the technology used in the main stage of a firm's production process. It includes the adoption of equipment which enhances the performance of core technologies, minor adaptive changes to core technologies, technology upgrading in peripheral stages of production (such as design), as well as improvements in inventory control, quality control and production planning.

Technological capabilities are defined as the skills and knowledge related to such technical change.

The analysis in this paper is based on data for a cross-section of Sri Lankan firms in the clothing and light engineering industries, gathered from a field survey undertaken in 1993. The sample includes 40 firms in the clothing industry and 35 firms in light engineering. The measure of technical efficiency used assumes that firms produce homogeneous products (see Section 3). To be consistent with this assumption each industry sample contains firms making broadly similar product lines.

The dataset contains detailed technology-related information as well as production and financial details required to estimate technical efficiency. The capital, labour and output information relating to technical efficiency is for a single period, the year 1992. The information about various types of incremental change and technical and technological capability relate to the 5 years prior to 1992, the period 1987-1992. The technical change information is described in more detail below.

2.1 A Profile of Incremental Technical Change

The dataset contains information on the types of incremental technical change undertaken by firms during the five year period 1987-1992. The patterns of incremental change observed in each industry are summarised in Table 1. They are classified into two categories - 'simple' and 'complex' - according to the degree of technological complexity involved.[1]

Table 1 : A Profile of Technical Change

The Clothing Industry

Type of Technical Change	% of firms undertaking change
Simple Change	
Use of specialised machines	66
Use of equipment to improve fabric handling	30
Upgrading quality control	45
Upgrading inventory control	55
Computerised production planning	12
Complex Change	
Use of CAD at the design stage	15

The Agricultural Machinery Industry

Type of Technical Change	% of firms undertaking change
Simple Change	
Substitution of raw materials	44
Improving components	35
Modifying specifications of core machines-	53
Changing plant layout	53
Complex Change	
Use of CAD at the design stage	7

The *clothing industry* is 'supplier dominated' and technical change mainly involves the adoption and assimilation of new equipment (Hoffman and Rush, 1987). Light casual wear is the main product. 'Simple' change included the addition of equipment with potential to enhance the productivity of the core technology (in this case, industrial sewing machines). For instance, equipment to fold fabric and to reduce handling was introduced by around a third of the sample. A high proportion of firms also introduced simple specialised machines which can increase productivity in small tasks such as button-hole and collar stitching. Upgrading quality control and inventory control systems and the introduction of computerised production planning were other types of 'simple' change observed.

A small proportion of firms in the sample introduced computerised equipment for grading fabric and for making guides for cutting. This type of technology is fairly sophisticated and its adoption is classified as 'complex' technical change.

For *agricultural machinery* the types of technical change observed are summarised in Table 1, where the level of technological complexity is also indicated. Most firms in this industry made such products as small hand tools, pumps, power tillers, sprayers, threshers and shellers. They undertook basic cutting, bending, forging and welding operations using general purpose tools and simple, powered equipment. In this industry, simple change to alter and modify the core production technology was fairly common. Around 40 per cent of firms undertook in-house efforts to improve the quality and performance of inputs and components. This was accompanied by efforts to alter production processes to cope with new materials and inputs. Efforts to extend and 'stretch' the life of capital equipment were also noted. Other types of simple change included changing plant layout to reduce time and effort spent on moving materials

In addition, a minority of firms introduced computer-aided technology at the design stage. This was the only form of 'complex' incremental change undertaken in this industry.

2.2 The Model of Technical Efficiency

Prior to investigating the impact of technology accumulation on technical efficiency, this section sets out the model to be used for this purpose and derives a firm-specific efficiency measure.

Technically efficient production is defined as achieving the maximum attainable quantity of output from given inputs. The microeconomic concept of technical efficiency is based on the frontier production function which defines the maximum potential output which can be achieved by firms, given a specified mix of inputs and technology (Aigner, Lovell and Schmidt, 1977; Meeusen and van den Broeck, 1977). Deviations from this maximum output are ascribed to technical efficiency. Firm-level technical efficiency in a given industry is measured relative to the best performing firms in that industry.

Estimating technical efficiency first involves estimating a frontier production function. This can be done using two alternative methodologies; deterministic and stochastic models. The deterministic model envelops the data from above by drawing a convex hull around all the observed production points. This has the drawback of assuming that all deviations from the maximum are due to technical inefficiency. Therefore, errors in data measurement and other random disturbances in the dependent variable are interpreted as indicating technical inefficiency.

The stochastic model overcomes these problems. It is based on the assumption that the frontier production function depends on production and technology-related parameters as well as random disturbances. Therefore measurement error and noise in the data are taken into account. A stochastic frontier model is used here to derive firm-specific technical efficiency.

The model assumes a function relating the maximum possible output to certain inputs, such that, for a given firm *i*.

$$y_i = f(x_i, b) + \varepsilon_i \qquad (1)$$

where $i = 1....n$; y_i is output for observation *i*, x_i is a vector of inputs for observation *i*; b is a vector of parameters and ε_i is a statistical random disturbance term for observation *i*.

Consider now a situation where the *i*th firm does not produce on its frontier, but somewhere below it, thereby obtaining an output less than its maximum potential. This 'slackness in production' is seen to be caused by various factors which are not included in Eq 1, and is represented by the disturbance term ε. The stochastic model postulates that this disturbance term is made up of two independent components

$$\varepsilon_i = v_i - u_i \qquad (2)$$

where v_i ~N(0, $\sigma^2{}_v$) is a two sided error term representing the statistical noise found in any regression equation and $u_i.\geq 0$ is the one-sided error component representing technical inefficiency.

The one-sided error term, u, in Eq (2) is defined in such a way that it takes the value zero or less than zero. If u takes the value zero, this means that there is no inefficiency in production and the *i*th firm is technically efficient and produces its maximum potential output. On the other hand, when u takes the value less than zero, this implies that there is inefficiency in the *i*th firms production and it produces less than its maximum possible output. The magnitude of the value of u specifies the 'efficiency gap'; that is, how far a given firm's output is from its potential output. Thus for a given firm,

$$\text{Technical Efficiency (TE)} = \frac{\text{actual output}}{\text{potential output}}$$

In order to compute technical efficiency it is, therefore, necessary to estimate potential output, which can be done by the econometric estimation of the stochastic frontier production function. From this production function, firm-specific measures of technical efficiency (u) are derived. The formal method of doing this is well explained in Jondrow et al (1982) and is briefly shown in the Appendix. TE derived in this way, therefore, indicates the ratio of observed output to frontier output for individual firms. It can also be interpreted as the conventional measure of total factor productivity at the firm-level.

3. Empirical Estimation of Efficiency

We estimate firm-specific technical efficiency using the stochastic frontier production function methodology. The frontier production function adopted in this paper is :

$$\text{LnQ}= \ + \text{LnK} + \text{LnL} + \text{VINT}+v +u$$

The Cobb-Douglas representation was adopted as the functional form.[2] The dependent variable, LnQ, is the natural logarithm of value added, with LnK and LnL as the natural logarithms of the capital and labour measures respectively. Capital is measured in terms of historic costs[3]. The capital stock measure was turned into a flow of capital services using the annuity formula assuming a discount rate of 10%. Labour was measured in terms of 'unskilled equivalent person days' which combines skilled and unskilled labour. The ratio of skilled to unskilled wages was used for the conversion. VINT is a capital vintage variable and is defined as the average age of the ‘core’ machinery used by a firm in the main stage of production. The variable is commonly used when estimating frontier production functions in order to control for the ‘level of technology’. All variables are for a single year, 1992.

The stochastic frontier model assumes a single ‘level of technology’. To make this empirically operational only firms using ‘core technologies’ of the same level of complexity were included in each industry sample. ‘Core technologies’ are defined as technologies used in the main stage of production. Thus, in the clothing industry all firms used conventional industrial sewing machines. In the agricultural machinery sector, all firms used general purpose machine tools.[4]

The results of the estimation of the stochastic frontiers for the two industries are given in Table 2. The method of estimation was maximum likelihood, using the David-Fletcher-Powell algorithm. Starting values for the maximum likelihood estimates were obtained from an initial Ordinary Least Squares (OLS) regression. Similar estimates are also used to obtain starting values for the variance parameters of the model. The parameter estimates for labour and capital have the expected signs and significance levels. The vintage variable is not significant. This is likely to be a reflection of the fact that our study has already controlled for the level of technology by restricting the samples to firms using similar technologies. Particularly relevant for our analysis are the variance ratios, $\sigma^2 u/\sigma^2$. They are 0.83 and 0.79 and significant at the 1 per cent level in the clothing and agricultural machinery industries respectively. This is interpreted as indicating that firm-specific technical efficiency, rather than random factors, is responsible for the difference between the firm’s potential and actual outputs. This implication depends on the statistical validity of both the parameterisation of y in Equation 1 and the modelling of the firm-specific efficiency related parameter u .

Table 2 Stochastic Frontier Estimates (Maximum Likelihood)

Dependent Variable	Clothing	Agricultural Machinery
Log (labour)	.72 (.18) ***	.78 (.20) ***
Log (capital)	.55 (.14) ***	.49 (.16)***
VINT	.62 (.51)	.28 (.21)
Constant	.77 (.66)	.75 (.87)
Variance ratio	0.84 (.16)	0.79 (.13)
Log Likelihood	-37.36	-27.59

standard errors in parantheses
*** denotes significance at the 1 per cent level

Firm-specific indices of technical efficiency are obtained from this model in the manner suggested by Jondrow et al (1982), with Table 3 showing a frequency distribution of the measures. In the clothing industry, this measure ranges from 30% to 94% , with a mean level of 60%. For agricultural machinery the range is from 32% to 88% with a mean of 55%. The figures are broadly comparable with other studies. For example Hill and Kalijaran (1993) report a mean technical efficiency level of 63% for the Indonesian garment industry, while Pitt and Lee (1981) report a figure of 67% for the Indonesian weaving industry.

The fact that there is a wide variation in technical efficiency among sample firms is important. It shows that analysing the causes of inter-firm efficiency differences in these two samples is a useful task. A high degree of homogeneity in efficiency scores would have made this less relevant. Prior to estimating the determinants of technical efficiency, Section 4 sets out several hypothesis relating to the issue, focusing on our main concern which is the effect of technology-related factors on technical efficiency.

Table 3 Frequency Distribution of Technical Efficiency Scores

TE Score	% of firms clothing	% of firms : Agric. Machinery
30-40	15	23.3
41-50	17.5	26.6
51-60	27.5	20
61-70	20	13.3
71-80	10	10
81-95	10	6.6
Mean TE	60.3%	55%

4. The Impact of Technology Accumulation on Technical Efficiency

The initial focus is on two aspects of technology accumulation, technical change and the acquisition of technological skills and capabilities.

4.1 Technical Change

Adaptive technical change is hypothesised to have a positive impact on firm-level technical efficiency. Recent theoretical models postulate a positive link between adaptive technical change and efficiency at the firm-level. In particular, evolutionary models of firm behaviour show that firms using similar technologies can achieve varying levels of productivity because technologies need to be operationalised and assimilated into firm-specific contexts (Nelson and Winter 1982: Dosi 1997). This process involves adaptive technical change and it is predicted that efficiency levels among firms using similar core technologies will be positively related to the extent of adaptive technical change undertaken.

Two variables are used to capture adaptive technical change. The variable, MINOR, captures simple adaptive change and is a dummy relating to whether a firm undertook at least one of the 'simple' changes shown in Table 1 . The variable, COMPLEX, captures more advanced types of adaptive change and is again a dummy relating to whether a firm undertook any of the complex changes listed in the table. Both variables relate to efforts undertaken over the period 1987-1992. As efficiency is estimated for the year 1992, we are able to test the causality between technical change and efficiency in a fairly straightforward manner.

4.2 Capabilities

The importance of technological capabilities in promoting manufacturing performance has been emphasised by several analysts (Bell and Pavitt, 1993; Lall and Teubal, 1998). In particular, the fact that even the simple types of manufacturing undertaken in developing countries require industry-specific technological skills has been noted. It is also hypothesised that technological capabilities have a positive impact on technical efficiency. Technological capabilities are measured in terms of formal technical education and training using the variable TECHED. In the clothing industry, this is defined as the proportion of a firm's workforce with formal qualifications in clothing technology. In the agricultural machinery sector it refers to the proportion of the total workforce who are graduate engineers. Both variables are averages for the period 1987-1992. This again allows us to test the direct causal effects on efficiency in 1992.[5]

A high proportion of the firms in both industries were owner managed with decision making power being highly centralised Therefore, we also hypothesise that the technological skills of managers positively influence efficiency independently of workforce capabilities. The variable TECHMAN captures the education and training of senior managers. In the clothing industry, it is a dummy variable relating to whether any senior managers have a formal qualification in clothing technology. In the agricultural machinery industry, it is a dummy variable relating to whether any senior managers were graduate level engineers.

4.3 Other Determinants of Efficiency

In order to isolate the effects of technology accumulation on efficiency, we also examine the effects of several other determinants conventionally used in studies of the sources of technical efficiency.

Age of the Firm. The effects of firm age on efficiency are ambiguous. On the one hand, a positive relationship can be expected due to learning-by-doing which occurs with cumulative production experience. On the other hand, older firms may have older capital equipment and may have developed inefficient production routines and practices, leading to a negative impact of age on efficiency. The variable AGE is defined as the number of years since the inception of the firm.

Exporting. It is hypothesised that exporting has a positive effect on technical efficiency as it exposes firms to international competition and allows them to benefit from scale economies. Previous studies have found export-orientation to improve efficiency at the firm level (Caves and Barton, 1990; Chen and Tang, 1987). The variable EXPORT is the proportion of firm's total sales exported. Given that the causality between exports and efficiency can take the reverse direction, we take the average level of exports for the five years prior to the year for which efficiency is estimated. This variable is only included for the clothing industry as all the agricultural machinery firms produced entirely for the domestic market.

Foreign Ownership. Firms which are partly or wholly foreign-owned may have higher levels of efficiency than those domestically-owned if they have better access to financial resources as well as 'intangible assets' such as technological knowledge, skills and superior management practices (Pitt and Lee, 1981). The variable FOREIGN is the percentage of foreign equity in a firm .

Firm Size. The effects of firm size on efficiency are ambiguous. A positive effect can be predicted on the grounds of scale economies and the availability of financial resources to invest in skills and technologies. Firm size may be negatively linked to efficiency if large firms experience diseconomies in production due to problems of management and supervision. The existing evidence from developing countries does not suggest a strong link between efficiency and firm size in either direction (Little et al, 1987; Cortes et al, 1987). To test the effects the variable SIZE is simply the total number of employees in a firm. Again to minimise problems of causality, we take the average number of employees for the five years prior to the year in which efficiency is estimated.

Capacity Utilisation. We also include the variable CU, which is the capacity utilisation rate in 1992. This variable is conventionally included as a control variable when estimating the sources of firm-level technical efficiency.

4.4. Estimating the Sources of Efficiency

The following single equation relating to the sources of technical efficiency is estimated separately for each industry using OLS regression. The dependent variable TE is the natural logarithm of the firm-specific technical efficiency measure derived in Section 2.2

$$TE = \alpha_0 + \beta_0 MINOR + \beta_1 COMPLEX + \beta_2 TECHED + \beta_3 TECHMAN + \beta_4 AGE + \beta_5 EXPORT + \beta_6 FOREIGN + \beta_7 SIZE + \beta_8 CU$$

Table 4.1
The Sources of Technical Efficiency: the Clothing Industry

	Eqn 3.1	Eqn 3.2
MINOR	.12 (2.21)**	
COMPLEX	.15 (2.7)**	
TECHED	.10 (2.2) **	
TECHMAN	.09 (2.3)**	
AGE	-.01 (-0.6)	.001 (0.58)
EXPORT	.07 (2.14)**	.01 (2.2)**
FOREIGN	.005 (1.06)	.002 (1.6)
SIZE	.009 (0.06)	-.006 (-.18)
CU	.01 (1.8)*	.12 (2.3) ***

TA		.29 (3.11)***
Constant	.16 (2.1)	.56 (3.07)***
R	.58 , F= (8.1)**	
N	40	40

t-values in parentheses
* denotes significance at 10 per cent level
** denotes significance at 5 per cent level
*** denotes significance at 1 per cent level

Table 4.2
The Sources of Efficiency : The Agricultural Machinery Industry

Dependent Variable	Equation 3.3	Equation 3.4
MINOR	.16 (2.4)**	
COMPLEX	.008 (0.94)	
TECHED	.09 (2.5)**	
TECHMAN	.12 (2.2)**	
AGE	.001 (1.13)	.008 (.25)
CU	.005 (1.9) *	.05 (3.1) **
FOREIGN	.0 2 (.26)	.001 (1.09)
SIZE	-.33 (-.23)	-0.19 (-.38)
TA		.26 (2.3)**
Constant	.23 (2.2)**	.60 (4.0) ***
R	.36 , F= 2.5 **	.39 F= 3.2**
N	35	35

The results of the estimations are given in Tables 4.1 and 4.2 . Several diagnostic tests were carried out to check the reliability of the estimations. The modified Glesjer test confirmed the assumption of homoskedasticity in both cases. The RESET test and tests for normality of errors indicated that the assumptions of linearity and normality were maintained.[6]

Several variables relating to technology accumulation are significant in the estimation. The dummy variable MINOR, is positive and significant at the 5 per cent level in both industries, indicating that minor technical changes promotes technical efficiency. Given that the dependent variable is expressed in natural logarithms, the antilog of the parameter estimate of MINOR shows the magnitude of the efficiency gains from this type of technical change. In the clothing industry, it improved efficiency by 13%, with the corresponding figure for the agricultural machinery sector being 17 %.

This finding indicates that even firms using similar technologies can achieve efficiency levels that vary partly according to the extent of minor technical change undertaken. It is consistent with theoretical claims about the need to adapt technologies to suit firm-specific conditions, with technologies rarely having pre-determined levels of efficiency which are easily achieved. Further, the few existing studies which have attempted to quantify the economic effects of adaptive technical change have focused on high technology industries (Katz, 1987; Aw and Batra, 1998). Our findings show that this type of technical change promotes efficiency even in technologically simple industries such as clothing and agricultural machinery.

The dummy variable COMPLEX, relating to more sophisticated forms of technical change (in this case, the introduction of computer-aided design technology), is significant at the 5 per cent level in the clothing industry. The parameter estimate indicates that the magnitude is considerable, with this type of technical change increasing efficiency by 16 percent. This is likely to reflect the greater accuracy and speed of computer-aided design systems in the clothing industry, compared with manual design making. The survey also indicated that the greater accuracy of CAD systems at the design stage meant fewer production problems at the sewing stage (for instance, production was less likely to be stopped for design mistakes to be corrected) . In addition, firms using CAD systems claimed to be more efficient in fabric use, although the lack of detailed data means that this cannot be investigated further.

In contrast, the variable COMPLEX is not significant in for the agricultural machinery industry. Complex technical change, which again involved the introduction of computer-aided design technologies, does not appear to improve efficiency in this industry. Several reasons for this can be suggested. Firstly, CAD technology may be the wrong choice for firms who manufacture simple products for the domestic market. They can probably be just as easily be designed by manual methods. Secondly, firms using CAD technology may not have the requisite skills and expertise to manage it efficiently and maximise its potential. The field survey pointed to the lack of skilled operators which meant that, in many firms, the new CAD systems were not used frequently.[7]

The two variables relating to technological skills TECHED and TECHMAN, were both positive and significant at the 5 per cent level in both industries, the results indicating that formal, industry-specific training and knowledge promote technical efficiency. The field survey indicated that firms with high proportions of clothing technologists and graduate engineers (i.e those with high values for the TECHED variable) had fewer production problems than those with less technically qualified employees. For instance, machine down-time and teething problems following the installation of new technology was considerably less in the former than the latter. Further, the magnitudes of the efficiency gains arising from this type of capability acquisition are also considerable. For instance, the owner/senior manager having formal, industry-specific qualifications increased efficiency by 9% in the clothing industry and 13% for agricultural machinery. The significance of the capability variables also indicates that specialised knowledge can boost efficiency even in low technology sectors. Previous research which found formal training and skills to have a positive effect on efficiency focused mainly on high technology industries (Aw and Batra, 1998).

The EXPORT variable (included only for the clothing industry) is significant indicating that exporters have higher efficiency levels than non-exporters. This accords with the findings of several previous studies (Aw and Batra, 1998; Rodrik, 1995). This result can partly be explained by the fact that exporting captures aspects of efficiency enhancing technological skills and knowledge not reflected by the capability variables TECHED and TECHMAN. It has been noted that exporters benefit from international flows of knowledge from foreign buyers and traders (Keesing and Lall, 1992; Pack, 1992). This may enhance their productive efficiency vis-à-vis firms producing solely for the domestic market.

The AGE variable is not significant in either estimation. This could be due to the positive effects of experience-related learning being outweighed by the negative effects of factors such as inefficient production methods which become established in firms over time. The variable relating to foreign equity, FOREIGN, was also not significant in either estimation. This contrasts with some previous studies which have found foreign ownership to have a positive influence on efficiency, after controlling for other factors such as firm size (Pitt and Lee, 1981). However, given that most of these studies did not control for the effects of technology accumulation, the significance of the foreign ownership variables may have partly been the result of their correlation with unobserved technology-related factors.

The variable, SIZE, is also not significant for either industry. This result accords with previous research which does not point to a particularly strong relationship between size and efficiency (Little, Page and Mazumdar, 1987; Cortes, 1987). We also investigated whether SIZE influenced technical efficiency jointly with the other independent variables by carrying out alternative estimations using interaction terms. However, none of the interaction variables were significant, indicating that such joint effects were not important in these industries. The capacity utilisation variable CU is significant at the 10 per cent level.

The analysis so far has focused on the effects of individual aspects of technical change and technological skills on efficiency. It is also interesting to examine whether the overall extent of technology accumulation in a firm has a significant positive influence on efficiency. Research has indicated that technology accumulation generally has a cumulative and combined effect on firm performance (Dosi 1997). To test this hypothesis we derived a single variable, TA, by aggregating several individual technical change and capability variables. This variable captures the total extent of technology accumulation undertaken by a firm and was derived as follows.

Firstly, a set of binary variables (taking the values 0 or 1) relating to technology accumulation was derived. This included variables relating to each of the individual aspects of technical change shown in Table 1. The binary variables related to whether or not a firm undertook each specified type of technical change listed in this table. In addition, the two capability variables, TECHMAN and TECHED were also included. TECHED which was a continuous variable in the earlier estimation was redefined as a binary variable taking the value 1 if a firm employed any formally qualified clothing technologists or engineers, 0 otherwise. The complete set of binary variables was then aggregated and standardised (divided by the number of variables) to obtain a firm-specific score.

This single technology accumulation variable, TA, is therefore essentially a single score reflecting technological dynamism (the higher the score, the more dynamic the firm) and ranges from 0 to 1. Table 5 gives a frequency distribution of TA which shows considerable inter-firm differences in the extent of total technology accumulation undertaken in each industry sample. In order to examine whether inter-firm differences in efficiency are related to differences in technology accumulation, **a**nother estimation of the sources of efficiency was then done, using this single variable TA instead of the individual technical change and capability variables used previously (Tables 4.1 and 4.2). This variable was positive and significant and the other results were largely unchanged. Technology accumulation, therefore, appears to have cumulative effects on efficiency in both industries[8].

Table 5 : Frequency Distribution of Technology Accumulation Scores

TA score	Clothing (% firms)	Agricultural Machinery (% firms)
0-.25	20	13.3
.26-.50	30	53.3
.51-.75	37.5	26.6.
.76-1	12.5	6.6

Some limitations of the empirical analysis in this paper must be noted. Firstly, due to data limitations our analysis was constrained by the use of a single period measure of efficiency. Some of the longer-term, dynamic effects of technology accumulation may not show up on a single period measure of performance. We tried to minimise this problem by observing technology accumulation during the five year period prior to the year for which efficiency was measured as this would allow for some lagged effects on efficiency. However, it is important for future research to verify our results further by examining the effects of technology accumulation on efficiency growth over a longer period. Secondly, we were unable to test the joint effects of the independent variables on technical efficiency. For instance, our analysis sheds little light on whether firms who are both technologically dynamic and exporters have higher levels of efficiency than those which display only one characteristic. Some preliminary regressions using interaction variables indicated that such joint effects were not important. However, these results were not seen as reliable as adding interaction variables led to reduced the degrees of freedom, given our relatively small sample sizes. Again, it is important for future research to investigate these issues further using larger samples of heterogeneous firms.

5. Conclusions

This paper has shown technology accumulation to have a significant and positive effect on firm-level technical efficiency in the clothing and agricultural machinery industries in Sri Lanka. In both cases the two aspects of technology accumulation considered – technical change and the accumulation of technological capabilities – could promote efficiency. The analysis showed that firms using broadly similar technologies can achieve varying levels of efficiency depending on the extent of incremental, minor technical change undertaken for adaptation and assimilation. Technological capabilities, as proxied by the formal technical qualifications of the workforce and of senior managers, also had a positive and significant effect on efficiency.

This study enhances existing research in several ways. Firstly, our findings provide micro-level support for arguments relating to the importance of technology development in developing countries. Few studies examine the economic effects of the informal types of technology accumulation typically undertaken by firms in developing countries using econometric analysis on samples of heterogeneous firms. Our analysis, therefore, fills this gap in the literature. Secondly, given that we isolated the effects of technology accumulation on efficiency, by controlling for other potential determinants, we also added a new dimension to the literature on efficiency determination in developing countries which has focused on factors such as firm size, export-orientation and foreign ownership, largely overlooking issues relating to technology. Finally, by analysing the economic effects of technology accumulation in low technology industries, this study provides a useful counterpoint to much previous research which has focused on heavy industries and high technology sectors. The clothing and agricultural machinery sectors are usually the 'first-rung' industries in the path of industrialisation in most developing countries. Understanding the economic effects of technology accumulation in these industries, therefore, has important wider implications.

Appendix : Deriving Firm-Specific Measure of Technical Efficiency

This follows from the discussion of the model of technical efficiency in Section 2.2. In order to obtain firm specific technical efficiency scores it is necessary to make specific assumptions about the distribution of the error term *u* in Eq (2) (Section 2.1). In this paper, we assume that the one-sided error term *u* follows an exponential distribution, satisfying the condition $u > 0$ for a firm whose output lies below the frontier. Then, firm-specific efficiency for each observation in the sample is given by the mean of the efficiency error (u) conditioned on the total error ($v-u$). Thus,

$$E(\mathrm{u}|\varepsilon) = \mu_* + \sigma_* \ [\, f(-\mu_*/\sigma_*)/\ 1 - F(-\mu_*/\sigma_*)] \qquad (3)$$

where f and F represent the standard normal density and cumulative density functions, respectively and $-\mu_*/\sigma_* = \varepsilon\lambda\sigma$ where $\lambda = \sigma_u/\sigma_v$. .

This yields the point estimate of u_i, which is then used to obtain firm-specific technical efficiency (Te_i) as given by

$$\mathrm{TE}_i = \exp(-\mu_I). \qquad (4)$$

References

Aigner, C. Lovell and P Schmidt (1977) 'Formulation and estimation of

Stochastic Frontier Production Function Models', *Journal of Econometrics* (6), pp 21-37.

Aw, B and G. Batra (1998) 'Technological Capability and Firm Efficiency in Taiwan', *World Bank Economic Review*, Vol. 12 No 1, pp 59-79 .

Bell, M and K. Pavit (1993) 'Accumulating Technological Capability in Developing Countries' *Proceedings of the World Bank Annual Conference on Development Economics 1992*, pp 257-81.

Caves, R and D. Barton (1990) *Technical Efficiency in US Manufacturing Industries*, (Cambridge:MIT Press).

Chen, J and D. Tang (1987) 'Comparing Technical Efficiency Between Import-Substituting and Export Oriented Firms in a Developing Country', *Journal of Development Economics* 26, (August), pp 277-89.

Cortes, M, A. Berry and A. Ishaq (1987) *Success in Small and Medium Scale Enterprises: Evidence from Colombia*, (Oxford:OUP).

Dahlman, C. and F. Fonseca (1987) 'From Technological Dependence to Technological Development; the case of the USIMINAS steel plant in Brazil' in J. Katz (ed) *Technology Generation in Latin American Manufacturing Industries* , (Basingstoke: Macmillan).

Dosi , G (1997) 'Opportunities, Incentives and Collective Patterns of Technological Change', *The Economic Journal* , 107, September, pp 1530-1547.

Evenson, R and L. Westphal (1995) ' Technological Change and Technology Strategy', in J. Behrman and T.Srinivasan (ed) *Handbook of Development Economics* Vol. 3A (Amsterdam: North -Holland).

Hanusch, H. and Hierl, M (1992) 'Productivity, Profitability and Innovative Behaviour in West German Industries', in F. Scherer and M. Perlman (eds) *Entrepreneurship, Innovation and Economic Growth* , (Ann Arbour: University of Michgan Press).

Hill, H and P. Kalijaran (1993) 'Small enterprise and firm level technical efficiency in the Indonesian garment industry', *Applied Economics*, Vol. 25, pp 1137-1144.

Hoffman, K and H. Rush (1987) '*Microelectronics and Clothing*', (New York; Praeger).

Jondrow, J,. K. Lovell. I. Materov and P. Schmidt (1982) ' On the estimtation of Technical Inefficiency in the Stochastic Frontier production Model', *Journal of Econometrics* , Vol. 19, No. 2/3, pp 233-238.

Katz, J (1987) 'Domestic Technology Generation in LDCs: a Review of Research Findings' in J. Katz (ed) *Technology Generation in Latin American Manufacturing Industries* (Basingstoke: Macmillan).

Keesing, D. and S. Lall (1992) Marketing Manufactured Exports from Developing Countries', in G. Helleiner (ed) *Trade Policy, Industrialisation and Development,* (Oxford: Clarendon Press).

Lall, S and M. Teubal (1998) ' Market stimulating Technology Policies in Developing Countries: a Framework with examples from East Asia', *World Development*, Vol 26, No 8 pp 1369-1385.

Lall, S (1993) 'Understanding Technology Development', *Development and Change,* Vol. 24, No. 4, pp 719-53.

Little, I., D. Mazumdar and J. Page (1987) *Small Manufacturing Entreprises: A comparative Analysis of India and Other Economies,* (Oxford:OUP).

Meeussen, W and J. van den Broeck (1977) 'Efficiency Estimations from Cobb-Douglas Production Functions with Composed Error Terms', *International Economic Review* Vol. 18, (June), pp 435-44.

Nelson, R. and S. Winter (1982) *An Evolutionary Theory of Economic Change* (Cambridge, Mass: Belknap Press of Harvard University).

Pack, H. (1992) ' Learning and Productivity Change in Developing Countries', in G. Helleiner (ed) *Trade Policy, Industrialisation and Development* (Oxford: Clarendon).

Pitt, M. and L Lee (1981) 'The Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry', *Journal of Development Economics,* Vol. 9 (August), 43-54 .

Rodrik, D. (1995) ' Trade and Industrial Policy Reform. in J. Behrman and T. Srinivasan (eds) *Handbook of Development Economics* Vol 3B (Amsterdam:North -Holland).

Notes

[1] This classification was done in consultation with technical experts from the industry.

[2] Whilst alternative functional forms such as the translog are more flexible, they consume more degrees of freedom and reduce the precision with parameters are estimated. Trial estimations of the translog functions showed them to suffer from problems relating to degrees of freedom.

[3] The dataset contained information on the acquisition costs of capital and on the dates of acquisition. These were deflated using 1982 prices and aggregated. The capital stock measure was turned into a flow of capital services

using the annuity formula and assuming a discount rate of 10 per cent. A similar measure of capital is used by Little et al (1987).

[4] Both samp les therefore excluded firms which used numerically controlled machinery in the main assembly stage of production.

[5] It is important to be careful about the direction of causality because causality can take the reverse direction, with more efficient firms earning higher profits and investing more in technology accumulation. Both the technical change and capability variables relate to the period prior to the year for which efficiency is estimated for this reason.

[6] The correlations between the independent variables was and the correlation matrix indicated that strong correlations between these variables did not exist.

[7] Data to test this econometrically was not available.

[8] This result can also be taken as indicating the robustness of our estimation to alternative specifications.