CHAPTER 2

EFFICIENCY AND TECHNICAL CHANGE IN MANUFACTURING

2.1 INTRODUCTION

Little is known about the extent of technical change and the level of manufacturing efficiency in South Africa during the last 25 years; yet, improved efficiency can be an important source of welfare gains, because firms are led to adopt new technology and reorganise operations to compete at the world market, while production shifts towards firms with better productive efficiency[16] (Pavcnik, 2000:3). The important policy issue of whether more exposure to increased trade improves the efficiency of industries requires more empirical investigation to generate an acceptable consensus in Africa. Indeed, while most analysts believe that increased trade raises manufacturing efficiency, there remains little direct evidence that has been marshalled in this respect in Sub-Saharan Africa (Naudé et al 2000:9). To test this hypothesis, a rich panel data set on manufacturing industries in South Africa is used. Efficiency and technical change scores for the manufacturing industries are calculated from an underlying production function. The evolution of technical change and industry efficiency are then examined as channels through which trade expansion could have affected manufacturing performance during the 1980-2002 period.

An examination of the evolution of technical change and industry efficiency in manufacturing helps us to see how industry responded to trade expansion, and,

[16] A quasi-experimental study employing a Ugandan data set found a significant increase in technical efficiency for firms that produce import competing products. This evidence was striking and clearly demonstrated that, subject to increased global competition from trade liberalisation, firms increased their technical efficiency (Kasekende, Abuka and Asea, 1999).

in particular, how they adjusted to remain competitive[17]. This research contributes to the development of studies regarding the behaviour and performance of industries at a disaggregated level, especially in isolating the impact of industry heterogeneity on technical efficiency. In a nutshell, this investigation applies panel data econometric techniques to estimate productivity losses due to technical inefficiency.

Chapter 2 sets out to provide empirical estimates of efficiency and technical change in South Africa's manufacturing sector. The rest of the chapter contains these results, beginning with the discussion of the literature relevant to efficiency estimation in Section 2.2. The empirical specification is presented in Section 2.3. The data investigated is discussed in Section 2.4. The results are provided in Section 2.5, which is followed by concluding comments in Section 2.6.

2.2 MEASURING EFFICIENCY AND TECHNICAL CHANGE

2.2.1 Importance of decomposing total factor productivity

One advantage of frontier production functions is that they offer the promise of decomposing productivity change into movements of the production surface (usually deemed to be "true" technological change) and movements toward or away from the surface (changes in efficiency,[18] with which a given technology is

[17] Under liberalisation firms should eliminate waste, reduce managerial slack and achieve a better cost control to remain competitive (Ferrantino et al, 1995). Labour laws may not allow this to happen.

[18] It is argued that liberalisation of the trade regime influences efficiency through various channels (Tybout and Westbrook, 1995). Liberalisation allows firms to achieve economies of scale by taking advantage of market expansion, it enables firms to absorb technologies and knowledge through participation in foreign markets, it pressures firms to reduce x-inefficiency in order to cope with competition from abroad and it forces firms to refrain from rent seeking behaviour. The finding of significant improvements in technical efficiency in manufacturing during the

applied). The presumption is that, over time, the production function will shift upward, associating larger quantities of output with smaller quantities of inputs, demonstrating the existence of technological progress. However, some panel estimates have shown that production surfaces may move in the opposite direction, as well, indicating what might be called "technological regress" (Piesse and Thirtle, 2000:490).

A number of studies employ national income accounting data to track productivity and efficiency change (De Wet, 1998 and Du Toit , 1999). However, the use of aggregate-level data tends to ignore industry specific characteristics that are fundamental from a productivity point of view (Mahedevan and Kim, 2003:670). Again, adopting the conventional growth accounting approach could yield estimates of total factor productivity without distinguishing the two components of productivity.

Moreover, the production process is not simply an engineering relationship between a set of inputs and observed output; hence, even a well defined function cannot describe production accurately, because variation in inputs does not necessarily result in a corresponding change in output (Han et al, 2002:402). Observed output is a result of a series of economic decisions, which influence the method of application of inputs; thus, variables associated with institutions will play an important part in a firm's output. Given these reasons, some firms are likely to produce not on but inside their optimum production possibility frontiers, with an actual gap between optimal and realized methods of production arising from the effects of organizational factors. Studies that measure productivity as a whole, and are unable to decompose it into measures of efficiency and technical change, will show output to be chiefly accounted for

period of trade expansion in South Africa would suggest that welfare may have improved as a result.

by input growth. Little is left over to be attributed to technical change (Mahadevan and Kalirajan, 2000:829).

The objective should be to decompose output growth into growth due to inputs, changes in the output gap and technical change. Improvements in efficiency measure how the output gap between optimal and realized production methods evolves over time. This effect can be substantial, and may outweigh gains from technical change itself. It is important to know how far one is off the production frontier at any point in time, and how quickly one can reach the frontier. Technical change on the other hand measures the movement of the production frontier over time. It reflects the success of explicit policies to facilitate the acquisition of foreign technology and can be interpreted as providing a measure of innovation (Han et al, 2001:404).

The recognition that improvements in efficiency as well as technical change are continuous processes implies that it is possible for high rates of technical change to coexist with deteriorating efficiency. It is also possible for relatively low rates of technical change to coexist with improving efficiency. Most importantly, different policy implications result from different sources of variation in productivity. Mahadevan and Kalirajan (2000:829) stress that the decomposition of productivity is a useful exercise in distinguishing adoption of new technology by efficient industries from the diffusion of technology. The coexistence of a low rate of technical change and a low rate of efficiency may reflect failures to achieve technological diffusion. Moreover, since the measure of technological mastery is highly correlated with the level of human capital development, it assumes a particular significance in an emerging economy's development process (Han et al 2003:405). Technical change shows the movement of the firm's actual output to its maximum possible output given technology. Improvements in efficiency result in increased output if given inputs and technology are used efficiently due to accumulation of knowledge in the learning-by-doing process, improvements in the instructions of combining inputs, diffusion of new technology and knowledge and improved managerial practice. Efficiency and technical change are analytically very different and it is important to distinguish between them for policy making (Mahedevan 2001:593).

2.2.2 The stochastic frontier production function

Stochastic frontier production functions have facilitated the measurement of firm level technical efficiency. Two measurement approaches are available. One of the approaches is deterministic, in the sense that all deviations from the frontier are attributed to inefficiency and the maximum output attainable in this case is represented as a scalar. The other approach is stochastic and represents a considerable improvement over the deterministic variant; in this case, the maximum output is a random variable or a distribution of outcomes making it possible to discriminate between random errors and differences in inefficiency (Griffin and Steel, 2004).

Stochastic frontiers have been used in the study of firm efficiency and productivity since they were first independently proposed by Aigner, et al (1977) and Meeusen and van den Broek (1977). A production frontier represents the maximum amount of output that can be produced from a given level of inputs. Since firms typically fall below the maximum that is possible, the deviation of actual from maximum output becomes the measure of inefficiency and is the focus of interest in most empirical work. However, the distribution to be used for the inefficiency error has been a source of contention (Griffin and Steel, 2004:2).

One problem with cross sectional data in inefficiency measurement is that technical inefficiency cannot be separated from firm specific effects that are not related to inefficiency (Battese and Coelli, 1995; Battese et al, 2000). Panel data avoids this problem,[19] and, indeed, the availability of panel data allows writing the stochastic frontier production function in the form:

$$Y_{it} = f(X_{it}, \beta) + \varepsilon_{it} \qquad (1)$$

where Y_{it} is the output or value added for the ith industry in year t, X_{it} is a vector of input variables and β is a vector of unknown parameters to be estimated and $f(.)$ denotes either a Cobb-Douglas or translog production function. Green (2000:395) indicates that in the stochastic model, it is the disturbance, which is the central focus of analysis rather than the catch-all for the unknown factors omitted from the regression.

This model, therefore, combines two stochastic elements in the error term, i.e., $\varepsilon_{it} = v_{it} - \mu_{it}$. The conventional symmetric error term v_{it} is assumed to be independent and identically distributed as $N(0, \sigma^2{}_v)$ and captures variation in output that results from factors that are beyond the control of the industry such as labour market conflicts, measurement pathologies in the dependent variable and excluded explanatory variables. The remainder component of the error term is the disturbance μ_{it}, which captures industry-specific technical inefficiency in production.

Different cases have been assumed for the distribution of the technical inefficiency effects. The first basic model specified that they are i.i.d random variables, which implies that there are no particular advantages in obtaining observations on a given industry versus obtaining observations on more industries at particular time periods. The second basic model assumed that

[19] While implementing efficiency measurement using panel data, it is important to distinguish technical inefficiency from firm and time specific effects. These effects are normally separate from exogenous technical progress. In a panel data context, it is possible to decompose the error into firm specific effects, time specific effects, the white noise and technical inefficiency (Kumbhakar, 1991).

technical inefficiency effects are time invariant. Battese and Coelli (1988) extended this model so that the technical inefficiencies had a generalised truncated-normal distribution as proposed by Stevenson (1980). Battese, Coelli and Colby (1989) further extended this model to allow use of unbalanced panel data. However, the assumption that technical inefficiency effects are time invariant becomes more difficult to justify especially as T becomes larger[20]. Although Kumbhakar (1990) proposed a stochastic frontier model for panel data, in which technical inefficiency effects vary systematically with time in a time varying specification, this model has not be widely applied. In response, Battese and Coelli (1992) suggested an alternative to Kumbhakar (1990) model in which the technical inefficiencies are an exponential function of time involving only one unknown parameter. One advantage of the time varying inefficiency model is that technical inefficiency changes over time can be distinguished from technical change.

2.2.2.1 Measuring technical efficiency

In Coelli (1996:8), technical efficiency of an individual firm is defined in terms of the ratio of the observed output to the corresponding frontier output, conditional on the level of inputs used by the firm. Technical efficiency of firm i at time t in the context of a stochastic frontier production function equals the ratio of observed output to estimated frontier output:

$$TE_{it} = \frac{Y_{it}}{\exp\left(f\left(X_{it};\alpha\right)\right)} = \exp(-\mu_{it}) \qquad (2)$$

Since μ_{it} is by definition a non-negative random variable, the technical efficiencies will lie between zero and unity, where unity indicates the firm is technically efficient.

[20] This is because managers learn from there previous experience in the production process and so their technical inefficiency effects would change in some persistent pattern over time (Coelli, Rao and Battese, 1998).

Battese and Coelli (1992) show that it is possible to estimate a stochastic frontier production function for panel data, which has firm effects that are assumed to be distributed as truncated normal random variables, which are also permitted to evolve systematically over time. Given the availability of panel data, a choice has to be made between time invariant or time varying efficiencies. The preferred model should be selected on the basis of statistical criteria.

2.2.2.2 Measuring technical change

A critical issue in panel data modelling is the specification of technical change,[21] because the specification reveals the time path of efficiency and whether inefficiency is transitory or permanent. According to Heshmati and Nafer (1998:183), technical change has traditionally been described as a single time trend. With the advent of the flexible functional form, technical change can be generalized by the introduction of quadratic terms in the time trend with inputs in production functions. This generalised index allows the rate of technical change to be both variable and non-neutral. The general index approach of Baltagi and Griffin (1988) can model pure technical change, because no *a priori* structure is imposed on its behaviour. A time dummy allows the time effects to switch from positive to negative and back to positive. In this case, an estimable Cobb-Douglas production function would be of the form:

$$\ln Y_{it} = \alpha_0 + \alpha_k \ln(K_{it}) + \alpha_l \ln(N_{it}) + \alpha_m \ln(M_{it}) + \sum_t \lambda_t D_t + \left(\nu_{it} - \mu_{it}\right) \qquad (3)$$

In this specification, D_t is a dummy variable having a value of one for the t^{th} time period and zero otherwise and λ_t are parameters to be estimated. The dummy variable D_t is introduced to model pure technical change in line with the general

[21] Stochastic frontier literature for panel models, has two main groups: (i) those that assume technical efficiency to be time invariant (Pitt and Lee, 1981, Schmidt and Sickles, 1984, Battese and Coelli, 1988, and (ii) those that assume technical efficiency is time varying (Cornwell et al, 1990, Kumbhakar, 1990, Battese and Coelli, 1992, Lee and Schmidt, 1993).

index approach of Baltagi and Griffin (1988). The change in λ_t between successive periods becomes a measure of the rate of technical change[22], which can be summarised as:

$$TC_{t,t+1} = \lambda_{t+1} - \lambda_t \tag{4}$$

The implication is that for the hypothesis of no technical change, $\lambda_t = k \quad \forall t$ in model (4).

2.2.2.3 Panel data production frontier models

Panel data contains more information than does a single cross section, it therefore enables some strong distributional assumptions used in cross-sectional data to be relaxed and while estimates of technical efficiency with more desirable statistical properties are obtained. There are three difficulties with cross-sectional stochastic production frontier models summarised in Kumbhakar and Lovell (2000:95).

First, maximum likelihood estimation of the stochastic production frontier and the subsequent separation of technical inefficiency from statistical noise requires strong distributional assumptions on each error component. Panel data on the other hand enables us to adapt conventional panel estimation techniques to the technical efficiency measurement problem without invoking the strong distributional assumptions. Second, maximum likelihood estimation also requires the assumption that the technical inefficiency error component be independent of the regressors. However, not all panel data estimation techniques require the assumption of independence of the technical efficiency error

[22] The assumption that technical efficiency is constant through time is a strong one if the operating environment is competitive and the panel is long (Kumbhakar and Lovell 2000). Although the assumption of time invariance of technical efficiency is justified by the fact that only about half of the panel period can be justified as actually competitive, it is possible to vary this assumption.

component from the regressors. Finally, technical efficiency of industries in the cross section cannot be consistently estimated since the variance of the conditional mean or mode for each individual industry does not go to zero as the size of the cross section increases. Panel data helps to avoid this drawback because adding more observations on each industry generates information not provided by adding more industries to cross section. Technical efficiency of each industry can be consistently estimated as $T \rightarrow +\infty$.

2.3 ECONOMETRIC SPECIFICATION

Estimation of stochastic frontier production functions is preferred, because it facilitates derivation of measures of efficiency and technical change. In addition, it deals with the weakness in the non-frontier methodology assumption that all industries are fully realising their capacity in the production process and are thus efficient (Mahadevan, 2001:588). This assumption can ignore possible gains from technical change because the total factor productivity residual is taken to be synonymous with disembodied technological progress. The two components are analytically very different and it is important to distinguish between them for policy making as shown in Obwona (1994:133) and Piesse and Thirtle (2000:478). In a panel context, the stochastic form of the translog functional form, using a general index formulation for time, can be stated in equation (5) as:

$$\ln(Y_{it}) = \alpha_0 + \alpha_k \ln(K_{it}) + \alpha_l \ln(N_{it}) + \alpha_m \ln(M_{it}) + \alpha_{kl} \ln(K_{it})\ln(N_{it}) + \alpha_{km} \ln(K_{it})\ln(M_{it})$$
$$+ \alpha_{lm} \ln(N_{it})\ln(M_{it}) + \left(\frac{1}{2}\right)\left\{\alpha_{kk}(\ln K_{it})^2 + \alpha_{ll}(\ln N_{it})^2 + \alpha_{mm}\ln(M)^2\right\}$$
$$+ \sum_t \lambda_t D_t + \left(\nu_{it} - \mu_{it}\right) \qquad (5)$$

where; $i = 1,........28$ defines the number of industries and $t = 1,.......23$ denotes the number of years 1980 to 2002. The variable Y is output or value added measured in 1995 prices and N is the number of employees (workers employed). Capital,

K, and intermediate material inputs consumed, M, are also measured at 1995 prices. The variable μ_{it} is the combined effect of the non-price and organizational factors that constrain firms from achieving their maximum possible output from the given set of inputs and technology at a given time and the remainder, v_{it} is the statistical random disturbance term.

The production function for the manufacturing sector is estimated from pooled cross sectional data from 28 manufacturing industries over 1980-2002. The explicit specification of the production function allows us to use statistical methods and inference to evaluate the reliability of the results. The proposed methodology allows for variation due to industry effects. Since the methodology allows for inter-industry differences within the sectors, it avoids omitted variable bias in estimating the underlying parameters. Time dummies are used to allow industry technical progress to vary across time[23].

2.4 THE DATA AND SAMPLE CHARACTERISTICS

The data used in this study covers the entire South African manufacturing sector over the period 1980-2002. There are 28 individual industries grouped under the three digit ISIC categorisation. The data set includes output, value added, labour employed and capital stock. The Sources of data are Statistics South Africa www.statssa.gov.za, South African Reserve Bank www.reservebank.co.za, and Trade and Industry Policy Strategies Secretariat www.tips.org.za.

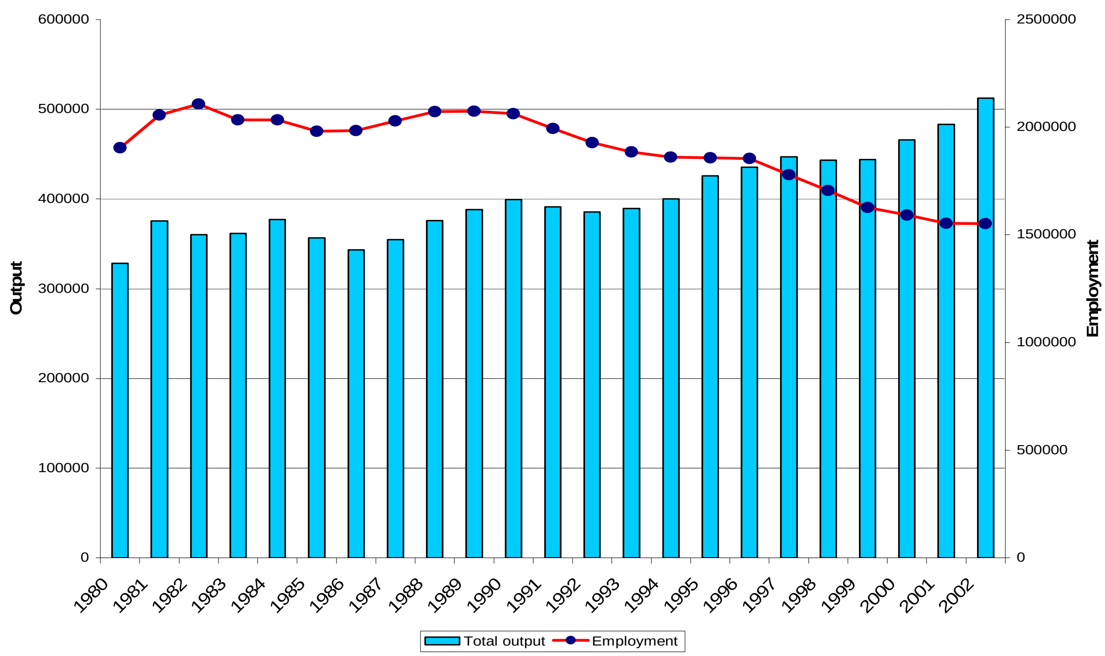
Output Y is the value of aggregate output produced on an annual basis. Value added V is defined as the difference between the value of output and the cost of materials and supplies, fuels, electricity and water, the value of contract and

[23] It is also possible to use industry dummies to allow for variation among industries within a particular year.

maintenance services done by external sources, and the cost of goods purchased for resale without transformation. Capital stock data on the industry is denoted K. Labour is denoted as N and is defined as the number of employees in an industry, while intermediate raw materials consumed are denoted by M. All variables expressed in value terms are given in constant 1995 prices.

Figure 5 shows the evolution of output and employment in South African manufacturing over the period under investigation. As indicated in the earlier analysis, the figure shows that from 1994 to 2002 there was a decline in employment and an increase in the level of output. This development can only be rationalised by a corresponding increase in labour productivity in the manufacturing sector. The increase in labour productivity is a manifestation of continuing efforts to improve the skill complement of South African workers.

Figure 5: Evolution of employment and output in manufacturing, 1980-2002



Note: Employment is defined in terms of number of employees
Source: www.statssa.gov.za, and www.tips.org.za.

2.5 ECONOMETRIC RESULTS

2.5.1 Univariate data analysis

2.5.1.1 Summary statistics

The empirical analysis is based on the entire South African manufacturing data base, which is composed of 28 sectors over a period (1980-2002) of 23 years. Table 7, below, shows the existence of substantial variability in the manufacturing sectors with regard to output, value added, capital stock and material input use.

Table 7: Summary statistics for inputs and outputs

Variable	Definition	Mean	SD	Minimum	Maximum
Y	Output	11608.3	10168.7	928.7	58197.1
V	Value added	3708.1	2672.9	276.7	11988.7
N	Number of employees	51947.5	43618.6	2091.8	207068.1
K	Capital	5653.3	8786.9	96.5	56357.3
M	Materials	7806.0	7947.9	356.8	45683.3

Note: Variables in 1995 prices and in millions of rand. Number of observations is 644.

Source: www.statssa.gov.za, and www.tips.org.za.

2.5.1.2 Correlation analysis

As part of exploratory data analysis, the nature of correlation between variables in the production function is investigated. Both parametric and non-parametric tests of hypothesis for correlation analysis are computed. Table 8 displays the results of the non-parametric covariance matrix for value added and total output and inputs. The results show that output and value added have strong positive correlations with the inputs.

Table 8: Correlation between inputs and output measures

Correlation between value added, capital, materials and labour				
Value added	Value added	Capital	Materials	Labour
Value Added	1.0000			
Capital	0.8010	1.0000		
Materials	0.8245	0.8110	1.0000	
Labour	0.6657	0.5075	0.6950	1.0000
Correlation between output, capital, materials and labour				
Output	Output	Capital	Materials	Labour
Output	1.0000			
Capital	0.8219	1.0000		
Materials	0.9206	0.8110	1.0000	
Labour	0.7120	0.5075	0.6950	1.0000

Note: The number of observations is 644
Source: Author's own computations, www.statssa.gov.za, and www.tips.org.za.

Table 9, on the other hand, displays two non-parametric test results. The tests include the Spearman and Kendall rank correlation coefficients. These two tests indicate correlation coefficients along with tests of the hypothesis that the variables are independent. The results show that output and value added have strong positive correlation with inputs, and the correlation computed is statistically significant. The significance level for the calculated correlation coefficients is indicated below the respective coefficients shown in Table 9.

Table 9: Non parametric tests for production function variables

Value added and inputs			
Value Added	Capital	Labour	Materials
Spearman's rho	0.7880	0.6288	0.8406
Prob > |t|	0.000	0.000	0.000
Kendal's tau-a	0.5902	0.4537	0.7075
Prob > |z|	0.000	0.000	0.000
Total output and inputs			
Output	Capital	Labour	Materials
Spearman's rho	0.8234	0.6827	0.9204
Prob > |t|	0.000	0.000	0.000
Kendal's tau-a	0.6241	0.4928	0.8166
Prob > |z|	0.000	0.000	0.000

Note: The number of observations is 644, p-values are defined as Prob > |t|and Prob > |z| for the Spearman's and Kendall's test respectively.
Source: Authors computations, www.statssa.gov.za, and www.tips.org.za.

2.5.1.3 Intuition behind panel unit root tests[24]

Evidence that has been gathered from testing non-stationary panels is that many test statistics and estimates of interest have normal limiting distributions[25]. This finding is in contrast to the non stationary time series literature where the limiting distributions are complicated functionals of Weiner processes (Baltagi, 2001:234). Application of panel data can help avoid the problem of spurious regression (Phillips and Moon, 1999 and Kao, 1999)[26]. Unlike the single time series spurious regression literature, panel data[27] spurious regression estimates give consistent estimates of the true value of the parameter as both N and T tend to ∞. This arises from the fact that panel estimators average across individuals and the information in the independent cross section data in panels generates a stronger overall signal than the pure time series case. In addition to other documented payoffs (Baltagi 2001:5-7), panel data techniques help us to combine the advantages of cross-section and time series by treating cross-sections as repeated draws from the same distribution, which is important, because some panel statistics converge in distribution to normally distributed random variables.

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[24] Just as in the case of time series, unit root tests are not used as an end themselves but to further specify regression equations.

[25] Certain panel statistics (estimators) converge in distribution to normally distributed random variables. In our panel there are more degrees of freedom. We dealing not just with 23 years of data but with 644 observations (23 years *28 industries).

[26] The overall conclusions on unit root tests can be examined by looking at Monte Carlo studies on size and power. Choi (2000) argues that the size of IPS tests and Fisher are reasonably close to 0.05 desired with small N, with large N Fisher test shows more distortion. Considering size adjusted power, Fisher seems to be a more powerful test. The performance of both tests worsens when a linear time trend is introduced. Karlsson and Loethgren (2000) examined the Levin and Lin and the IPS and concluded that for large T the tests have good power. However, one needs to watch inference conclusions. Large T gives the panel unit root tests high power and there is the potential risk of concluding that the whole panel is stationary even when there is only a small proportion of stationary series in the panel. The problem is reversed for small T.

[27] The debate has been whether panel data can solve some of the shortcomings found in time series analysis namely low power of time series tests, nonstandard limiting distributions of time series and the spurious regression problem in which the t-statistics diverge in miss-specified regressions of two I(1) variables. The overall answer is that panel data can help but at the cost of introducing a new issue, how homogeneous is the panel?

The importance of testing for unit roots in time series arises from the fact that a regression equation with integrated variables is likely to yield spurious results, unless there is cointegration in the relationship. In the case of panel data, Phillips and Moon (1999) have shown that, under quite weak regularity conditions, the pooled time and cross-section data improve the degrees of freedom required for estimating long run relations that may exist in cointegrated variables. Unit root tests are classified on the basis of whether there are restrictions on the autoregressive processes across cross-sections. The tests either assume a common unit root process (Levin, Lin and Chu (2002), Breitung (2000) and Hadri (2000)) or an individual root process (Im, Pesaran, and Smith (2003) and the Fisher ADF or Fisher PP shown in Maddala and Wu (1999)[28] and Choi (2001)). Levin, Lin and Chu (2002) assume existence of a common unit root process across cross-sections and employ a null hypothesis of a unit root. The basic ADF specification considered is:

$$\Delta y_{it} = \alpha_i y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-j} + X_{it}' \delta + \varepsilon_{i,t} \qquad (6)$$

Where it is assumed $\alpha = \rho - 1$ is the lag order for the difference terms, ρ_i varies across cross-sections. The null and alternative hypotheses are respectively:

$$H_0 : \alpha_i = 0 \text{ and } H_1 : \alpha_i < 0 \qquad (7)$$

Levin, Lin and Chu (2002) show that, under the null, a modified t-statistic for the resulting $\hat{\alpha}$ is asymptotically normally distributed:

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[28] This test is constructed with the idea of improving on the Levin and Lin and IPS tests. The IPS test assumes T is constant for all cross sections while both Levin and Lin and IPS have critical values that depend on the lag order employed. The Maddala and Wu (1999) test does not require balanced panel, it can accommodate different unit root tests and can be adapted for less restrictive assumptions about cross-correlations based on bootstrap techniques. The Maddala and Wu (1999) test is a Fisher (1932) based test which combines information on unit root test p-values. It has the advantage of being an exact test while the IPS test is based fundamentally on the ADF test.

$$t_{\alpha_i^*} = \frac{t_{\alpha i} - \left(N\tilde{T}\right)S_N{}^{\hat{\sigma}-2} se(\hat{\alpha})\mu_{m\bar{T}^*}}{\sigma_{m\bar{T}^*}} \to N(0,1) \quad (8)$$

Where t_{α_i} is the standard t-statistic, $\hat{\alpha}_i = 0$, $\hat{\sigma}^2$ is the estimated variance error term, $se(\hat{\alpha}_i)$ is the standard error of $\hat{\alpha}_i$, and $\tilde{T} = T - \left(\sum_i p / N\right) - 1$. The two terms $\mu_{m\bar{T}^*}$ and $\sigma_{m\bar{T}^*}$ are adjustments for the mean and standard deviation, respectively. The Breitung (2000) method differs from the Levin, Lin and Chu (2002) approach in the construction of standardized proxies. Breitung shows that his resulting estimator for α_i^* is asymptotically distributed as a standard normal. Hadri's (2000) panel unit root test is similar to the Kwaitkowsky, Phillips, Schmidt, Shinn (KPSS) unit root test and has a null hypothesis of no unit root in any series in the panel. The test is based on the residuals from individual OLS regressions of y_{it} on a constant, or a constant and time trend. The test is a Lagrange multiplier application and reports two Z statistic values, one of the Z values relies on underlying homoskedasticity across i, while the other Z statistic allows for heteroskedasticity across i. Hadri (2000) shows that under mild assumptions:

$$Z = \frac{\sqrt{N}(LM - \xi)}{\zeta} \to N(0,1) \quad (9)$$

Im, Pesaran and Shin (2003), hereafter designated (IPS), and the Fisher-Dickey Fuller and Phillips Perron tests following Maddala and Wu (1999) allow for individual unit root processes so that ρ_i may vary across cross sections. These tests are characterised by combining the individual unit root tests to derive a panel-specific result. In the case of Im, Pesaran and Shin (2003) the null hypothesis is written as:

$$H_0 : \alpha_i = 0 \text{ for all } i \quad (10)$$

while the alternative hypothesis is given by:

$$H_1 : \alpha_i = 0 \text{ for } i = 1,2,......N_1 \tag{11}$$

In general, where the lag order in equation (6) is non-zero for some cross sections, IPS (2003) show that a properly standardised $\bar{t}_{NT}$ has an asymptotic standard normal distribution:

$$W_{tNT} = \frac{\sqrt{N}\left(t_{NT^{-N^{-1}}} \sum_{i=1}^{N} E\left(t_{iT}\left(\rho_i\right)\right)\right)}{\sqrt{N^{-1}\sum_{i=1}^{N} \operatorname{var}\left(t_{iT}\left(\rho_i\right)\right)}} \rightarrow N(0,1) \tag{12}$$

The expressions for the expected mean and variance of the ADF regression t-statistics are provided by IPS for various time periods T and for various values of lag order ρ. An alternative approach to panel unit root results proposed by Maddala and Wu (1999) and by Choi (2001) uses Fisher's (1932) results to obtain tests that combine the ρ values from individual unit root tests. Assuming π_i is the ρ-value from any individual unit root for cross-section i then, under the null of unit root for all N cross-sections, an asymptotic result is obtained such that $-2\sum_{i=1}^{N}\log(\pi_i) \rightarrow \chi^2_{2N}$ and Choi (2001) shows that:

$$Z = \frac{1}{\sqrt{N_{i=1}}} \sum_{i=1}^{N} \phi^{-1}(\pi_i) \rightarrow N(0,1) \tag{13}$$

Where ϕ^{-1} is the inverse of the standard normal cumulative distribution function. In Table 10, below, the results of the group unit root tests from these methods on the variables used for the estimation of the production function are reported.

Table 10: Group unit root tests for production function variables

Variable/method	Value Added	Capital stock	Labour employed	Materials input
LLC Statistic	-0.24[0.40]	-13.98[0.00]	-0.77[0.22]	-0.69[0.247]
Breitung $t-statistic$	0.84[0.80]	0.55[0.71]	-1.43[0.08]	-0.11[0.46]
IPS Statistic	-0.20[0.42]	-14.47[0.00]	0.40[0.65]	1.97[0.98]
ADF-Fischer χ^2 Statistic	63.17[0.24]	290.36[0.00]	56.11[0.47]	46.25[0.82]
PP-Fischer χ^2 Statistic	49.69[0.71]	25.952[1.00]	37.12[0.98]	44.62[0.86]
Hadri $Z-statistic$	9.92[0.00]	6.86[0.00]	10.41[0.00]	10.56[0.00]
Cross sections	28	28	28	28
Integration order	I(1)	I(1)	I(1)	I(1)

Notes: Probabilities are in brackets. The probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality. Variables are in logarithmic transformation
Source: Authors own computations, www.statssa.gov.za, and www.tips.org.za.

The results in Table 10, indicate that output, value added, capital stock and material inputs are integrated of order 1. These variables are stationary in the first difference specification. Therefore a test for cointegration should be performed before regression analysis can be conducted.

2.5.1.4 Testing for cointegration in the production function

The literature on testing for cointegration in panel data has tended to follow two broad directions. The first is based on a null hypothesis of no cointegration and uses residuals from static regressions to construct test statistics (Pedroni, 1995 and Kao, 1999). The second approach is based on a null of cointegration and adopts a residual based test in the spirit of McCoskey and Kao (1998). In the same vein, McCoskey and Kao (2001) generate a test that is suited to heterogeneous panels and allows for individual cointegrating vectors. The test is constructed in a similar style to the IPS test for unit root. It is based on the average of individual cointegration test statistics and is then normalised with appropriate mean and variance for standard normal limiting distribution. The moments allow for intercept and no time trend and since they are based on a asymptotic simulation the results are the same for ADF and Phillips Perron based tests. The test is constructed as:

$$\bar{Z} = \frac{\sqrt{N\left(AD\bar{F} - \mu\right)}}{\sqrt{\sigma^2}} \sim N(0,1) \tag{14}$$

Where N is the number of cross-sections, $AD\bar{F}$ is the average of the ADF or PP statistics, μ is the mean and σ^2 is the variance (or standard deviation). The means and variances based on Monte Carlo simulated moments are provided in McCoskey and Kao (2001:186). The null hypothesis H_0 : is that none of the relationships is cointegrated and the alternative H_A : is that at least one of the relationships is cointegrated. The intuition behind the testing arises because cointegration provides that there should exist a long run relationship between the natural logs of value added, capital, labour and material inputs. If there exists a long run relationship between these variables, then some or all the panels in the regression in Table 11, below, should show cointegrated relations. The test results reject the null of no cointegration at the 5 percent level, suggesting that there is a long run relationship in the estimated manufacturing production function. The test results are reported in Table 11, below.

Table 11: Production function cointegration

Equation	Method	Z Statistic	Critical value (5%)	Observations	Cross-sections
$v_{it} = f(k_{it}, n_{it}, m_{it})$	IPS Statistic	-1.876	-1.645	644	28
	PP Statistic	-1.808	-1.645	644	28

Notes: The test assumes asymptotic normality.
Source: Authors computations, www.statssa.gov.za, and www.tips.org.za.

The test results for cointegration indicate evidence of the existence of a long run relationship between value added, capital, labour input and materials. This result is expected intuitively because economic theory has provided a direct linkage between output and inputs of labour and capital used to generate it (Solow, 1957).

2.5.2 Multivariate model results: production functions

Three important estimation steps are conducted in this section. First, traditional production frontiers for efficiency measurement are estimated. Second, aware that autocorrelation and heteroscedasticity are likely to be problems in panel data, production functions that employ the Panel Corrected Prais-Winsten adjustment are estimated. Third, the results from the above two steps are used to explain the evolution of efficiency and technical change in South African manufacturing.

The frontier models based on Battese and Coelli (1992:160) contain estimators that have two components. One component, μ_{it}, is assumed to have a strictly non-negative distribution and the other component, v_{it}, is assumed to have a symmetric distribution. In the economics literature μ_{it} is the inefficiency term and v_{it} is the idiosyncratic error. Two basic traditional models are estimated for comparison purposes. One of these models takes inefficiency to be time-invariant, while the other analyses inefficiency within a time-varying decay format.

2.5.2.1 A time invariant inefficiency model

In this specification, the inefficiency term is assumed to have a truncated normal distribution that is constant over time within the panel hence $\mu_{it} = \mu_i$. However, the idiosyncratic error term is assumed to have a normal distribution with mean zero. The only panel specific effect is the random inefficiency term.

Table 12 provides estimates of the input elasticities for the time invariant inefficiency model with an underlying Cobb-Douglas function. The Cobb-Douglas functional form is attractive for its simplicity, the logarithmic transformation provides a model which is linear in the logarithms of the inputs[29]. The parameter estimates had significant t-ratios. The corresponding output elasticities with respect to capital, labour and materials are 0.43, 0.40 and 0.20 respectively.

Table 12: Time invariant inefficiency: Cobb-Douglas production function

Stochastic frontier model: Dependent Variable ln(v)							
Variable	**Parameter**	**Coef.**	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf. Interval]**	
$\ln(K)$	α_k	0.4331	0.0385	11.25	0.000	0.3577	0.5085
$\ln(N)$	α_n	0.3663	0.0382	9.51	0.000	0.2908	0.4418
$\ln(M)$	α_m	0.1850	0.0335	5.53	0.000	0.1195	0.2506
Constant	α_0	0.8167	0.6423	1.27	0.204	-0.4421	2.0755
mu	μ	1.6816	0.4821	3.49	0.000	0.7368	2.6264
Group variable		Sector		Obs per group: min		23	
Time variable		Year		Obs per group: avg		23	
Log likelihood		184.0881		Obs per group: max		23	
Number of obs		644		Wald chi^2		498.73	
Number of groups		28		Prob>chi^2		0.0000	

Note: Coefficients on time dummies are not reported
Source: STATA Regression output from data obtained from www.tips.org.za, www.statssa.gov.za and www.resbank.co.za

The translog is a flexible production function because it imposes no restrictions upon returns to scale or substitution possibilities[30]. Table 13 presents the results for the translog specification. The translog functional form accommodates multiple inputs without necessarily violating the curvature conditions, it is also

[29] This simplicity is however, associated with a number of restrictive properties. The Cobb-Douglas production function has constant input elasticities and returns to scale for all the industries in the sample.
[30] A discussion of the translog is provided in Christensen et al (1973). The drawback of the translog is that susceptible to multicollinearity and degrees of freedom problems. The solution to these problems can be attained by using systems estimators that are more difficult to compute and also have other problems associated with their estimation (Coelli et al, 1998).

flexible because it provides second order approximation to any well behaved underlying production frontier and it forms the basis for much of the empirical estimation and decomposition of production efficiency (Kumbhakar and Lovell, 2000). About 70 percent of the parameters in the translog were significant. The variance parameter, γ, for the translog model of 0.91, is higher than that in the Cobb-Douglas of 0.89. The inefficiency parameter is significant in both models, showing that inefficiency is an important component of the manufacturing production process. The corresponding average output elasticities with respect to capital, labour and materials are 0.42, 0.45 and 0.48 respectively.

Table 13: Time invariant inefficiency: Translog production function

Stochastic frontier model: Dependent Variable ln(v)							
Variable	**Parameter**	**Coef.**	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf. Interval]**	
$\ln(K)$	α_k	1.6468	0.3519	4.68	0.000	0.9569	2.3367
$\ln(N)$	α_n	0.0659	0.3582	0.18	0.854	-0.6363	0.7681
$\ln(M)$	α_m	-1.1080	0.3237	-3.42	0.001	-1.7424	-0.4736
$(\frac{1}{2})\ln(K^2)$	β_{kk}	0.0166	0.0448	0.37	0.711	-0.0712	0.1043
$(\frac{1}{2})\ln(N^2)$	β_{nn}	0.2229	0.0432	5.16	0.000	0.1382	0.3076
$(\frac{1}{2})\ln(M^2)$	β_{mm}	0.2865	0.0652	4.39	0.000	0.1587	0.4145
$\ln(K)\times\ln(N)$	β_{kn}	-0.1436	0.0259	-5.55	0.000	-0.1943	-0.0929
$\ln(K)\times\ln(M)$	β_{km}	-0.0019	0.0422	-0.04	0.965	-0.0845	0.0808
$\ln(N)\times\ln(M)$	β_{nm}	-0.0981	0.0399	-2.46	0.014	-0.1763	-0.0199
Constant	α_0	2.8977	2.3023	1.26	0.208	-1.6148	7.4102
Mu	μ	1.7014	0.5057	3.36	0.001	0.7103	2.6926
Group variable			Sector	Obs per group: min			23
Time variable			Year	Obs per group: avg			23
Log likelihood			243.4149	Obs per group: max			23
Number of obs			644	Wald chi²			745.82
Number of groups			28	Prob>chi²			0.0000

Note: Coefficients on time dummies are not reported
Source: STATA Regression output from data obtained from www.tips.org.za, www.statssa.gov.za and www.resbank.co.za

2.5.2.2 A time varying inefficiency decay model

This analysis follows the Battese-Coelli (1992) parameterisation of time effects. The inefficiency term is modelled as a truncated-normal random variable multiplied by a specific function of time:

$$\mu_{it} = \mu_i^* \exp\left[\eta^* (t - T)\right] \qquad (15)$$

where T corresponds to the last time period in each panel, η is the decay parameter to be estimated, and μ_i are assumed to have $N(\mu, \sigma_\mu)$ distribution. As in the previous model, the idiosyncratic error term is assumed to have a normal distribution with mean zero. In Table 14[31], the Cobb-Douglas model capital has an elasticity of 0.48, the labour input has an elasticity of 0.35 while material inputs record an elasticity of 0.18.

Table 14: Time varying inefficiency: Cobb-Douglas production function

Stochastic frontier model: Dependent Variable ln(v)							
Variable	Parameter	Coef.	Std. Err.	Z	P>|z|	[95% Conf. Interval]	
$\ln(K)$	α_k	0.4796	0.0353	13.58	0.000	0.4104	0.5489
$\ln(N)$	α_n	0.3519	0.0372	9.47	0.000	0.2790	0.4247
$\ln(M)$	α_m	0.1822	0.0334	5.45	0.000	0.1167	0.2477
Constant	α_0	0.7640	0.5686	1.34	0.179	-0.3505	1.8785
mu	μ	1.5634	0.3475	4.50	0.000	0.8823	2.2445
eta		0.0065	0.0019	3.36	0.001	0.0027	0.0104
Group variable		Sector	Obs per group: min			23	
Time variable		Year	Obs per group: avg			23	
Log likelihood		189.1682	Obs per group: max			23	
Number of obs		644	Wald chi2			523.73	
Number of groups		28	Prob>chi2			0.0000	

Note: Coefficients on time dummies are not reported
Source: STATA Regression output from data obtained from www.tips.org.za, www.statssa.gov.za and www.resbank.co.za

[31] In Appendix A.2 results using output rather than value added in the framework of Battese and Coelli are provided for comparison purposes only. They are generated using Frontier 4.1 program.

Table 15 provides translog function estimates of the input elasticities for the time varying inefficiency decay model. About 31 percent of the parameters in the translog were insignificant. Both the Cobb-Douglas and translog models have a statistically significant μ parameter showing that inefficiency is an important component of the South African manufacturing production process. The computed average elaticities for the translog model show that capital has an elasticity of 0.20, the labour input has an elasticity of 0.48 while material inputs record an elasticity of 0.47.

Table 15: Time varying inefficiency: Translog production function

Stochastic frontier model: Dependent Variable ln(v)							
Variable	**Parameter**	**Coef.**	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf. Interval]**	
$\ln(K)$	α_k	1.8339	0.3572	5.13	0.000	1.1334	2.5340
$\ln(N)$	α_n	0.4601	0.3883	1.18	0.236	-0.3011	1.2212
$\ln(M)$	α_m	-1.5408	0.3512	-4.39	0.000	-2.2293	-0.8523
$(\frac{1}{2})\ln(K^2)$	β_{kk}	0.0150	0.0451	-0.33	0.739	-0.0733	0.1034
$(\frac{1}{2})\ln(N^2)$	β_{nn}	0.1906	0.0457	4.17	0.000	0.1010	0.2801
$(\frac{1}{2})\ln(M^2)$	β_{mm}	0.3131	0.0655	4.78	0.000	0.1846	0.4416
$\ln(K)\times\ln(N)$	β_{kn}	-0.1688	0.0278	-6.07	0.000	-0.2233	-0.1143
$\ln(K)\times\ln(M)$	β_{km}	0.0024	0.0421	0.06	0.955	-0.0801	0.0845
$\ln(N)\times\ln(M)$	β_{nm}	-0.0784	0.0395	-1.98	0.047	-0.1558	-0.0009
Constant	α_0	1.7322	2.232	0.78	0.437	-2.6426	6.1072
/mu	μ	1.8410	0.4536	4.06	0.000	0.9521	2.7299
/eta	η	-0.0073	0.0022	-3.28	0.001	-0.0117	-0.0029
Gamma	γ	0.9307	0.0196			0.8810	0.9606
Group variable			sector	Obs per group: min			23
Time variable			Year	Obs per group: avg			23
Log likelihood			229.76505	Obs per group: max			23
Number of obs			644	Wald chi²			685.17
Number of groups			28	Prob>chi²			0.0000

Note: Coefficients on time dummies are not reported
Source: STATA Regression output from data obtained from www.tips.org.za, www.statssa.gov.za and www.resbank.co.za

2.5.3 Technical change in South African manufacturing

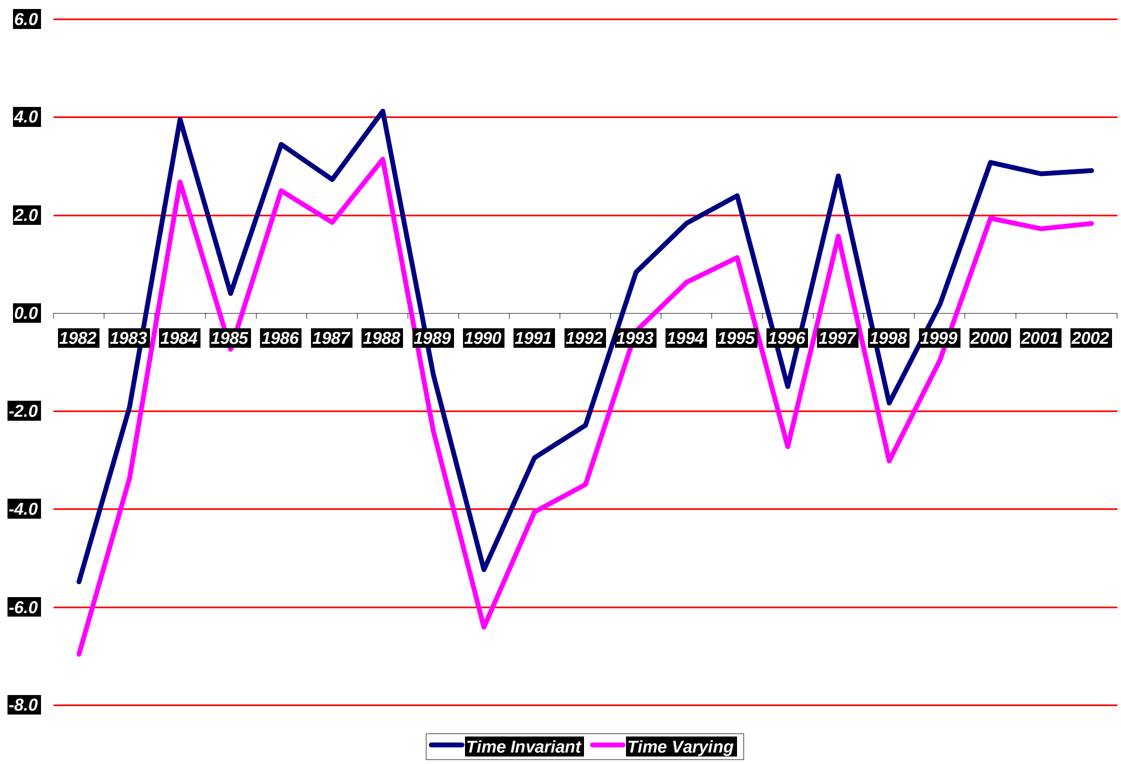
Technical change is measured as the difference between the coefficients of two time dummies associated with two consecutive periods as shown in equation (4), above. A comprehensive analysis of the results from the models reported in Tables 12 to 17 shows that the rate of technical change recorded during the period under review for the Cobb-Douglas specification ranges from a minimum of –7.0 per cent in 1982 to a maximum of 4.2 per cent in 1984. The highest overall mean growth rate recorded during the period is 0.5 per cent per annum. Over the 23 year period, 8 years of technical regress are indicated by the model results. In the translog specification, the rate of technical change in manufacturing ranges from a minimum of –4.9 per cent in 1982 to a maximum of 5.8 per cent per annum in 1984. The mean growth rate recorded during the period fell between 0.3 to 0.5 per cent per annum. Over the 23 year period, the translog records a maximum of 9 years of technical regress.

Overall, two central messages arise. First, South African manufacturing industries experienced very erratic, but slow, technical progress during the period under review. Second, the results indicate that from 1999 onwards, the pattern of technical change appears to be turning positive.

The main reasons for the rather low levels of technical change in the manufacturing sector experienced during most of the period under review appear to be related to a pattern of low innovation and modernisation in industries during the periods of technological regress. Apart from ordinary production tasks, industrial sectors need to engage in significant innovation and experimentation to achieve higher rates of technical change (Mouelhi and Goaied, 2003).

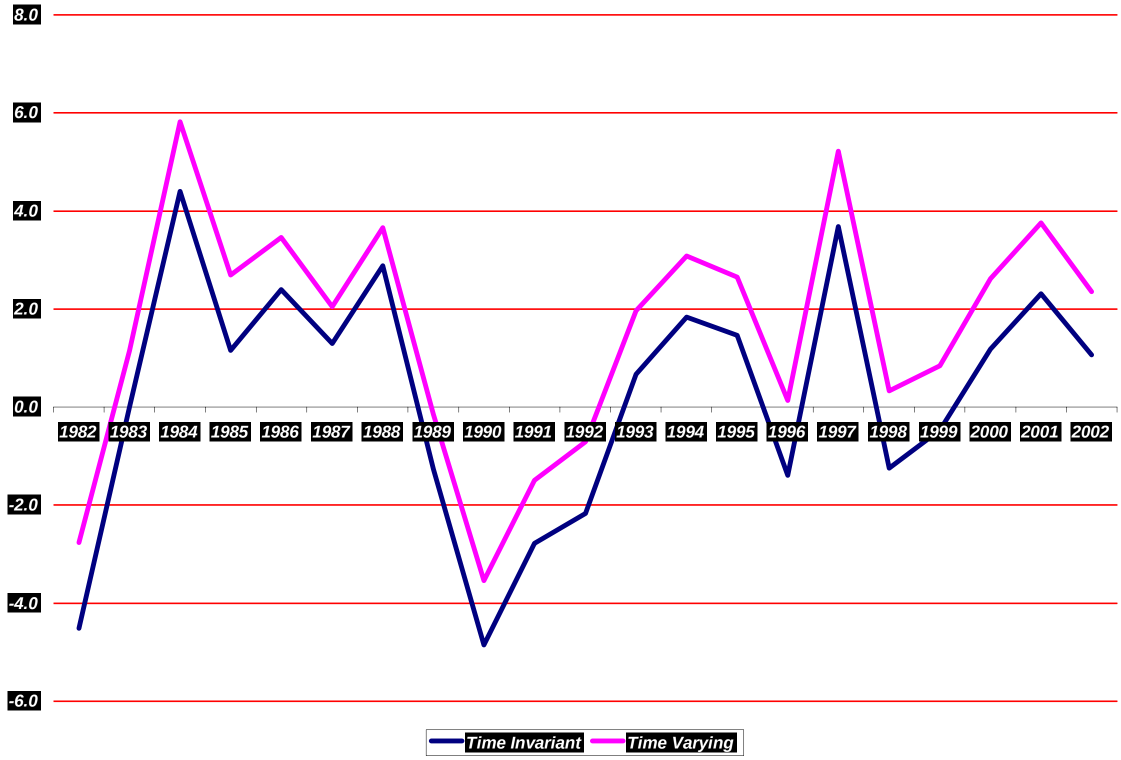
Figure 6, below, shows the evolution of technical change in South Africa. There is a marked collapse from 1989 to 1990 and a recent noticeable recovery from 1999 to 2002. This recent recovery could be related to the increased openness of the economy. Figures 6 and 7 trace the patterns of technical change using the Cobb-Douglas and Translog production functions.

Figure 6: Technical change in manufacturing: Cobb-Douglas function



Notes: Cobb-Douglas production function
Source: Author's own computation.

Figure 7: Technical change in manufacturing: Translog function



Note: Translog production function

Source: Author's own computation.

2.5.4 Technical efficiency in South African manufacturing

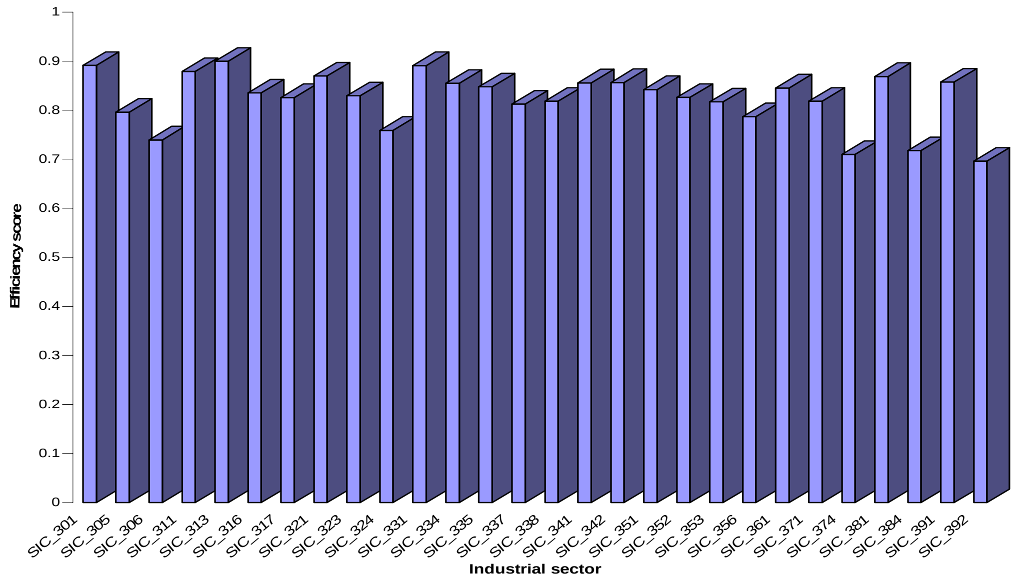
Again, a comprehensive review of the underlying efficiency estimates from the six models provides important insights. The descriptive statistics for technical efficiency measures show an average technical efficiency level of 86.8 percent. The minimum efficiency score is recorded at 84.5 per cent, while, the maximum efficiency score is recorded at 94.5 per cent. The efficiency estimates indicate that some South African manufacturing industrial sectors can improve their output level by as much as 14 per cent with the same set of inputs. Figure 8 shows the distribution of technical efficiency scores for the manufacturing sector.

A number of reasons explain deviation of actual industrial output from the estimated frontier output over this period. One explanation may be due to the sanctions that the economy was subjected to from 1985 to 1992; these could have limited competition within the economy. Another reason could be related to the fact that some sectors of South African manufacturing[32] have remained relatively protected as measured by openness indicators. Continued protection could have limited the degree of competition and exposure of these chapters to the world market.

Evidence from correlation analysis in Table 18, below, suggests an association between openness and efficiency scores. Indeed sectors (such as machinery and equipment, television, radio and communication equipment, professional and scientific equipment and other transport equipment, whose export output ratios improved or that experienced increased import pressure) recorded generally higher levels of efficiency compared to the mean level of the entire manufacturing sector.

[32] Some of the sectors that have appeared relatively protected include textiles, clothing, motor vehicles and parts, food processing and chemicals and rubber products.

Figure 8: Technical efficiency scores by sector



Source: Average sectoral efficiency scores computed by the Author.

In Table 18, simple non parametric tests of the correlation between efficiency scores and trade measures are presented. The results show that efficiency scores and exposure to trade have strong positive correlation and the correlation computed is statistically significant.

Table 16: Non parametric tests correlation tests for efficiency and trade

Efficiency score	Export exposure	Import pressure
Spearman's rho	0.1238	0.6288
Prob > |t|	0.002	0.000
Kendal's tau-a	0.0863	0.4537
Prob > |z|	0.001	0.000

Note: The number of observations is 644, p-values are defined as Prob > |t|and Prob > |z| for the Spearman's and Kendall's test respectively. Import pressure is defined as import intensity of a sector.
Source: Authors computations, www.statssa.gov.za, and www.tips.org.za.

To formally verify the results of the association and correlation experiment shown in Table 18, a simple model of the determinants of industry level efficiency is discussed in Section 2.5.6 and the results reported in Table 19. In

Section 2.5.5 below, the channels through which a liberal trade regime affects efficiency are discussed. In addition, the studies and the data that has been applied to this issue in Africa are outlined. The brief review suggests that the debate regarding the direction of causality between trade and efficiency in African manufacturing sectors is far from resolved.

2.5.5 The relationship between trade and manufacturing efficiency

Bigsten et al, (1998) outline mechanisms that trade economists think a liberal trade regime should affect efficiency in manufacturing. The first mechanism arises from the fact that in order to compete against international producers, domestic firms must adopt newer and more efficient technology or use the same technology with less x-inefficiency in order to reduce costs. The second reason arises from the difficulty of replacing imports of intermediate and capital goods by domestically produced goods. Increased availability of better as well as differentiated imported intermediates and capital goods should lead to higher output and improved efficiency for industries in developing countries. The third explanation for efficiency improvement in a liberal trade regime is that higher volumes of imports and exports increase international technical knowledge spillovers. The knowledge spilled over enables researchers from industries in developing countries to obtain insights from using these goods. Increased access to knowledge in turn leads to better improvements to the manufacturing processes. Efficiency may however not be enhanced if it was the protected sectors that previously enjoyed economies of scale. If there is a reduction in scale efficiency because industries are now competing with imports, the import pressure could lead these producers to contract or exit the domestic market (Rodrik, 1988 and 1991). Studies that have examined the issue of causality between exposure to trade and efficiency in Sub-Saharan Africa are briefly mentioned below.

2.5.5.1 Causality between trade and manufacturing efficiency

Since 1992, firm level data has been collected under the Regional Programme on Enterprise Development (RPED). The RPED initiative was coordinated by the World Bank. In the sample countries of Burundi, Cameroon, Ghana, Kenya and Zimbabwe, the initial waves of data capture covered a span of three years at different intervals in each country over the period 1991 to 1995. Using the RPED data Bigsten et al, (1999) found that exporters were more efficient than non-exporters. Most importantly, exporters also tended to increase their efficiency more rapidly than non-exporters, while new entrants into exporting had the largest subsequent gains in efficiency. Indeed one additional year of exporting was found to raise efficiency of continuous exporters by 13 percent, while the coefficient on new exporters showed that the first year of exporting raised efficiency by as much as 14 percent (Bigsten et al, 2000). The effect of exporting on efficiency[33] appeared to be larger in the African sample than in comparable studies in other regions. This finding regarding the impact of exporting on efficiency appeared to be consistent with the smaller size of domestic markets in Africa.

The important policy issue of whether more exposure to increased trade improves the efficiency of firms requires more empirical investigation. While most analysts believe that increased trade raises industry level efficiency, there

[33] Evidence has also been found of learning by exporting as well as self selection of the most efficient firms into exporting (Bigsten et al, 2000). This is contrary to the general belief that trade liberalisation and export oriented strategy increase firm level efficiency that is found in Krugman, 1987; Rodrik, 1991; Grossman and Helpman, 1994. Evidence that exporting and efficiency are associated is also reported in Harrison (1994) and Aw and Hwang (1995). In view of these controversies, the debate that exporting causes efficiency gains will only be resolved through the availability of more systematic empirical evidence (Bigsten et al 2000). This is because causality may run in the other direction suggesting that efficient firms may self select into the export market. In Ghana efficiency is unimportant for entry but of considerable importance for the exit decision (Söderbom, 2000).

remains little direct evidence that has been marshalled in this respect in Sub-Saharan Africa (Naudé et al 2000:9). Most importantly, studies examining causality between liberalisation and efficiency continue to report mixed results[34]. For example, a positive association between export status and productivity could be due to self selection of relatively more efficient plants into foreign markets. Strong evidence of learning-by-doing has been hard to come by, except in the case of the Moroccan apparel and leather industries investigated by Clerides et al, (1998). While, Kray (1997) argued that exporting caused faster growth in efficiency, Bigisten et al (2000) uncovered self selection as an important factor, suggesting that firms with higher past efficiency were more likely to become exporters. Self selection was due to the presence of high sunk costs of breaking into foreign markets, which implied that past exporters were even more likely to remain strong in the export market, providing yet more support for the learning-by-exporting hypothesis. In Section 2.5.6, a simple model to investigate the impact of trade measures and industry characteristics on efficiency is discussed.

2.5.6 Some determinants of manufacturing efficiency.

Industry level technical efficiency scores computed from the production function can be used to determine the impact of trade on industry performance. Following Kraay (1997) and Bigisten et al (2000) the level of industry efficiency as the dependent variable is interacted with measures of exposure to increased competition, and industry characteristics, such as skill competency and measures

[34] Firm efficiency affects the decision to export because more efficient firms will find it easier to compete in export markets. One of the reasons why large firms export more is because they tend to be more efficient, but it also seems that by increasing exports, efficiency of the firm may be raised. Exporting and internationalisation are important for the survival of manufacturing firms because of the potential they provide for enhancing sales growth, increasing efficiency and improving quality (Schmitz, 1994). Evidence from South Africa that is reported in Naudé and Zake (2001) indicates that firm efficiency is important for success in exports, a 10 percent increase in efficiency will increase the probability of exporting by 19 percent and the intensity of exports by 12 percent.

of technology transfer (Biggs & Raturi, 1997: 28). The basic specification is stated as follows:

$$te_{it} = \beta_0 + (\beta_1)'trade_{it} + (\beta_2)'ind_{it} + \varepsilon_{it} \qquad (16)$$

Where te_{it} is the efficiency score of industry i at time t and $trade_{it}$ is an indicator of trade impact such as the import penetration ratio of industry i at time t. The variable ind_{it} captures industry level characteristics such as the level of skill intensity and expenditure on machinery and equipment[35]. The impact of the business cycle is captured either by the evolution of the terms of trade or by the level of capacity utilisation in an industry. The remainder term is the familiar error component. The regression results for this simple model are provided in Table 17 below.

Table 17: Determinants of efficiency

Feasible generalised least squares : Dependent variable efficiency scores						
Variable	Coefficient.	Std. Err.	Z	P>|z|	[95% Conf. Interval]	
Import penetration	0.54894	.2479252	2.21	0.027	0.0630	1.03486
Skill intensity	0.80218	.1985005	4.04	0.000	0.4131	1.19123
Machinery expenditure	0.13119	.0662571	1.98	0.048	0.0013	0.26106
Terms of trade	0.67563	.3381428	2.00	0.046	0.0129	1.33838
Import penetration ratio × skill intensity	-0.16026	.0683204	-2.35	0.019	-0.2942	-0.02636
Constant	-8.13002	1.89911	-4.28	0.000	-11.852	-4.40783
Panels	Homoskedastic		Correlation			0
Group variable	Sector		Number of groups			28
Time variable	Year		Estimated coefficients			6
Number of observations	644		Time periods			23
Estimated covariances	1		Wald chi2(5)			70.35
Log likelihood	-406.7566		Prob > chi2			0.000

Note: import penetration is the ratio of imports to domestic demand, skill intensity is the ratio of skilled employees to the total number of employees in the industry, machinery expenditure is expenditure of industries on machinery and equipment and the terms of trade index takes base year of 1995.
Source: STATA estimation results by the author

The measure of exposure to trade in this regression is import penetration. The results show that a 1 percent increase in the import penetration ratio will raise the level of manufacturing efficiency by 0.55 per cent. The significance of this

35 The variable definitions are provided in Appendix A2.

variable indicates that trade brings industries into contact with international best practice, fostering learning and efficiency growth, possibly as a result of exposure to information on product characteristics and improved technology. It may also be due to the fact that sectors with higher import shares could have attracted a disproportionately higher level of foreign participation, which could help explain the higher levels of efficiency recorded. Sectors closed from international competition and oriented to the domestic market may have missed opportunities for upgrading, quality improvements, cost reductions and productivity improvements that follow from increased competition.

The measure of skill intensity in industry is also significant at the conventional levels. The skill elasticity is 0.88 suggesting that a 1 per cent improvement in skill intensity boosts overall manufacturing efficiency by 0.88 per cent. This indicates that skill improvements for the labour force are important for industry efficiency gains[36], because the mix of goods produced and the factor proportions used to manufacture them depend on the skill competencies of local technicians. Skill competency is important for the labour force to produce at its full potential and to avoid factor and time waste. With more trade, South African employees in the manufacturing sector will find it relatively easier to obtain the know-how necessary for further technological upgrading, as well as efficiency growth. Indeed Hunt and Tybout (1998) report that a large majority of industries with productivity gains under liberalisation experienced an increase in their skill labour intensity of production. Increased skill intensity implies an improved underlying product mix or an increase in industry technological sophistication as a result of increased foreign competition.

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[36] According to Miller and Upadhay (2000) too little openness does not allow a country to leverage its stock of human capital. Human capital investment without liberalisation of the external sector may lead to less efficiency and under utilisation of the skilled human resource.

A measure of technology infusion into industry is in form of new machinery and equipment expenditure by industries. An increase in machinery and equipment expenditure by 1 per cent will improve manufacturing sector efficiency by 0.13 per cent. This variable is also significant, suggesting that since a substantial amount of machinery, equipment and intermediate inputs into the South African manufacturing sector are imported, it implies that significant improvement in industry efficiency will continue to depend on the level of openness of the national trade policy. More importantly, efficiency scores are also likely to be related to how the skilled labour force adjusts to these imported inputs. Indeed Schor (2004) reports that industries in Brazil in which increased competition occurred, new access to inputs that embody better foreign technology also contributed to productivity gains after trade liberalisation.

A frequently suggested issue is the sensitivity of measured efficiency scores to the business cycle. Industry efficiency scores could be higher during booms and lower during recessions. To deal with this problem, terms of trade are added to the base line model as another independent variable. The estimated coefficient on this variable is positive and strongly significant, suggesting that the levels of efficiency in particular industry in a given year do not necessarily indicate improvements in the application of technology. Indeed a 1 per cent improvement in the terms of trade will raise the level of industry efficiency by 0.68 per cent.

2.6 CONCLUDING REMARKS

This chapter provided estimates of technical change and efficiency within an error components framework. Use is made of time invariant models and time varying decay models. In addition, a generalised time index is also employed to introduce more flexibility to the measures of technical change. The empirical analysis is based on a balanced panel of South African manufacturing industries over the period 1980 to 2002. The models are able to account specifically for periods of technological progress as well as periods that were characterised by regress. Analysis of these periods helps to suggest some explanations for the relatively low level of technological progress experienced in manufacturing during the period of the study.

The results from the preceding investigation indicate that there is scope for some of South Africa's industrial establishments to significantly improve their output level with the same set of inputs. The results suggest that greater exposure of industrial sectors to trade helped reduce negative deviations from the frontier output over the study period. Sectors with limited exposure to trade during the period of sanctions could have missed opportunities for efficiency gains. There is also evidence that more open sectors recorded generally better efficiency levels than the mean level of the entire manufacturing sector. Sectors closed from international competition and oriented to the domestic market may have missed opportunities for upgrading, quality improvements, cost reductions and productivity improvements that follow from increased competition. More importantly, since efficiency scores are likely to be related to how the labour force adjusts to imported inputs, skill improvements for the labour force will remain fundamental, because the mix of goods manufactured and the factor proportions used to produce them will increasingly depend on the skill competencies of local technicians. Skills allow the labour force to produce at its full potential and to avoid waste of inputs as well as time.

In the next chapter, attention is focused on modelling the determinants of total factor productivity and emphasis is placed on the channels through which trade affects manufacturing productivity. Indeed, since openness affects efficiency, there is a further need to answer two questions. The first regards the sign and magnitudes of the interaction between trade and productivity, which is investigated in Chapter 3. The second relates to how efficiency affects labour use in manufacturing; this aspect is the subject of Chapter 4. It should be noted that a potential direction for future investigation could involve the computation of a malmquist measure of productivity change, comparing the results obtained with those generated in this chapter (Coelli et al, 1998).