Technical and Environmental Efficiency of Kenya's Manufacturing Sector: A Stochastic Frontier Analysis*

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Abstract

The overexploitation of environmental resources for production purposes has become a major source of environmental degradation threatening the entire ecosystem. For the manufacturing sector, overdependence on fossil fuel for production makes it a significant contributor to environmental degradation. The technical efficiency of firms should therefore not only be defined from an economic perspective but also from an environmental perspective. This study estimates the technical and environmental efficiency of Kenya's manufacturing sector using a stochastic frontier approach. Further, it explores the causes of variations in environmental efficiency across firms and seeks to establish the relationship between technical and environmental efficiency. It is evident that manufacturing firms in Kenya are generally technically inefficient as indicated by the magnitude of the technical inefficiency term, u which is 4.13, significant at 10%. Environmental efficiency measure is negative implying that firms are also environmentally inefficient. After accounting for variations in environmental efficiency across firms, the magnitude of technical inefficiency term, u, drops to 0.44. Technical inefficiency and environmental efficiency are inversely related implying that technical efficiency and environmental efficiency move together. The findings suggest that there is a gain in efficiency for firms when environmental concerns are incorporated in business objectives.

Key Words: Stochastic Frontier Analysis, Environmental Efficiency, Technical Inefficiency

1.0: Introduction

The increasing interest in good environmental governance requires that firms check the environmental impact of their production processes in order to reduce their carbon footprints. This necessitates that efficiency of a firm be defined putting environmental concerns into consideration and the inputs be differentiated according to their potential impact on the environment. This study explores the technical and environmental efficiency of Kenya's manufacturing sector in the presence of an environmentally detrimental input. While technical efficiency emphasizes that maximum output be produced from a given set of inputs, environmental efficiency goes further to consider the environmental impact of the inputs requiring that output be maximized but with the efficient level of the environmental detrimental input.

The manufacturing sector is a significant driver of economic expansion. In Kenya, it contributes approximately 13% of the Gross Domestic Product (GDP) and this contribution has been on the upward trend. In 2005, the growth rate of GDP was 4.7% which rose to 6.3% in 2006. The demand for energy in Kenya has been growing at a rate of 6% which is largely driven by investors in manufacturing sector. African countries including Kenya are faced with the dual challenge of meeting economic development needs without increasing dependence on fossil fuel or inefficient technologies while simultaneously mitigating the diverse and complex impacts of climate change. In most countries, economic pressures to increase industrial output have contributed to rising levels of pollution and this trend is likely to continue if current development patterns persist. It is therefore paramount for the government to encourage firms to adopt cleaner production processes by ensuring energy efficient practices and documenting their carbon footprint as a starting point to improved environment management. A shift towards cleaner fuels as a source of energy will also aid the environmental agenda.

The objectives of this study are fivefold. First, it examines the impact of a firm's choice of energy on the level of output. Energy is considered as an environmental detrimental input and is categorized as either dirty fuel or clean fuel depending on the source. Energy from fossil fuel is deemed to be dirty fuel while energy from electricity and renewable sources is considered to be clean fuel. Secondly, the study estimates the level of technical efficiency and technical inefficiency at firm's normal operational level where both sources of energy are combined. Next, using the estimated technical inefficiencies and parameters of the model, a measure of environmental efficiency is estimated for each firm. Next, the study attempts to account for variations in the estimated environmental efficiency across firms and estimates a conditional environmental efficiency measure. Finally, the study seeks to establish the relationship between technical inefficiency and environmental efficiency and also compares the trends of technical efficiency, environmental efficiency and conditional environmental efficiency for each firm.
This study adopts a stochastic frontier approach using Kenya's RPED data.

After this introduction, the next section 2.0 discusses stochastic frontier analysis in literature. Section 3.0 discusses the methodology used in the analysis of technical and environmental efficiency; section 4.0 discusses the empirical findings while section 5.0 presents the conclusion and recommendations

2.0: Stochastic Frontier Analysis in Literature

Frontier methodologies have emerged as an important development for estimating efficiency and productivity which originated with the theoretical contribution by Farrell in 1957. Farrell (1957) created a framework to analyze firms that are not fully efficient. He suggested that efficiency could be evaluated by comparing firms to “best practice” efficient frontiers formed by the dominant firms in an industry. Empirically, efficiency is measured by estimating best practice efficient frontier based on a relevant sample of firms. The firms on the frontier are considered to be the best practice firms in the industry in the sense that their performance is at least as good as that of other firms with similar characteristics. The efficiencies of other firms in the market are measured in comparison to the efficient frontier. There are two major classes of efficiency estimation methodologies, and they are the econometric, which is also known as the parametric approach, and the mathematical programming approach which is nonparametric in nature.

Stochastic efficient frontiers emerged through the works of Aigner, Lovell and Schmidt (1977), Battese and Corra (1977), and Meeusen and van den Broeck (1977). Stochastic frontier technique can be formulated in two steps: firstly, an appropriate function such as a production, cost, revenue or profit function is estimated using an econometric method such as ordinary least squares, non-linear least squares or maximum likelihood; then secondly, the estimated regression error terms are separated into two components, usually a two-sided random error component and a one-sided inefficiency component. This produces an estimate of efficiency for every firm in the estimation sample. In the mathematical programming approach, the implementation that is used most frequently is data envelopment analysis (DEA), which was originated by Charnes *et al.* (1978). The method can be used to estimate production, cost, revenue and profit frontiers and provides a particularly convenient way for decomposing efficiency into its components.

Aigner and Chu (1968) proposed a deterministic frontier model to measure technical inefficiency which was a parametric programming approach. However, their model could not account for the random factors that may move production off the frontier. Various stochastic production frontier models were introduced to take these factors into account among them and Meeusen and van den Broeck (1977) which used a statistical approach. Work on the estimation of parametric frontier production functions began with specifying a composed errors term either in additive or multiplicative forms to measure technical and economic efficiency (see Aigner *et al.* 1977). Later, the technical inefficiency was decomposed into a persistent and a residual component in panel data model (see Kumbhaker and Heshmati 1995).

Some scholars who have attempted to explain the presence of these technical inefficiencies include Pittman and Lee (1981) who used a two-stage methodology by first predicting the technical inefficiencies from stochastic frontier estimation and then using the predicted inefficiencies, which are assumed to be independently identically distributed, in a second stage regression model where the technical inefficiencies are the dependent variable. This two stage approach has been criticized as inconsistency by Kumbhakar *et al*. (1991) and Battese and Coelli (1995) arguing that this contradicts the assumptions imposed on the technical inefficiency term in the stochastic frontier. In the first stage of the two-stage estimation, the error is assumed to be independently and identically distributed. Therefore, specifying the predicted inefficiency effects in the second stage as a function of a number of firm-specific factors contradicts the assumption that the errors are identically distributed.

Kumbhakar *et al*., (1991) proposed a model for the technical inefficiency effects where the parameters of the stochastic frontier and technical inefficiencies are estimated simultaneously given the appropriate distributional assumptions. This is possible following the maximum likelihood estimation methodology proposed by Coelli *et al*. (1998). When the explanatory variables for the technical inefficiency effects model are firm-specific variables only, this results to Battese and Coelli (1995)'s neutral production frontier model (see Lokina, 2008) but when both inputs and firm-specific variables are included as explanatory variables for the technical inefficiency effects model, this results to a non-neutral production frontier model originally proposed by Huang and Liu (1994) (see Battese and Broca, 1997). Battese (1998) further notes that the non-neutral models have important bearing upon the estimation of the elasticity of the mean output with respect to an input variable, which is also an explanatory variable for the inefficiency effects.

Stochastic frontier analysis has been found useful in investigating the influence of environmental variables on technical efficiency. One of the first attempts to explicitly model environmental efficiency was Reinhard *et al.,* (1999) who estimated a stochastic production frontier relating the environmental performance of individual farms to the best practice of environment-friendly farming. By modeling the environmental effect as a conventional input rather than as an undesirable output, he provides separate estimates of technical efficiency and environmental efficiency.

Srivastava and Shrivastava (2002) apply the stochastic frontier production technique to measure environmental efficiency of Indian Agriculture. They find that although the adoption of new technologies resulted into enhanced productivity, it also gave rise to problems of environmental degradation because of intensive use of modern inputs. They provide estimates of farm efficiencies due to adverse impact of environmentally detrimental inputs, positive (eco-friendly) impact of environmentally recuperative inputs and impact of basic inputs. They suggest that a unique and best combination of all three types of inputs is likely to yield enhanced productivity and sustainability of modern agriculture in India, ultimately providing a sustainable farming strategy to farmers and policy makers.

From the revealed studies, it is evident that while a lot of empirical work has been done on technical efficiency and inefficiency, very little effort has been made to incorporate environmental issues into efficiency studies. The few environmental efficiency studies that have been done are in the developed world and touch mainly on the agricultural sector. Moreover, while studies on technical efficiency and many other aspects of the manufacturing sector have been done in Kenya and Africa in general, evidence on environmental efficiency of the manufacturing sector remains scanty which is mainly as a result of lack of environmental data. This study attempts to bridge this gap by combining both technical efficiency and environmental efficiency of Kenya's manufacturing sector in order to assess the level of technical efficiency in the presence of environmental detrimental input.

The next section discusses the methodology.

3.0: Methodology

This section presents and discusses the methodology used in the analysis of technical and environmental efficiency of the firms in the sample. It begins with the specification of the models for both technical and environmental efficiency and then a model that accounts for variations in environmental efficiency. The next sub-section provides the analytical framework.

3.1: Model Specification

3.1.1: Estimation of Technical and Environmental Efficiency

Following Reinhard *et al* (1999), a stochastic frontier production function model is specified as

$$Y_{it} = f(X_{it}, Z_{it}; \beta)\exp\varepsilon_{it} \quad \text{……………………………………………………..(1)}$$

where all firms are indexed with a subscript *i* and all years are indexed with a subscript *t;* Y_{it} is the vector of output; X_{it} is the vector of convectional inputs, Z_{it} is a the environmental detrimental input[1] in this case energy; β is a vector of parameters to be estimated; ε_{it} is a composite error term specified as

$$\varepsilon_{it} = v_{it} - u_i \quad \text{………………………………………………………(1a)}$$

Where u_i is a non-negative random error term, independently and identically distributed as N(u, δ_u^2), which captures the firm specific technical inefficiency in production. v_{it} is the convectional stochastic error term which is assumed to be an independently and identically distributed (iid) normal random variables with mean zero and constant variance, N(0, δ_v^2).

[1] This is deemed as a environmental detrimental input because of the fact that even if it is necessary for production, it is also a source of pollution. The type of energy used in a firm has a bearing on air quality.

The technical efficiency of production of the i^{th} firm given the level of inputs, is defined by;

$$TE_i = \frac{Y_{it}}{f(X_{it}, Z_{it}; \beta)\exp(v_{it})} = \exp(-u_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where $u_i \geq 0$ and $0 \leq \exp(-u_i) \leq 1$

From equation (2), it is necessary to separate technical inefficiency from statistical noise in the composite error term. Battese and Coelli (1988, 1992) define the estimator of technical efficiency (TE) as

$$TE_i = E\left(\frac{\exp(u_i)}{\varepsilon_{it}}\right) = \left(\frac{1-\Phi\left[\sigma_* - (\gamma\varepsilon_i/\sigma_*)\right]}{1-\Phi(\gamma\varepsilon_i/\sigma_*)}\right)\exp\left(\gamma\varepsilon_i + \sigma_*^2/2\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2a)$$

Where $\Phi(.)$ is the distribution function of a standard normal random variable, $\gamma = \sigma^2 \big/ \left(\sigma^2 + \sigma_v^2\right)$ and $\sigma_* = \gamma(1-\gamma)\left[\sigma^2 + \sigma_v^2\right]$. The technical inefficiency score is computed as minus the natural log of the technical efficiency via $E\left(u_{it} \big/ \varepsilon_{it}\right)$

To derive a stochastic version of the environmental efficiency measure, we need to specify a functional form for the stochastic production frontier in equation (1). To do this we need a functional form with variable output elasticities as opposed to constant elasticities of output (Reinhard, 1999). In this case, a translog functional form is preferable. Another important factor is the distribution of the technical inefficiency term, *u.* This study follows Battese and Coeli (1988) specification of a generalized truncated-normal distribution of u_i which was first proposed by Stevenson (1980). This is because it is known to accommodate a wider range of distribution shapes including ones with non-zero modes.[2] In this case a translog stochastic production function is specified as

$$\begin{aligned} \ln Y_{it} &= \beta_0 + \sum_j \beta_j \ln X_{itj} + \beta_z \ln Z_{it} + \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln X_{itj} \ln X_{itk} \\ &+ \sum_j \beta_{zj} \ln X_{itj} \ln Z_{it} + \frac{1}{2}\beta_{zz}\left(\ln Z_{it}\right)^2 + v_{it} - u_i \end{aligned} \qquad \ldots\ldots\ldots\ldots\ldots\ldots(3)$$

where $\beta_{jk} = \beta_{kj}$[3]. When u_i=0, $\ln Y_{it}$ becomes $\ln Y^*_{it}$ and the producer is deemed to be technically efficient using X_{it} and Z_{it} to produce Y^*_{it}. Z_{it} is an environmentally detrimental input. The absence of the technical inefficiency term in the model is what guarantees technical efficiency. However, the producer is environmentally inefficient due to use of environmentally detrimental input in production.

A producer who takes environmental factors into consideration will choose to minimize the environmental impact of the production process by using Z^F_{it}, which is clean fuel, deemed environmental friendly, as opposed to Z_{it}, which is dirty fuel, hence environmental unfriendly.. A producer who uses X_{it} and Z^F_{it} in production produces the level of output, Y^F_{it}, which is the environmentally efficient output.

The translog stochastic production function for an environmentally efficient producer is therefore specified as

$$\begin{aligned} \ln Y^F_{it} &= \beta_0 + \sum_j \beta_j \ln X_{itj} + \beta_z \ln Z^F{}_{it} + \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln X_{itj} \ln X_{itk} \\ &+ \sum_j \beta_{zj} \ln X_{itj} \ln Z_{it} + \frac{1}{2}\beta_{zz}\left(\ln Z^F{}_{it}\right)^2 + v_{it} \end{aligned} \qquad \ldots\ldots\ldots\ldots\ldots(4)$$

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[2] Other distributions such as the half-normal and the exponential distributions have a mode at zero implying relatively higher technical efficiency, which may not be true in reality

[3] If β_{jk} = 0 the model reduces to a Cobb Douglas functional form

This level of output is both technically efficient due to the absence of u_i in the model and environmentally efficient due to the substitution of Z_{it} with Z_{it}^F.

From here, it is possible to isolate logarithm of the stochastic environmental efficiency measure by equating Y_{it}^* to Y_{it}^F and solving for $\ln Z_{it}{}^F - \ln Z_{it}$ which is the logarithm of the stochastic environmental efficiency measure, EE. This can be expressed as a quadratic formula shown below and solved for the positive root.

$$LnEE_{it} = \begin{bmatrix} -\left(\beta_z + \sum_j \beta_{zj} \ln X_{itj} + \beta_{zz} \ln Z_{it}\right) \\ \pm\left\{\left(\beta_z + \sum_j \beta_{zj} \ln X_{itj} + \beta_{zz} \ln Z_{it}\right)^2 - 2\beta_{zz} u_i\right\}^{.5} \end{bmatrix} / \beta_{zz} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

The positive root is the stochastic environmental efficiency measure.

3.1.2: Accounting for Variations in Environmental Efficiency

After establishing the presence of environmental efficiency, the next task of this analysis is to account for the variations in environmental efficiency. The standard method of using OLS or Tobit to regress the estimated technical efficiencies (TE) against a set of explanatory variables has been objected by Battese and Coelli (1995) citing that technical efficiencies TE is estimated from an error component u_i which is assumed to be independently identically distributed (iid) hence TE is not ideal for use as a dependent variable. The alternative is to use the estimates of EE as a dependent variable which is calculated from parameter estimates and the one-sided error component (Reinhard *et al.,* 2002).

Following Reinhard *et al.* (2002), a stochastic environmental efficiency frontier is estimated in order to obtain revised estimates of environmental efficiency that are conditioned on variations in the explanatory variables. Using stochastic frontier analysis is advantageous in the sense that it characterizes fully the relationship between best practice environmental efficiency and the explanatory variables and is able to isolate any other deviations in efficiency after accounting for inefficiency associated with explanatory variables. This is not possible with OLS and Tobit.

Generally, the environmental efficiency stochastic frontier is specified as

$$EE_{it} = g(Z_{it}, \delta)\exp\varepsilon_{it}^{*} \qquad (6)$$

where all firms are indexed with a subscript *i* and all years are indexed with a subscript *t;* EE_{it} is the vector of environmental efficiency measures; Z_{it} is the vector of explanatory variables likely to influence the environmental efficiency of a firm; δ is a vector of parameters to be estimated; ε_{it}^{*} is a composite error term specified as $\varepsilon_{it}^{*} = v_{it}^{*} - u_{i}^{*}$; with the assumptions that $v_{it}^{*} \sim i.i.d.$ and $N(0, \sigma_{v*}^{2})$ while $u_{i}^{*} \sim i.i.d.$ and $N^{+}(u, \sigma_{u*}^{2})$. From equation (6) a conditional environmental efficiency measure (CEE) can be defined as

$$CEE_{it} = \frac{EE_{it}}{g(Z_{it}, \delta)\exp v_{it}^{*}} = \exp(-u_{i}^{*}) \qquad (7)$$

Comparing equation 2 and equation 7, it is evident that conditional environmental efficiency measure (CEE) is the level of technical efficiency after accounting for variations in environmental efficiency.

The next section presents the empirical analysis of both environmental efficiency and technical efficiency.

4.0: Empirical Analysis

This section discusses the empirical findings of the technical and environmental efficiency of Kenya's manufacturing firms. The section commences with descriptive statistics are presented and discussed after which various results from estimated models are presented and discussed. This includes reporting the estimated technical efficiency and environmental efficiency of firms, the discussion of causes of variations in environmental efficiency and discussion of the conditional environmental efficiency. Finally a comparison of technical inefficiency and environmental efficiency is presented as well as the trend of technical efficiency, environmental efficiency and conditional environmental efficiency. The sub-section below describes the data and defines the variables.

4.1: Descriptive Statistics

The variables in levels are highly skewed (see appendix 1) and hence this analysis uses all the variables in logs in which case they are fairly normally distributed. Table 1 below presents some descriptive statistics for the sample employed to estimate the stochastic frontier models for technical efficiency and environmental efficiency. About two thirds (61%) of the firms in the sample are located in Nairobi which is the capital city, 14% in Mombasa, 13% in Eldoret with 7% and 5% located in Nakuru and Kisumu respectively. The mean value of all inputs does not vary much across the years. The mean of output is the same across all years with a reasonably low standard deviation. On average, firms are more labour-intensive than capital-intensive which is expected in developing countries. The mean of clean fuel is higher than that of dirty fuel with that of total energy being even higher. This would imply that firms are conscious of the need to embrace clean technology in production hence the percentage of clean fuel in the total energy is higher.

Table 1: Summary Statistics in Years

Variable	Overall	2000	2001	2002
Log of output	18.62 (1.85)	18.65 (1.82)	18.55 (1.88)	18.68 (1.87)
Log of Capital	15.56 (2.21)	15.52 (2.31)	15.46 (2.16)	15.72 (2.18)
Log of labour	15.84 (1.71)	15.85 (1.67)	15.85 (1.74)	15.85 (1.73)
Log of energy	15.59 (2.13)	15.65 (2.30)	15.60 (2.13)	15.53 (1.94)
Log of Material Intensity	-0.81 (1.20)	-0.88 (1.35)	-0.69 (1.24)	-0.86 (0.96)
Log of dirty fuel	14.45 (2.11)	14.54 (2.21)	14.34 (2.14)	14.47 (1.96)
Log of clean fuel	14.88 (2.28)	14.90 (2.42)	14.94 (2.32)	14.77 (2.08)
Log of inputs	17.82 (2.00)	17.77 (2.19)	17.85 (1.88)	17.83 (1.92)
No EMP	0.26 (0.44)	0.27 (0.45)	0.25 (0.43)	0.25 (0.44)
Poor EMP	0.66 (0.48)	0.63 (0.48)	0.66 (0.48)	0.68 (0.47)
Average EMP	0.07 (0.26)	0.08 (0.27)	0.08 (0.27)	0.07 (0.25)
Good EMP	0.01 (0.12)	0.02 (0.14)	0.02 (0.14)	0 (0)
Nairobi	0.61 (0.49)	0.64 (0.48)	0.63 (0.49)	0.57 (0.50)
Mombasa	0.14 (0.35)	0.14 (0.35)	0.13 (0.34)	0.15 (0.36)
Nakuru	0.07 (0.26)	0.08 (0.27)	0.06 (0.24)	0.08 (0.27)
Eldoret	0.13 (0.33)	0.11 (0.31)	0.12 (0.32)	0.15 (0.36)
Kisumu	0.05 (0.22)	0.03 (0.17)	0.07 (0.25)	0.05 (0.23)
Firm age	25 (15.52)	25 (16.17)	25 (14.90)	25 (15.65)
N	294	100	102	92

Source: Computed from RPED Data set; The figure in parentheses is the standard deviation

Looking at the dummy variables, 26% of the firms show no efforts towards environmental sustainable practices, more than half (66%) have made some efforts to have in place some sort of environmental management policies, in an attempt to adhere to the recently enacted environmental management regulations (see EMCA, 1999 for a detailed description of the regulations). However, only 8% show evidence of proactive environmental management policies which are rated as either average or good. Examining the mean output for this categories, (reported in parentheses in figure 1 below) good performers were found with the highest mean (22.27) followed by average performers (20.91); poor performers had 18.73 while those with no EMP reported 17.48. This may be suggestive that it is costly to implement an EMP policy therefore the higher the income of a firm (implied by level of output), the more rigorous the EMP policy. Low income firms have no capacity to implement any EMP.

4.2: Estimation of Technical and Environmental Efficiency

This section presents the estimation and analysis of both the technical efficiency and environmental efficiency models. The aim is to establish how a firm's choice of energy, which is considered as an environmental detrimental input, affects the technical efficiency of the firm. The estimated level of technical inefficiency is then used to calculate the level of environmental efficiency. The analysis is stepwise where first a pooled OLS model is first estimated followed by the stochastic frontier model implemented in two stages. Under pooled OLS estimation, the interest is to see how different inputs affect the level of output. In order to capture the effect of different sources of energy, three variations of the model are estimated. The first is an environmental detrimental model where the firms choose dirty fuel as the source of energy; the second one is the environmental conscious model where the firms mix both dirty and clean fuel in production while the third is the environmental sustainable model where firms only use clean sources of energy. Under the first stage stochastic frontier analysis, the environmental conscious model is adopted where total energy is used as input as this is the normal operation of the firms. In the second stage stochastic frontier analysis, the sources of energy are differentiated into dirty and clean fuel in order to capture their environmental impacts.

4.2.1: Pooled OLS

A pooled OLS model assumes that there are no technical inefficiencies hence excludes u_i from the regression equation. This gives the level of output of a technically efficient firm. As suggested by Coelli *et al*. (1998) the parameters for the regressors may be unbiased but that of the intercept and the variance term could be biased. The results of OLS estimation are reported below in table 2 below.

At all levels, the R-squared shows a good fit and all input variables are significant. Capital and labour are reported to have a positive impact on output which is consistent with theory. Energy also reports a positive relationship implying it is useful in the production process. Material intensity reports a negative sign. This may be assumed to imply that even though the actual level of inputs is increasing, they are not being used efficiently so they don't translate into output but most of them end up as waste.

The dummy variables for no_EMP and poor_EMP are significant and negatively signed while that of average EMP is insignificant and positive. The location and year dummies are all insignificant apart from the location dummy for Eldoret dummy which is significant.

Table 2: Results of Pooled OLS

Variable	Environmental Detrimental	Environmental Conscious	Environmental Sustainable
Constant	5.775*** (0.854)	5.623*** (0.848)	6.087*** (0.881)
Log of Capital	0.225*** (0.033)	0.214*** (0.035)	0.225*** (0.037)
Log of Labour	0.452*** (0.061)	0.421*** (0.064)	0.486*** (0.065)
Log of Energy	0.177*** (0.039)	0.219*** (0.047)	0.130*** (0.041)
Log of Material Intensity	-0.162* (0.104)	-0.152 (0.107)	-0.153 (0.107)
No_EMP dunmmy	-0.621** (0.295)	-0.647** (0.288)	-0.854*** (0.272)
Poor_EMP dunmmy	-0.423* (0.265)	-0.469* (0.263)	-0.601** (0.249)
Average_EMP dunmmy	0.053 (0.294)	0.290 (0.289)	-0.366 (0.276)
Loc_NRB dunmmy	-0.037 (0.193)	-0.005 (0.184)	-0.075 (0.179)
Loc_MSA dunmmy	0.140 (0.245)	0.124 (0.237)	0.064 (0.234)
Loc_NKR dunmmy	-0.053 (0.242)	0.037 (0.238)	0.055 (0.248)
Loc_ELD dunmmy	-0.494* (0.286)	-0.425* (0.283)	-0.442* (0.283)
R-Squared	0.791	0.794	0.784
Skewness of Residue	-0.646	-0.609	-0.526

*Source: From Pooled OLS with robust standard errors using Stata 10; The figures in parenthesis are the Standard errors, ***,**, and * denote* Significance levels at 1% , 5% and 10% respectively based on t-statistics; N = 294

4.2.2: Hypothesis testing

In stochastic production frontier analysis, given the underlying assumption that $u_i > 0$, negatively skewed residual, $\varepsilon_i = v_i - u_i$, implies the presence of technical inefficiency in the data A positive skewness of the residual is therefore considered problematic because it cannot be reconciled with a one-sided distribution of inefficiencies that is positively skewed. Reinhard *et* *al*., (2002) suggested a way of testing the appropriateness of the frontier specification, by computing the skewness of the OLS residuals. Waldman (1982) suggest that when an industry shows positive skewness of the residuals, it is assumed that there are little if any inefficiencies. Green and Mayes (1991) argue that, apart from possible misspecification of the production functions, this either indicates 'super efficiency' (all firms in the industry are efficient and hence the variance of v = 0) or the inappropriateness of the technique of frontier production function analysis to measure inefficiencies. Carree (2002) shows that a positive skewness of the residual suggests a one-sided distribution that has low probabilities for small inefficiencies and high probabilities of large inefficiencies.[4]

Examining the pooled OLS residuals reported in table 2 above reviews that they are not normally distributed. They are negatively skewed at all levels. The negative skewness is consistent with the theory of stochastic frontier estimation; hence the methodology is appropriate for this analysis. Another assumption associated with the error term is that the two error components are independent of each other. v_{it} is independently and identically distributed (*iid*) with N(0, δ_v^2) while u_i is independently and identically distributed and has a normal-truncated distribution (with a non-null average μ) with NT(u, δ_u^2). This serves as an alternative method to check the appropriateness of the model. If the mean inefficiency, μ, is significantly different from zero, it shows that the normal truncated distribution is an appropriate assumption. The mean inefficiency is reported as 4.12 which is different from zero.

[4]Hence, only a small fraction of the firms attain a level of productivity close to the frontier while a large fraction attains considerable inefficiencies The case of a negative skewness implies that only a small fraction of firms are lagging behind, with most of them being efficient..

Statistically, the generalized likelihood ratio test is used to establish the presence of technical inefficiency effects in the model. The likelihood ratio test statistic in this case is insignificant hence the null hypothesis is rejected implying that there are technical inefficiency effects in the model.

Stochastic frontier production functions can assume either a trans-logarithmic or a Cobb-Douglas functional form and a decision is made using the generalized likelihood ratio test. In this case, the computed likelihood ratio test statistic is 63.32 which is significant at 5% significant level, as it is greater than the critical value of 17.67 for the degrees of freedom equal to 10 (Kodde and Palm,1986). Thus, the null hypothesis that the Cobb-Douglas frontier is an adequate representation of the data, given the specifications of the translog function is rejected. This result is reasonable because the translog offers more flexibility than the Cobb-Douglas functional form.

4.2.3: Stochastic Frontier Estimation

Following Battese & Coelli (1992) parameterization the technical inefficiency component is treated as time-varying hence a time-varying decay model is estimated. For comparison purposes, a time-invariant inefficiency model is also estimated following Schmidt and Sickles (1984). Table 3 reports the results of the translog stochastic frontier estimations.

Examining the results of the time-varying decay model, it is observed that 10 out of the inputs coefficients (including the products and cross products as well as constant) are significant. However, contrary to what is expected, the coefficients of capital and labour are signed negatively. The coefficients of material intensity and energy are positive.

Table 3: Results of Translog stochastic frontier estimation

Variable	Time Varying Decay Model No dummy variables	Time Varying Decay Model With Dummy variables	Time Invariant Model With dummy variables
Constant	8.781*	7.023	7.222***
	(5.746)	(7.225)	(49.93)
Log of Capital	-0.103	-0.096	-0.096
	(0.274)	(0.261)	(0.261)
Log of Labour	-0.114	0.323	0.383
	(0.625)	(0.633)	(0.618)
Log of Energy	1.260***	1.427***	1.409***
	(0.406)	(0.421)	(0.419)
Log of Material Intensity	1.052**	0.976**	0.955**
	(0.471)	(0.456)	(0.453)
(½)Log (K x K)	0.0003	-0.002	-0.002
	(0.016)	(0.015)	(0.015)
(½)Log (L x L)	0.122**	0.106**	0.102*
	(0.057)	(0.055)	(0.054)
(½)Log (E x E)	-0.058**	-0.050**	-0.050**
	(0.023)	(0.022)	(0.023)
(½)Log (II x II)	-0.093***	-0.102***	-0.102***
	(0.015)	(0.014)	(0.014)
Log (K x L)	-0.030	-0.027	-0.027
	(0.028)	(0.027)	(0.027)
Log (K x E)	0.047**	0.044**	0.045**
	(0.020)	(0.019)	(0.019)
Log (K x II)	0.085***	0.086***	0.087***
	(0.022)	(0.021)	(0.020)
Log (L x E)	-0.059*	-0.078**	-0.077**
	(0.039)	(0.038)	(0.038)
Log (L x II)	-0.012	-0.012	0.010
	(0.064)	(0.062)	(0.061)
Log (E x II)	-0.159***	-0.157***	-0.158***
	(0.020)	(0.046)	(0.046)
Mu	4.136*	4.525	5.003
	(2.643)	(4.869)	(49.65)
Gamma	0.743	0.788	0.790
Sigma-squared	0.796	0.833	0.837

N = 294

*Source: From Stochastic Frontier Analysis using Stata 10 .The figures in parenthesis are the Standard errors, ***,**, and * denote* Significance levels at 1% , 5% and 10% respectively based on t-statistics

The technical inefficiency parameter *u* is significant at 10% level of significant which shows that inefficiency is part of the production processes of the firms under consideration. The variance parameter, γ, is approximately 0.74. This implies that of the total variation captured by sigma squared, which is 0.79, (which is actually the sum of sigma-v squared and sigma-v squared) 74% is as a result of the technical inefficiency in production processes while 26% could be attributed to other stochastic errors. This is also clear from the values of sigma-u and sigma-v which are 0.59 and 0.20, respectively.

One of the underlying objective of this study is to examine how environmental performance of the firms impact on the firm's technical efficiency. It is therefore important to explore what happens to the estimated model in the presence of environmental performance dummy variables. When environmental performance dummy variables are included in the estimation, the No EMP and Poor EMP are significant at 1% and 5% levels of significance, respectively while the average EMP variables is insignificant[5]. The inefficiency term is now insignificant which implies that the technical inefficiency reported in the first model could be associated with poor environmental practices by the firms. It is further noted that all environmental performance dummy variables are negatively signed. This could be interpreted to mean that while firms that take no environmental initiative may incur additional costs through penalties hence affecting them negatively, it is also costly to implement environmental management systems. Hence all the dummy variables affect the firm's productivity negatively. The estimated level of technical efficiency is quite low, 0.022 with a variability of 0.025. This implies that firms are generally technically inefficient. This is confirmed by the level of estimated technical inefficiency which is 4.13. Including environmental dummy variables doesn't improve the situation.

[5] Good EMP dummy variable is dropped due to dummy variable trap

Although most of the parameters of the translog function are significant, the results are not convincing because some of the basic inputs of the production function are insignificant and they have a negative sign. This violates one of the basic assumptions of the production function which requires the marginal products to be nonnegative. This justifies the progression to estimate a Cobb-Douglas function, the results of which are given in table 4 below.

Table 4: Results of Cobb-Douglas Stochastic Frontier Estimation

Variable	Time Varying Decay Model No dummy variables	Time Varying Decay Model With Dummy variables	Time Invariant Model With dummy variables
Constant	8.854	10.53*	10.94
	(29.51)	(6.482)	(40.20)
Log of Capital	0.139***	0.122***	0.123***
	(0.032)	(0.032)	(0.032)
Log of Labour	0.451***	0.440***	0.441***
	(0.059)	(0.059)	(0.059)
Log of Energy	0.237***	0.197***	0.196***
	(0.046)	(0.047)	(0.047)
Log of Input Intensity	-0.241***	-0.241***	-0.241***
	(0.046)	(0.039)	(0.039)
Mu	3.442***	3.140	3.568***
	(29.52)	(6.387)	(40.18)
Gamma	0.585	0.610	0.610
Sigma-squared	0.787	0.783	0.784
Sigma_u	0.460	0.478	0.478
Sigma-v	0.327	0.306	0.306

N=294
Source: From Stochastic Frontier Analysis using Stata 10
*The figures in parenthesis are the Standard errors, ***,**, and * denote* Significance levels at 1% , 5% and 10% respectively based on t-statistics; *Dummy variables are not reported*

For the Cobb-Douglas function, the results reveal that the marginal effects are all positive as expected and they are all significant at 1% level of significance. The inefficiency parameter u is significant which shows that inefficiency is part of the production processes of the firms under consideration. The variance parameter, γ, for the Cobb-Douglas function is approximately 0.59.

This implies that of the total variation captured by sigma squared 59% is associated with technical inefficiency. Again including the environmental dummy variables renders the inefficiency term insignificant implying that environmental performance has an effect of the technical efficiency of the firms. The estimated level of technical efficiency is 0.040 with a variability of 0.026 and technical inefficiency is 3.43.

The estimated technical inefficiency from the translog time varying decay model together with the estimated parameters (see table 3) are used to calculate the environmental efficiency measure following equation 7. Table 5 reports the summary statistics of the predicted technical inefficiency term and that of the computed environmental efficiency measure (EE). The mean of environmental efficiency measure is -0.528 with a variability of 0.08. It is interesting to note that it takes a negative sign which implies that the firms are characterized by environmental inefficiency.

4.3: Accounting for Variations in Environmental Efficiency

It is inevitable to try and investigate the sources of these environmental inefficiencies. Environmental inefficiencies may arise from the use of environmentally detrimental inputs. In this study, energy is the detrimental input. To capture the environmental impact of energy, total energy is differentiated by source isolating dirty fuel from clean fuel and the impact of each is observed separately. The use of raw material is also deemed to have environmental impact. If the raw materials are not used efficiently, they generate a lot of solid waste. The actual amount of raw materials may be rising but the resource productivity may be going down and waste going up.

In this second stage analysis, environmental efficiency measure (EE) is the variable which is used as a dependent variable. Unlike the technical inefficiency term that is assumed to be independently identically distributed, no such assumption is attached to the environmental efficiency measure hence it is appropriate to be used as a dependent variable. In this second stage analysis, the aim is to establish if controlling for the environmental impacts associated with raw materials, dirty fuel and clean fuel has an impact on technical efficiency. This involves estimating a stochastic frontier model with environmental efficiency as the dependent variable with the variables that are deemed to have an environmental impact being the explanatory variables. The technical efficiency of each firm is then re-estimated.

The dependent variable is assumed to be time invariant which is reasonable because environmental efficiency is not expected to vary much given the short panel of data. Furthermore, it is calculated from time invariant technical inefficiency term and parameters of the models which are also time invariant. Hence a time invariant inefficiency model is adopted. A Cobb-Douglas functional form is adopted and results presented in table 5 below. For comparison purposes, two time-invariant inefficiency models, with and without environmental dummy variables, are estimated.

The results reveal that input and clean fuel variables are significant while the dirty fuel variable is insignificant as well as the firm age variable although the magnitude of the marginal effects are very low. Considering that the environmental efficiency term is negative, which indeed is environmental inefficiency, all variables have the expected sign.

Table 5: Results of Cobb-Douglas Time Invariant Model

Variable	Time Invariant Model Without dummy variables	Time Invariant Model With dummy variables
Constant	0.097 (0.263)	0.255 (0.384)
Log of dirty fuel	0.001 (0.001)	0.0003 (0.001)
Log of Clean Fuel	-0.003*** (0.001)	-0.004*** (0.001)
Log of Raw Materials	-0.008*** (0.001)	-0.009*** (0.001)
Firm age	0.000 (0.000)	0.000 (0.000)
Mu	0.440* (0.262)	0.437 (0.377)
Sigma squared	0.010	0.010
Gamma	0.992	0.992
Mean Tech. Inefficiency	0.438	0.436
Conditional Env. Efficiency	0.648	0.649

Source: From Stochastic Frontier Analysis using Stata 10
*The figures in parenthesis are the Standard errors, ***, **, and * denote* Significance levels at 1% , 5% and 10% respectively based on t-statistics; *Dummy variables are not reported*

Dirty fuel increases the environmental inefficiency of firms hence the positive sign while the clean fuel impacts negatively on a firm's environmental inefficiency. For raw materials, the direction of the impact is determined by how efficiently they are utilized. The negative sign here is an indication that they are used efficiently hence reduce the environmental inefficiency of the firm. The inefficiency term is significant when environmental dummy variables are omitted and become insignificant when the environmental dummy variables are included. The magnitude of the sigma squared shows that only 1% of the variations are unexplained which is an indicator that the larger proportion of environmental inefficiency captured in stage one of this analysis is associated with the raw materials and fuel choices a firm makes other than factors exogenous to the firm. Of the total unexplained variation still existing after accounting for variations that result from the firm choices, 99% is attributed to technical inefficiencies as shown by the large size of the γ parameter.

The level of technical inefficiency which was 4.13 now drops significantly to 0.44. Moreover, the level of technical efficiency which was 0.022 now rises to 0.649. The new level of technical efficiency is what is referred to as conditional environmental efficiency by Reinhard. *et al*., (2002). The mean conditional environmental efficiency is higher than the first-stage technical efficiency and environmental efficiency score because a portion of the environmental efficiency has been explained by the second stage explanatory variables.

4.4: Graphical Analysis of Efficiency and Inefficiency Levels

4.4.1: Technical Inefficiency and Environmental Efficiency

Technical efficiency is postulated to be both necessary and sufficient for environmental efficiency (Reinhard *et al.* 1999). Looking at the mean values of technical inefficiency and environmental efficiency in table 6 below, it is evident that on average firms are generally characterized by high levels of technical inefficiency (and low technical efficiency) which translate to high level of environmental inefficiency (negative environmental efficiency)

Table 6: Summary Statistics for Technical Inefficiency and Environmental Efficiency Score

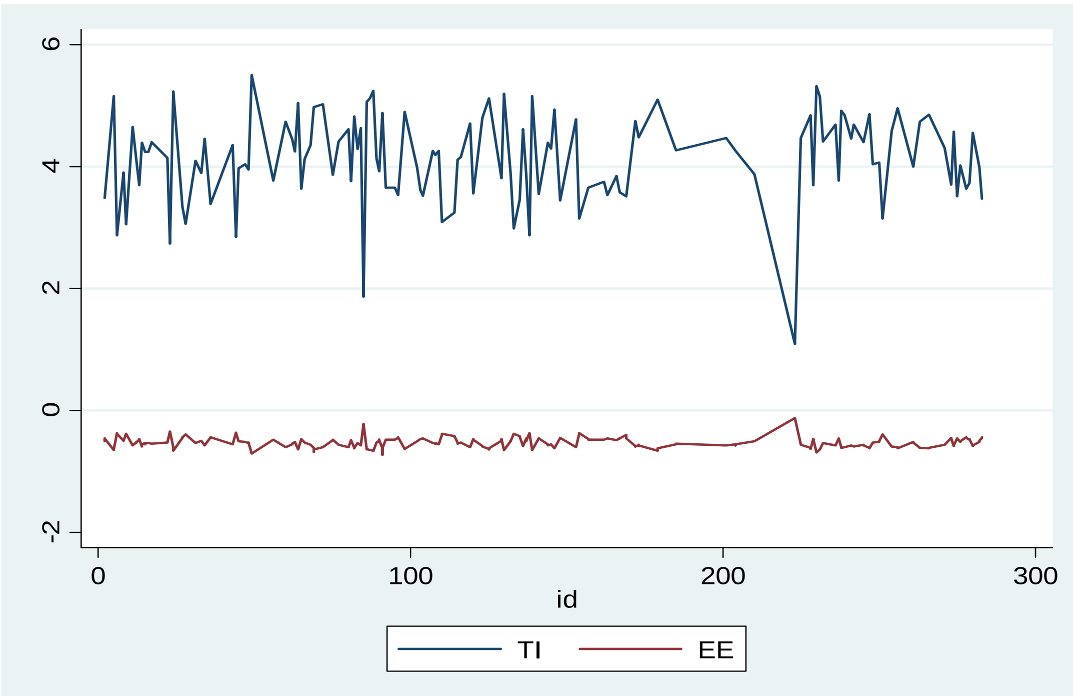
Variable	Mean	Standard Error	Maximum	Minimum
Technical Inefficiency	4.129	0.667	5.509	1.085
Environmental Efficiency	-0.528	0.084	0.128	-0.730

N = 295
Source: From Stochastic Frontier Analysis using Stata 10

To fully understand this relationship, a graphical analysis would be more appropriate. Figure 3 below shows the relationship between technical inefficiency and environmental efficiency before accounting for variations in environmental efficiency.

It is evident that technical inefficiency and environmental efficiency are inversely related which implies that technical efficiency and environmental efficiency are positively related

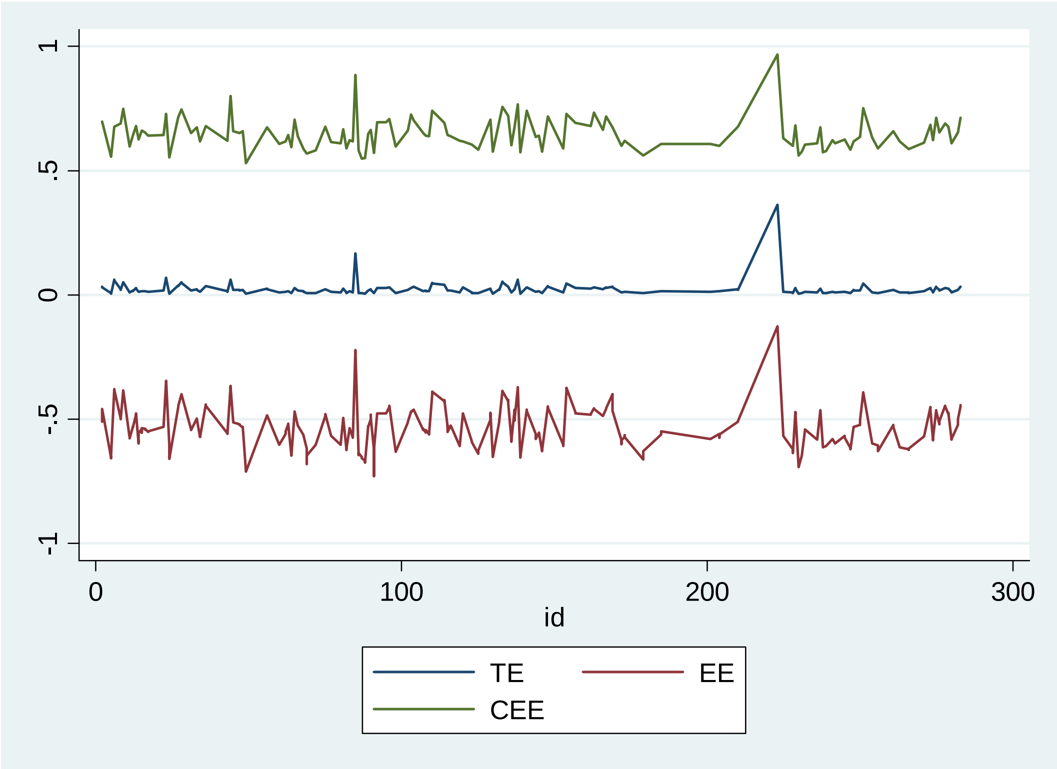
Figure 3: Relationship between Technical Inefficiency and Environmental Efficiency



4.4.2: Technical/Environmental Efficiency and Conditional Environmental Efficiency

Another way to analyze the postulated relationship between technical efficiency and environmental efficiency is to account for the environmental impacts associated with the environmentally detrimental inputs. To examine the movements of technical efficiency, environmental efficiency and conditional environmental efficiency (this is technical efficiency after accounting for variations in environmental efficiency), a graphical analysis is appropriate which is presented in figure 4 below.

Figure 4: Trends of Technical Efficiency, Environmental Efficiency and Conditional Environmental Efficiency



From this analysis, it is evident that technical efficiency is higher after the variations in environmental efficiency that result from environmentally detrimental inputs are accounted for. It can therefore be deduced that most of the technical inefficiency reported in the first stage of this analysis could be associated with the raw materials and fuel choices a firm makes. This is because while the mean technical efficiency[6] before accounting for variations is 0.022, it improves dramatically to 0.649. This shows that if firms can endeavour to make environmentally sustainable choices, they can be more efficient in production which would translate to higher profits.

[6] Coelli et al., (1998) suggest that the mean technical efficiency is the arithmetic average of the predictors for the individual technical efficiencies of the sample firms

5.0: Conclusion and Recommendations

This study provides the firm-level estimates of both technical and environmental efficiency using the time-varying inefficiency decay model within a composite error framework. Further, factors that determine variations in environmental efficiency are established and a comparison is made of technical efficiency and environmental efficiency both before and after accounting for variations in environmental efficiency. The analysis is based on an unbalanced panel of Kenya's manufacturing firms over a three year period, 2000-2002.

From this analysis, it is evident that the manufacturing sector in Kenya is far from being efficient. The inefficiency observed is endogenous to the firm since the technical inefficiency is largely associated with the firms' choice of energy and raw materials. There is evidence that firms could improve their technical efficiency by being more environmental efficient which entails choosing inputs that have less environmental impact. Even though there is a notable improvement in technical efficiency after accounting for variations in environmental efficiency, technical inefficiency remains significant which calls for further investigation of the variations by including other environmentally detrimental variables.

Given the fact that a large proportion of the technical inefficiency can be associated by the use of dirty fuel, and that using clean fuel offers some environmental gain and financial gain to the firms, policy makers should provide incentives to encourage the use of clean fuels. This could be through rewarding firms that endeavour to adopt clean production technologies. The activities of the Kenya National Clean Production Centre (KNCPC) could be a good starting point where firms reap some benefits by voluntary opting for clean production processes.

6.0: References

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