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Technical Efficiency Analysis of the Kenya Agro-Processing Industry

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Abstract:

This study sought to provide empirical evidence on technical efficiency levels and trend of the Kenya Agro-processing industry. The major problem of the industry is that it has been under performing in terms of value addition and Kenya is known to be a net exporter of primary agricultural produce instead of high-quality value-added products. This study sought to determine the efficiency estimates of the industry and analyzed the trend in efficiency changes. Panel data covering three years (2011, 2012, and 2013) for 41 firms in this industry was collected from the Kenya National Bureau of Statistics (KNBS). Econometric production frontiers were estimated in each period. The findings showed that the industry had an overall efficiency score of 44 percent. The efficiency score was distributed as 53 percent, 60 percent and 57 percent for the food, beverage, and non-food subsectors. This study concluded that an average 56 percent technical potentiality was not achieved by the industry in the period 2011, 2012 and 2013. This study recommends that the policy export promotion of locally processed products of the Kenyan government should be complemented with an industrial policy that enhances the technical efficiency of local exporting firms to increase international competition of Kenyan manufacturers.

Keywords: Efficiency measure, Agro-processing, Stochastic production frontier function, Decision making unit.

1. Introduction

Industrial production in Kenya is composed of four sectors. These sectors include: mining and quarrying sector, manufacturing sector, electricity, gas, steam and air conditioning supply sector and water supply; sewerage, waste management and remediation activities sector. This classification is informed by the international standards of industrial classifications of all economic activities (ISIC) Revision 4. The manufacturing sector in Kenya is the largest among all the industrial production activities where it accounts for 99 percent of all industrial activities in Kenya (Kenya National Bureau of Statistics, 2013).

Kenya Vision 2030 identifies the manufacturing sector especially the agro-processing industry as one of the key drivers for realizing a sustained annual GDP growth of ten percent. The Kenya manufacturing sector is made of the following subsectors: building mining and construction (4%), chemical and allied (9%), energy electrical and electronics (6%), agro-processing (38%), metal and allied (8%), motor vehicle and allied (5%), paper and board (4%), pharmaceuticals and allied (5%), plastic and rubber (11%), services and consultancy (9%), (Kenya Association of Manufacturers, 2014).

Agro-processing is the action taken by manufacturers of transforming raw agricultural products into products suitable for consumption. The agro – processing process begins with the main activity of agriculture. Activities such as farming, livestock, horticulture and forestry take place. Thereafter, these raw materials are supplied to manufacturers, who then begin the activity of processing the raw materials through actions such as milling, fermenting, slaughtering, blending, cutting and moldings. The manufactured products are then packaged and supplied to the wholesale and retail markets to be sold to consumers. Agro- processing is a widely diverse subsector and is vital to the production of food, beverages and non-food products like tobacco, sisal as well as the treatment of wood for furniture and paper products (South Africa Small Enterprise Development Agency, 2012).

1.1. Government Policy towards the Agro-Processing Industry in Kenya

The National Industrialization policy statement for the agro- processing industry in Kenya seeks to achieve the broader objective of encouraging local manufacturers to produce high value added products for domestic consumption and exports. The policy provides incentives for investment in high value processing of agricultural products such as tea, coffee, pyrethrum, cotton and nuts. In addition,

the policy not only promotes the local manufacture of agro-processing machinery and equipment's such as tractors, combine harvesters, cotton ginneries, tea picker, juicing and pulping equipment by providing technical information and support for research. But also encourage clustering of industries around specific agricultural resources for example coconut and cashew nut, honey processing and fish farming and processing (Government of Kenya, 2010).

This study was motivated by the performance of the Kenya manufacturing sector, which has remained below the expectations of the Kenya vision 2030 and the Kenya national industrialization policy. This study narrowed down to the agro-processing industry, since this industry forms the largest component of the Kenya manufacturing sector. The agro-processing industry forms thirty-eight percent of the Kenya manufacturing sector, therefore, efficiency estimates of the agro-processing industry can be used for general conclusions about the Kenya manufacturing sector for the period 2011 to 2013 (Kenya National Bureau of Statistics, 2013).

To achieve a desired growth rate of 10 percent per year, as envisaged by the Kenya Vision 2030 the government has come up with initiatives to strengthening production capacity and local content of domestically-manufactured goods; increasing the share of locally manufactured products in the regional market through implementation of Medium Term Performance (MTP) and the national industrialization policy strategies. However, the productivity of the Kenya manufacturing sector and the agro-processing industry has remained below the expected performance. The Kenya Vision 2030 expects the manufacturing sector to grow at a rate of 10 percent annually and contribute 30 percent to the GDP. The contribution to GDP has stagnated at 10 percent and 3 percent for the manufacturing sector and the agro-processing industry respectively over the years and an annual growth rate averaging at 3.16 percent (Bigsten *et al.*, 2010).

The amounts of fresh products from the agricultural sector that are processed by the agro-processing industry have been significantly low making Kenya a net exporter of primary products. Agricultural products form 65 percent of Kenya's total exports and only 20 percent of the total agricultural products exported are processed. This has been attributed to several factors that include: inadequate supplies of raw materials that are seasonal; high production cost with respect to raw material handling, distribution and marketing; slow development and implementation of policies. For Kenya to achieve the much needed growth it has to utilize the available resources efficiently (Bigsten *et al.*, 2010).

This notwithstanding, a detailed determination of the actual level of efficiency in the agro-processing industry in Kenya and the distribution of levels of efficiency to the beverage subsector, food subsector and non- food subsector had not yet been done. This study, therefore, attempted to fill this gap by estimating the level of efficiency and analyzing the trend of efficiency in the agro-processing industry over the time period 2011-2013. The paper is organized as follows. Section 2 briefly discusses the literature review. The methodology and data are discussed in Sections 3, section 4 presents the empirical results, section 5 discusses the conclusions while section 6 presents the policy implications of this study.

2. Literature Review

The concept of efficiency involves a comparison between optimal values and expected values of output and input of a production line. The comparison can take the form of the ratio of minimum potential to observed input required to produce a given output or, the comparison can take the form of the ratio of observed to maximum potential output obtainable from given set of inputs. In these two comparisons, the optimum was defined in terms of production possibilities and efficiency was technical. Technical efficiency reflects the ability of the firm to maximize outputs given inputs, (output-oriented) or minimize inputs used in the production of a given outputs. Economic efficiency reflects the production of given outputs at minimum cost or, the utilization of given inputs to maximize revenues or the allocation of inputs and outputs to maximize profits (Kumbahakar and Lovell, 2000).

The theoretical literature reviewed has given a detailed analysis of the approaches for measuring technical efficiencies of manufacturing sectors using graphical approaches, parametric methods which include Stochastic Frontier Analysis (SFA) and finally the non- parametric method which is dominated by Data Envelope Analysis (DEA). The theoretical literature analysis described the simple approaches to estimation of efficiency by bench marking other Decision Making Units (DMUs) against the best practicing one in the sample. Besides, there is evidence that both the parametric and non- parametric approaches of efficiency estimation seem to converge on the level of average efficiency, but diverge on efficiency estimates of individual (DMUs) (Schmidt and Lovell, 1979).

Lundvall and Battese (2000)who used an unbalanced panel data for period 1993-1995, estimated a translog production function for the Kenya manufacturing sector. The output variable used in the empirical analysis was the value added of all output produced by the firm in a given year. The input variables consisted of capital which was defined as "the replacement cost of existing machinery and other equipment employed in the production process, multiplied by the degree of capacity utilization", Wages which included the total wage bill including all allowances for the firm in one year. This study reported average technical efficiencies of 77 percent, 80 percent, 76 percent and 68 percent for the food, metal, textile and wood subsectors.

Ghahula (2012) investigated the relative efficiency of commercial banks operating within the east African community. This study used Data Envelopment Analysis (DEA) for the period 2008 to 2011. The estimated results show sharp decline of Technical efficiency. The findings show that most commercial banks in east Africa are operating under a decreasing return to scale. Therefore, inefficient utilization of input resources (technical inefficiency) could be one of the reasons for the inefficiency of commercial banks in East Africa; therefore, banks should make use of underutilized resources and reduce operating expenses to be relatively efficient in the production frontier.

Ngui and Muniu (2012) sought to empirically determine the technical efficiency of firms in the Kenyan manufacturing sector by looking at the food, metal and textile sub-sectors using data covering two periods: 1992/1993 - 1994/1995, and 2000/2001 - 2002/2003. The translog specification of the production frontier was rejected and cob-Douglas specification was found to be the best functional form to represent the technology. The stochastic frontier approach was used in the analysis. The results showed the average

technical efficiency of 52 percent, 58 percent, and 60 percent for the food, metal and textile sub-sectors, respectively, imply that nearly 48 percent, 42 percent, and 40 percent technical potentialities were not achieved in the 1992/1993 -1994/1995 period. On the other hand, the average technical efficiency of 48 percent, 42 percent, and 68 percent for the food, metal and textile sub-sectors, respectively, imply that nearly 52 percent, 58 percent, and 32 percent technical potentialities were not achieved in the 2000/2001 - 2002/2003 periods.

Harron and Chelakumar (2012) determined the efficiency performance of the Kenya manufacturing companies over the period of 2009 to 2011. The study also provided some policy recommendations to ensure maximum productivity of the Kenya Manufacturing sector based on the results of their study. The study estimated efficiency levels of 30 manufacturing companies in Kenya using the Non parametric approach (DEA). The input variables were the raw materials, staff expenses and plant and machinery and two output variables were net sales and earnings after tax. Data was gathered from Kenya Association of Manufacturers (KAM) database. The results indicated that small-sized company has the highest relative efficiency compared to medium-sized and large size company. In addition, the study finds that 1 large-sized company, 2 medium-sized companies and 3 small-sized companies operated under the most productive scale size throughout the three-year period.

Empirical literature reviewed, indicated that technical efficiency of firms can be estimated by either estimating a stochastic production frontier or a stochastic cost function. In the estimation of the production frontiers empirical literature revealed that, both ordinary least squares and maximum likelihood methods were used. Empirical literature reviewed also revealed that the inputs variables used in the estimation of the stochastic production function are mostly labor, capital, and cost of raw materials while the output variables used can be value added and/or return on investments. Apart from (Lundvall and Battese 2000) most of the studies reviewed estimated a Cobb-Douglas production function. Empirical literature specific to the efficiency estimation of an agro-processing industry in Kenya was not available. Therefore, this paper contributed towards filling this gap.

3. Methodology and Data Sources

3.1. Data Type and Sources

This paper utilized panel data. The secondary data was collected from various agencies and bodies including the Ministry industrialization and enterprise development, Kenya tea development agency. The Kenya daily board, The Kenya sugar board, the export processing zone departments and the Kenya association of manufacturer's directory. Data was also mined from the annual financial statements and annual reports of firms that are published online by selected firms. Most of the data was obtained from the Kenya National Bureau of Statistics.

The output variable was the value added which was computed as the gross proceeds from sales of the manufactured products less value added tax and other levy paid by the firms per year. The independent variables consisted of the cost of raw materials, the cost of labor and capital all these variables were measured in terms of the Kenya shillings. The variables were defined as: cost of raw materials Constituted cost of raw materials, fuels and electricity consumed in the production process per year. Cost of labor Included: salaries and allowances, staff performance bonus, pension defined benefit scheme, provident fund, staff insurance, staff gratuity provision payment of social security fund and leave pay paid to workers per year. Capital Constituted: land, buildings, plant and machinery and other fixed assets which were expected to have a productive life of more than one year and was in use by the sampled firms for the manufacturing activity.

3.2. The Empirical Model

Production function $y_i = f(x_i; \beta)$ can be written as a stochastic production frontier used in the estimation of technical efficiency by adding a composite error term \mathbf{e}_i , (see Aigner *et al.* 1977, Meeusen and Broeck 1977).

$$\ln \mathbf{y}_i = \mathbf{f}(\mathbf{x}_i ; \mathbf{B}_i) + \mathbf{e}_i \tag{3.1}$$

 $\mathbf{e}_{i} = \mathbf{v}_{i} - \mathbf{u}_{i}$ Is an error term comprising two components: \mathbf{v}_{i} is a random error having zero mean, $N(0; \mathbf{\delta}_{\psi}^{2})$. \mathbf{v}_{i} is associated with random factors which the firms do not have control over them such as measurement errors in production and weather. It is assumed to be symmetric independently distributed as $N(0; \mathbf{\delta}_{\psi}^{2})$ random variables and independent of \mathbf{u}_{i} . On the other hand, \mathbf{u}_{i} is a non-negative half normal, $N(0; \mathbf{\delta}_{\psi}^{2})$ random variable associated with firm-specific factors, which leads to the \mathbf{i}^{eh} firm not attaining maximum efficiency of production; \mathbf{u}_{i} is associated with technical inefficiency of the firm and ranges between zero and one. However, \mathbf{u}_{i} can also have other distributions such as gamma and exponential, (Coelli *et al.*, 2005). The stochastic production frontier given in (3.2) can be extended to the case of panel data, which is specified as: $ln\mathbf{v}_{i} = X_{in}\mathbf{B} + \mathbf{v}_{in} - \mathbf{u}_{i}$

$$(3.2)$$

Where i= 1, 2...I and j= 1,2...J and t= 1,2...T. J represents the j^{th} input of the i^{th} firm at time t. **B**, v_{it} and uit is the parameters to be estimated. This model gives the time-varying production inefficiency.

$$Lny_{i} = \alpha_{0} + \sum_{k=1}^{3} \alpha_{k} lnx_{ki} + \frac{1}{2} \sum_{k=1}^{3} \sum_{j=1}^{3} \alpha_{kj} lnx_{ki} lnx_{ji} + e_{i}$$

This study adopted a panel of three years, Ln denotes natural logarithms, y and x variables. α 's are parameters to be estimated. The stochastic frontier can be obtained from (3.4) in two ways. "First, if no explicit distribution for the efficiency component is made, and then the production frontier could be estimated using a stochastic version of corrected ordinary least squares (COLS). However, if an explicit distribution is assumed, such as exponential, half-normal, truncated normal or gamma distribution, then the frontier is estimated by maximum likelihood estimates (MLE)." According to (Coelli *et al.* 2005), MLE makes use of the specific distribution of the disturbance term and this is more efficient than COLS.

$$TE = \frac{y_i}{\exp(\beta_i x_i)} = \exp(-u_i) \, i = 1, 2 \dots N.$$
(3.4)

In order to estimate efficiency level of each firm, distribution assumption of u was assumed to follow the half normal model. Equation 3.4 gives the efficiency estimates and generates variance parameters, (i.e.) "Lambda, $\lambda = (\delta_u / \delta_v)$; variance of the model (Sigma δ), variance of the stochastic model δ_v^2 and variance of the inefficiency model δ_u^2 ." Technical efficiency of an individual firm is defined in terms of the ratio of the observed output to the corresponding frontier output, conditioned on the level of inputs used by the firm. Technical inefficiency is therefore defined as the amount by which the level of production for the firm is less than the frontier output (Kumbahakar and Lovell, 2000).

4. Empirical Results

4.1. Descriptive Statistics

The summary statistics indicated that for all the outputs and inputs under consideration the standard deviation was higher than the mean. (Harron and Chelakumar 2012) also found the same in their study. The finding implies that the firms in the Kenya agroprocessing industry had a high level of heterogeneity in period under consideration, since the variations were on inputs and outputs; the high standard deviation suggested heterogeneity in the scale of operations by the firms. The Parametric method of efficiency estimation ignores the scale differences among decision-making units (Coelli *et al.*, 2005).

The correlation analysis revealed that here was a positive correlation between the various inputs and outputs. That is the variables chosen as output and inputs moved in the same direction. This result implies that for the firms to increase their output they had to increase their inputs in the production process. These results also indicated that the independent variables were not highly correlated with each other; therefore, MLE gave unbiased and consistent results.

4.2. Regression Results

The best functional form of the production function to adopt between the translog production function and the Cobb-Douglass production was based on the likelihood ratio test; $LR = -2[lnL_{ur} - lnL_r]$ where lnL_{ur} and lnL_r ; are the maximum values of the log likelihood functions of the unrestricted and restricted model respectively. The log likelihood functions of the unrestricted and restricted model respectively. The log likelihood function by use of frontier 4.1 program

The results of the log likelihood test statistic were compared with Kodde and Palm critical values as summarized by Table 1

Null Hypothesis	Test Statistic	Degrees of Freedom	Critical Value
$H_0: B_i = B_1 \dots = B_6 = 0$	LR=1.247208	6	11.911
Translog specification			
$H_0: \sigma_i = \sigma_1 \dots \sigma_6 = 0$	λ ~=6.147163	6	1.645
No inefficiency			

 Table 1: Results of hypothesis testing-either to use Translog or Cobb-douglas specification

 Source: Authors calculations

A simple z-test was used to test the hypothesis that all firms were technically efficient. The test statistic is given by
$$Z = \frac{\lambda^{\sim}}{se(\lambda)} \sim N(0,1)$$
, where λ^{\sim} is the ML estimator of $\lambda = \sigma_u / \sigma_v$ and $se(\lambda)$ is the estimator of its standard error.

Results presented in Table 1 indicated that, the first null hypothesis was not rejected hence Cobb Douglas was considered to best represent the data. (Ngui and Muniu, 2012), while estimating technical efficiency of the Kenya manufacturing sector also did reject a translog production function, while (Kibaara 2005), estimating the technical efficiency of Kenyan farmers accepted the translog production function. (Lundvall and Battese 2000) also accepted the Translog specification. The second null hypothesis explored the test that specified that each firm was operating on the technically efficient frontier. This was rejected in favor of the presence of inefficiency effects.

4.3. Diagnostic Testing

Before proceeding to estimate the Cobb-Douglas production frontier, the panel data was diagnosed for heteroskedasticity and whether it assumed random effects or random effects. F-test was used to test for fixed effects; the LM test was used to test for random effects. Levin, Lin and chu (2002) and Im, Pesaran, and Shin (2003) approach were used to test for the presence of heteroskedasticity. The results as shown by Table 2 revealed that there were no fixed effects in the data.

Fixed and random effect testing					
Method	od Null Hypothesis		P- value	Decision	
F-Test	Y1=Y2=Y3=0	Dummies for all the years are equal to zero	Prob > F= 0.8233	No Fixed effects	
LM Test	Test $Var(u1) = Var(u2) \dots = Var(uN) = 0$ variances across entities are zero (No		Prob >CHI = 0.000	Random effects	
	panel effect)			present	

 Table 2: Diagnostic testing Results-Tests of the Panel Data used for the study
 Source: Authors calculations

Random effects were found to be present in the data; this result suggested that inefficiency effects reported in the test of hypothesis Table 1 were random and not fixed among the firms in the industry. The attempt to test for unit root did not give any significant result; this was attributed to the small times series aspects of the data. (Baltagi 2001) notes that heteroskedasticity is a problem to macropanels.

4.4. The Estimated Stochastic Frontier Model

Based on the data used, the MLEs for the assumed half normal distribution of the inefficiency term in the frontier model are shown in Table 3.

Value added	Coefficient.	Std. Err.	Z	P>z
Cost of raw materials	-0.1222	0.0642	-0.35	0.729
Cost of labor	0.488	0.9591	5.09	0
Capital	0.3688	0.1076	2.03	0.042
constant	11.7643	1.9695	5.97	0
/Insig2v	3.7765	1.0702	3.53	0
/Insig2u	0.3122	0.2339	1.33	0.0182
sigma_v2	0.0559	0.009		
sigma_u2	1.3105	0.3203		
sigma2	1.3664	0.3196		
lambda	0.9591	0.0119		

 Table 3: Estimates of the stochastic frontier model

 Source: Authors' compilation

The results of the stochastic frontier model in Table 3 revealed that, if all the inputs were to change by the same proportion the output would decrease. This is because the sum of the elasticities of cost of raw material, capital and labor were less than one. This study therefore concluded that the Cobb-Douglas production function estimated exhibits a Decreasing Returns to Scale (DRTS). The output from frontier includes estimates of the standard deviations of the two error components, σ_v and σ_u , which are labeled sigma_v and sigma_u, respectively. In the log likelihood, they are parameterized as $\ln \sigma_v$ and $\ln \sigma_u$, and these estimates are labeled /lnsig2v and /lnsig2u in the output. Frontier 4.1 program also reports two other useful parameterizations. The estimate of the total error variance $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$ is labeled sigma2, and the estimate of the ratio of the standard deviation of the inefficiency component to the standard deviation of the characteristic component, $\lambda = \sigma_u/\sigma_v$ is labeled lambda.

4.5. Efficiency Estimation Results

Table 4 presents efficiency estimates for the agro-processing industry for the period 2011-2013. The results were computed from frontier 4.1 program using the stochastic model specified by Table 3. The mean technical efficiency of the agro-processing industry in Kenya was 44 percent. The efficiency estimates had an increasing trend from 43 percent to 44 percent and 45 percent for the years 2011, 2012 and 2013 respectively. This finding suggested that the industry's efficiency levels were increasing throughout the study period under consideration.

Period	Efficiency Estimate
2010/2011	0.42732
2011/2012	0.43195
2012/2013	0.44732
Mean	0.435528

 Table 4: Efficiency estimates for the agro-processing industry in Kenya

 Source: authors' calculations

Technical inefficiency can be calculated as, technical inefficiency =1- technical efficiency. Therefore, the technical inefficiency for the Kenya agro-processing industry was 57, 56 and 55 percent respectively for the years 2011, 2012 and 2013 respectively. This result indicated that the efficiency performance of the Kenya agro-processing industry was below average for the period under consideration, whereby 56 percent of the inputs in this industry were not optimally used to get maximum production from the industry for the period under consideration.

4.5.1. Efficiency Distribution among The Beverage, Food and Non-Food Subsectors

The agro-processing industry is a diverse industry that can be broadly classified into three main subcategories. This industry is involved in processing, packaging and value addition of the fresh agricultural produce produced through activities of farming, livestock keeping and forestry by the Kenya agricultural sector. Figure 1 shows the efficiency estimates for the food subsector, beverages subsectors and non- food subsector for period 2011 to 2013.

The mean efficiency estimate for the food subsector was 52 percent for the year 2011 and 53 percent for the year 2012 and 2013. This was an average performance whereby 47 percent of the inputs in this subsector were not being utilized efficiently. The beverage subsector mean efficiency estimate was 63, 60 and 58 percent for 2011, 2012 and 2013 respectively, showing that on average 40 percent of the inputs into this subsector were not being utilized efficiently to achieve a maximum production. The non- food subsector had efficiency estimates at 56, 59 and 58 percent respectively for the period under consideration, this means that on average 43 percent of the inputs into this industry were not being used effectively. Comparing the efficiency levels of the three subsectors the food subsector recorded the least score at 53 percent and then non-food subsector at 60 percent. The beverage subsector recorded the highest efficiency score. This result suggested that the beverage subsector probably had many big sized firms with high efficiency scores. The results revealed that the efficiency estimates for food subsector were constant, the efficiency estimates for the beverages subsector declined, while that of the non-food subsector had an increasing trend. Increase in the efficiency levels can be attributed to improved management practices over the years, (Lundvall and Battese 2000). This result suggested that the non- food subsector was the best in terms of efficiency improvement for period under consideration.



Figure 1: The overall efficiency trend of each subsector from 2011 to 2013

The findings of this study are consistent with other similar studies on the Kenyan manufacturing sector which found a large potential of improvement among the analyzed firms. For instance, (Ngui and Muniu 2012) using the subsectors of food, metal and textile and found the efficiency scores to be 52 percent, 58 percent and 60 percent respectively. (Harron and Chelakumar 2012) found that smallsized companies were more relatively efficient with 73 percent as compared to medium and large companies with 68 percent and 69 percent respectively which were higher than the estimates of this study. (Lundvall and Battese 2000) reported average technical efficiencies of 77 percent, 80 percent, 76 percent and 68 percent for the food, metal, textile and wood subsectors respectively, which were higher than the estimates of this study. However, in this study the efficiency scores were not directly comparable to those of (Lundvall and Battese 2000) and (Harron and Chelakumar 2012) since different models were used. Empirical evidence shows that efficiency estimates are sensitive to the estimation or computation methods, assumptions about the distribution of the error terms, data levels and data samples.

4.5.2. Test for Equality of Distribution in the Efficiency Estimates

Kolmogorov Smirnov test(K-S Test) was done across the years and among the subsectors to test for equality of distribution. Two sample K-S test for 2010/11 and 2010/12, 2010/11 and 2012/13, and 2011/12 and 2012/13 was done. The results revealed no significant difference in the distributions of efficiency estimates for the period 2011-2013 at 5 percent level of significance. This result suggested that the distribution of efficiency estimates was consistent for period under consideration as shown by Figure 2.



Figure 2: K-S test comparison percentile plot for efficiency estimates time period 2011 2012 and 2013

Test for equality of distribution among the subsectors revealed no systematic difference in the distribution of efficiency estimates between the three subsectors as shown by Figure 3.



Figure 3: K-S test comparison percentile plot for efficiency estimates for the Food, Beverage and Non-food subsectors

The study assumed that, firms in the same subsector were homogenous in nature and portrays similar characteristics. This result revealed the firms in the industry were possibly facing the same factors which influence technical performance of the firms, for instance the management practices, quality of labor and raw materials could have been the same across the subsectors for period under consideration (Lundvall and Battese 2000). This result indicates that policy recommendations given in this study cut across the food, beverages and non-food subsectors. This result was not directly comparable to other studies for instance (Ngui and Muniu 2012) found that the distribution of efficiency estimates was different in the food, metal and textile subsectors.

Considering the value added of the firms, the firms were further categorized into three groups small, medium and large. The firms with a value added less than Kenya shillings 500 million were regarded as small, firms with value added between Kenya shillings 500 million and one billion were considered as medium firms. Finally, firms with value added above one billion Kenya shillings were regarded as large firms. This classification resulted in 13 small firms, 13 medium firms and 15 large firms.

The K-S test comparison percentile plot for efficiency estimates for the small, medium and large firms' classification revealed systematic difference in the distribution of efficiency estimates between the large and the small firms as shown by Figure 4.



Figure 4: K-S test comparison percentile plot for efficiency estimates for the small, medium and large firms

The results showed that the medium sized firms curve crossed the large and small sized firms at various points. This study concluded that, the larger the firms the higher the efficiency levels, this finding confirmed the prior expectation that multinational corporations in the agro-processing industry had higher efficiency estimates levels. This can be attributed to the fact that Multinationals as Foreign direct investment are sources of innovations in the Kenya Manufacturing sector. This finding was consistent the results of (Harron and Chelakumar 2012) and (Ngui and Muniu 2012).

5. Conclusions

The overall technical efficiency level for the agro- processing industry was 44 per cent for the period under consideration. This result indicates a reduced efficiency performance of the Kenya agro-processing industry that on average 56 per cent technical potentialities of the agro-processing were not achieved for period 2011-2013. The efficiency distribution in the beverage, food, and non-food subsectors scored 53, 60 and 57 per cent respectively. This efficiency scores for the subsectors were higher than the efficiency scores for the industry this was attributed to large sample (asymptotic) property which was not present in the subsectors. The sample size for the food, beverages, and non-food subsectors were 13, 14 and 13 respectively. A similar challenge was experienced by Ngui and Muniu (2012), Lundvall *et al.* (2002) and Sotnikov (1998).

K-S test for equality of distribution of technical efficiency estimates among the subsectors revealed that, there was no significant difference in the distribution of efficiency estimates among the subsectors and across the years. Distribution of efficiency estimates was found to be different significantly on basis of firm size. The larger the firms the higher the efficiency industry for period under consideration needs to be improved so that this industry can reach a maximum production.

Test for equality of distribution revealed that there was no systematic difference in the distribution of efficiency estimates among the subsectors and across the years. This result revealed that the firms in the industry were possibly facing the same factors which influence technical performance of the firms for instance the management practices, quality of labour and raw materials could have been the same across the subsectors for period under consideration (Lundvall and Battese, 2000). This result indicates that policy recommendations given in this study cut across the food, beverages and non-food subsectors.

6. Policy Implications

The agro-processing industry did not achieve 56 percent potentiality in the year 2011-2013. This study recommended that the technical potentiality of the firms in the agro-processing industry be improved to make sure the investors in this industry get maximum returns from their investments. In light of the study findings, the following recommendations are made:

The results of this study revealed that the overall technical efficiency for the agro-processing industry was below average for the period under consideration. This study recommends that polices of that promotes exports of locally processed products should be complemented with an industrial policy that enhances the technical efficiency of local exporting firms to increase international competition of Kenyan manufacturers. For example, the government should ensure competitive pricing of inputs by not only investing heavily in human resource development, but also adopting selective and targeted strategies for foreign direct investments and local investments.

The negative relationship between firm size and efficiency for the agro-processing industry for the period 2011-2013, could be partly explained by operation of excessively large firms driven by increases in factor inputs rather than improvements in productivity, hence leading to higher complexity in larger firms that makes identification of inefficiency more difficult than in smaller firms. Hence, support programmes should not only be geared towards stimulating the growth in size rather than number of firms, but also improving the technical efficiency and consequently the total factor productivity of the firms. In addition to this foreign direct investment are considered as a credible source of innovations. This study recommends that small firms should improve their product innovations, marketing innovations and process innovations by taking advantage of the spillover effects from the multinational corporations in the

agro-processing industry, since the results of this study indicated that large firms had high efficiency estimates than small firms in the industry for the period under consideration.

The raw materials for the agro-processing industry comes from the agricultural sector, this implies that technical efficiency improvement of the agro-processing industry can help to leverage the success of the agricultural sector. This study therefore, recommends that the government strengthens the agricultural sector. For instance, the agricultural sector can be strengthened through coming up with innovative farming techniques, for example biotechnology, coming up with more irrigation schemes to make sure that the agricultural sector remains productive even in the dry seasons. The government should also provide incentives to the small and medium enterprises willing to invest in the agro processing industry by providing subsidized electricity and fuel for industrial production.

8. References

- i. Aigner D., J. Lovell C. A. K., and Schmidt, P. (1977). Formulation and determination of stochastic frontier function models. Journal of Econometrics, 6, 21-37.
- ii. Baltagi, B. (2001). Econometric analysis of panel data (3rd ed.). New York: John Wiley and Sons Ltd.
- iii. Battese, G. E, and Coelli, T. J. (1992). Frontier production functions technical efficiency and panel data: with application to paddy farmers in India. Journal of Productivity Analysis, 3, 153-169.
- iv. Bigsten, Arne, Peter Kimuyu, MånsSöderbom, Adam C., Collier P. and Ndung'u N. (2010). The Kenya manufacturing sector: policies for prosperity. Oxford University press and Central Bank of Kenya.
- v. Coelli, T. (1995). Estimators and hypothesis tests for a stochastic frontier function. Journal of Productivity Analysis, 6(4), 247–68.
- vi. Coelli, T., Rao D. S. P., and Battese G. E. (1998). An introduction to efficiency and productivity analysis. Boston: Kluwer Academic Publishers
- vii. Coelli, T. J., PrasadaRao, D. S., O'Donnell, C. J., and Battese, G. E. (2005). An introduction to efficiency and productivity analysis (2nd ed.). New York: Springer.
- viii. Farell, M.J. (1957). The measurement of productive efficiency. Journal of the Royal Statistical Society Series A (General), 120, 253-290.
- ix. Forsund, F.R., and Hjalmarson, L. (1979). Generalized Farell measures of efficiency an application to milk processing in Swedish daily production. The Economic Journal, 89, 294-315.
- x. Forsund, F.R., Lovell, C.A.K, and Schmidt, P. (1980). A survey of frontier production functions their Relationship to efficiency measurement. Journal of Econometrics, 13, 5 25.
- xi. Ghahula, R. (2012). Efficiency of commercial banks in East Africa: a non- parametric approach. International Journal of Business and Management, 8(4), doi:10.5539/ijbm.v8n4p50.
- xii. Government of Kenya (2013).Kenya Vision 2030 progress report, accessed from http: //www.vision2030.go.ke/cms/vds/Vision_2030-_ score_booklet.pdf on 25 th July 2013.
- xiii. Government of Kenya (2010).Kenya national industrialization policy frame work: ministry of Industrialization. Nairobi: Government Printer.
- xiv. Government of Kenya (2007). The Kenya vision 2030. Nairobi: Government Printer.
- xv. Im, K. S., Pesaran, M. H., and Shin, Y. (2003). Testing for Unit roots in Heterogeneous Panels, Journal of Econometrics, 115, 53-74.
- xvi. Kenya Association of Manufacturers (2014). Kenya manufacturers and exporters' directory. Nairobi: Government Printer.
- xvii. Kenya National Bureau of Statistics (2013). Report on 2010 census of industrial production. Nairobi: Government printer.
- xviii. Kenya National Bureau of Statistics (2014). Statistical abstract. Nairobi: Government Printer.
- xix. Kibaara, B.W. (2005). Technical efficiency in Kenyan's maize production: an application of the stochastic frontier approach. Fort Collins, Colorado: Colorado State University.
- xx. KIPPRA (2012). Kenya economic report: imperatives for reducing the cost of living. Nairobi: Government Printer.
- xxi. KIPPRA (2013). Kenya economic report. Nairobi: Government Printer.
- xxii. Kodde, D.A., and Palm F.C. (1986). Wald criteria for jointly testing equality and inequality restrictions. Econometrica, 54(5), 1243–48.
- xxiii. Kumbhakar, S. C., and Lovell, C.A. K. (2000). Stochastic frontier analysis. Cambridge: Cambridge University Press.
- xxiv. Levin, A., Lin C.F. and Chu J. (2002). Unit root in panel data: Asymptotic and finite-sample Properties, Journal of Econometrics, 108(1), 1-24.
- xxv. Lundvall, K. and Battese, G.E. (2000). Firm size, age and efficiency: evidence from Kenyan manufacturing firms. Journal of Development Studies, 36(3), 146–63.
- xxvi. Lundvall, K. W., Ochoro, and L. Hjalmarsson (2002). Productivity and technical efficiency, in A. Bigsten and P. Kimuyu (eds.). Structure and performance of manufacturing in Kenya. New York: Palgrave, 151–72.
- xxvii. Haron, M. and Chellakumar A. (2012). Efficiency performance of manufacturing companies in Kenya: evaluation and policies. India: Nadu Tamil.
- xxviii. Musleh-Ud D., Ghani E., and Mahmood, T. (2007). Technical efficiency of Pakistanis manufacturing sector stochastic frontier and data envelope analysis. Pakistan: spring.
- xxix. Meeusen, W. and Vandenbroeck, J. (1977). Efficiency estimation from Cobb-Douglas production Functions with composed

error. International Economic Review, 18, 435-444.

- xxx. Ngui-Muchai, D.M. and Muniu, J.M. (2012). Firm Efficiency Differences and Distribution in the Kenyan Manufacturing Sector. African Development Review, 24(1) 52–66.
- xxxi. Sekaran, U. (2003). Research methods for business: a skill building approaches (4th ed.). New York: John Wiley and Sons Inc.
- xxxii. Schmidt, P. and Lovell, C.A.K., (1979). Estimating technical and allocative inefficiency relative to stochastic production and cost frontiers. Journal of Econometrics, 9, 343-366.
- xxxiii. Schmidt, P. and Lovell, C. A.K., (1980). Estimating stochastic production and cost frontiers when technical and allocative inefficiency are correlated. Journal of Econometrics, 13, 83-100.
- xxxiv. Sotnikov, S. (1998).Evaluating the effects of price and trade liberalization on the technical efficiency of agricultural production in a transition economy: the case of Russia. European Review of Agricultural Economics, 25, 31-412.
- xxxv. South Africa small enterprise development agency (2012). Research on the performance of the manufacturing sector. South Africa: Umjwali.
- xxxvi. Sudarin, R. and Huang, W. (2012). Efficiency evaluation of food and beverage companies in Thailand: an application of relational two stage data envelopment analysis. International Journal of Social Science and Humanities, 3(3), 216-225.
- xxxvii. Varian, H. (2006). Micro economic analysis (7th ed). New York: Norton and Company.