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DOES TECHNICAL EFFICIENCY MATTER IN KENYAN MANUFACTURING FIRMS? EVIDENCE FROM A DATA ENVELOPMENT ANALYSIS APPROACH

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Abstract

The study broadly analyses the technical efficiency scores of Kenyan manufacturing firms. It makes use of cross sectional data from the World Bank Kenya Enterprise Development Survey for 2013. The study conducts a two-part analysis, we first test efficiency using a non-parametric technique, after which the Tobit model is estimated. The average technical efficiency is 74.4 percent, with 79.78 percent, 18.03 percent and 2.16 percent of the firms examined working under increasing returns, decreasing and constant returns to scale respectively. The Tobit model estimates, shows an upward concave relation between technical efficiency and the size of the firm, whereas the manager's experience portrays a downward concave relationship and both of the coefficient are significant. Human capital is positively related with technical efficiency in Kenyan manufacturing firms. Firms that have formal training of employees are more technically efficient than firms without formal training programs. Also, firms located in Nyanza, Mombasa, Nairobi and Nakuru are found to be less technically efficient relative to the ones in Central region. The study offers a mix of policy prescription that could potentially lead to improvement in efficiency levels and greater competiveness of manufacturing firm.

Keywords: Technical efficiency; DEA; Kenyan manufacturing firms; Non-parametric

INTRODUCTION

The role of manufacturing sector in driving development cannot be overstated. Economist and development experts have typically argued that this sector is the engine to economic development. Manufacturing sector is vital for economic development through; creating backward and forward linkages in the economy, value addition, trade effects and employment effects, all which are mechanisms that stimulate growth (Lavopa and Szimai, 2012). According to Kaldor (1966) there is a positive correlation between the Manufacturing Value Added (MVA) growth rate and the Gross Domestic Product (GDP) growth rate.

In spite of sectoral significance, its share to Kenyan GDP has over the years stagnated at around 10 percent and stood at 9.2 percent in 2016, with the share of MVA fluctuating around 12 percent (KNBS, 2017). Haron and Chellakumar (2012) evaluated the efficiency performance of Kenyan manufacturing firms and concludes that large and medium-sized firms are less efficient relative to small-sized companies. Although, approximately 90 percent of the manufacturing sector comprises of the micro and the small sized firms, and only contribute to a tune of 20 percent of the sector's GDP. Whereas, medium and large firms comprise of less than 5 percent and contributes to a tune of 60 percent of the sector's GDP (KNBS, 2017). Therefore, to rejuvenate the sector requires increasing productivity level and performance of manufacturing firms.

Often performance in firms is proxy in terms of efficiency levels (Coelli *et.al*, 2005). Basically, efficiency is at the point where a firm is producing at optimal levels. Greene (1997) contends that producers are thought to be efficient if they are producing the highest attainable output given the inputs employed at the least cost. Technical efficiency is usually applied to understand if a firm is producing optimal outputs from a given vector of inputs. Koopmans & Debreu (1951) and Farrell (1957) are credited for their initial contribution to matters concerning efficiency and its measures. Technical efficiency measures the use of factor inputs to produce the maximum output level given the feasible technology (Farrell, 1957). The production frontier is used to reflect the recent technological state at play in the industry hence the firm that operates at such frontier is considered to be technical efficient.

Technical efficiency is mostly estimated using two approaches; Stochastic Frontier Analysis (SFA) and the Data Envelopment Analysis (DEA). Both measures have some similarities and differences that exist between them. The DEA is a non-parametric measure of efficiency while the SFA uses a parametric approach to measure efficiency. A non-parametric approach assumes that the production frontier is deterministic. Essentially, the disturbances that might arise from a non-parametric approach will not be taken care off. The parametric approach takes account of these disturbances by choosing a specific production function form but eventually the problems of estimation and model specification are likely emerge (Coelli *et.al*, 2005).

Efficiency is key to understanding the performance of any firm and several empirical papers have attempted to investigate the determinants of technical efficiency. Empirically, factors that affect technical efficiency can be broadly summarized as firm's ownership, specific attributes, market structure and technological change (Caves, 1992; Caves and Barton, 1990). The firm's ownership status, can either be between public and private ownership or between foreign and domestic ownership. The specific attributes of a firm include; firm size, location, nature of organization and its capital accumulation process. The structure of the market defines the nature of competition and lastly is the random factors generated either from the demand or production side of the firm, for instance, a technological change or changes in the demand patterns.

Various empirical papers demonstrate how these factors behave in relation to technical efficiency. The firm size positively influences technical efficiency of a firm, in that large firms signify investment in technology acquisition which accelerates efficiency (Gumbau-Albert and Maudos, 2002).) Similarly, efficiency relates positively to firm size until firms reach an optimal size then efficiency starts to decline (Niringiye *et.al*, (2010).However, the firm size effect on technical efficiency varies with ownership structure (Chow and Fung, 1997). Firm size can also have negative effects on the firm's technical efficiency (Cheruiyot, 2017). Empirically, ownership is an important factor in explaining efficiency variation in manufacturing firms (Bottasso and Sembenelli, 2004; Bitros, 2003; Goldar *et.al*, 2004).

This paper broadly seeks to estimate the technical efficiency scores in Kenyan manufacturing sector and to analyze factors affecting technical efficiency levels. The study specifically focuses on the following: to determine the technical efficiency scores of Kenyan manufacturing firms; to determine the scale efficiency of the Kenyan manufacturing firms; to understand the contributing factors to technical efficiency in Kenyan manufacturing firms; and more importantly prescribe policy options.

Fundamentally, this paper proffers insights in explaining factors that affect technical efficiency levels of manufacturing firms. Over the past, empirical studies done on manufacturing firms operating in Kenya have focused on estimating firm productivity and differences in technical efficiency (Ngui-Muchai*et.al*, 2012; Lundvall and Battese, 2000; Siggel, 1992; Mathews, 1991). Ostensibly lacking is evidence on factors affecting technical efficiency of Kenyan manufacturing firms. Cheruiyot (2017) argues there exist a substantial room for efficiency improvement within Kenyan manufacturing firms. According to the World Bank development indicators, the share of manufacturing has largely stagnated around 12 percent from 2000-2015. Perhaps, the stagnation could be explained due to low technical efficiency caused by either firm specific characteristics or external factor. Hence, the extent to which specific firm characteristics affect technical efficiency of manufacturing firms is worth exploring.

The purpose of the paper is to provide technical information that is relevant to a firm's decision making process. We evaluate the efficiency levels of Kenyan manufacturing firms and assess the effect of firm specific factors on observed efficiency scores. This information on efficiency in the manufacturing sector is critical especially at the time the sector's share of GDP has stagnated. Therefore, this paper is meant to contribute to the current policy and academia discourse on improving productivity and efficiency levels of manufacturing firms. The results offer policy makers with evidence which can be used to inform policy intended to increase productivity and efficiency levels. Equally, firms can particularly pay attention to the specific firm factors analyzed in this paper to improve efficiency and productivity.

The subsequent section of the paper discusses the methodology approached employed in the paper. Thereafter, nature of data and variables, we then present results and we wrap up with conclusion and policy implications.

METHODOLOGY

The Study

We employ the DEA technique as it offers technical advantage over SFA. DEA uses linear programming techniques to envelop observable input-output vectors (Boussofiane *et al*. 1991). This technique is widely used as it imposes less restriction in terms of the functional form and is able to allow for multiple input and output technologies. Additionally, one can either choose the input or output orientation analysis based on prior information (Coelli *et.al*, 2005; Charnes *et. al*. 1978).

The study is done in two parts. The first part estimates the technical efficiency scores of Kenyan manufacturing firms and the second part analyses the specific firm characteristics likely to have an effect on the technical efficiency of these firms.

Estimation of Efficiency

Technical Efficiency

The study employs the DEA technique presented by Charnes, Cooper and Rhodes (1978) that proposes an input orientation model. DEA can either be input or output oriented based on which quantities the decision making units (DMU) has control over (Coelli *et.al*, 2005). Input orientation is preferably suitable in the Kenyan context as firms have control on inputs and are primarily the decision variables. DEA model maximizes the efficiency level of a unit which is expressed as a fraction of weighted outputs and weighted inputs. This model restricts the fraction for every DMU to less or equal to one (unity).

By employing the DEA technique, the technical efficiency score of the n[th] firm is specified as follows:

Max $E_0 = \frac{\sum_i^M U_i Y_{io}}{\sum_j^N V_j X_{jo}}$ (1)

Subject to

$\frac{\sum_I^M U_{\ i} Y_{iq}}{\sum_j^N V_{\ j} X_{jq}} \leq 1$, q=1, 2 … k (2)

The variables u_i and v_j are the output and input weights respectively. Solving the above requires finding optimal $u_i v_j$ that maximize the efficiency level given the set constraints. However, one of the problem encountered is the existence of infinite solutions. Therefore, to evade this, we will employ Charnes-Cooper (1962) transformation but imposing the following constraint:

$\sum_{j=1}^n V_j X_{j0} = 1$ (3)

Our linear programming problem is now represented as follows:

Max $E_0 = \sum_{i=1}^m u_i Y_{io}$ (4)

Subject to

$\sum_{i=1}^m u_i Y_{iq} - \sum_{j=1}^n v_j X_{jq} \leq 0$ For all q=1, 2 ... k (5)

$\sum_{j=1}^m v_j X_{jo} = 1$ (6)

$u_i \ v_j \geq 0, i = 1, 2,3, \dots, m \ and \ \mathrm{j} = 1, 2, 3 \ \dots \ \mathrm{n}$ (7)

The dual problem from the above linear programming problem is:

Min $E_0 = \Theta_o$ (8)

Subject to

$\sum_{i=1}^m \lambda_i Y_{iq} \geq y_{io}$ i=1, 2 … m (9)

$\Theta_o X_{io} - \sum_{j=1}^n \lambda_j X_{jq} \geq 0$ j=1, 2 … n (10)

$\lambda_j \geq 0$ (11)

The dual linear problem above yields optimal solution Θ^* which is a constant returns to scale (CRS) technical efficiency. The score is less or equal to unity given each DMU is constrained by input-output combination (Farrell, 1957). In the above linear programming there are no other constraints imposed on weights other than non-negative conditions which implies a CRS. To obtain variables return to scale (VRS) we introduce convexity condition on the weights λ_j (Banker *et.al*, 1984). The condition is given as follows:

$\sum_{j=1}^n \lambda_j = 1$ (12)

Given the additional constraint the linear programming problem can now be rewritten as follows:

Min $E_0 = \Theta_o$ (13)

Subject to

$\sum_{j=1}^{m} \lambda_i Y_{iq} \geq y_{io}$ i=1, 2 … m (14)

$\Theta_o X_{io} - \sum_{j=1}^{n} \lambda_j X_{jq} \geq 0$ j=1, 2 … n (15)

$\sum_{j=1}^{n} \lambda_j = 1$ (16)

$\lambda_j \geq 0$ (17)

In the above linear programming each DMU gives the Banker, Charnes and Cooper (BCC) efficiency and is interpreted the same way as the CCR model. The results obtained in BCC efficiency are stated as pure technical efficiency score given they are obtained by allowing VRS and thus excluding the scale part of efficiency analysis.

Scale efficiency

Cooper *et.al* 2000 defines scale efficiency as a ratio of the overall technical (TE_{CRS}) and pure efficiency (TE_{VRS}). Thus, scale efficiency is given as follows:

SE=$\frac{TE_{CRS}}{TE_{VRS}}$ (18)

Econometric Framework

The study employs Tobit model to evaluate the firm specific effects on technical efficiency levels in the manufacturing firms. Tobit model is most preferably owing to the nature of dependent variable which is a censored variable ranging between 0 and 1 (Barth *et. al*. 2013). Here, Tobit model is estimated by maximizing the likelihood estimators. Subsequently, following Wooldridge (2002) Tobit Model can be represented in matrix form as follows:

$Y_p^* = \beta' X + \varepsilon_p$ ε_p~N (0,σ^2)

Where

$$Y_p = \begin{cases} Y_p^*; & 0 \leq Y_p^* \leq 1 \\ 0; & Y_p^* \geq 0 \\ 1; & Y_p^* \leq 1 \end{cases}$$

β' is represented in matrix form and encompasses parameters which are to be estimated and X represents the explanatory variables in the model. Y_p represents the efficiency level of the p^{th} firm,$\varepsilon_p$is the error term accounting for other factors not captured in our model and it also affects the level of technical efficiency in manufacturing firms. Y_p^* represents the latent variable, and the observed value Y_p is a function of a latent dependent variable Y^*. Given as;

$Y_p = G(Y_p^*)$

We can simplify the firm technical efficiency model as follows:

$$Y_p = f\left(Size, experience, gender, H\_capital, innovation, ownership, training, , \varepsilon_p\right)$$

Where Y_p represents the technical efficiency as estimated in DEA. These variables are likely to significantly affect the technical efficiency of manufacturing firms and ε_p is the typical error term. Therefore, we specify the Tobit regression equation as follows:

$$Y_p = \beta_0 + \beta_1 \ln Size + \beta_2 \ln Size^2 + \beta_3 \ln Expr + \beta_4 \ln Expr^2 + \beta_5 H\_capital + \beta_6\ Innovation + \beta_7 Ownership + \beta_8 Training + \beta_5 Female + \varepsilon_p$$

The dependent variable Y_p represents the efficiency score as estimated by the DEA technique. Variable $\ln Size$ represents the natural log of firm size and is measured as total number of employees in the firm. Variable $\ln Expr$ represents the natural log of manager experience as measured by number of experience years. Variable H_capital represents the human capital of employees' proxy by the skilled production workers over total production workers. Ownership is dummy measured in terms of the structure of ownership if domestically owned or foreign owned with foreign ownership taking the value 1 and zero otherwise. The location is defined as they region the firm is located. Innovation is a dummy variable taking the value 1 if the firm has been innovative in the last three years and the value 0 otherwise. Similarly, training is a dummy variable taking the value 1 if employees receive formal training and 0 otherwise. We also incorporate the gender of the top manager with male being the reference. Finally, we have included the square for firm size and manager's experience to factor for non-linearity and concavity in the variables with respect to efficiency score.

The Data

The study utilizes enterprise survey data (2013) obtained from the World Bank database. The data is cross sectional and contains 781 enterprises of which manufacturing firms are 414. Due to some missing values our study focuses on 183 on which we have full data to analyse technical efficiency of these firms. Their technical efficiency scores are estimated by making use of a two input Cobb Douglas production function. Where output is proxy by the total value of sales by the firm in the year 2013. Capital is proxy by total value of plant, machinery and firm's equipment in the year 2013 and firms' labour is given by the total number of employed workers in 2013.

We use the following variables to account the difference in technical efficiency in the Kenyan manufacturing firms: firm size; human capital; managerial experience and managers gender; firm location; firm ownership; training and innovation. The total number of employees is the measure of the firm size. Human capital is proxy by the skilled production workers over total production workers. Ownership is dummy measured in terms of the structure of ownership if domestically owned or foreign owned with foreign ownership taking the value 1 and zero otherwise. Firms' location is a categorical variable measured in terms of the region the firm is based. We incorporate managerial experience measured in terms of years and the gender of the manager measured in terms of female or male with female taking the value 1 and zero otherwise. Finally, innovation is a dummy taking the value 1 if the firm has been innovative in the last three years and the value 0 otherwise.

RESULTS AND DISCUSSIONS

Technical Efficiency estimations for Kenyan Manufacturing Firms

We transformed the firm output, firm capital and firm size into logarithmic form to exclude the manifestation of outliers in the dataset, and hence this exercise normalizes the variables. Table 1 presents the variables that are used to calculate the technical efficiency scores and Tobit estimators alongside their summarized statistics. The firms are drawn from the following sub-sectors: food; textile; garments; fabricant, machinery; non-machinery; furniture; chemical; plastic; leather; and paper. From table 1 the average firm capital is 17.28, the average number of firm production workers is 138 and the average firm output is 18.38. The average firm human capital used in a firm is 0.67 while the average managerial experience is 22 years.

Table 1: Summary Statistics of Manufacturing Firms under Study

Variable	Number of firms	Mean	Standard deviation	Minimum	Maximum
Capital in logarithm form	183	17.28685	2.340282	11.51293	23.52663
No. of production workers	183	138.9235	559.5624	2	7000
Logarithm of Output	183	18.38065	2.351956	13.45884	25.15408
Firm Size	183	217.776	658.6817	4	8000
Firm Age	183	28.16393	18.24032	2	92
Managerial experience (years)	183	22.22404	10.35995	1	44
Human capital	183	.6726513	.2921656	.0433333	1
Innovation	183	.7540984	.4318019	0	1
Formal Training	183	.5300546	.5004652	0	1
Dummy Foreign Ownership	183	.0710383	.2575935	0	1
Dummy Female Managers	183	.0437158	.2050231	0	1
Dummy Central	183	.1857923	.3900061	0	1
Dummy Nyanza	183	.0601093	.2383413	0	1
Dummy Mombasa	183	.1857923	.3900061	0	1
Dummy Nairobi	183	.5027322	.5013643	0	1
Dummy Nakuru	183	.0655738	.2482147	0	1

The study uses input-oriented DEA to generate the technical efficiencies as opposed to out-oriented. The decision to choose between the two is based on which variables are controlled by the DMU (Coelli *et.al*, 2005). Firms have control on inputs and more often are the decision variables. Essentially, the input orientation indicates the amount of factor inputs that can be reduced with output levels remaining constant.

Table 2 presents a summary statistics of input-oriented technical efficiency score per sector. The results indicate food sub sector has nine efficient firms and garments, chemical, furniture sub-sectors each have one efficient firm. The firms operating on the efficiency frontier totaled 13 out of 183 firms. From the results, the average technical efficiency score is 74.37. This result suggests that substantial improvements can be made, on average it is potentially feasible for firms reduce inputs without necessarily reducing output. For this to be feasible, they need to reduce inputs by approximately 25.63 per cent. Though, the reduction would vary from one sub-sectors to another. This result slightly differs with Cheruiyot (2017) who found average technical efficiency of 68.3 using World Bank 2007 enterprise survey data. However, from this result, it points to a significant increase in technical efficiency of Kenyan manufacturing firms. We also find that 79.78 per cent of firms work under increasing returns to scale whereas 18.03 per cent work under decreasing returns to scale. Only 2.16 per cent of the firms examined where working on a constant returns to scale.

Table 2: Technical Efficiency Scores (input-oriented DEA results)

Industry sector	**Number of firms**	**CRS T.E (percent)**	**VRS T.E (percent)**	**S.E (percent)**	**Number of Efficient firms**	**Number of inefficient firms**
Food	63	71.84	78.54	91.59	9	54
Textile	21	66.63	71.77	92.98	0	21
Leather	5	70.61	72.26	97.77	0	5
Garments	3	69.57	82.84	84.31	1	2
Chemicals	14	65.02	68.83	94.51	1	13
Fabric	13	67.72	74.57	91.09	0	13
Basic Metals & Machinery	18	68.6	74.35	92.68	0	18
Wood & Furniture	10	70.23	79.27	89.01	1	9
Electronics	5	65.62	68.31	96.07	0	5
Transport Equipment's	12	68.42	74.61	91.86	0	12
Publishing	5	70.27	78.30	89.53	1	4
Others	14	66.48	68.83	96.61	0	14
Total	183				13	170
Mean		**68.42**	**74.37**	**92.33**		

Table 2...

T.E. score (Min)	0.5449
T.E. score (Max)	1.000
CRS	4(2.16%)
IRS	146(79.78%)
DRS	33(18.03%)

Estimating the Factors Affecting Technical Efficiency for Firms in Kenyan Manufacturing sector

By taking into account the factors likely to affect technical efficiency in Kenyan manufacturing firms, is the first step to significantly increase the efficiency scores. Table 3 presents the second part of efficiency estimation. We estimate two models; the first model contains the variable of interest while the second model incorporate the dummy variables region to capture the regional effect on technical efficiency of manufacturing firms.

We carry out several robust check to ensure the estimated models are fit. Specifically, we test for the model specification, heteroscedasticity, specification of explanatory variables to ensure the appropriateness of our model. To test for model specification, we made use of the link test that tests for the explanatory power of the predicted hat and hat squared. The null hypothesis is that the specification of the model is not correct compared to the alternative hypothesis that the model is correctly specified. The results in table 3 shows the predicted hat and hat squared are rejected at 5% level of significance in both models. This indicates the models are well specified. To correct for heteroscedasticity, we make use of robust standard errors in both models to ensure our inference is not affected.

Table 3: Tobit Model for Technical Efficiency of Kenyan Manufacturing Firms

Variables	Model (1)	Model (2)
Ln firm size	-.1932565(-6.09) ***	-.1891515(-5.48)***
Ln firm size sq.	.0167661(4.74)***	.0165927 (4.37)***
Ln Manager experience	.1183327(2.48)**	.0964052 (1.97)**
Ln Manager experience sq.	-.0232802(-2.44)**	-.018827 (-1.94)*
Female Managers Dummy	.0840169 (1.51)	.0798364 (1.42)
Human capital of workers	.0548283 (2.46)**	.0551653 (2.46)**
Innovation Dummy	-.0145828(-0.97)	-.01212 (-0.78)
Training Dummy	.0353198(2.71)**	.0350413 (2.73)**
Foreign ownership Dummy	.0661943 (1.87)*	.0655604 (1.77)*
Nyanza Dummy		-.0662725 (-2.08)**

Table 3...

Mombasa Dummy		-.0306011 (-1.34)
Nairobi Dummy		-.0398333 (-1.80)*
Nakuru Dummy		-.031588(-0.96)
Constant	1.045389 (11.83)***	1.085853 (11.54)***
Sigma	.0882966	.086769
Observations	183	183
Diagnostics		
Wald Test		
F- Statistic	F (9, 170) = 12.95	F (13, 170) = 11.05
Prob > F	0.0000***	0.0000***
Link Test		
Hat	.8801112 (0.66)	-.0502925 (-0.04)
Hat Squared	.0765802 (0.09)	.6729497 (0.78)

The parentheses presents the t-values

*The significance levels at 10%, 5%, and 1% are represented by *, **, and *** respectively*

The Tobit estimates are presented in table 3. Model 1 presents the main model while model 2 incorporates the dummy variable region. From the results in model (1) the coefficient of ln (firm size) is -0.1932565 and that of ln (firm size squared) is 0.0167661. ln (firm size) and ln (firm size squared) are both significant at 1 percent in both model (1) and model (2). Hence, this suggest the existence of an upward concavity between the firm size and technical efficiency. The turning point indicates a U-shaped relationship between log (firm size) and technical efficiency computed by solving the Tobit estimates in model (1) as follows:

$$TE = 1.045389 - 0.193256 \ln firmsize + 0.0167661 \ln firmsize^2$$

By taking the first order condition with respect to the natural log of firm size yields the following:

$$\frac{\partial(TE)}{\partial(\ln firmsize)} = 2(0.0167661 \ln firmsize) - 0.193256 = 0$$

Solving the above equation and taking the second order condition, the optimal size of the firm is 317 which is measured by firms' number of employed personnel'. This implies technical efficiency declines with every additional increase of employees up to 317 and thereafter efficiency increases with additional increase in the size of the firm. The result is still consistent after incorporating the dummy variable location. Cheruyoit (2017) finds a similar result of a U-shaped curve that indicates the nature of relationship between size of the firm and technical efficiency. However, the results seem to contradict the findings of Niringiye *et.al* (2010) where they established an inverted U-shape relationship between size of the firm and technical efficiency. It is plausible to argue smaller firms are more likely to be efficient than medium and large firms due to the organizational structure and less bureaucratic in decision making.

The coefficient log manager experience is 0.1183327 and log manager experience squared is -0.0232802. Both the variables are significant at 5 percent in model (1). In model (2), the log manager experience coefficient is 0.0964052 and log manager's experience squared coefficient is -0.018827. The log experience coefficient is significant at 5 percent while coefficient of log experience squared is significant to 10 percent. The results suggest a downward concavity relationship between manager's experience and technical efficiency. The concavity relationship is computed as follows:

$$TE = 1.045389 + 0.1183327 \ln experience - 0.0232802 \ln experience^2$$

By taking the first order condition with respect to the natural log of experience yields the following:

$$\frac{\partial(TE)}{\partial(\ln experience\ )} = 0.1183327 - 2(0.0232802 \ln experience) = 0$$

After solving the above equation and taking the second order condition, the optimal manager's experience is 12.7 years. This implies the technical efficiency increases with every additional year of the manager's experience until it reaches the 12th year and thereafter technical efficiency declines. The positive relationship between manager's years of experience is consistent with Backman *et.al*. (2011) where they find experience enters the technical efficiency positively. It is possible to argue that a more experienced manager is likely to be more innovative and make more informed decision on the factor inputs employed in production than an inexperienced one. However, beyond a certain point of experience the manager becomes less likely to be innovative and lose touch with the industry dynamics.

Human capital of production workers enters the technical efficiency of manufacturing firms positively. The coefficient of human capital is 0.0548283 and is significant at 5 percent. Increase in human capital by one unit increases the technical efficiency of manufacturing firms by 0.055 percentage points. This finding is consistent with Alvarez and Crespi (2003) who also found a positive relationship between human capital and technical efficiency of firms. Formal training coefficient is significant at 5 percent. The results suggest that firms that offer formal training to employees have a higher technical efficiency than those who don't offer formal training. The ownership coefficient is also significant at 10 percent indicating firms that are owned by foreigners have a higher technical efficiency than firms owned by locals. Perhaps, this is due to fact that foreign ownership brings in expertise from other countries and thus enhancing the technical efficiency of firms.

The dummy variable of innovation relates with technical efficiency negatively, contrary to our expectation, however, the coefficient is insignificant. Similarly, the coefficient of top female manager is insignificant though it positively relates with technical efficiency of manufacturing firms.

Finally, the effect of the firm's location on technical efficiency in the manufacturing sector is significant. The Tobit results indicate that firms located in Nyanza region are less technically efficient than firms located the Central Kenya region at 5 percent level of significance. Whereas, firms in Nairobi city are also less technically efficient than firms located in the Central Kenya region at 10 percent level of significance.

CONCLUSION

The paper conducts a two-part analysis of the technical efficiency. The first part estimate technical efficiency of Kenyan manufacturing using input-oriented DEA approach. After which, an average efficiency of 74.37 percent is established. In essence this means there is a considerable room for efficiency improvement. We find that 79.78 percent, 18.03 percent 2.16 percent of firms examined are working under increasing, decreasing and constant returns to scale respectively. Additionally, we note that food processing firms have a higher efficiency level relative to other firms.

The second part of analysis estimate Tobit model to establish the factors likely to affect the firm's technical efficiency. Tobit results show an upward concave relation between the size of firm and technical efficiency. We estimate the optimal size of the firm to be 317. Also, we find a downward concave relationship between manager's experience and the technical efficiency. The optimal years of experience is 12 years beyond which technical efficiency starts to decrease. Human capital is significant and enters the technical efficiency of Kenyan manufacturing firms positively. Firms with formal training programs for employees are more technically efficient than firms without formal training programs.

Lastly, concerning firms' location with central being the reference region. Firms in Nyanza, Mombasa, Nairobi and Nakuru are found to be less technically efficient relative to the once in Central region, but with coefficients of Mombasa and Nakuru being insignificant. In addition, results from innovation and firms' top managers' gender were also not significant.

Therefore, for firms to potentially increase their efficiency levels and competitiveness, they should take stock of the firm specific factors to ensure they operate under the technical efficiency frontier. Particularly, firms should pay a great attention to the firm's size, the manager's experience, human capital of workers and deploy a considerable amount of resources in formal training.

A limitation to this study is that it focuses on effects of firm specific characteristics on technical efficiency with non-inclusion of effects from externalities. This was due to unavailability of data for those external variables. Further research on this area is required to incorporate the effects of external factors. Particularly, the effects of competition environment, industrial policies, and tax policies on technical efficiency of the Kenyan manufacturing firms. This will enable policymakers develop more robust policy framework for the development of the sector.

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