Technical Efficiency of Agro-Processing Industries: In case of Projects Financed by Development Bank of Ethiopia

Nanecho DamtewBalcha[1]

ABSTRACT

The study aims at determining the level of technical efficiency of the food and non-food Agro-processing industries over time using stochastic frontier production function model. All the parameters of the frontier function and the inefficiency model have been estimated simultaneously using Maximum likelihood estimation. The study considered 55food processing and 25 non-food agro-processing industries for the period of 2014/15-2018/19(annex 2 and 3). The cob Douglas functional form with maximum likelihood estimation better explains the production behavior of food producing as well as non-food agro-processing industries. It shows that there is technical efficiency difference among industries in the sector. The mean technical efficiency of food Agro-processing was 0.53 while that of non-food industries was also 0.42, showing an increasing trend in both industries. Poor quality of raw materials, poor linkage between private and state farms and poor technology are the main constraint of the sector. Food agro-processing industries, slightly speaking, have better efficiency and scale of operation as compared to non-food agro-processing industries mainly attributed to the linkage between raw material producing firms with food producing industries. External constraints including lack of modern marketing skill, financial resources and lack of sufficient professional food technologist contribute more to the low level of development of the sector. In order to effectively utilize agricultural resource and benefit from this sector, efforts have to be made in improving linkage between farms with food and noon food agro-processing companies, working to scale up the production of best quality of raw materials, infrastructure development, technical and skill development and availability of updated marketing information system. The creation of conductive business environment enhances the productivity of the sub-sector.

Key words: *Agro- processing sector, stochastic production function and technical efficiency.*

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[1]Civil Service University P.O.Box 5648 Addis Ababa, Ethiopia

INTRODUCTION

Ethiopia is endowed with abundant agricultural resources and has diverse ecological zones. Agriculture is the mainstay of the economy. The Government of Ethiopia (GOE) has identified key priority intervention areas to increase productivity of smallholder farms and expand large-scale commercial farms. Particularly, the GOE under the new administration has given renewed emphasis to develop the agriculture sector and ensure food security. Among the top priorities identified by the GOE include: small and large-scale irrigations development, agricultural inputs supply financing, increasing productivity of crops and livestock, improving agricultural production methods using mechanization, post-harvest loss reduction, developing research-based food security system, and natural resources management.

To meet its agro-processing objectives, the GOE is building Integrated Agro-Industrial Parks (IAIP) in four pilot areas: Amhara, Oromia, SNNP, and Tigray regional states. The pilot areas selected for establishment of the Agro-Industrial Parks are mainly based on the potential of existing agricultural resources and allied sectors, infrastructure, and facilities.The expected growth from these agriculture-related industries offers numerous opportunities for agricultural input sales, such as tractors and harvesters, farm trucks, fertilizer, irrigation equipment, grain handling systems, food and livestock processing equipment, as well as cold storage facilities. There are also expanding opportunities for grocery sales to retail and wholesale outlets that are starting to spring up all over Addis Ababa.

Efficiency is the most widely used concept in economics. It is measured by comparing the observed output against the feasible (frontier) output. The scarcity of resources is the major factor that makes the improvement in efficiency so important to an economic agent or to a society. To meet the agro-processing industries ensuring efficiency of production of industries is very vital by improving input output ratio. Thus, this research designed to measure the technical efficiency of Agro-processing industries financed by Development Bank of Ethiopia.

This notwithstanding, level of efficiency in the agro-processing industry and the distribution of levels of efficiency to the food and non-food subsectors as well as measuring performance in the agro-processing industry in Development Bank of Ethiopia financed projects in the two sub-sectors (i.e food subsector and non- food subsector) has not yet been done up to the level of researcher review of the available literature. 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 2015-2019.

The main objective of the study is to quantify the level of efficiency of agro-processing industry in case of Development Bank of Ethiopia financed projects from the period 2015-2019.

- ❖ To determine the level and trend of technical efficiency of the agro-processing industry in case of Development Bank of Ethiopia financed projects from the period 2015-2019.
- ❖ To measure efficiency performance among the two sub-sectors.
- ❖ To derive the policy implications of the study's findings to national industrialization policy.

Literature Review

The literatures with regard to agro processing sector efficiency are scanty. N. Simon Ndicu et.al (2016), studied the technical efficiency of agro-processing industry in Kenyan Agro-processing firms using panel data of three years covering 2011-2013 of 41 firms with variables such as Value addition as output variables and Capital, Labor cost and raw materials used as input variables for the technical efficiency found that even though there is increment in technical efficiency over the period it couldn’t achieved an average of 56% technical potentiality by the industry.

In Ethiopia Technical efficiency studies are more focused to the agriculture sector. Genet (2009) has focused on the measurement technical efficiencies of tanneries and leather footwear industries in the country over the period of 2003-2007. She compared technical efficiency levels of more value-adding tanneries with less value-adding tanneries as well as those of exporting leather footwear industries with non exporting leather footwear industries. She used stochastic frontier model, developed by Battese and Coelli (1995), to estimate the production of these industries based on panel data of 11 tanneries and 28 leather footwear industries for the year 2003-2007. A log-likelihood ratio test showed that production processes of tanneries and leather footwear industries were better specified as a translog production function and estimated with maximum likelihood estimation. The result shows that the average technical efficiency for tanneries was 0.77 and there was an increasing trend over the considered period. Tanneries utilized 78% of their production capacity. There was large disparity among industries in production and in production capacity utilization. While the leather footwear industries had an average efficiency of 0.84, implying less potential for efficiency improvement as compared to tanneries. Like the tanneries, the leather footwear industries' efficiencies had increased over the period 2003-2007.

Study by Alemu and et al. (2009) tries to fill the gap by investigating efficiency variations and factors causing (in) efficiency across agro-ecological zones in East Gojjam, Ethiopia. Data were collected from 254 randomly selected households. Stochastic frontier production function was estimated and the results of the analysis revealed a mean technical efficiency of 75.68% (ranging from 32.15% to 92.66%). F-test also showed a statistically significant difference in technical efficiency among agro-ecological zones with highland zones scoring the highest leading to a rejection of the hypothesis of no significant efficiency difference. On the other hand, maximum likelihood estimates indicated positive and significant elasticities for inputs such as land, labor, draft power and fertilizer. Besides, education, proximity to markets, and access to credit were found to reduce inefficiency levels significantly. However, neither extension visits nor trainings on farmland management brought positive impacts in affecting the efficiency level of farmers. Thus, future endeavors may need to find ways to envisage better extension services provisions that are tailored to the peculiarities of the agro-ecological zones. Last but not least, improved market outlets and reduced liquidity constraints should be considered to change things for the better.

For instance, in their analysis on technical efficiency of smallholder farmers in Girawa district of Ethiopia, Ahmed, et al. (2013) confirmed that technical efficiency of farmers is positively associated with education, extension services, livestock holdings and use of irrigation. Thus, education and extension services increases efficiency of a farmer by increasing awareness and ability on the proper use of farm inputs control of pest and crop diseases and overall management of farm productions.

GetahunGemechu (2014) in the analysis of Off-Farm Income and Technical Efficiency of Smallholder Farmers in Ethiopia, confirmed household size, education of the head, soil conservation, extension services and off-farm income are major factors for differences in technical efficiency among farmers. By using stochastic frontier model, Cobb-Douglas form, the estimation results show that size of farm land, household size, off-farm income, gender and education of the household head are the most significant variables determining the value of farm output.

The conceptual framework for this study is based on the institutional analysis and development (IAD) approach of the new institutional economics (NIE). In the IAD approach by Dorward and Omamo (2005) it is assumed that an exogenous set of variables influences situations of the agents and the behavior of the agents in those situations. This leads to outcomes which provide feedback to modify the exogenous variables, the agents and their situations.

The framework is operationalized as shown in Figure below, which represents how various factors inter-relate to influence agro-processing productivity and hence the benefit of producers. The policy environment is characterized by the existing political and economic trends in the country which have an influence on the industry system and indirectly determine the output.

An industry that is technically, efficient is therefore expected to realize higher output as compared to one that is less efficient in production. But on the other hand, such a firm is hypothesized to incur less production costs leading to higher returns from the enterprise. This therefore has positive spillover effects on the welfare of the agro-processing.

Research Methodology

Data Type and Sources

The study based on panel data set of 80 firms. The data has been gathered and compiled from Development Bank of Ethiopia financed agro-processing industries. The paper aims at estimating industry-level technical efficiency over time and comparison was made between food and non-food medium and large scale agro-processing industries. So the study utilized panel data sets involving 80 industries for the period of year 2014/15-2018/19.

Sampling Technique

The target population as per the data collected from Bank reports there were 100 agro-processing industries projects financed by the Development Bank of Ethiopia. Due to this, simple random sampling technique was employed to draw a representative sample. Using Taro Yamane's (1967) simplified formula 80 firms were selected which are operational from 2014/15-2018/19 in Development Bank of Ethiopia.

Methods of Data Analysis

To analyze the data, both Descriptive and Econometric methods were employed. Accordingly, in the descriptive part, frequency distribution, percentages, mean and ratio were utilized to describe the socio-economic characteristics of the respondents; while in the Econometric analyses, a Stochastic Frontier Approach was used to estimate the level of technical efficiencies and the relation between farm level socio-economic and institutional variables and inefficiencies.

Efficiency Estimation

There are two approaches that can be used in measuring efficiency namely: the parametric and non-parametric models, which differ in two ways. First, they differ on assumptions of the distribution of the error term that represents inefficiency. Second, they differ in the way the functional form is imposed on the data. Parametric methods use econometric approaches to impose functional and distributional forms on the error term whereas the non-parametric methods do not. Nevertheless, parametric models suffer from the same criticism as the frontier deterministic models, in the sense that they do not take into account the possible influence of measurement errors and other noises in the data as do stochastic frontier models. The results can also be misleading because they do not allow for random error as is the case with stochastic parametric approaches. Besides, non-parametric methods also lack statistical tests that would tell us about the confidence of the results. For this reason, this study adopts the stochastic frontier model to measure and explain inefficiencies in the industries.

The biggest advantage of the stochastic production frontier models is the introduction of a disturbance term representing noise, measurement error and exogenous shocks that are beyond the control of the production unit in addition to the efficiency component. Hence, Technical efficiency measures obtained from stochastic frontiers are expected to reflect the true ability of the firm given the inputs.

The stochastic statistical frontier method requires a prior specification of the functional form, among others, Cobb-Douglas, Translog, etc. In fact, in this study the Maximum likelihood ratio test was conducted to select the appropriate functional form that best fits the data. The value of the generalized likelihood ratio (LR) statistic to test the hypothesis that all interaction terms including the square specification is equal to zero (H_O: βij=0) is calculated as:

LR= -2(LC-LT) ………………………………… (4.1)

Where:

LR= Generalized log-likelihood ratio;

L_C= Log-likelihood value of Cobb-Douglas frontier; and

L_T= Log-likelihood β value of Translog frontier.

This value is then compared with the upper 5% point for the χ^2 distribution and the decision is made based up on the model result. If the computed value of the test is bigger than the critical value, the null hypothesis will be rejected and the Cobb-Douglas frontier production function better represents the production technology of farmers.

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

Stochastic frontier is an econometric analytical technique, which allows for variation of output of individual producers from the frontier of maximum achievable level to be accounted for by the firm (Battese, *et al*., 1997).

The model in its implicit form is as follows:

$$Y = f(X_i; \beta) + e_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (4.2)$$

$$ei = V_i - U_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.3)$$

Where:

Y = output (Value Added)

X_i = vector of the inputs used by the industries

β = a vector of the parameter to be estimated

e_i = composed error term

V_i = random error beyond the control of producers

U_i = technical inefficiency effects

f(Xi; β) = appropriate functional form of the vector.

A general Stochastic Frontier Production model following Aigner, et al., (1977) is expressed implicitly as:-

$$ln\ Y_i = \beta_0 + \Sigma\ \beta_j lnX_j i + V_i - U_i \ldots\ldots\ldots\ldots\ldots (4.4)$$

The stochastic frontier model for estimating the technical efficiency of agro-processing industries is specified by the Cobb- Douglas frontier production function, which is defined by:

$$InYi = \beta_0 + \beta_1 InRM_i + \beta_2 InL_i + \beta_3 InK_i + v_i - u_i \ldots\ldots \ (4.5)$$

Where:

In = natural logarithm to base e

Y_i = Output (Value Added)

β_0 = constant or intercept

$\beta_1 - \beta_3$ = unknown scalar parameters to be estimated

RM_i= Raw Material used (In Birr)

L_i = Labor Cost

K_i = Capital

C_i = random errors

u_i = Technical inefficiency effects predicted by the model

i = number of industries (1-80 sample respondents)

The technical efficiency effect model (Coelli&Battesse, 1995) in which both the stochastic frontier and factors affecting inefficiency are estimated simultaneously in which the ML estimates of technical efficiency effects of the model given above would be estimated using a software package ***Stata version 13***. Coelli&Battesse, 1995 (1995) stated that the TE of a farmer is between 0 and 1 and is inversely related to the level of the technical inefficiency. Technical efficiency is defined as the ratio of observed output to maximum feasible output. TE_i = 1 shows that the i^{th} firm obtains the maximum feasible output, while TE_i< 1 provides a measure of the shortfall of the observed output from maximum feasible output. It is estimated as; TE_i = Observed Output / Frontier Output

Technical inefficiency = 1 – TE……………….. (4.7)

The stochastic frontier function has been used in the estimation, since this is the model which is available for measuring the efficiency of a productive unit while considering a single output and a set of inputs (Sekaran, 2003).

Definition and Measurement of Variables

The following variables were considered to estimate the inefficiency scores and the inefficiency effects:

Gross value of Output (Y_{it}): Output of a certain enterprise could be measured either in gross value of output or in terms of value added. Both measures have their own strengths and weaknesses. Production is the result of the interplay of raw materials, fixed assets and other industrial inputs and it is relatively less affected by measurement errors when calculated at the firm level. Thus, considering gross value of output as a measure of output to be used as a dependent variable is more reasonable.

Wage rate for Manual Labor, Wage rate for Non-Manual Labor and salary (X_{1it}): In the frontier production, the amount of wages and salaries paid to the workers in each time proxies the labor cost. This is done because labor is a heterogeneous input not only in terms of biological make-up of workers but also in education, work experience and other similar attributes. Therefore, wages and salaries are presumed to consider such differences and better represent the extent of labor input use. This variable includes all payments in cash or kind made to the workers during the reference period in connection to the work done for the firms.

Industrial cost (X_{2it}): Industrial cost includes raw materials, fuels, electricity and other supplies consumed and industrial services rendered by the firm.

Fixed capital (X_{3it}): It represents those assets of the establishments with a productive life of one year or more. It shows the net book-value at the beginning of the reference year plus new capital expenditure minus the value of sold and disposed machinery and equipment and depreciation during the reference period.

Total cost (TC_{it}): is an aggregate of fixed cost (fixed capital) and variable cost(wage rate and industrial cost

RESULT AND DISCUSSION

Descriptive Results

Average annual production of food producing agro-processing industries during 2014/15-201/19 at Bank industry level was Birr 292.1 million. The average wage for employed labor, industrial cost and fixed capital was Birr 240.2million, 19.3million and 191.9 million, respectively (Table 4-1).

Table Error! No text of specified style in document.**-1Descriptive Statistics of food industries during 2014/15-2018/19**

Statistics	Wage	Industrial cost	Fixed Capital	Out put
Average	240,230	19,398	191,964	292,167
Max	815,051	60,168	595,427	906,230
min	137,208	11,142	110,260	167,813
standard deviation	156,704.19	12,336.06	122,078.85	185,802.04

Source: Own calculation based on DBE data

Among the fifty five food producing industries, MEAD food complex PLC had the maximum amount of average production of Birr 906.2 million in the time period between 2014/15-2018/19 followed by Gonder Malt factory which had Birr 987.1 million (annex 2). MEAD food complex PLC food complex also utilized the highest capital and industrial cost of Birr 595.4 million and 527 million, respectively. In terms of labor employment, however, MEAD food complex PLC was the leading, by employing 550 persons.

The minimum average annual producer in the time period considered was YegenetTebeta Farm and Agro processing PLC. It produced a value of Birr 167.8 million. Gonder Malt factory had the minimum average industrial cost and fixed capital worth of Birr 59.5 million and 589 million respectively. In the same period the industry level average annual employment was 495 persons. The highest and the minimum employment were 550 and 93 persons. The average production capacity utilization was 45% of the average annual production. MEAD food complex PLC was the only factory which had capacity utilization above 50% while YegenetTebeta Farm and Agro processing PLC was the lowest with 20 %.(annex 2).

Twenty Five non-food producing industries under consideration had an average annual production, wage and industrial cost of Birr 221.1 million, Birr 3.2 thousand and Birr 80.02million, respectively, during 2014/15-2018/19. On average, the industries employed Birr 28.8 million worth of fixed capital (Table 4-2).

Table Error! No text of specified style in document.**-2Descriptive statistics of non-food producing industries annual performance in the period 2014/15-2018/19 (in '000 Birr)**

Statistics	Wage	Industrial cost	Fixed Capital	Out put
Total	80,122,509	2,000,570,665	722,494,546	5,529,076
Average	3,204,900	80,022,827	28,899,782	221,163
Max	12,628,521	391,895,128	123,476,581	1,159,150
min	12,903	241,209	16,996	468
standard deviation	3,780,209	105,135,968	38,893,865	330,415

Source: own calculation based on DBE data

MERT cleaning PLC had the maximum average annual production of Birr 1.5 billion million while Joe flowers PLC had the minimum of Birr 5 million (annex 3). The average annual employment at industry level for the period considered was 158 persons. The highest and the minimum employment were 430 and 100 persons, in which there was a significant disparity between industrial level employments. During the same year, non food producing industries utilized 59% of their average annual production capacity on average.

MajedNadi PLC was the most efficient industry which had utilized its 95% of capacity of production while the minimum capacity utilization was 30%, which was that of Joe flowers PLC. Only six industries had more than 80% capacity utilization. In general, non-food industries showed underutilization of production capacity (Annex 3).

There was an increase in annual agro processing industry production with an average growth rate of 23% during 2014/15-2018/19. Wage declined by average rate of 16.6% while capital declined at the rate of 7.5%. Partial productivity of labor which shows the value of output produced by one Birr of labor increased by 15% and capital which shows the value of output produced by one Birr worth of capital increased with average growth rate of 62%. In food producing industries average annual output increased by 2.6%, in non-food producing industries while it grew by 23%. Labor and capital productivity showed an increase with an average growth rate of 7% and 1% in food producing industries while the growth in the non-food producing industries was 19% and 56%, respectively (annex3).

Econometric Results and Discussions

Diagnostic Testing

Before proceeding to the estimation of the model parameters, checking whether the stochastic production frontier is more appropriate than a conventional production function, testing whether there exists technical inefficiency in the production process or not and a test was made for multicollinearity among the explanatory variables.

In this analysis individual level of technical efficiency were estimated, the functional form that can better fit to the data at hand was selected by testing the null hypothesis that the coefficients of all interaction terms and square specifications in the translog functional forms are equal to zero ($H0 = \beta ij = 0$). The test was made based on the value of likelihood ratio (LR) statistics which can be computed from the log likelihood values of both the Cobb-Douglas and Translog functional forms using equation (3.1). Then, the value was compared with the upper 5% critical value of the χ^2 at the degree of freedom equals to the difference between the numbers of explanatory variables used in both functional forms (in this case df =15).

In other words, the degrees of freedom are the number of interaction terms and square specifications in the translog case restricted to be zero in estimating the Cobb-Douglas functional form. The log likelihood functional values of both Cobb-Douglas and Translog production functions were -20.3 and -11.1, respectively. The LR value computed therefore was 16.2 and this value is greater than the upper 5% critical value of the χ^2 at the degrees of freedom equal to fifteen. This shows that the coefficients of the interaction terms and the square specifications of the input variables under the Translog specifications were different from zero. As a result, the null hypothesis was rejected and the Cobb-Douglas functional form best fits the data (table 4-3).

Table 4-3 Hypothesis testing on the Stochastic Frontier Functional form

Efficiency estimation	**Log-likelihood value**		(LR)χ^2cal	χ^2df,0.95a
H_o**: β_1=β_2=β_3…= 0	Cobb-Douglas (L_c)	Translog (L_t)		
Agro-processing	-20.3	-11.1	16.2	15**

Source: Model output, 2020

A Degree of freedom (df) is equal to the number of restrictions (number of parameters equated to Zero). Here the number of restrictions is 11.

***Significant at 5 %*

The second hypothesis is checking whether the stochastic production frontier is more appropriate than a conventional production function, i.e. testing whether there exists technical inefficiency in the production process or not. The test was carried out by estimating the stochastic frontier production function and conducting a Likelihood-ratio test assuming the null hypothesis of no technical inefficiency.

As indicated in table 4.3.the inefficiency component of the disturbance term (u) is significantly different from zero. Therefore, the null hypothesis of technical inefficiency (H0: Sigma u=0) is rejected. This indicates that there is statistically significant inefficiency in the data. The lamda (λ) value is also greater than one in all the cases. This is a further indicator of the significance of inefficiency. On top of that, the value of gamma indicates that there is 80% variation in output due to technical inefficiency. This means that technical inefficiency is likely to have an important effect in explaining output among farmers in the sample.

A test was made for multi-collinearity among the explanatory variables using the Variance Inflation Factor (VIF) method. The VIF values of all variables entered in to the model were below ten, which is an indicator for the absence of severe multicollinearity among the proposed explanatory variables given the specification of Cobb-Douglas functional form. Hence; all inputs are included in the maximum likelihood estimation of production function.

Estimation Results

As explained in the model specification sub section, the model that better fits the data is the stochastic frontier production function technique to assess the technical efficiency of agro processing industry. In particular, the Cobb-Douglas stochastic frontier production with the distributional assumption has advantages over the other functional forms (Kalirajan and Flinn, 1983; Dawson and Lingard, 1989; Coelli and Battese, 1996, etc.). Since the panel data used in this study and the sample number is not very high, the transom specification could not be tried. The parameters of the stochastic frontier model were estimated using maximum likelihood estimation (MLE). The MLE method has been found to be better than Corrected Ordinary Least Squares (COLS) method, where the contribution of the inefficiency effects of the total variance was large, and hence the preferred estimation technique whenever possible (Coelli, Rao and Battese 1998). MLE methods were used for food and non-food producing industries. All the coefficients for each input variables and their interaction terms and the parameters (γ, η, μ,d^2) were estimated. The z-ratios for the coefficients and the log likelihood function were also provided. Tables 4.4 report these estimation results.

In the MLE of Cobb-Douglas functional form of the Agro-processing industries, the coefficients of the labor, industrial cost, output and fixed capital had the expected positive signs. The coefficients of factors of production show the responsiveness of total cost to a unit change in the use of respective input and output. The estimated coefficients show that industrial cost which includes raw materials and other industrial expenses had very significant contribution to the total cost for production of agro processing industries.

The coefficient of labor input shows that a unit increase in labor corresponds to a 0.07 unit increase in total cost for output production and it was significant at 5% level. Industrial cost and fixed capital input coefficients are also significant at 5% level. The significant value of γ (0.16) explains that the share of industry level inefficiency in total output variation attributable to external factors is 16%. It also implies that in the agro processing industries, inefficiency contributes less to random external factors of production (Table4.4).

Table Error! No text of specified style in document.**-4 MLE of Cobb-Douglas Production Function for agro-processing Industries**

Variables	**Parameters**	**ML Estimates**	
		Coefficients	**z**
Constant	βo	2.13	1.32*
Wage(X1it)	β1	0.055	2.01*
Industrial cost (X2it)	β2	0.54	18.20*
Fixed capital (X3it)	β3	0.22	10.03*
Output(X4it)	β4	0.09	3.01*
Sigma Square	ɗ	0.09	-15.23*
Gamma	γ	0.16	-2.01*
Mu	μ	2.0	0.99
Eta	η	0.3	2.03*

*Note: * z-value significant at 5% level*

4.1.1.1. Production Efficiency of non-food producing industries for 2014/15-2018/19

The mean efficiency for non-food producing industries for the considered period was 0.42, which means 58% inefficiency in production. On average, the non-food producing industries produce 50% of the maximum attainable output level over the period considered. The deviation from the expected unitary value of efficiency of non-food producing industries shows the existence of potential for improvement. Which means that, given existing resources and technology, output could be increased by 58% by solving production inefficiency problems. The maximum average technical efficiency of non-food producing industries was 0.75, the minimum being 0.25, with slight variation among them. Most of these industries had average efficiency level of 0.42. (Table 4.5).

Table Error! No text of specified style in document.**-5 Mean Production Efficiency of food and non-food industries for 2014/15- 2018/19**

Average	0.42
Max	0.75
Min	0.25
Standard deviation	0.009

Source: Own calculation based on DBE data

The average efficiency level increased at the rate of 0.42, implying a slight efficiency increment during the period. The result indicates that the efficiency of the non-food producing industries increased over the recent few years. This might be because in this time period there was high supply compared to demand of raw material which is the main inputs for non-food production. Other justification might be the past five years industrial policy of the country gives more attention for import substituting industries. There is no as such active exporter of private non-food products industry in the sector (Table 4.6).

Table Error! No text of specified style in document.**-6 Mean Production Efficiency Trend for non-food agro-processing industries for 2014/15-2018/19**

Efficiency measure	**2015**	**2016**	**2017**	**2018**	**2019**	**Average**
Average efficiency	0.422	0.462	0.410	0.415	0.420	0.42
Growth rate in efficiency	0.038	0.045	0.043	-0.05	0.019	0.038

Source: Own calculation based on DBE data

4.1.1.2. Production Efficiency of Food Processing Industries

The mean technical efficiency for food processing industries for the period under consideration was 0.53, which means inefficiency of 0.47 in production. It also implies that, on average, the food processing Industries produced 45% of the maximum attainable output level over the period under consideration. The highest average technical efficiency of 0.65 and the lowest of 0.35 were attained by these industries (Table 4.7).During the period food processing Industries had better average efficiency (0.53) than non-food counterparts (0.42). Almost all of food processing industries had more than 10% efficiency level.

This result does not confirm with the descriptive analysis and the hypothesis that non-food industries have better efficiency than food ones. The possible reason might be in the food producing industries there is a linkage between raw material farms with industries. In the input market, which is the main raw material for agro processing production, there is some state intervention. Raw material farms sometimes rather than supplying through auction they give priority to food producers. This market supply chain might improve industries' efficiency.

Table Error! No text of specified style in document.**-7Mean Technical Efficiency of food processing industries during 2014/15-¬2018/19**

Average	0.45
Max	0.65
Min	0.35
Standard deviation	0.005

The average efficiency level increased at the rate of 0.05, implying a slight efficiency increment during the period. The result indicates that the efficiency of the food processing industries increased over the recent few years (Table 4.8).

Table Error! No text of specified style in document.**-8 Mean Technical Efficiencies Trend in food processing Industries during 2014/15-2018/19**

	2004/05	**2005/06**	**2006/07**	**2007/08**	**2008/09**	**Average**
Average efficiency	0.400	0.405	0.409	0.414	0.419	0.409
Growth rate in efficiency	0.046	0.046	0.042	0.044	-	0.045

Source: Own calculation based on DBE data

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CONCLUSION AND RECOMENDATION

This study has focused on the measurement of technical efficiencies of agro-processing industry financed by Development Bank of Ethiopia over the period of 2014/15-2018/19. It analyzed technical efficiency levels of food and non-food producing agro-processing industries over these periods. A stochastic frontier model, developed by Battese&Coelli (1995), was used to estimate the production of these industries based on panel data of 55 food type and 25 non-food producing agro-processing industries for the year 2014/15-2018/19. Theories showed that production processes of these industries were better specified as a Cobb- Douglas production function and estimated with maximum likelihood estimation.

The result shows that the overall technical efficiency level for the agro-processing industry was 48 per cent for the period under consideration. This result indicates a reduced efficiency performance of the agro-processing industry that on average 52 per cent technical potentialities of the agro-processing were not achieved for period 2014/15-2018/19. The efficiency distribution in the food and non-food agro-processing subsectors scored 53 and 42 percent respectively over the periods.

Non-food processing industries had an average annual production growth rate of 23% over the period of 2014/15-2018/19. Industrial cost showed significant contribution to the production of Agro-processing as compared to other inputs. These industries used capital-intensive technologies utilizing 66% of their production capacity. There was large disparity among industries in production and in production capacity utilization.

The average technical efficiency for non-food agro processing industries was 0.42 and there was an increasing trend over the considered period. This inefficiency results mainly from poor quality of raw material, obsolete machinery, lack of skilled labor and poor managerial skills. The food producing agro-processing industries showed an average annual production increment of 260% with the utilization of only 44% of their production capacity. These industries had an average efficiency of 0.53, implying high potential for efficiency improvement. Like the non-food industries, the food processing industries' efficiencies had increased over the period 2014/15-2018/19 at the rate of 0.05%.

In general, there exists a potential to increase output in the agro-processing sector by improving efficiency of utilizing the existing resources as well as tackling external problems hindering the development of the sector. These include improvement in the quality of raw materials, better production and marketing system.

Finally due to the influence of such factors on the technical efficiency levels of agro-processing industries, based on the data obtained from the sample industries the result of the study signifies that technical inefficiency has a great contribution in the analysis of agro-processing in the study area.

RECOMMENDATION

The results of the study suggest some recommendations, which can be forwarded as follows:-

- To improve the quality of raw material supply of agro-processing industry, the focus needs to start from commercial farm system.

- Ethiopian Agricultural Research Institute should work to scale up the production of agro-processing input variety through creating linkage among farmers and processers and compensating farmers for the law productivity by providing price premium.
- Farm mechanization be provided and be made affordable and accessible to farmers, so that they could increase agricultural production for higher yield. This will reduce the over-dependence on primitive tools and its associated limitations in agricultural production.
- 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.

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