Efficiency Of Indian Food Processing Industry :A Stochastic Frontier Approach

Mannu Jain (IES probationer) under the supervision of Prof. Mausumi Das, Prof. Arup Mitra and Ms. Sonali Chadha

Contact: 9958619056, mannujain824@gmail.com

Abstract

This paper attempts to analyse the efficiency of various subgroups (Dairy, Beer and alcohol, vegetable oil, sugar and tea industry) of the Indian food processing industry. It estimates the technical efficiency and factors affecting technical efficiency for five major subgroup of industries using stochastic frontier analysis for the cross- sectional data of period 2018-2019. We found that sugar industry is most efficient among them, but it is also just 74% efficient, so existing inputs needs to be utilised efficiently.

Introduction

With the increase in population of country, ensuring food security is one of the biggest challenge. At the same time with the increase in food production, it is important to ensure that wastage of food can be minimised and by promoting food processing industry, employment and income level can be improved. India is primarily an agrarian economy and a sizeable portion of agricultural produce in India is wasted mainly due to lack of better harvesting methods, unsystematic ways of processing, problems in storage, marketing of finished products, and the like. India also stands number second in the production of food grains and various horticulture products. Given the huge potential of India we can become major exporter of the processed food.

Food processing is the process through which raw material is converted inti a product some other product which has commercial value, it also includes value addition of products through methods such as preservation, drying etc to enhance the shelf life and quality.Processing can be delineated into primary and secondary processing. Rice, sugar, edible oil and flour mills are examples of primary processing. Secondary processing includes the processing of fruits and vegetables, dairy, bakery, chocolates and other items.

Most processing in India can be classified as **primary processing**, which has lower value-addition compared to secondary processing. There is a need to move up the value chain in processed food products to boost farmer incomes. For instance, horticulture products, such as fruits and vegetables, carry the potential for higher value-addition when compared to cereal crops.

The Gross Value added (GVA) in the food processing sector was Rs.2.24 lakh crore in 2019-20 contributing 1.69% of the total GVA in the country. The GVA in food processing sector was 9.87% of GVA in Manufacturing and 11.38% of GVA in Agriculture, Forestry and Fishing sectors respectively.

Food Processing Industry is highly significant as it provides vital linkages and synergies which helps both the sectors of economy that is agriculture and industry. It creates direct and indirect employment, will also help in increasing the income of farmers as they can provide raw material to this industry and food fortification can reduce nutritional gap in the population. NITI Aayog had also estimated that annual post harvest losses of close to Rs. 90000 crores, this wastage can be reduced by processing food. Processing increases the shelf life of the food thus keeping supplies in tune with the demand thereby controlling food-inflation. For e.g., Frozen Safal peas are available throughout the year. This industry also preserves the nutritive quality of food and enhances the quality and taste of food.

India is the world's second largest producer of fruits & vegetables after China but hardly 2% of the produce is processed. In spite of a large production base, the level of processing is low (less than 10%). Approximately 2% of fruits and vegetables, 8% marine, 35% milk, 6% poultry are processed. Lack of adequate processable varieties continues to pose a significant challenge to this sector. India’s livestock population is largest in the world with 50% of the world's buffaloes and 20% of cattle, but only about 1% of total meat production is converted to value added products.

At present, major proportion of food processing firms are in unorganized sectors. Indian food industry mainly face problem related to Financing, inadequate transport and cold storage facility, high advertising cost.

In this paper, stochastic frontier approach has been used to estimate the technical efficiency of various subgroups (Dairy, Beer and alcohol, vegetable oil, sugar, tea and other industry) for cross sectional data of firms for period 2018-2019. Then, impact of other factors like credit availability and marketing intensity on technical efficiency is checked.

The rest of the paper is organised as follows: The second section comprises of literaturereview. The third section presents the SFA and the methodology adopted for this analysis. The fourth section describes the data and variables taken in this analysis. The fifth section presents the results and the last section concludes the study.

Literature Review

(Battese, 1992) in this paper various econometric tools of modelling of frontier production functions associated with the estimation of technical efficiency of individual firm have been analysed. A survey of empirical applications in agricultural economics is also done using these tools

(Addai-Asante and Sekyi, 2016) find out the level of technical efficiency of pharmaceutical manufacturing firms in Ghana and analyse the factors that determine their efficiency level. A stochastic frontier analysis based on the Cobb-Douglas production functional form was applied to estimate the technical efficiency of production among firms. Subsequently, the ordinary least square (OLS) was used to determine the factors that influenced technical efficiency levels of firms.

***(*Bhandari, 2016),** he applied data envelopment analysis to calculate the technical efficiency for Indian food processing industry for the panel data. He also evaluated the factor affecting the technical efficiency.

(Padmavathi N,2019) study adopted the Stochastic Frontier Analysis (SFA) as part of examining the efficiency of the unorganised food processing industry using NSS 73rd (2015-16) round unit-level data. The analysis is carried out by grouping the entire industry under six sub-sectors.

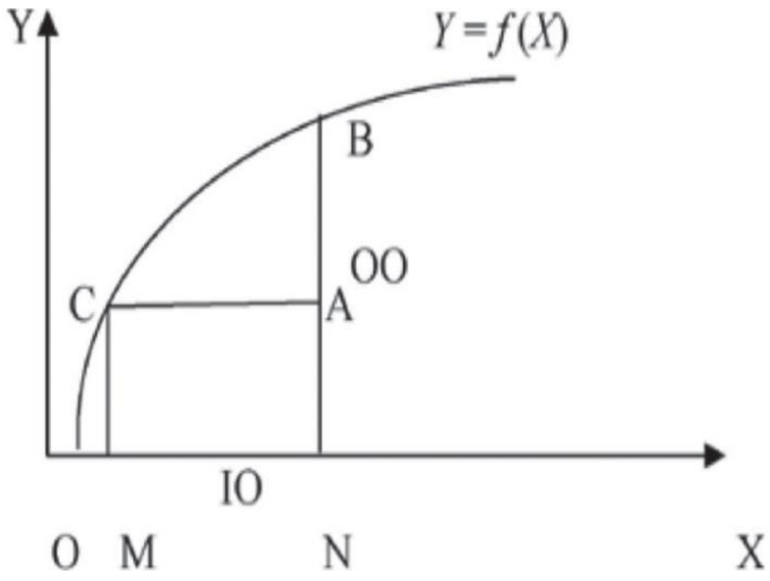
Methodology

SFA is a statistical analysis technique which was primarily used to estimate the production frontier of a firm given a certain set of inputs. The SFA differs from the regression approach in one important aspect. In a regression, the firms can underperform or over perform relative to their output potential. However, in SFA analysis, the firms cannot exceed the output potential. The gap between the production frontier and actual output is termed the technical inefficiency of the firm. Similarly, in our case, firms have a maximum production capacity (productionfrontier) depending on labour and capital employed by the firm and given the existing technology available to firms.

The gap between the production frontier and actual level of output is termed technical inefficiency. Technical efficiency can be either input oriented or output oriented.

Input oriented technical efficiency is one where we see the possibility of changing input levels while keeping the output level constant, in other words we are trying to quantify the extent to which we can reduce our inputs that is labour and capital without changing our output level.

Output oriented technical efficiency – in this the objective is to hold inputs constant and then try to see the possibility to increase the output level. So, we want to quantify the extent to which we can increase our output without necessarily having to change our inputs or that in time series framework, we would also hold our technological progress constant and see how it is possible to increase output.



Input and output-oriented technical efficiency.

In this graph, OO represent output oriented.

A is the actual level of output

B is the potential level of output

X axis represent the input level, Y represent the output level.

By keeping the input level constant at N, it is possible to increase output level from A to B, means if firm become highly efficient. This represents output oriented technical efficiency.

In this graph, IO represent output oriented

If we reduce the input level from N to M, it is possible to produce the same level of output. So this represents input oriented technical efficiency.

Corrected ordinary least square method as proposed by Winsten (1957) can also be used to estimate production frontier model. This model is deterministic frontier model as it excludes the statistical error v_i , and it can be written as

Ln y_i = ln y_i^* - u_i where $u_i \geq 0$ (1)

Ln y_i^* = f (x_i ; β) (2)

This model does not allow any random error v_i and therefore the function is non stochastic. In this two stage procedure is used.

In the first stage , we run an OLS regression of logy on inputs and obtain

Lny_i = β'_o + x'_i β'_1 + e'_i (3)

Where e'_i are OLS residuals . β'_o is the biased estimate of β_o . OLs estimation produces the consistent estimate of slope coefficients but a biased intercept .

At the second stage , the OLS intercept is adjusted upward by the amount of max { e'_i} , so that the adjusted function bounds observations from the above . The residual become

e'_i - max { e'_i} = ln y_i - {[β'_o + max { e'_i}] + x'_i β'_1 } ≤ 0 (4)

And

u'_i = - (e'_i - max { e'_i}) ≥ 0 where ,

u'_i is the estimated inefficiency for model. Technical efficiency of each observation can then be calculated as TE = exp(-u'_i)

COLS estimates of technical inefficiency are easy to calculate but this simplicity comes at a price. In this model deviation from the estimated frontier are entirely attributed to inefficiency and there is no role for other randomness such as data errors, atypical events (unusually good weather not experienced by all farmers) or luck. One of the consequences of this is that estimated inefficiency is highly sensitive to outlier. If the data set has large value on y_i observations , COLS would overestimate the efficient frontier ,therefore making estimated technical inefficiencies larger than they otherwise would be.

Aigner et al. (1977) and Meeusen and van den Broeck (1977) were the first to estimate the stochastic frontier model which has both u_i and v_i in the model . A stochastic production frontier model with output-oriented technical inefficiency can be specified as

Ln y_i = ln y_i^* - u_i where $u_i \geq 0$ (5)

Ln y_i^* = f (x_i ; β) + v_i (6)

Where the subscript i denote the observations, in our study it shows the firms , y_i is observation output , x_i is a j×1 vector of the corresponding coefficient vector , v_i is a zero-mean random error and $u_i \geq 0$ is a production inefficiency. Given x , the frontier gives the maximum possible level of output , and it is stochastic because of v_i . Given that $u_i \geq 0$, observed output (y_i) is bounded below the frontier output level (y_i^*) . This can also be written as

Ln y_i = f (x_i ; β) + $\in_i$

Where $\in_i$ is the composite error term.

The term u_i in equation (5) is the log difference between the maximum and the actual output , therefore u_i × 100% is the percentage by which actual output can be increased using the same inputs if production is fully efficient , or we can say it gives us the percentage of output that is lost due to technical inefficiency , or u_i is referred as output – oriented technical inefficiency, if it is close to zero , this implies that firm is fully efficient.

Exp(-u_i) = y_i / y_i^*

Exp(-u_i) gives the ratio of actual output to the maximum potential output . the ratio is referred to as the technical efficiency of firm . Exp(-u_i) × 100% is the percentage of maximum output that is produced by producer i .

Vi is representing measurement and specification error, the Vi's are assumed to be independently and identically distributed with (0 ,σ_v^2) (also known as idiosyncratic error), Vi's are independently distributed of the Ui's; The Ui's are a one sided disturbance, representing inefficiency and they are assumed to be independently distributed, such that Ui is obtained by truncation (at zero) of the normal distribution with mean, μ, and variance, σ_u^2 This assumption of ui following a truncated normal distribution is needed to make the model estimable.

The distributional assumption required for the identification of the inefficiency term implies that this model is usually fit by maximum likelihood (ML).

The method of maximum likelihood is proposed for simultaneous estimation of the parameters of the stochastic frontier and the model for the technical inefficiency effects. The ratio of the standard deviation of the inefficiency component to the standard deviation of the idiosyncratic component is labelled as lambda ($\lambda = \sigma_u / \sigma_v$). The estimated λ is non-negative and significant. Lambda provides information on the relative contribution of both error components in the total error term.

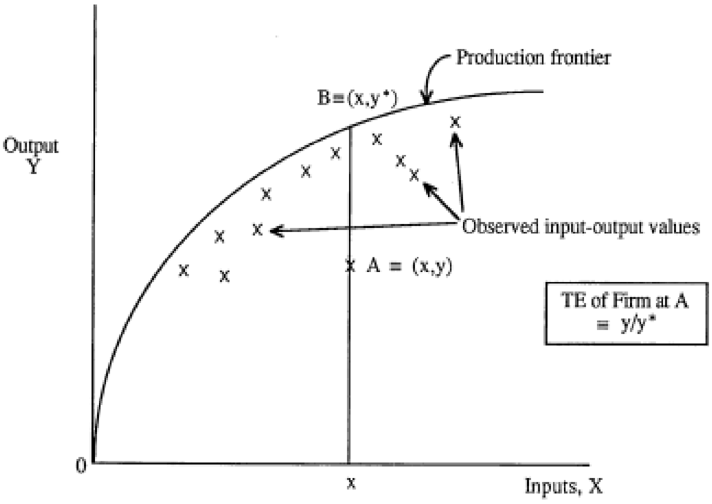


Fig. 2. Technical efficiency of firms in input–output space.

A measure of the technical efficiency of the firm which produces output, y, with inputs, x, denoted by point A, is given by y /Y *, where y * is the 'frontier output' associated with the level of inputs, x (see point B).

Pre- test of the stochastic frontier (screening test)

Schmidt and Lin (1984) propose an OLS residual test to check for the validity of the model's stochastic frontier specification. The idea behind the test is that, for the production – type stochastic frontier model with the composite error , $u_i \geq 0$ and v_i distributed symmetrically around zero , the residuals from the corresponding OLS estimation should skew to the left (i.e. , negative skewness) . They suggested a sample –moment based statistic for the skewness test. The statistic is

$\sqrt{b1}$ = m3 / m2 $\sqrt{m2}$

Where m2 and m3 are the second and the third sample moments of OLS residual, respectively. If the estimated value of this statistic is less than zero, it indicates that the OLS residual are skewed to the left. Under the null hypothesis of no skewness, the statistic should be statistically indifferent from zero. The Stata command sktest performs this test. The distribution of statistic is nonstandard, and its critical values are tabulated in a number of studies including D'Agostino and Pearson (1973) .

Coelli (1995) suggests a variant of this test. He notes that under the null hypothesis of no skewness, the third moment of the OLS residuals is asymptotically distributed as a normal random variable with mean 0 and variance 6 m_2^3 / N . Thus, the statistic

$$\text{M3T} = m_3 \,/\, \sqrt{6\, m_2^3 \,/\, \text{N}}$$

has an asymptotic distribution of a standard normal random variable. The main advantage of this alternative test is that the critical values of the distribution are commonly available.

Post diagnostic check

Gamma parameter

$\gamma = \sigma_u^2 \,/\, \sigma_u^2 + \sigma_v^2$

This statistic measure proportion of variation accounted in output due to technical inefficiency.

If it is close to 1 , then much variation in output is being accounted for by technical inefficiencies and therefore SFM would be the most appropriate one.

For more complicated models, such as one that has a two-parameter inefficiency distribution (e.g., the truncated-normal) or one that parameterizes inefficiency by nonconstant variables, the gamma parameter does not convey useful information regarding the presence of the one-sided error. So LR test can be used.

LR test

Central to the stochastic frontier model is the one-sided error specification which represents technical inefficiency. It is therefore important to test the existence of the one-sided error for the model. If evidence for the one-sided error specification is not found, the model then reduces to a standard regression model for which a simple OLS estimation would suffice. This amounts to a test for the presence of in the model, and a generalized likelihood ratio

(LR) test for the null hypothesis of no one-sided error can be constructed based on the log-likelihood values of the OLS (restricted) and the SF (unrestricted) model.

This residual test is easy to perform since it requires only an OLS estimation of the model. Although useful as a screening device, the test does not use the information from the distribution functions of the random error. The LR test introduced here is more precise to the specific model we are estimating, but the disadvantage is that it can only be conducted after the ML estimation of the model has been undertaken.

LR test statistic

$$-2[\mathrm{L}(H_0) - \mathrm{L}(H_1)]$$

Where $\mathrm{L}(H_0)$ and $\mathrm{L}(H_1)$ are log-likelihood values of the restricted model (OLS) and the unrestricted model (SF), respectively and the degree of freedom equals the number of restrictions in the test.

LR test statistic does not have a standard chi-square distribution. Coelli (1995) shows that, in such cases, the test has a mixture of chi-square distributions. The critical values of the mixed distribution for hypothesis testing are tabulated in Table 1 of Kodde and Palm (1986).

critical values of the mixed chi-square distribution

	significance level						
dof	0.25	0.1	0.05	0.025	0.01	0.005	0.001
1	0.455	1.642	2.705	3.841	5.412	6.635	9.500

source: Table 1, Kodde and Palm (1986, Econometrica).

If the computed value is greater than the values in the table for a particular level of significance, in that case we reject the null of no technical inefficiency, indicating that there is technical inefficiency.

Data and variables

Data base is from prowess IQ for the period 2018-2019, took data for various subgroups under food processing industry like dairy , tea, sugar, beer and alcohol and vegetable oil

Dependent variable –

Output – sales is taken as proxy of output , then it is taken in logarithmic term

Inputs

Labour – salaries and wages are taken as proxy , then divided by wage rate to calculate number of workers . Wage rate is calculated using ASI database.

Capital- calculated by adding net property , plant and equipment and rent and lease.

Factors affecting technical efficiency –

Major factors are credit availability and marketing intensity.

Credit availability – sum of current liabilities and long term borrowings is divided by total assets .

Marketing intensity- selling and distribution expenses divided by total expenses.

Results

Dairy industry

Dairy industry	Corrected OLS estimates		
Log(output)	Coefficient	Standard error	P-value
Constant	-.1172159	.6508198	0.857
Log(labour)	**.5117008*** **	**.1031977**	**0.000**
Log(capital)	**.2999562*** **	**.0891553**	**0.001**
No. of observations	**90**		
	Mean	Minimum	maximum
Technical efficiency	.0570378	.0004199	1
Screening test	Skewness	P value	

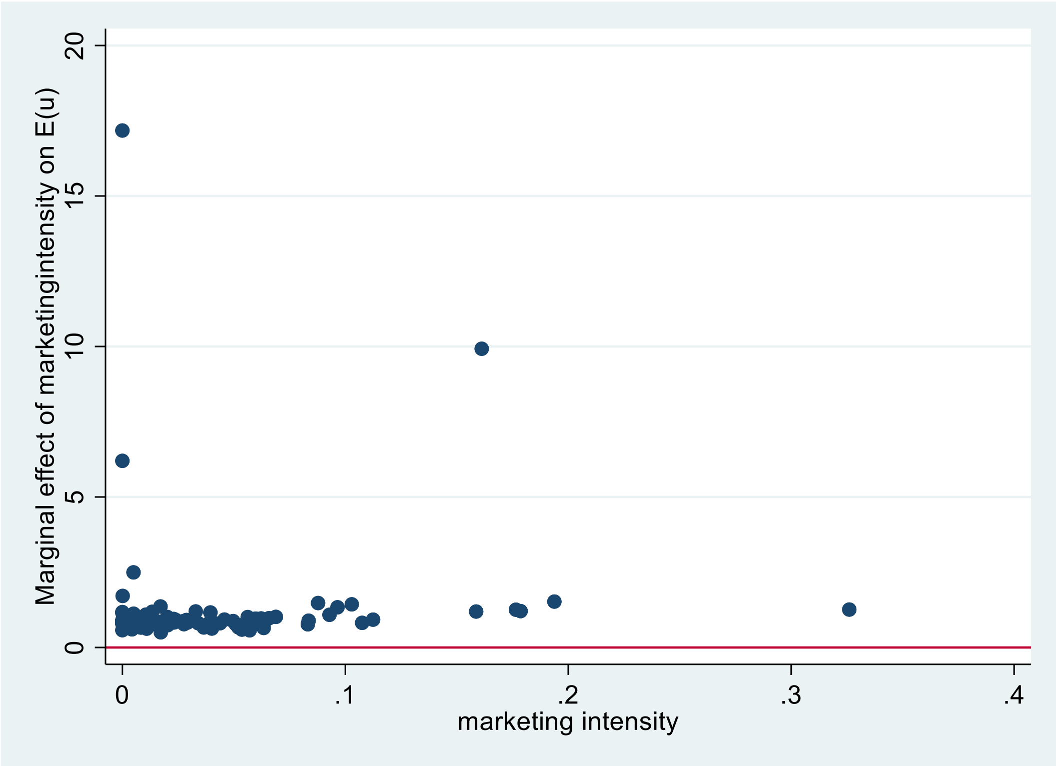
Skewness test	-.3745512***	0.0014	

The result of COLS for dairy industry suggest that labour and capital both impact output positively and are highly significant. If labour increase by one percent, output increase by 0.51% . similarly if capital increase by one percent then , output increase by 0.29%. the estimates shows that on average technical efficiency of the dairy industry is 5% , which is not supported by literature. So we did screening test , we found that there is negative skewness in residuals and highly significant , this supports the idea of using maximum likelihood method.

Dairy industry	ML estimates		
Log(output)	Coefficient	Standard error	P-value
Constant	1.505078	.6263696	0.016
Log(labour)	**.3899958**	**.0898656**	**0.000**
Log(capital)	**.3136857**	**.0738687**	**0.000**
No. of observations	**90**		
	Statistic value		
Gamma	0.929013		
LR Test	17.50199		
Log likelihood function	**-132.6915**		

Technical inefficiency	**Coefficient**	**Standard error**	**p-value**
Marketing intensity	**4.933914*** **	**.5479539**	**0.000**
Credit availability	**-.4188239**	**.2916356**	**0.151**
Constant	**4.150334*** **	**.3730456**	**0.000**
	Mean	Minimum	maximum
Technical efficiency	**.5700113**	.0105297	.826412
Note: *** statistically significant at 1 percent ** statistically significant at 5 percent * statistically significant at 10 percent			

The result of stochastic frontier analysis for dairy industry also shows that labour and capital impact output positively and are highly significant. If labour increase by one percent, output increase by 0.39% . Similarly if capital increase by one percent then , output increase by 0.31%. The estimates shows that on average technical efficiency of the dairy industry is 57%. Gamma value is 0.93 which shows that 93% of the variation in output is attributed to technical inefficiency , so SFA is most appropriate ,but more complicated model like truncated normal distribution , gamma parameter does not convey useful information so we apply LR test. So the presence of technical inefficiency was tested by the likelihood ratio (LR) test which was 17.50199 which is greater than critical chi square value (given by kodde and palm, 1986) ,therefore the null hypothesis of no technical inefficiency is rejected. Marginal effect of marketing intensity and credit availability on average technical inefficiency is shown through the graph presented below, increase in marketing intensity increases the technical inefficiency, most of the firms are clustered in 0-5% range, and this relation is also significant. An increase in credit availability is likely to reduce the technical inefficiency and this is also supported by our data as most of the observations are clustered in range 0-0.5% , but the result is not significant.


Marginal effect of marketingintensity on E(u)
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20
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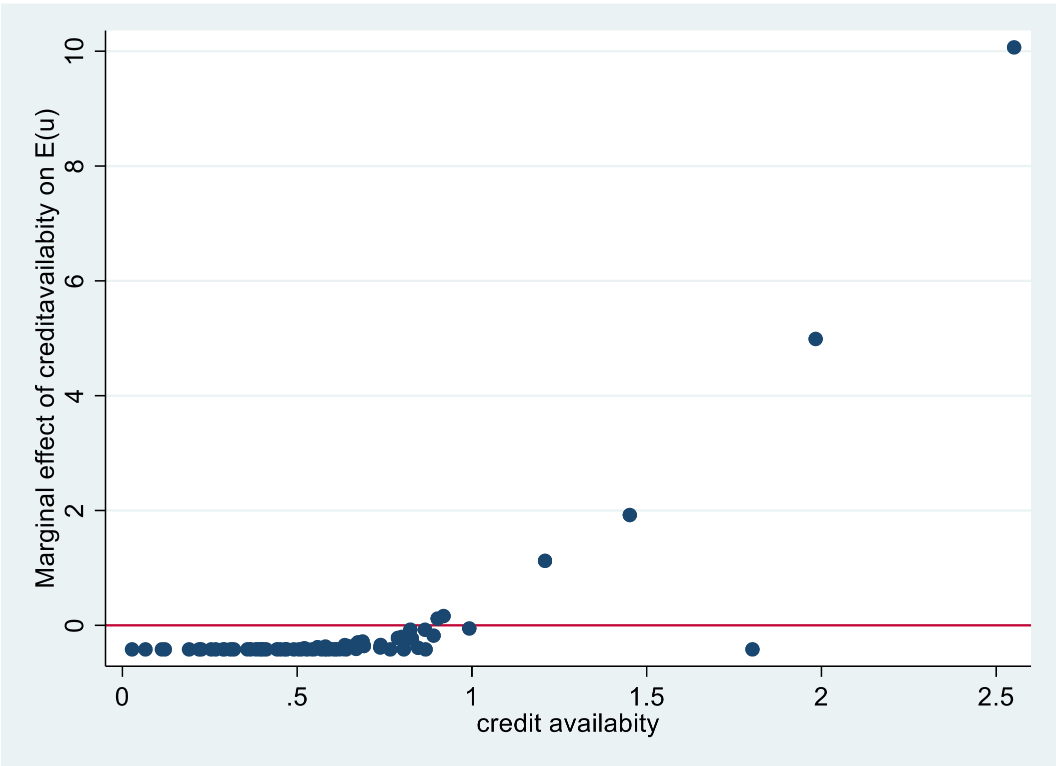
.2
.3
.4
marketing intensity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credit availabity

Vegetable oil

Vegetable oil industry	Corrected OLS estimates		
Log(output)	Coefficient	Standard error	P-value
Constant	.4453693	.4453693	0.345
Log(labour)	**.5107958*****	**.0795731**	**0.000**
Log(capital)	**.3584664*****	**.082359**	**0.000**
No. of observations	**165**		
	Mean	Minimum	maximum
Technical efficiency	.1804869	.0023013	1
Screening test	Skewness	P value	
Skewness test	-.8155264***	0.0000	

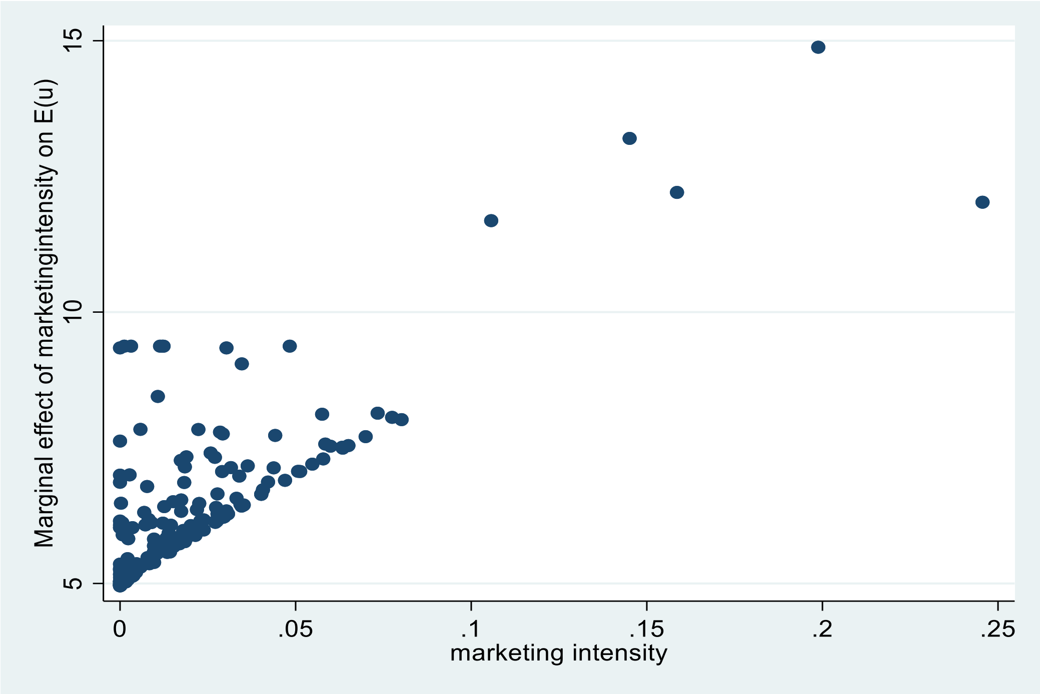
The result of COLS for vegetable oil suggest that labour and capital both impact output positively and are highly significant. If labour increase by one percent, output increase by 0.51% . similarly if capital increase by one percent then , output increase by 0.35%. the estimates shows that on average technical efficiency of the vegetable oil industry is 18% , which is not supported by literature. So we did screening test , we found that there is negative skewness in residuals and highly significant , this supports the idea of using maximum likelihood method.

Vegetable oil industry	ML estimates

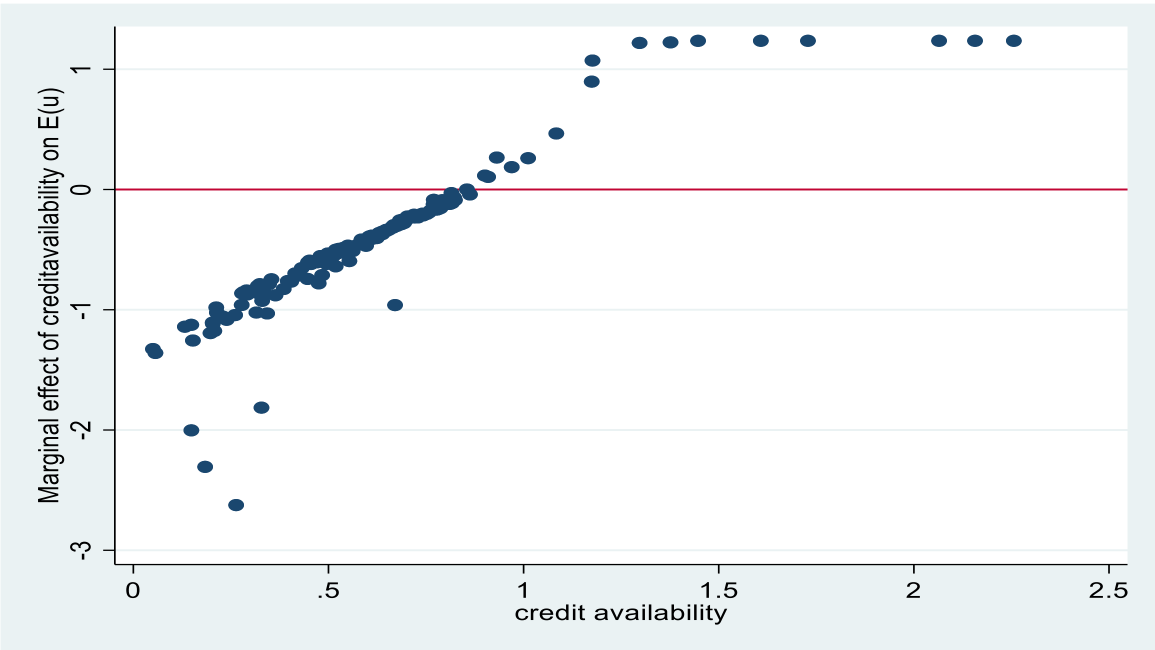
Log(output)	Coefficient	Standard error	P-value
Constant	1.288612	.7235942	0.075
Log(labour)	**.4697575**	**.0892878**	**0.000**
Log(capital)	**.3901054**	**.0777575**	**0.000**
No. of observations	**165**		
	statistic		
Gamma	0.989592		
LR Test	29.40479***		
Log likelihood function	**-224.6642**		
Technical inefficiency	**Coefficient**	**Standard error**	**p-value**
Marketing intensity	**9.372639**	**6.652607**	**0.159**
Credit availability	**1.23651**	**.7502459**	**0.099**
constant	**-1.033326**	**1.144633**	**0.367**
	Mean	Minimum	maximum

Technical efficiency	.5614387	.1107568	.8372757
Note: *** statistically significant at 1 percent ** statistically significant at 5 percent * statistically significant at 10 percent			

The result of stochastic frontier analysis for vegetable oil industry also shows that labour and capital impact output positively and are highly significant. If labour increase by one percent, output increase by 0.47% . Similarly if capital increase by one percent then , output increase by 0.39%. The estimates shows that on average technical efficiency of the vegetable oil industry is 56%. Gamma value is 0.99 which shows that 99% of the variation in output is attributed to technical inefficiency , so SFA is most appropriate ,but more complicated model like truncated normal distribution , gamma parameter does not convey useful information so we apply LR test. So the presence of technical inefficiency was tested by the likelihood ratio (LR) test which was 29.40479 which is greater than critical chi square value (given by kodde and palm, 1986) ,therefore the null hypothesis of no technical inefficiency is rejected. Marginal effect of marketing intensity and credit availability on average technical inefficiency is shown through the graph presented below, increase in marketing intensity increases the technical inefficiency, most of the firms are clustered in 5-10% range, but this relation is not significant. An increase in credit availability is likely to reduce the technical inefficiency and this is also supported by our data as most of the observations are clustered in range -1.5 to -0.25.



Vegetable oil



Vegetable oil

Sugar industry	Corrected OLS estimates		
Log(output)	Coefficient	Standard error	P-value
constant	-1.588072	.4420833	0.000
Log(labour)	**.6201967*** **	**.066355**	**0.000**
Log(capital)	**.3031171*** **	**.0586777**	**0.000**
No. of observations	**128**		
	Mean	Minimum	maximum
Technical efficiency	.2395317	.2395317	1
Screening test	Skewness	P value	
Skewness test	-2.695573***	0.0000	

The result of COLS for sugar industry suggest that labour and capital both impact output positively and are highly significant. If labour increase by one percent, output increase by 0.62% . similarly if capital increase by one percent then , output increase by 0.30%. the estimates shows that on average technical efficiency of the sugar industry is 24% , which is not supported by literature. So we did screening test , we found that there is negative skewness in residuals and highly significant , this supports the idea of using maximum likelihood method.

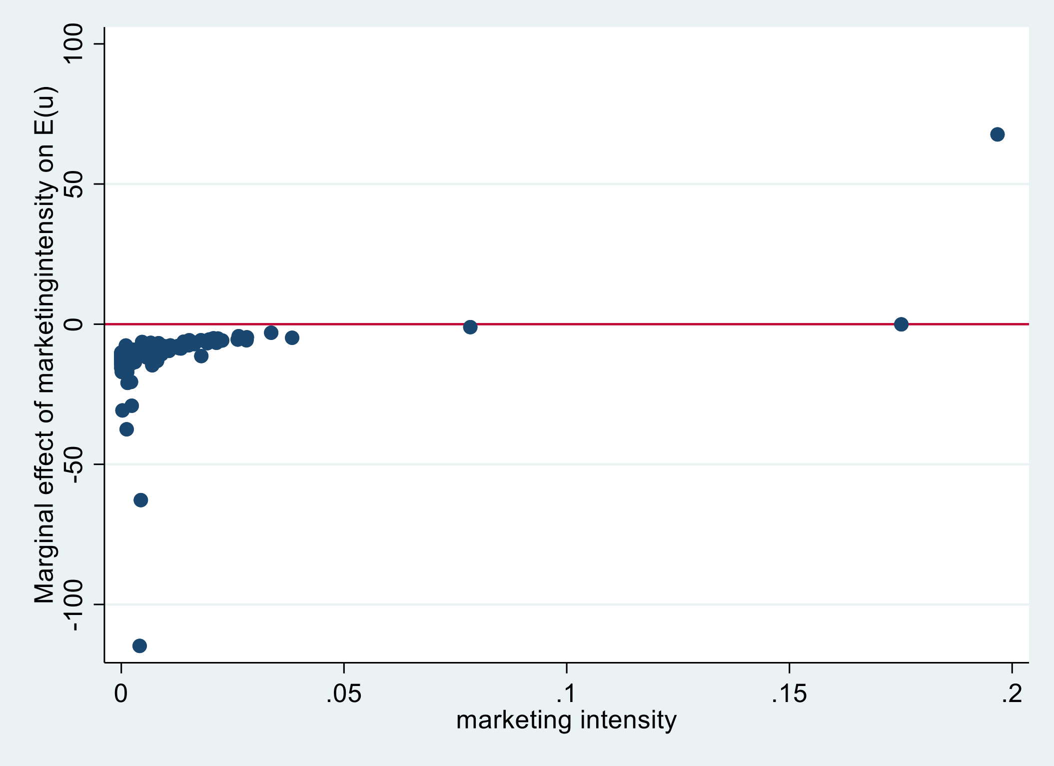
Sugar industry	ML estimates		
Log(output)	Coefficient	Standard error	P-value
constant	-.68015	.3884755	0.080
Log(labour)	**.545959*** **	**.0553294**	**0.000**
Log(capital)	**.3272402*** **	**.0500964**	**0.000**
No. of observations	**128**		
	statistic		
Gamma	0.978537		
LR Test	54.79778		
Log likelihood function	**-90.9509**		
Technical inefficiency	**Coefficient**	**Standard error**	**p-value**
Marketing intensity	**67.70704**	**68.18199**	**0.321**
Credit availability	**-13.41434**	**16.59654**	**0.419**
	Mean	Minimum	maximum
Technical efficiency	.7366901	.0113758	.997055

Note: *** statistically significant at 1 percent

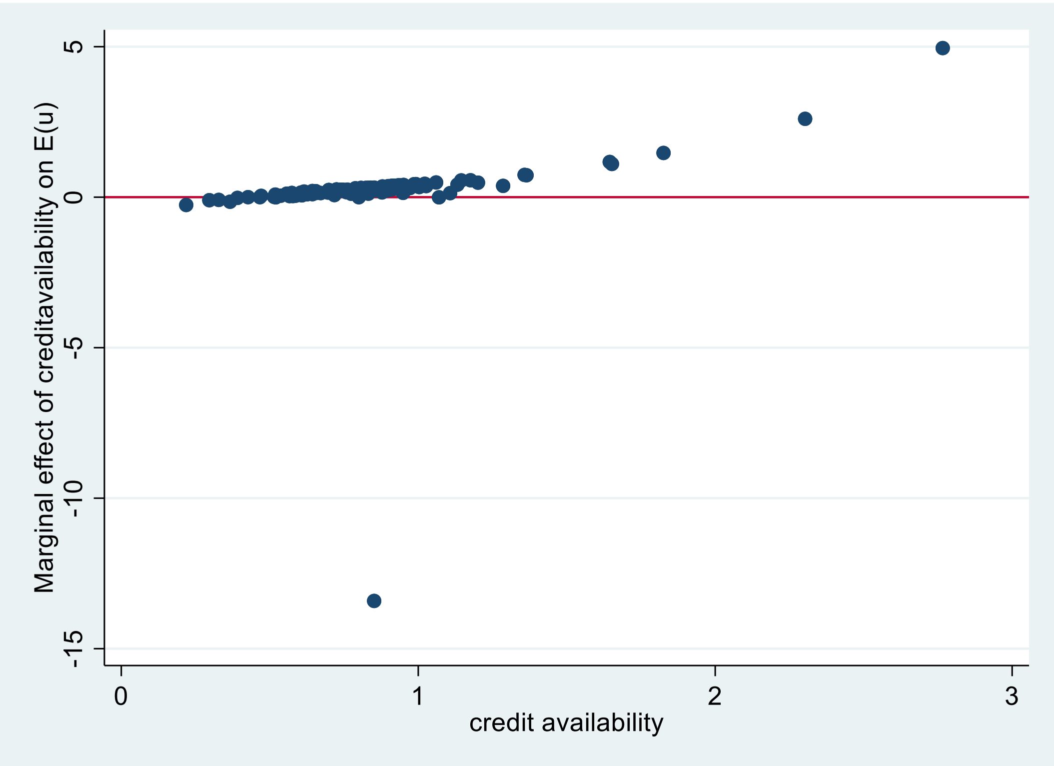
** statistically significant at 5 percent

* statistically significant at 10 percent

The result of stochastic frontier analysis for sugar industry also shows that labour and capital impact output positively and are highly significant. If labour increase by one percent, output increase by 0.55% . similarly if capital increase by one percent then , output increase by 0.33%. The estimates shows that on average technical efficiency of the sugar industry is 74%. Gamma value is 0.98 which shows that 98% of the variation in output is attributed to technical inefficiency , so SFA is most appropriate ,but more complicated model like truncated normal distribution , gamma parameter does not convey useful information so we apply LR test. So the presence of technical inefficiency was tested by the likelihood ratio (LR) test which was 54.79778 which is greater than critical chi square value (given by kodde and palm, 1986) ,therefore the null hypothesis of no technical inefficiency is rejected. Marginal effect of marketing intensity and credit availability on average technical inefficiency is shown through the graph presented below, expected relation is that increase in marketing intensity increases the technical inefficiency, most of the firms are clustered in negative range, but this relation is not significant. An increase in credit availability is likely to reduce the technical inefficiency , most of the firms are clustered in positive range but this relation is also insignificant. So we don’t have conclusive results about the factors affecting technical inefficiency in sugar industry.



Sugar industry



Sugar industry

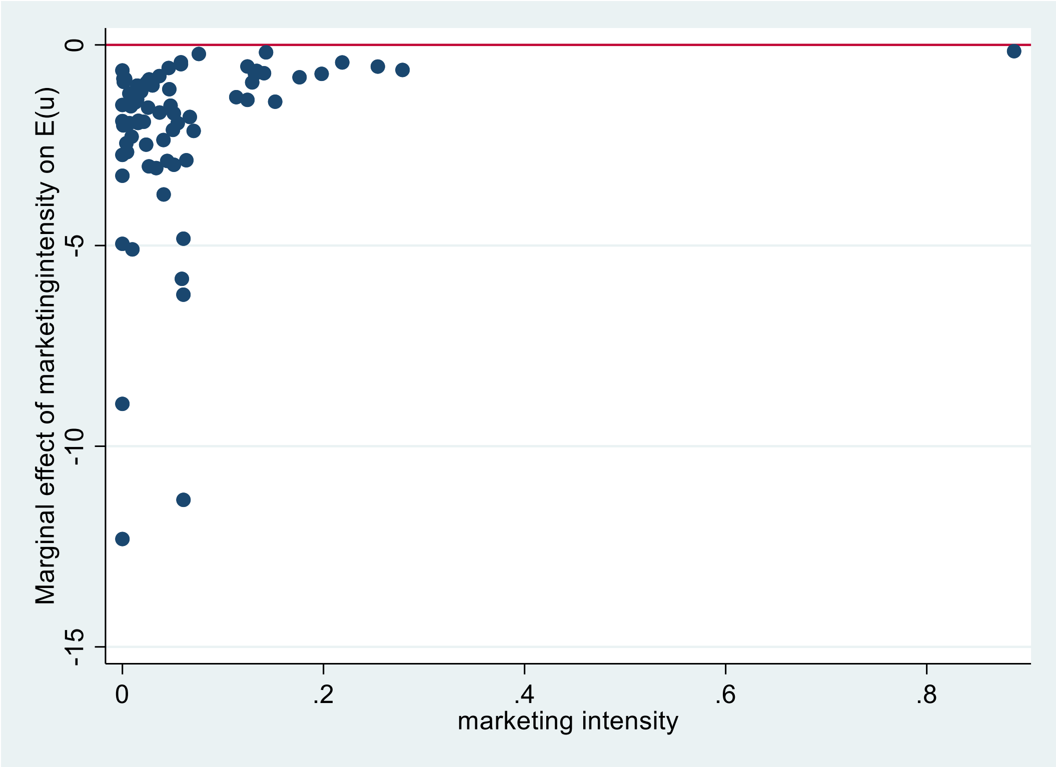
Beer and alcohol industry	Corrected OLS estimates		
Log(output)	Coefficient	Standard error	P-value
constant	-4.836339	.7648016	0.000
Log(labour)	**1.133124**	**.1152559**	**0.000**
Log(capital)	**.077164**	**.0994439**	**0.440**
No. of observations	**73**		
	Mean	Minimum	maximum
Technical efficiency	.2316292	.0074631	1
Screening test	Skewness	P value	
Skewness test	-.5428848	0.1190	

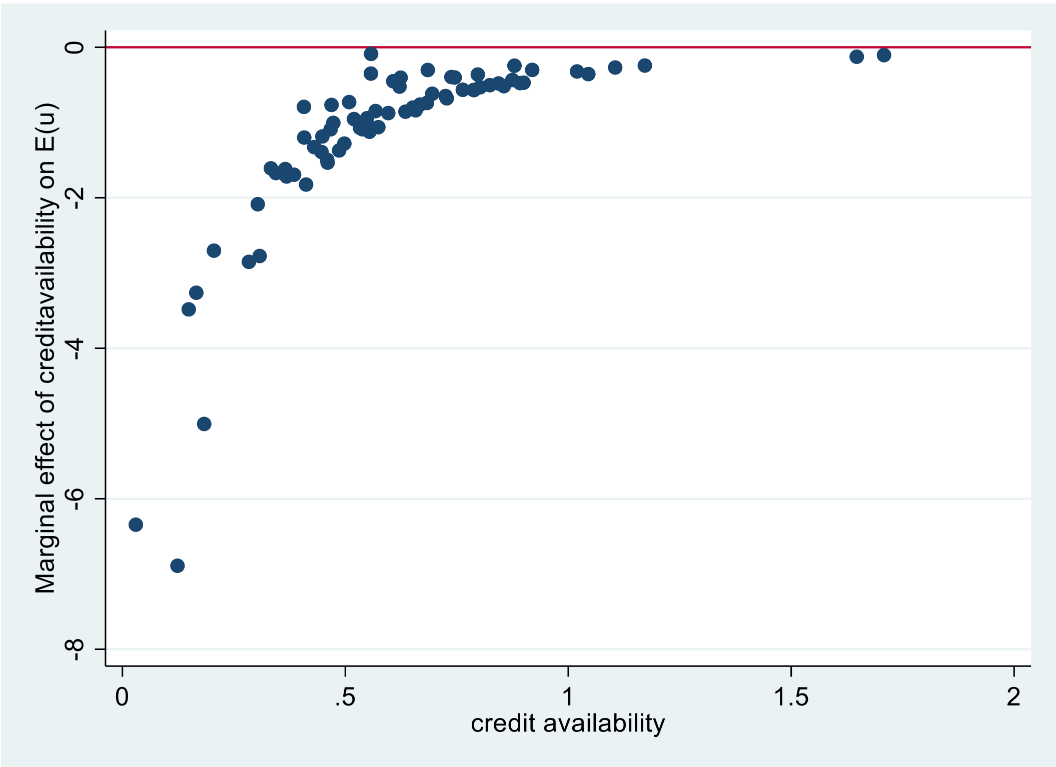
The result of COLS for beer and alcohol industry suggest that labour and capital both impact output positively and only labour is highly significant, not the capital. If labour increase by one percent, output increase by 1.13% . similarly if capital increase by one percent then , output increase by 0.07%. The estimates shows that on average technical efficiency of the beer and alcohol industry is 23% , which is not supported by literature. So we did screening test , we found that there is negative skewness in residuals and highly significant , this supports the idea of using maximum likelihood method.

Beer and alcohol industry	ML estimates		
Log(output)	Coefficient	Standard error	P-value
constant	**-2.884886**	**.8967267**	**0.001**
Log(labour)	**.9194098 *** **	**.1204959**	**0.000**
Log(capital)	**.2266333** **	**.096299**	**0.019**
No. of observations	**73**		
Gamma	0.962853		
LR Test	10.8015		
Log likelihood function	**-101.8245**		
Technical inefficiency	**Coefficient**	**Standard error**	**p-value**
Marketing intensity	**-64.54046**	**254.3367**	**0.800**
Credit availability	**-36.12074**	**124.8902**	**0.772**
	Mean	Minimum	maximum
Technical efficiency	.5849616	.0356256	.8779296

Note: *** statistically significant at 1 percent ** statistically significant at 5 percent * statistically significant at 10 percent

The result of stochastic frontier analysis for beer and alcohol industry also shows that labour and capital impact output positively and both are significant. If labour increase by one percent, output increase by 0.92% . similarly if capital increase by one percent then , output increase by 0.23%. The estimates shows that on average technical efficiency of the beer and alcohol industry is 58%. Gamma value is 0.96 which shows that 96% of the variation in output is attributed to technical inefficiency , so SFA is most appropriate ,but more complicated model like truncated normal distribution , gamma parameter does not convey useful information so we apply LR test. So the presence of technical inefficiency was tested by the likelihood ratio (LR) test which was 10.8015, which is greater than critical chi square value (given by kodde and palm, 1986) ,therefore the null hypothesis of no technical inefficiency is rejected. Marginal effect of marketing intensity and credit availability on average technical inefficiency is shown through the graph presented below, expected relation is that increase in marketing intensity increases the technical inefficiency, most of the firms are clustered in negative range, but this relation is not significant. An increase in credit availability is likely to reduce the technical inefficiency , most of the firms are clustered in negative range but this relation is also insignificant. So we don’t have conclusive results about the factors affecting technical inefficiency in beer and alcohol industry.





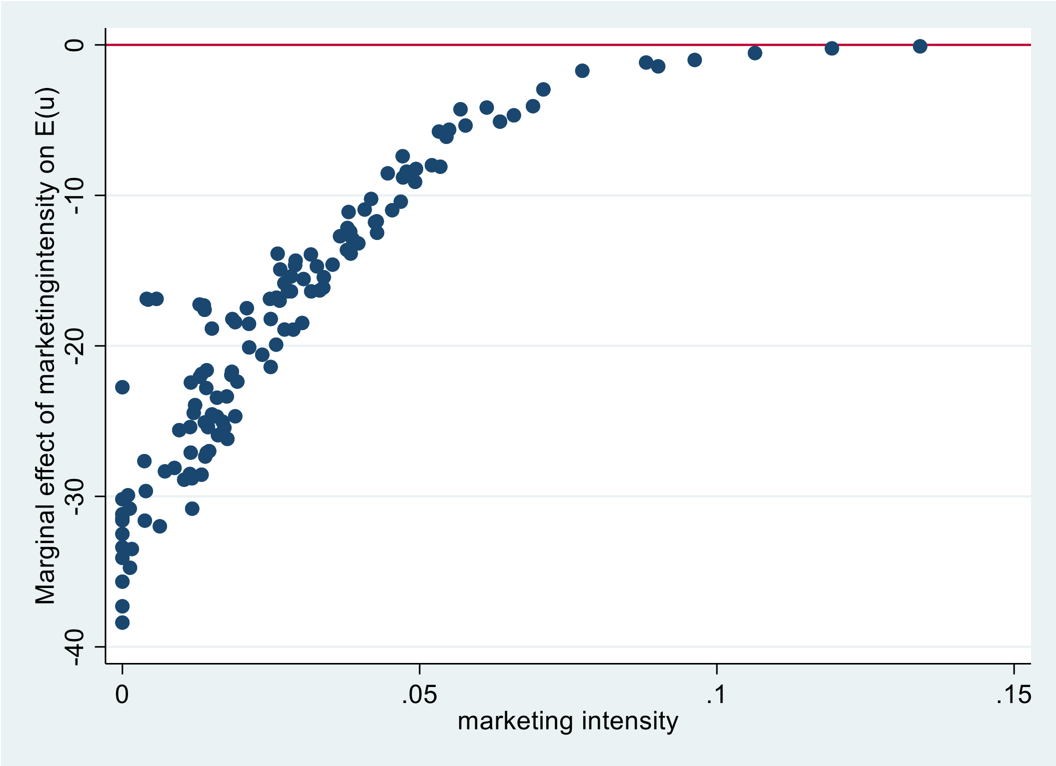
Tea industry	Corrected OLS estimates		
Log(output)	Coefficient	Standard error	P-value

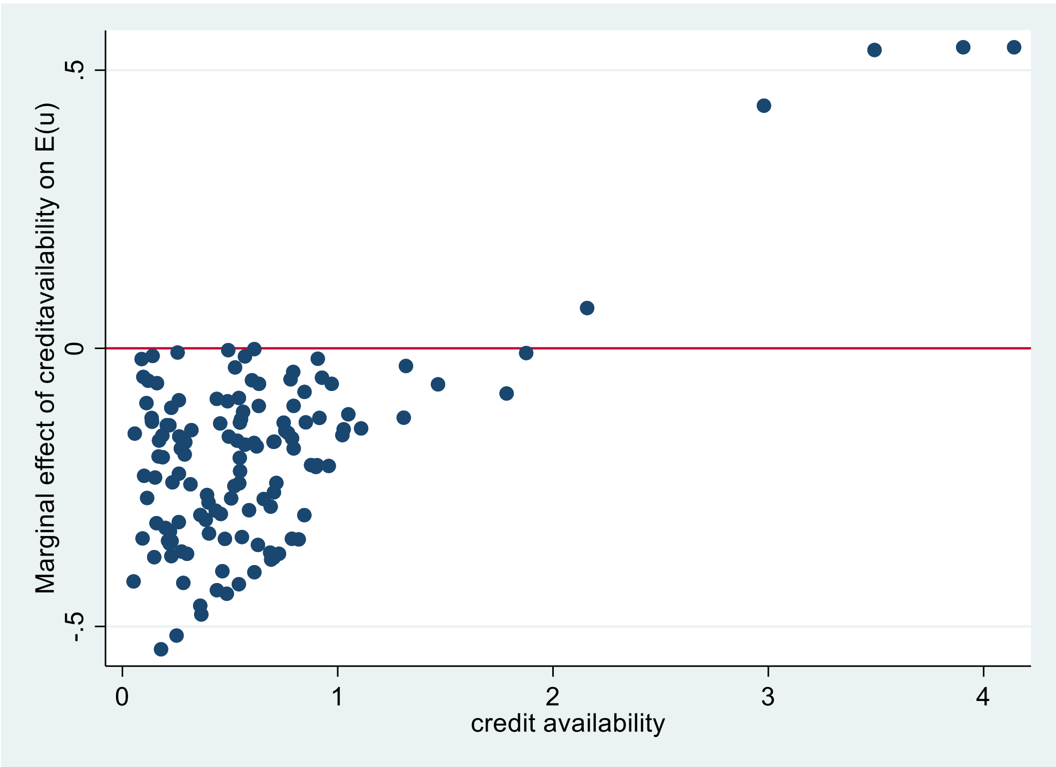
constant	-2.63762	.4875407	0.000
Log(labour)	**.5910333**	**.0659878**	**0.000**
Log(capital)	**.3230857**	**.0653292**	**0.000**
No. of observations	**132**		
	Mean	Minimum	maximum
Technical efficiency	.09733	.0151991	1
Screening test	Skewness	P value	
Skewness test	1.279143	0.0000	

The result of COLS for sugar industry suggest that labour and capital both impact output positively and are highly significant. If labour increase by one percent, output increase by 0.59% . similarly if capital increase by one percent then , output increase by 0.32%. The estimates shows that on average technical efficiency of the sugar industry is 9% , which is not supported by literature. So we did screening test , we found that there is positive skewness in residuals and highly significant. As the results are not supported by theory so we went ahead with the expensive method of SFA and then did LR test to check for its appropriateness.

Tea industry	ML estimates		
Log(output)	Coefficient	Standard error	P-value
constant	.0139491	1041.298	1.000

Log(labour)	**.5378039**	**.0567225**	**0.000**
Log(capital)	**.3261244**	**.0555022**	**0.000**
No. of observations	**132**		
Gamma	0.69814		
LR Test	40.26141		
Log likelihood function	**-144.1612**		
Technical inefficiency	**Coefficient**	**Standard error**	**p-value**
Marketing intensity	**-17.16183**	**2.61379**	**0.000**
Credit availability	**.0702524**	**.1010241**	**0.487**
	Mean	Minimum	maximum
Technical efficiency	.6320751	.1622375	.998158
Note: *** statistically significant at 1 percent ** statistically significant at 5 percent * statistically significant at 10 percent			





The result of stochastic frontier analysis for tea industry also shows that labour and capital impact output positively and both are significant. If labour increase by one percent, output increase by 0.53% . similarly if capital increase by one percent then , output increase by 0.33%. The estimates shows that on average technical efficiency of the tea industry is 63%. Gamma value is 0.70 which shows that 70% of the variation in output is attributed to technical inefficiency , so SFA seems appropriate ,but for more complicated model like truncated normal distribution , gamma parameter does not convey useful information so we apply LR test. So the presence of technical inefficiency was tested by the likelihood ratio (LR) test which was 40.26141 , which is greater than critical chi square value (given by kodde and palm, 1986) ,therefore the null hypothesis of no technical inefficiency is rejected. Marginal effect of marketing intensity and credit availability on average technical inefficiency is shown through the graph presented above, expected relation is that increase in marketing intensity increases the technical inefficiency, most of the firms are clustered in negative range, and this relation is significant which means that in tea industry marketing intensity reduces the technical inefficiency so improves efficiency. An increase in credit availability is likely to reduce the technical inefficiency , most of the firms are clustered in negative range but this relation is insignificant. So we cannot draw definite conclusion.

Conclusion :

- Results shows that sugar industry is the most efficient one, and it is also only 74% efficient , so there is a lot of scope for improvement in all the industries ,overall improvement is possible by efficient utilisation of existing resources.
- In order to improve efficiency of existing resources, other exogenous factors need to be developed:
    - Credit availability need to be improved as it improves the efficiency of most of the industries
    - providing a mechanism to link agricultural production to the market by bringing together farmers, processors and retailers so as to ensure maximizing value addition, minimizing wastages, increasing farmers’ income and creating employment opportunities, particularly in the rural sector (mega food parks), this will reduce the selling and distribution expenditure (marketing intensity) therefore will increase the efficiency of firms.

References :

- Technical Efficiency of Unorganised Food Processing Industry in India: A Stochastic Frontier Analysis, Padmavathi N (2019)
- Efficiency and related technological aspects of the Indian food processing industry: A non-parametric approach , Anup Kumar Bhandari and V Vipin, 2016
- Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India, G. E. Battese & T. J. Coelli, 1992
- A practitioner's guide to stochastic frontier analysis using Stata by Alan P. Horncastle, hung-jen wang , and Subal Kumbhakar
- Stochastic Frontier Analysis of Production Technology: An Application to the Pharmaceutical Manufacturing firms in Ghana , Johnson Addai-Asante , Samuel Sekyi, 2016