Technical efficiency of Indian farmers in sugarcane production-A panel stochastic frontier approach

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Abstract

Aim: To estimate the technical inefficiency of Indian farmers in sugarcane production.

Methodology: Although various stochastic frontier models for panel data are available, six of them were considered for the study, which is frequently applied in empirical research. Based on the log likelihood ratio, results are interpreted only for kumbhakar, lien and hardaker (KLH) model.

Results: Indian farm's overall technical efficiency ranged from minimum 0.11 to maximum 0.93 with a mean value of 0.70, it means that with same resource based average sugarcane growers can increase their yield up to 23% and most technical inefficient grower can increase their yield up to 82% in order to achieve overall technical efficiency level (93%) of efficient fellow grower in study area. Though, Tamil Nadu has the highest overall technical efficiency score in sugarcane production (0.76), the negative growth rate indicates its decline in technical efficiency. Haryana has a negative growth rate in persistent, residual and overall technical efficiency in sugarcane production.

Interpretation: Among the seven states, Uttaranchal showed the highest scope of improving the sugarcane yield with 36%, followed by Uttar Pradesh (34%), Haryana (33%), Maharashtra (30%), Karnataka (30%), Andhra Pradesh (25%) and Tamil Nadu (24%). Results of parameter estimates confirmed that area in hectare, machine usage in hours, seed quantity in kilograms, manure usage in quintals and total fertilizer usage in kilograms are significant and positively influence the sugarcane production. The coefficients of dummy for farm size reveals that medium and large sugarcane farms are less efficient compared to small farms. Similarly, the share of own machine-hours has a negative impact on sugarcane production. Based on the empirical results appropriate policy is suggested for the study.

Key words: Frontier, Panel data, Production, Sugarcane, Technical efficiency

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Introduction

Agriculture and allied sector in India contribute 17.32% to gross domestic product (MoSPI, 2020). Sugar industry is the second largest agro-based industry in India next to textiles. It plays a vital role in the agricultural and industrial economy. Though sugarcane and sugar beet are the main sources of sugar in the world. Most of the sugar in India is produced only from sugarcane. More than 80% of the world's share in sugarcane production and area is contributed by Brazil, China-mainland, Colombia, Cuba, India, Mexico, Pakistan, Philippines, Thailand and the United States of America (FAOSTAT, 2018). Brazil ranks first in area (10.04 million ha with a share of 38.22%) and production (746 million tons with a share of 39.16 %) of sugarcane. India occupies a second major share in the area as well as production with a share of 18.00% (4.73 million ha) and 19.76% (376.90 million tons), respectively. The productivity of India's sugarcane (69.74 tons per hectare) is lesser than the world's productivity (79.68 tons per hectare), though it ranks second in area and production. Sugarcane accounts for 3.2% of net sown area, 95.53% of irrigated area and 5.45% percent of total fertilizer consumption. In 2018-19, Uttar Pradesh occupied a major share in sugarcane area (43.93%) and production (44.33%) but states like Puducherry, Kerala and Tamil Nadu occupied top position in sugarcane productivity. In the case of productivity, Peru has the highest productivity with a yield of 121.83 tons per hectare. On the other hand, India's per capita sugar consumption has been growing at a steady rate of 3% and is currently 19.5 kg. Because of high domestic demand and occasional fluctuation in production, India has a minimal share in sugar export (Solomon, 2011). The sugar demand of the country is growing consistently with population growth. Without the contribution of efficient sugarcane production, meeting such a huge domestic demand for sugar is impossible and would have warranted massive sugar import (Malaikarasan *et al.*, 2019). Production of sugarcane depends on the use and combination of inputs. These combinations are considered as Technology. Variations in technology affects sugarcane yield. Many studies have confirmed that there is a gap between potential and realized yield of sugarcane in India (Surendran *et al.*, 2016; Rao, 2012; Shanthi, 2011). Particularly in developing countries like India, inefficiency in production is one of the core factors hindering the exploitation of full potential of innovated technologies (Sekhon *et al.*, 2010; Kalirajan and Shand, 1989; Banik, 1994; Thomas and Sundaresan, 2000). Variations in the input management and output levels among farms are varying over the years. Therefore, it is not enough to know how farms are technically efficient but how farms are persistent in production technical efficiency will be helpful to meet our future sugar demand. With this scenario, the core objective of this study was to assess how overall technical efficiency and persistent technical efficiency in sugarcane production vary over the years and across states and to assess the relationship of technical efficiency on firm size and share of own machine hours.

Materials and Methods

Cost of cultivation of principal crops (CCPC) data was used for this study. This data was collected from a comprehensive survey initiated in 1970-71. This survey covered 29 crops (choice and the number of crops depend on their importance to the State) covering 16 states. The data considered for the present study is an unbalanced farm-level panel data from 2011-12 to 2013-14 with time gaps. This panel data consists of 944 observations from seven states (Andhra Pradesh, Haryana, Karnataka, Maharashtra, Tamil Nadu, Uttar Pradesh and Uttarakhand). Estimated inefficiency with cross-section data has been reported (Parikh and Shah, 1994; Dlamini *et al.*, 2010; Felix *et al.*, 2018; Ambetsa *et al.*, 2020). But, estimating inefficiency with cross-section data have three major problems (Schmidt and Sickles, 1984). First, the formula used to estimate inefficiency index (JLMS) depends on distributional assumptions for the noise and inefficiency components. An assumption, at least for a single equation the technical inefficiency component should be independent of regressors is unlikely true if firms maximize profit (Mundlak, 1961). Finally, when the cross-sectional units are more the conditional mean $u(v-u)$ never approaches u , leading to inefficiency index estimator as an inconsistent one. Hence, panel data was used for this study. Panel data has an advantage over cross-sectional which takes into account of heterogeneity by introducing individual effect (time-invariant and individual-specific).

Model 1 : Pitt and Lee, 1981 (Time-Invariant Technical Inefficiency model) : This model assumes that efficiency is individual specific and time variant. It can be written as

$$y_{it} = f(x_{it}; \beta) + \epsilon_{it},$$

$$\epsilon_{it} = v_{it} - u_i, u_i \geq 0, i = 1, \dots, N; t = 1, \dots, T$$

where, $f(x_{it}; \beta)$ is a linear function of the variables in the vector x_{it} and $u_i \geq 0$ is the time-invariant technical inefficiency of individual i . This model can be estimated by assuming either u_i is a fixed (Fixed effect model) or a random variable (Random effect model). In fixed and random effect model, u_i does not follow any distribution. Although distribution-free assumption may be desirable, it can also estimate with MLE by imposing distributional assumptions on v_{it} and u_i (Pitt and Lee, 1981).

It can be written as

$$y_{it} = f(x_{it}; \beta) + \epsilon_{it},$$

$$\epsilon_{it} = v_{it} - u_i,$$

$$v_{it} \sim N(0, \sigma_v^2) \text{ and } u_i \sim N^+(\mu, \sigma_u^2).$$

The likelihood function for i^{th} observation is presented below

$$\ln Li = \text{constant} + \ln \phi \left(\frac{\mu_i}{\sigma_v} \right) + \frac{1}{2} \ln(\sigma_v^2) - \frac{1}{2} \left\{ \frac{\sum_t \epsilon_{it}^2}{\sigma_{2v}} + \left(\frac{\mu}{\sigma_v} \right)^2 - \left(\frac{\mu_i}{\sigma_v} \right)^2 \right\} - T \ln(\sigma_v) - \ln \phi \left(\frac{\mu}{\sigma_u} \right)$$

Model 2 : Kumbhakar, 1990 and Model 3 : Battese Coelli, 1992 (Time-Varying Inefficiency Models with Deterministic and Stochastic Components) : In this model, the inefficiency term u_{it} is not fixed, it varies over time and across individuals. This u_{it} has two distinct inefficient components $G(t)$. First is a non-stochastic time component and the second is a stochastic individual component u_{it} .

$$y_{it} = f(x_{it}; \beta) + \epsilon_{it},$$

$$\epsilon_{it} = v_{it} - u_{it},$$

$u_{it} = G(t)u_i$, $v_{it} \sim N(0, \sigma_v^2)$ and $u_i \sim N^+(0, \sigma_u^2)$, where $G(t) > 0$ is a function of (t) .

Based on the forms of $G(t)$ Model 2 and 3 were considered for the study Kumbhakar (1990) model assumes $G(t) = [1 + \exp(\gamma_1 t + \gamma_2 t^2)]^{-1}$ and Battese Coelli (1992) model assumes $G(t) = \exp(\gamma(t - T))$, where T is the terminal period of the sample.

Model 4 : Greene, 2005 (Separate Firm Heterogeneity from Inefficiency) : This model consist a persistent inefficiency term. It also represents individual specific effect (heterogeneity).

$$y_{it} = \alpha_i + x'_{it}\beta + v_{it} - u_{it}$$

The term $-u_{it}$ represents time varying inefficiency and this model treats α_i , $i = 1, \dots, N$ as a fixed parameter. (Greene, 2005).

Model 5 : Kumbhakar and Heshmati, 1995 (Separate Persistent and Time-Varying Inefficiency) : The persistent inefficiency reflects the effect of inputs like management as well as other unobserved inputs which vary across firms but not over time unless a change in government policy, change in firm-ownership and so on (Mundlak, 1961). In contrast, the residual inefficiency component might change over time without any change in the operation of the firm.

$$y_{it} = \beta_0 + x'_{it}\beta + \epsilon_{it},$$

$$\epsilon_{it} = v_{it} - u_{it},$$

$$u_{it} = u_i + T_{it}$$

here the error term ϵ_{it} is decomposed into two ($\epsilon_{it} = v_{it} - u_{it}$), where, u_{it} is technical inefficiency and v_{it} is random error. The technical inefficiency term further decomposed into two terms ($u_{it} = u_i + T_{it}$), where u_i is the time invariant persistent component and T_{it} is time varying residual inefficiency term. The persistent component is firm specific but residual term is both firm and time specific.

Model 6 : Kumbhakar, Lien and Hardaker, 2014 (Separate Firm Effects, Persistent Inefficiency and Time-Varying Inefficiency) : This model was introduced by Kumbhakar, Lien, and Hardaker (2014) and Colombi *et al.* (2014). It overcomes some of the limitations of the above said model. By taking into account of different factors affects output for given level of input, the error term is split into four components of which two (η_i and u_{it}) are inefficiency term and other two are firm effect (μ_i) and noise (v_{it}).

$$y_{it} = a_0 + f(x_{it}; \beta) + \mu_i + v_{it} - \eta_i - u_{it}$$

The first component captures firm's latent heterogeneity (Greene, 2005), second component captures time varying inefficiency, third component captures persistent or time invariant inefficiency (Kumbhakar and Hjalmarsen, 1993, 1995; Kumbhakar and Heshmati, 1995) and last component captures random noise.

For the present study, the above model was estimated by single stage maximum likelihood method based on distributional assumptions on the four components (Colombi *et al.*, 2011)

The above equation is rewritten as

$$y_{it} = \alpha_i^* + f(x_{it}; \beta) + \alpha_i + \epsilon_{it}$$

where, $\alpha_i^* = a_0 - E(\eta_i) - E(u_{it})$; $\alpha_i = \mu_i - \eta_i + E(\eta_i)$; and $\epsilon_{it} = v_{it} - u_{it} - E(u_{it})$

The above model was estimated in three steps

Step 1: Random effect panel regression was performed to estimate β . This estimation also provided predicted values of α_i and ϵ_{it} .

Step 2: The time varying technical inefficiency (u_{it}) was estimated from predicted values of ϵ_{it} . Standard stochastic frontier technique $\epsilon_{it} = v_{it} - u_{it} - E(u_{it})$ was used to estimate the time varying residual technical inefficiency term u_{it} (Jondrow *et al.*, 1982). By assuming v_{it} is i.i.d. $N(0, \sigma_v^2)$ and u_{it} is $N^+(0, \sigma_u^2)$, which means $E(u_{it}) = (\sqrt{2/\pi}\sigma_u)$.

Step 3 : η_i was estimated from the best linear predictor of α_i from step 1. This persistent technical inefficiency was estimated from $PTE = \exp(-\eta_i)$. The overall technical efficiency was obtained by multiplying the persistent- and residual-technical efficiency.

Variables employed for the present study

Dependent variable : $\ln_YLD$: Natural logarithm of sugarcane production in quintals

Independent variables : $\ln_ARE$: Natural logarithm of total area used for cane production in hectares; $\ln_ANL$: Natural logarithm of total animal labour used for cane production in hours; $\ln_MCN$:

Natural logarithm of total machine labour used for cane production in hours; $\ln_SED$: Natural logarithm of total seed used for cane production in kilograms; $\ln_MRE$: Natural logarithm of total manures used for cane production in quintals; $\ln_INC$: Natural logarithm of total insecticides used for cane production in rupees; $\ln_FER$: Natural logarithm of total fertilizers used for cane production in kilograms; $\ln_SMC$: Natural logarithm of share of own machine hours used for cane production in hours (it's the ratio of own machine hours divided by total machine hours); $SDU2$: Dummy for medium firm=1, if the area is >2 ha to <=4 ha; otherwise=0; $SDU3$: Dummy for large firm=1, if the area is >4 ha; otherwise=0

Results and Discussion

The descriptive statistics of model are presented in Table 1. It is evident that an average of 1.50 ha sugarcane farm produces an average of 1205.25 quintal sugarcane with 39.47 hrs of animal labor, 26.08 hrs of machine labor, 55.19 quintals of manures, 1028.89 rupees of insecticide cost and 578.12 kilograms of fertilizers. It is evident from Fig. 1, Model-4 had the highest mean technical efficiency of 0.74 because it did not consider the firm effects to be inefficiency, leading to high-efficiency scores (Fig. 1) and low dispersion (Fig. 2). Greene

(2005) also found in a study of the US banking industry that the 'true' random effects results had higher and less dispersed technical efficiency scores than results for other models considered. Similarly, Model-5 had the lowest mean technical efficiency of 0.37 because it has the assumption that inefficiency won't change over the period.

Model-6 overcomes the problem of Model-4 and -5 by decomposing the time-persistent noise into a firm effect and a persistent technical inefficiency effect. The efficiency scores of Model-6 lies between the scores for Models-4 and -5 (Fig.2). The mean overall efficiency score for Model 6 is 0.70, and the score spread is between that of Model 4 (low spread) and Model-5 (high spread; Fig. 2).

A perfect match between the two models would showed up as presence of straight line in the graph revealing perfect match between the two models. The pattern of results between Model- 1 and -2, Model-1 and -3, Model-2 and -3, and between Model-5 and -6 seem to be most consistent, *i.e.*, these model comparisons have least dispersed scatter plots, strongest congruence, and most consistent rankings. The scatter plot between Models-1 and -2, Model-1 and -3, Model-2 and -3 seem quite linear with high correlation values of 0.9993, 0.9891 and

Table 1: Descriptive statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
YLD	overall	1205.24	1360.41	6.50	18721.25	N= 2018
	between		1206.69	6.83	12762.28	n= 944
	within		566.43	-4753.74	8940.07	bar=2.13
ARE	overall	1.50	1.48	0.02	20.09	N= 2018
	between		1.34	0.02	14.87	n= 944
	within		0.55	-5.66	8.66	bar=2.13
ANL	overall	39.47	89.37	0.00	1443.00	N= 2018
	between		80.46	0.00	941.00	n= 944
	within		40.62	-716.53	541.47	bar=2.13
MCN	overall	26.08	50.01	0.00	529.50	N= 2018
	between		43.59	0.00	352.00	n= 944
	within		25.13	-188.58	262.92	bar=2.13
SED	overall	42.03	67.58	0.00	1069.00	N= 2018
	between		49.19	0.00	479.67	n= 944
	within		47.40	-437.64	631.36	bar=2.13
MRE	overall	55.19	506.77	0.00	17915.00	N= 2018
	between		430.79	0.00	11283.13	n= 944
	within		270.41	-6576.69	6687.06	bar=2.13
INC	overall	1028.89	3480.71	0.00	79495.81	N= 2018
	between		2895.84	0.00	60443.68	n= 944
	within		1702.48	-22638.20	41888.08	bar=2.13
FER	overall	578.12	734.90	0.00	9891.50	N= 2018
	between		663.21	0.00	7708.75	n= 944
	within		301.43	-1987.52	3604.12	bar=2.13
SMC	overall	0.27	0.41	0.00	1.00	N= 1486
	between		0.39	0.00	1.00	n= 810
	within		0.11	-0.40	0.93	bar=2.13

Fig. 1 : Kernel density technical efficiency distribution sugarcane farms for Model 1-6.

Table 2 : Log likelihood ratio test

Test	Model 1	Model 2	Model 3	Model 4	Model 5
LLR	37.39	2074.77	2065.55	2074.44	259.47
Critical values of mixed Chi-square distribution Significance level					
dof	0.25	0.1	0.05	0.025	0.01
1	0.46	1.64	2.71	3.84	5.41

Source: Kodde and Palm (1986, Econometrica)

0.957, respectively, indicating that the efficiency scores are rather consistent for these models.

However, the plot between Models 6 and 5 indicates a systematically lower correlation (0.834) and efficiency score in high score group, resulting in non-linear pattern (Fig.3). Finally, the results of log likelihood ratio test indicated that Model 6 had the best fit for data considered for this study (Table.2). This result is consistent with Kumbhakar (2014).

Stochastic frontier : Estimates of different frontier production functions (Model-1 to 6) are presented in Table 3. Based on the

log likelihood results, best-suited model results are discussed in this section. The estimated lambda (λ) parameter for selected model was 1.15 (Model 6), which means that the total error variance was mainly due to inefficiency, whereas random errors are less important. The γ value (57.01 percent) indicates relative variability of one-sided error term to total error-term. Hence, 57.01 % variation in sugarcane production was due to differences in technical efficiencies remaining due to random errors. These random errors include biotic/abiotic stress during its active growth phases, climatic factors and other factors which are not included in the present model (Singh *et al.*, 2019; Misra *et al.*, 2019; Malaikarasan *et al.*, 2020). It can be observed from Table 3 that

Fig. 2 : Technical efficiency of sugarcane farms over the years for Model 1-6.

variables like area in hectare, machine usage in hours, seed quantity in kilograms, manure usage in quintals and total fertilizer usage in kilograms are significant and positively influence sugarcane production. As expected, it shows a positive relationship between total farm size and production but the coefficients of dummy for farm size reveals that medium and large sugarcane farms have a negative impact on sugarcane production. These results are reflected in Fig.4 that except small sugarcane farms, medium and large farms have a negative impact on farm size. This shows that medium and large sugarcane farms are less efficient compared to small farms (Hoque, 1988). Though overall machine hours have a positive impact on sugarcane production, the share of own machine-hours has a negative impact. It indicates that as compared to own machine-hours, hired machine hours are efficient for sugarcane production because 86.20% of the farmers in India are small and marginal farmers. As per the Agricultural Census 2015-16, the average size of operational holdings in India is only 1.08 ha. So, owing such a costly machine for cultivating marginal and small farm would not be an efficient one.

The results are similar to Fig.5 that across all farm sizes, the share of own machine-hours has a negative impact on overall technical efficiency in sugarcane production. The results are in line with the results of Larsén (2010), that hired pieces of machinery are more efficient in production. The return to the elasticity of 0.8655 implies a slight decreasing return to scale, which indicates that the farmers are engaged in sugarcane production on a nonoptimal scale.

Persistent technical efficiency : In 2011-12, the persistent technical efficiency score of Indian sugarcane farmers was 0.84, it increased to 0.84 in 2012-13 and 0.85 in 2013-14 with a compound annual growth rate of 0.29%. Triennium average persistent technical efficiency score of Indian sugarcane farmers was 0.85 with a growth rate of 0.29%. Among seven states, Haryana and Uttar Pradesh had a negative compound annual growth rate in their persistent technical efficiency. Haryana had the highest negative growth rate in the persistent technical efficiency of sugarcane farmers with a value of 0.83%. It showed that the Haryana and Uttar Pradesh's sugarcane farmers' production efficiency has declined over the years due to better

Fig. 3 : Scatter plot matrix of pair wise technical efficiency.

Table 3: Estimates of parameters from different frontier production functions

Particulars	Model1	Model 2	Model 3	Model 4	Model 5	Model 6
ln_ARE	0.824*** (0.018)	0.825*** (0.018)	0.824*** (0.018)	0.827*** (0.017)	0.818*** (0.019)	0.818*** (0.019)
ln_ANL	-0.001 ^{NS} (0.005)	-0.001 ^{NS} (0.005)	-0.001 ^{NS} (0.005)	-0.003 ^{NS} (0.004)	0.001 ^{NS} (0.005)	0.001 ^{NS} (0.005)
ln_MCN	0.031*** (0.007)	0.032*** (0.007)	0.031*** (0.007)	0.038*** (0.006)	0.031*** (0.007)	0.031*** (0.007)
ln_SED	0.001 ^{NS} (0.005)	0.001 ^{NS} (0.005)	0.001 ^{NS} (0.005)	-0.011** (0.005)	0.002** (0.005)	0.002** (0.005)
ln_MRE	0.024*** (0.004)	0.025*** (0.004)	0.024*** (0.004)	0.033*** (0.004)	0.022*** (0.005)	0.022*** (0.005)
ln_INC	0.002 ^{NS} (0.003)	0.003 ^{NS} (0.003)	0.002 ^{NS} (0.003)	0.003 ^{NS} (0.002)	0.002 ^{NS} (0.003)	0.002 ^{NS} (0.003)
ln_FER	0.248*** (0.013)	0.248*** (0.013)	0.249*** (0.013)	0.260*** (0.012)	0.257*** (0.013)	0.257*** (0.013)
ln_SMC	-0.050*** (0.016)	-0.050*** (0.016)	-0.050*** (0.016)	0.028 ^{NS} (0.019)	-0.054 ^{NS} (0.016)	-0.054*** (0.016)
SDU2	-0.080*** (0.028)	-0.08***027	-0.079*** (0.028)	-0.110*** (0.025)	-0.078*** (0.028)	-0.078*** (0.028)
SDU3	-0.216*** (0.047)	-0.215*** (0.047)	-0.215*** (0.047)	-0.240*** (0.042)	-0.208*** (0.048)	-0.208*** (0.048)
Constant	5.378*** (0.073)	5.378*** (0.073)	5.374*** (0.073)	5.339*** (0.07)	4.991*** (0.071)	4.991*** (0.071)
Sigma ² u ()	2.556*** (0.044)	2.862*** (0.044)	2.556*** (0.044)	2.743*** (0.078)	2.743*** (0.078)	3.993*** (0.085)
Sigma ² v ()	1.738*** (0.093)	2.596*** (0.498)	1.764*** (0.106)	1.608*** (0.088)	2.707*** (0.083)	3.011*** (0.132)
	1.213	1.050	1.204	1.306	1.007	1.152
	59.525	52.437	59.167	63.043	50.330	57.010

Note: *** indicates one percent significant level; ** indicates five percent significant level and NS indicates Non significant

Fig. 4 : Overall technical efficiency of sugarcane farms across farm size.

returns from the paddy-wheat combination as compared to sugarcane, and also due to long maturing period of sugarcane, farmers are shifting to intercropping with onion, wheat, gram, garlic, etc. to earn extra income. Among seven states, Uttaranchal sugarcane farmers have the highest growth rate in the persistent technical efficiency with 1.81%, followed by Karnataka (1.60%), Andhra Pradesh (1.55%), Maharashtra (0.79%) and Tamil Nadu (0.05%). Though, Tamil Nadu sugarcane farmers rank fifth in the growth rate of persistent technical efficiency, it ranks first in the triennium persistent technical efficiency score with 0.89. In contrast, though Uttaranchal has the highest growth rate of persistent technical efficiency in sugarcane production, it ranks last in the triennium persistent technical efficiency score (0.80) among seven states. It reveals that Uttaranchal has a vast scope in increasing its persistent technical efficiency.

Triennium average residual technical efficiency of Indian sugarcane farmers is 0.83 with a positive growth rate of 0.18%. Except for Haryana and Tamil Nadu, all the states included in the model have a positive growth rate of residual technical efficiency

in sugarcane production. Haryana has the highest negative growth rate of 1.67%, followed by Tamil Nadu with 0.70%. Labor shortage may be a reason for the shortfall of their residual technical efficiency. Among the seven states, Karnataka has the highest positive growth rate with 4.95% followed by Uttaranchal (2.21%), Maharashtra (0.58%), Uttar Pradesh (0.43%) and Andhra Pradesh (0.03%). Among the states, Tamil Nadu ranks first in residual technical efficiency score with 0.85. Though, Tamil Nadu ranks first, it has a negative growth rate in residual technical efficiency. Andhra Pradesh ranks second with a score of 0.85 followed by Karnataka (0.83), Maharashtra (0.82), Haryana (0.82), Uttar Pradesh (0.81) and Uttaranchal (0.80).

Indian farmer's overall technical efficiency in sugarcane production is 0.70 with a positive growth rate of 0.47%. Among the seven states, Tamil Nadu has the highest overall technical efficiency score in sugarcane production with 0.76 but with a negative growth rate of 0.59%. It shows that Tamil Nadu farmer's overall technical efficiency in sugarcane production is declining. Andhra Pradesh (0.75) ranks second with a positive growth rate of 1.64%, followed by Karnataka (0.70) with a positive growth rate

Fig. 5 : Overall technical efficiency of sugarcane farms and share of own machine hours across farm size.

of 6.09%, Maharashtra (0.70) with a positive growth rate of 1.43%, Haryana (0.67) with a negative growth rate of 2.44%, Uttar Pradesh (0.66) with a positive growth rate of 0.20% and Uttaranchal (0.64) with a positive growth rate of 3.93%, respectively.

The variable total fertilizer usage has a positive and high elasticity of sugarcane production. Being a long-duration crop, its nutritional requirements are high. Appropriate measures need to be taken to increase the use of fertilizers. Though machinery usage increases the yield of sugarcane, the share of own machine usage has a negative impact on yield. Hence, the starting of Agricultural Machinery Custom Hiring Centres (CHC) in each district will benefit the farmers, especially small and marginal farmers. India's overall technical efficiency in sugarcane production is 0.70. It indicates that sugarcane yield could be increased by 30%, through proper input management. Among the seven states, Uttaranchal has the highest scope of improving the sugarcane yield with 36%, followed by Uttar Pradesh (34%), Haryana (33%), Maharashtra (30%), Karnataka (30%), Andhra Pradesh (25%) and Tamil Nadu (24%). Hence, the necessary

action should be taken to increase their technical efficiency in sugarcane production.

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