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Investigate The Impact Of Technical Inefficiency On The Response Of Small-Holder (Peasant) Farmers

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ABSTRACT

India has embarked on a massive irrigated agricultural development program over the last decade, including both large- and small-scale irrigation initiatives in an effort to increase crop output and productivity. But poverty persists, and agricultural yield per acre of land in India is low. To boost crop output and productivity, as well as smallholder farmers' livelihoods and food security, it is crucial to examine the degree of technical efficiency (TE) among farmers. Poor extension services and outdated agronomic practices have resulted in a low average TE among farmers (44.33 percent), according to the study's findings. This indicates that improving the TE of smallholder farmers in the research locations may boost crop yield without the need for costly investments in cutting-edge agricultural technology.

KEYWORDS: Smallholder, Farmer, technical efficiency, crop production.

INTRODUCTION

In today's interconnected world, agriculture remains an essential industry. About 95% of all farmland is used for crop production, and 90% of all agricultural outputs come from smallholder farms. In general, smallholders produce 98% of coffee, the primary cash crop, and 94% of food crops, while private and state commercial farms contribute 2% of coffee and 6% of agricultural output. Despite the current administration's emphasis on agriculture, crop yields have never been lower due to a variety of interconnected socioeconomic and climatic issues such as overgrazing, overcultivation, population growth, tenure insecurity, weak extension services, inadequate infrastructure, and a lack of fertilizer and pesticides.

Since smallholder farming communities rely heavily on agricultural and forest resources that are sensitive to climate, they may feel the effects of climate change in both direct and indirect ways. It's possible that India isn't a good candidate for mitigation because of the country's historically low levels of investment in its industrial sector. The most self-sufficient option for smallholders to deal with climate change consequences may instead be adaptation, which includes the use of several better types of crops, the planting of trees, soil conservation, and modifying the timing of planting.

LITERATURE REVIEW

Samuel Mburu et.al (2014) This research aims to increase national wheat output by analyzing the impact of farm size on economic efficiency among wheat farmers and making recommendations based on those findings. This research aims to quantify technical, allocative, and economic efficiency among a representative sample of 130 large- and small-scale wheat growers in Nakuru District, Kenya. Economic efficiency in wheat production has been analyzed, and the social and economic elements that affect it have been identified. Based on the data, small-scale wheat producers have technical efficiency indices of 84%, allocative efficiency indices of 96%, and economic efficiency indices of 84%. For commercial farms, the percentages rise to 91%, 94%, and 88%. There is a high correlation between the size of a farm, the farmer's education level, and their level of productivity. Contrary to popular assumption, tiny farms may be just as technologically advanced as large ones when it comes to wheat production.

Massimo Filippini et.al (2015) One aspect of a company's productive efficiency is stable, whereas the other is more ephemeral. Despite their importance, these two dimensions of evaluating productive efficiency have received very little attention in the mainstream empirical literature. Ahn and Sickles presented several approaches to this problem. Despite bringing up the possibility, Greene was doubtful that the difference could be established experimentally. The new proposal of a tractable model based on panel data by Kumbhakar, Tsionas, and Colombi promises to offer independent estimates of the two components of efficiency. We provide a maximum simulated likelihood estimator for the model that is feasible and accurate even when missing data are present. This method employs all of the information about the sample distribution to get estimates, and it is both very effective and remarkably easy to implement. The method is used in an analysis of the effectiveness and economy of the Swiss railway system.

Raju Ghimire et.al (2015) We utilized cross-sectional data from a survey during the 2013 crop season and a probit model to assess the chance that smallholder farmers in the two major agro-ecological zones of Central Nepal would adopt NIRVs. Access to resources including information, extension services, and seeds was shown to have a significant impact on adoption decisions. Large farms, favorable terrain, and animal labor are all factors that increase the possibility of NIRVs being used. Adoption behavior may be partially explained by technology-specific factors, indicating that farmers' preferences regarding varietal traits should be taken into account when designing a research and development program. Given the importance of extension and access variables in determining the rate of adoption of new rice varieties, more effort has to be put into disseminating information, conducting field demonstrations, and involving farmers in research and training programs. As a result, it's clear that educational opportunities for farm families and programs providing farmers with access to diverse pools of rice germplasm should be prioritized in terms of policy intervention. To improve adoption rate, productivity, and food security, initiatives like this encourage farmers adopt more profit-oriented behaviors.

Benjamin Tetteh Anang et.al (2016) Agriculture is still the backbone of the economy in many third world nations like Ghana. However, smallholders, who are often thought of as resource-poor, undertake the bulk of the work in agriculture. As a result, it is essential to assist in increasing productivity in the small farm sector by helping smallholder farmers make the most of their limited resources. To boost agricultural output, it is also vital to get insight into farmers' current productive capacity in light of the available technology and the elements influencing their efficiency. This study aimed to determine what variables contribute to the poor technical efficiency of 300 randomly chosen smallholder farming households in Northern Ghana. We used a multistage stratified random sampling strategy to obtain our data, and we used an inefficiency effects model to fit it to a stochastic frontier production function. Thus, at the present level of technology, producers in the research region have the ability to raise efficiency by 36.2% without raising the existing level of input consumption. All traditional inputs, excluding seed, significantly impacted yield. Male farmers, as well as those with less formal education, tended to be more productive. It was also observed that producers with a greater degree of expertise in rice cultivation, such as those who belong to a farmers' association, are more effective farmers. Because to irrigation, the production frontier has moved uphill, signifying more productivity. Also situated on a greater production frontier were farmers in the Northern Region and those who practiced twin cropping. The research suggests that to improve the productivity of farmers in the study region, irrigation access should be widened and farmer-based groups should be incentivized. The availability of irrigation services will increase rice output in Northern Ghana by allowing for double planting. In addition, the Upper East Region is particularly in need of research into, and solutions for, the reasons restricting production efficiency among its farmers.

John Kanburi Bidzakin et.al (2018) Increases in agricultural output due to increasing use of irrigation technology may help the world's population eat. This study examined how irrigation ecology affects the technical, allocative, and economic efficiency of farm families among smallholder rice producers. There were a total of 350 rice farmers surveyed cross-sectionally from both rain-fed and irrigated systems. If you compare the technical efficiency of rice grown under irrigation settings to that grown under rain-fed conditions, you'll find that the former is somewhat more efficient. Since irrigation ecology has a roughly 0.33 impact on allocative efficiency, farmers who utilize irrigation are more allocatively efficient in rice production than those who depend on rain fed systems. Irrigation increases the economic efficiency of rice production by roughly 0.23 percentage points for farmers, compared to rain-fed alternatives. Farmers should be encouraged to enhance their output while using irrigation because of the ecological benefits this has on productivity.

METHODS

Hypothesis Test

The following assumptions have been tested to determine whether there is inefficiency, whether the provided model is sufficient, and if external variables are important in explaining the (in)efficiency component. It has also been argued that the (in)efficiency component's (Ui) truncated normal distribution assumption is false, as has the availability of common technology across different kinds of farm systems. Using the standardized likelihood-ratio (LR) statistic, several theories have been examined:

$$\mathrm{LR} = -2[\ln\{L(\mathrm{H0})\} - \ln\{L(\mathrm{H1})\}]$$

where the likelihood function L(H0) and L(H1) are shown as their corresponding values under the alternative and null hypotheses. (1) H0: βji = 0: In the trans log model, the coefficients of the second-order variable are all zero. Table 1 shows that a value of 53.085 for the LR statistic is equivalent to passing the test at the 1% level of significance.

Table 1. Hypotheses test results

Hypothesis	LR Statistics (λ)	LR Critical ($\chi^2_{0.01}$/mixed $\chi^2_{0.01}$)	Decision on the Null HyPothesis
1. H0: $\beta ji = 0$	53.085	16.704	Rejected
2. H0: $\sigma^2_{u,\,i} = 0$; $\mu = 0$	205.312	50.284	Rejected
3. H0: $\mu = 0$	104.192	28.485	Rejected
4. H0: $\sigma^2_{v,i} = 0$	24.622	8.273	Rejected
5. H0: β_L = β_S = 0; β_AL = β_AS = 0; β_BL = β_BS = 0; β_CL = β_CS = 0	246.360	19.384	Rejected

Smallholder farmers apply the same technologies across all three agricultural systems. Contrary to the null hypothesis of using the same technical assumptions across models, the LR test result suggests that the pooled model may not be appropriate for the data. Therefore, we use interaction variables of the input farming system type.

DATA ANALYSIS

As can be seen in Table 2, the combined estimates of the truncated-normal stochastic production frontier and the (in)efficiency effects models provide a statistically meaningful SFPF model for this investigation. All three inputs exhibit positive signals in the predicted first-order coefficients, However, only two of these factors had a substantial impact on crop yield in the study area at the 1% and 5% levels of significance. However, this study does not find any statistically significant cross-product calculated parameters. Despite sharing a comparable agroecological zone, the intercept of the production border seems to be somewhat different across the two districts in this research region.

Table 2. Results of translog SFPF model estimates.

Frontier	Coefficients and S.E			Inefficiency Model	Coefficients and S.E		
Constant	9.527		(0.254)	Constant	0.316		(0.287)
lnA	0.393		(0.280)	lnSize	0.696	***	(0.124)
lnB	1.123	***	(0.186)	Education	−0.017	**	(0.007)
lnC	0.398	**	(0.200)	Gender	−0.094		(0.101)
SlnAlnA	0.222		(0.211)	Extension	−0.008		(0.025)
SlnBlnB	0.269	**	(0.104)	Plot soil quality	−0.151	***	(0.031)
SlnClnC	−0.233		(0.169)	Improved storage facilities	−0.119	*	(0.065)
lnAlnB	0.137		(0.100)	Crop dry facilities	0.128	*	(0.073)
lnAlnC	0.071		(0.126)	Irrigation options	0.640	***	(0.172)
lnBlnC	−0.040		(0.091)	Irrigation water availability	−0.440	***	(0.092)
SSIlnA	−0.070		(0.217)	Dependency ratio	−0.116	***	(0.030)
SSIlnB	0.103		(0.154)	Crop type	−0.488	***	(0.065)
SSIlnC	0.301		(0.237)	Crop rotation	0.301	***	(0.068)
LSIlnA	−0.063		(0.200)	Mixed cropping	−0.041		(0.076)
LSIlnB	−0.169		(0.155)	Row planting	−0.179	**	(0.057)
LSIlnC	0.064		(0.231)	**Heteroskedasticity Model Vsigma ($\sigma^2_{v,i}$)**			
LSIU	1.912	***	(0.575)				
SSIU	0.511		(0.448)	Constant	−1.920	***	(0.191)
District	0.360	***	(0.081)	lnSize	0.348	*	(0.386)
				Diagnostic statistics			
σ_v	0.531			Wald chi2(18)	774.470		
σ_u	0.263			Prob > chi2	0.000		
σ^2	0.351			Log likelihood	−938.033		
γ	0.197			Number of obs (N)	1026.000		

Technical (in)efficiency determinant parameter estimations are shown in Table 2. Eleven out of a total of fourteen technical (in)efficiency factors were found to have a statistically significant impact on the predicted SFPF model. Factors (gender, extension, and mixed cropping) that have a negative effect on technical (in)efficiency are not significant. It is unexpected that the extension variable is statistically insignificant given that extension agents are supposed to assist farmers adopt optimal agricultural techniques and increase productivity. Although Turner discovered that mixed cropping had a favorable influence on the TE of Australian smallholder farmers, we did not find that to be the case in our research. Possible causes for this outcome include insufficient training for farmers and a lack of information about the benefits of mixed cropping.

Table 2's calculated (in)efficiency component characteristics provide very limited insight into how various factors affect the efficiency gap. These variables, and not the (in)efficiency (Ui) estimates themselves, have a significant impact on the i-th parameter of the truncated normal distribution of (in)efficiencies. Table 3 displays the average marginal effects of (in)efficiency factors and the mean TE scores. In the research regions, where the average TE score is 44.33 percent with variance, there is greater space to boost crop output by reducing the technical (in)efficiency of smallholder farmers without investing in innovative agricultural technology. This result is less than what empirical researchers in Africa reported for TE scores. Farmers in India who employ either contemporary or traditional irrigation systems have TE scores between 77% and 97%.

observed a variation in India TE score from 59% under the TFE to 30% using the more conventional model formulation. Estimates of economies of scale and scope may be inaccurate if all agricultural system types are assumed to use the same technology. Similar to how a high

TE score might come from an incorrect assumption of Ui leading to inconsistent parameter estimations and a biased (in)efficiency index.

Table 3. Yield gap due to technical (in)efficiency.

Output	Smallholder Farmers with Farm System Types				
	Large-Scale Irrigation User	Small-Scale Irrigation User	All Irrigation User Farmers	All Non-User Farmers	Overall Farmers
Mean of value of observed output	43,358 (70,435)	26,067 (20,352)	33,881 (50,381)	7430 (7208)	21,919 (39,827)
Mean of value of potential output	187,138 (173,904)	45,327 (38,267)	109,420 (139,392)	16,045 (14,959)	67,192 (113,568)
Average yield gap/output loss/	−143,781 (124,026)	−19,260 (23,255)	−75,538 (105,264)	−8616 (9263)	−45,273 (84,935)

Table 3 shows that average TE scores varied across the research area's smallholder farmers based on their agricultural method. Farmers using SSIU farm systems had the greatest average TE score (60.30 percent), while those with LSIU farm systems had the lowest (21 percent). When comparing the average TE scores of farmers who use irrigation to those who don't, the users (at 42.56%) fared worse than the non-users (at 46.48%). Farmers in the LSIU were less TE than those in the SSIU and NU, despite the fact that better irrigation infrastructure increases productivity for small farms. The low cost of irrigation water and the lack of expertise among LSIU smallholder farmers in the study region may explain why they are less productive than their SSIU and NU counterparts. LSIU smallholder farmers may be able to boost their economic efficiency and reduce income loss if reasonable pricing are set for irrigation water. (see Table 4).

Table 4. TE scores and marginal effects of inefficiency determinants.

TE Scores of Smallholder Farmers by Farm System Types										
Farmers Type	Overall Farmers		Large-Scale Irrigation Users		Small-Scale Irrigation Users		All Irrigation Users		All Non-User Farmers	
TE score %	44.33	(0.21)	21.05	(0.12)	60.29	(0.18)	42.56	(0.23)	46.47	(0.15)

Marginal effect (ME) of TE determinates					
TE determinates	ME	S.D	TE determinates	ME	S.D
lnSize	0.619	(0.14)	Irrigation Water availability	−0.426	(0.05)
Education	−0.013	(0.01)	Dependency Ratio	−0.194	(0.16)
Plot soil quality	−0.119	(0.06)	Crop type	−0.439	(0.09)
Improved Storage Facilities	−0.162	(0.10)	Crop rotation	0.243	(0.11)
Dry Facilities	0.116	(0.02)	Row planting	−0.133	(0.09)
Irrigation Options	0.622	(0.08)			

Table 4 also shows the marginal impacts of some of the most important factors in determining (in)efficiency. Larger values of the variable among smallholder farmers are associated with greater (lower) TE levels, as shown by the variable's negative (positive) coefficients. Statistically significant positive coefficients on variables like family size, crop dry facilities, crop rotation, and irrigation options suggest that the more resources available to smallholder farmers, the lower their TE (and the higher their technical inefficiency). The reliance ratio in the home explains the statistically substantial detrimental impacts of family size on the TE. This is because, on average, smallholder farmers in the research region cultivate crops on plots of land that are less than half a hectare in size, making it difficult to accommodate the huge number of employees required for agricultural production. The dependence ratio decreases as family size increases because more people may contribute to the economy (work as part of the household). As a consequence, if a farm only has a relatively limited plot area, then increasing the number of workers involved in the agricultural production process would only decrease the TE.

CONCLUSION

The findings show that smallholder farmers' TE averaged about 44% across the different agricultural system types in the research locations. The farmers at LSIU had the lowest TE score (21), followed by those at NU (46) and SSIU (60). Poor agronomic practices, primitive postharvest handling mechanisms, traditional soil conservation measures, ineffective extension services, a low education level of the household head, and too cheap irrigation water prices in the study area resulted in annual average losses of 143,781 ETB, 19,260 ETB, and 8615 ETB for LSIU, SSIU, and NU smallholder farmers, respectively. If smallholder farmers' technical (un)efficiency can be improved, crop yields in the study regions might rise without further expenditure on cutting-edge agricultural technology. Furthermore, the results suggest that investing in better irrigation infrastructure may move the frontier upward and boost productivity amongst smallholder farmers.

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