American International Journal of Agricultural Studies
Vol. 2, No. 1; 2019
ISSN 2641-4155 E-ISSN 2641-418X
Published by American Center of Science and Education, USA

Vegetable Production Efficiency of Smallholders' Farmer in West Shewa Zone of Oromia National Regional State, Ethiopia

Aman Rikitu Dassa
PhD Candidate
Haramaya University, Ethiopia
E-mail:aman.rikitu@gmail.com

Bezabih Emana Lemu
General Manager
HEDBEZ Business & Consultancy
PLC P.O.Box 15805, Addis Ababa, Ethiopia
E-mail:emana_b@yahoo.com

Jema Haji Mohammad
Haramaya University
College of Agriculture and Environmental Science, Ethiopia
E-mail:jemmahaji@gmail.com

Ketema Bekele Dadi
Haramaya University
College of Agriculture and Environmental Science, Ethiopia
E-mail:ketmimi@yahoo.com

Abstract
This study tried to identify factors affecting vegetable production efficiency using cross-sectional data obtained from 385 randomly and proportionally sampled households from three districts of West Shewa zone, Ethiopia. The data were analyzed using descriptive statistics such as mean, percentage, chi-square and mathematical approach data envelopment analysis DEA, econometrics model such as Tobit. Accordingly, DEA identify the average TE, AE and EE of farm households which encounter for 49.5%, 33.7% and 17.4% respectively. Factors affecting the inefficiency of vegetable production were identified using Tobit model. This model confirmed that age of households, education level, land size, access to irrigation, extension contact access to information and pesticide use were significantly affect TE, while age of the household, land size, access to irrigation, extension contact, access to information and pesticide use were factors affect AE of the farm households. Finally EE of the farm households was affected by age of the households, education level, land size, access to irrigation, access to information and pesticide use. The result suggested that improving the above problem can increase farmers' economic efficiency in the study area.

Keywords: TE, AE, EE, DEA, Tobit, West Shewa, Ethiopia.

1. Introduction

Horticulture is a part of agricultural sciences that employs scientific understanding to supply vegetables, fruits and flowers and enrich human diet (Christopher 2009; USID 2005). It's used by each, individuals and industries to reinforce the organic process and economic standards (Fanos 2015; Welderufael 2016). This series of vegetation might support to fulfill basic requirements of human health and well-being. Farming crops are the first supply of poverty reduction in most agriculture-based economies (Fufa 2017). The enlargement of granger farming will cause a quicker rate of poverty alleviation, by raising the incomes of rural cultivators and reducing food expenditure, and so reduces financial gain difference. In Ethiopia, farming crops as well as fruits, vegetables and root crops contribute 25 percent of the crop production (BV 2013).

Vegetable production is an important economic activity in Ethiopia, which ranging from gardening smallholder farming to commercial state and private farms (Rahiel Abraha and Gebresilasie *2018*; Bezabih Tesfaye and Milkessa 2015). It is an efficient way to address poverty reduction, take care of the health and well-being of the consumers, and offers new market opportunities for farmers, consumers, and agro-industry (Banjaw 2017; Chala and Chalchisa 2017). Vegetable production is integrated into mixed farming system where different types of crops are produced on the same plot of land or in sequence with other crops in rotation (Girma, n.d.; Asfaw, 2015).

Depending on availability of land and crop suitability for intercropping, some vegetables are grown either as sole or intercropped with other vegetables or cereals (Hailu 2015). Vegetables such as tomato, potato, beetroot, carrot, cabbage, onion, sweet potato and hot pepper are dominantly grown in Ethiopia. From these vegetable production tomato, potato and onion are the major vegetables production of West Shewa zone (WSZIAO, 2017). Integrating vegetable production in a farming system has contributed substantially to food and nutrition security as the vegetables complement stable foods for a balanced diet by providing vitamins and minerals (Gani and Adeoti 2011; Afari-sefa and Dinssa, 2015).

Vegetables crops are sources of vitamins, minerals and dietary fiber, however their cultivation isn't wide practiced in developing countries, like Ethiopia because of small-scale farming systems and poor pre- and post-harvest handling techniques (Rahiel Abraha and Gebresilasie 2018). Vegetables are high value crops, which require intensive cultural practices, financial, and labor inputs involved are therefore greater than those required for most staple crops.

Vegetable production is problem sensitive relative to other agricultural production. These problems cannot be easily solved if it is not managed at the right time and right way. Even if a number of research works were done in Ethiopia on problems of vegetable production as perceived by the farmers, however no significant impact of such research works had been observed. An understanding of problem perceived by the farmers in vegetable production efficiency will be helpful for planning and implementation of program. This study was undertaken to determine the problem faced by the farmers in vegetable production, compare the severity of the problems faced by the vegetable producers, determine some selected characteristics of the farmers and explore the relationship of the selected characteristics of the farmers with problem faced in vegetable production efficiency.

From existing literature, research in this direction in West Shewa still remains out of the attention, even though vegetables occupy a few positions in both domestic and foreign food trade of Ethiopia. Therefore, it is very essential to analyze vegetables (tomato and potato) farmers' production efficiency in West Shewa zone. Along these lines, the investigation might produce on the concurrent communication of family choices of vegetable production efficiency and the most affecting elements of the efficiency of smallholder farmers in West Shewa, Ethiopia.

2. Materials and Methods

Three districts namely, Abuna Gindeberet, Dire Inchini and Ejersa Lafo were ecologically stratified and randomly selected from West shew zon, oromia National regional state, Ethiopa for the purpose of this study. Finally, 385 respondents were selected from nine kebekes which randomly and proportionally selected from three districts.

Economic efficiency may be estimated principally by two approaches. They embrace econometric and mathematical approach. In econometrics approach, random frontier production perform is used to work out economic efficiency and its determinants. Alternative approaches involving econometric approaches are random profit frontier perform and value frontier function methods. Mathematical approach involves data envelopment analysis (DEA) approach. Advantages and drawbacks of econometrics model and mathematical approaches are discussed by Battese and Coelli (1995). Within the gift study, we've adopted random production frontier perform to seek out economic efficiency level in vegetable production.

Therefore, to determine the problem of economic efficiency of vegetables production technical efficiency and allocative efficiency must consider. To analyze technical efficiency and allocative efficiency DEA was utilized as the following.

2.1 Data Envelopment Analysis

To analyze technical efficiency data envelopment analysis presented as the following. Suppose the number of DMU is n. Tj-th DMU is characterized as DMUj (j=l,2,…n). The input vector of DMUj is Xj=(X1j, X2j…Xmj)T, and the output vector is Yj= (Y1j, Y2j…Yrj) ^{T}. Here, m is the number of input, r is the number of output. The corresponding weight coefficient is V=(V1, V2…Vm) and U=(U1, U2…Ur) respectively. Also suppose Xij is the i-th input value of the j-th DMU, Ykj is the k-th output value of the j-th DMU. Vi, Uk is the weight coefficient of the i-th and the k-th index respectively. Then the corresponding appraisal efficiency index of the j-th DMU is:

$$H_i = \frac{u^T y_j}{v^T x_j} = \frac{\sum_{k=1}^{s} u_k y_{kj}}{\sum_{i=1}^{m} v_i x_{ij}} \quad (1)$$

Choosing the suitable weight coefficient V and U to let $H_i \leq 1$. High hj indicates that DMU can use relative less input to obtain relative more outputs.

Generally, to determine the relationship between socioeconomic and institutional factors and the computed indices of efficiencies, a Tobit regression model will be utilized again. This model will be adopted because the efficiency scores are double truncated at 0 and 1 as the scores lie within the range of 0 to 1. The functional form of this Tobit model is:

$$y^* = \beta_o \Sigma \ \beta_m x_{jm} + \mu_j \quad (2)$$

Where y_i* representing the non-observed efficiency latent variable scores of farm j,
β = a vector of unknown parameters,
x_{jm} = a vector of explanatory variables m (m = 1, 2, ..., k) for farm j and
μ_j = an error term that is independently and normally distributed with mean zero and variance σ2
Denoting y_i as the observed variables,

$$y_i = \begin{cases} 1 & if \quad y_i^* \geq 1 \\ y_j^* & if \quad 0 < y_i^* < 1 \\ 0 & if \quad y_i^* \leq 0 \end{cases} \quad (3)$$

In the Equation (21), the distribution of the dependent variable is not normally distributed rather its value varies between 0 and 1. Therefore, the maximum likelihood estimation which can yield the consistent estimates for unknown parameters vector for it has been used than the ordinary least square (OLS) estimation which gives biased estimates (Maddala, 1999).

3. Result and Discussion

This chapter presents the results of the study and discusses in comparison with the results of similar studies. It is organized under two sections; the first section deals with the description of demographic, socio-economic and resource allocation of the sample farmers using descriptive statistics. The second section identifies factors affecting vegetables technical, allocate and economic efficiency using Data envelopment analysis and Tobit model.

3.1 Descriptive Statistics Results

3.1.1 Demographic Characteristics of Households

As showed in Table 1, out of the total sampled household 7.79 percent of them are female-headed households while 92.21 percent are male-headed households. It indicates male-headed household's dominance in vegetables farming in the study area. The average age of the sample households' head is 46.89 with the standard deviation of 11.95. This indicates that more of the sampled households' are in the range of productive age. The average family size of the farm household head was 7.15 persons, which is in comparable to West shewa zone average population of 5 persons and larger than the Ethiopian average population which accounted to 4.6 persons per- household (CSA, 2016). In the study area most of the farm households used own family labor for specific activities. The study showed that the average family labor of the farm households is 4.48 person-day equivalents. This indicates that most of the farm households were used family labor than hired labor.

As presented in Table 1, the average education level of household head of farm households head is 5.07 (schooling years?) of formal education. This indicates that, on average the sample farm household attended the minimum (first cycle) education which was deemed enough to understand what development agents provide in agricultural production guide line for them in order to improve their productivity.

Table 1: Demographic characteristics of sampled households

Variables	Total		x^2 or F-test
	Frequency mean	Percent std.	
Female headed HHs	[30]	[7.79]	-0.17
Age of the household	46.89	11.94	1.19
Family size	7.15	2.76	2.94***
Family labour PDe	4.48	3.10	0.80
Education level of HHs	5.07	3.91	290.91***

Note: The number in the [ ] shows frequency and percent and *** show less than or equal to 1 percent significant level Source: own surveyed data of 2018 computed by author

3.1.2 Farm Characteristics and Land Allocation of Sample Households

In the study area, most of the sampled farm, households produced potato depending on rainfall but all tomato producers used irrigation in vegetables production. This production seasonality and perishability of the vegetables farming caused farm households to earn less income from vegetable production. As indicated in Table 2 below, the average potato yield during the survey season is 981.09 kg while tomato yield is 841.12 kg. From the three-selected districts on average Ejersa lafo is the highest potato and tomato producer with the annual average production of 1741.356 kg and 1743.875 kg respectively.

Based on survey data as showed in Table 2 the average total cultivated land of the sampled farm household is 0.922ha covered by different crops. Out of this cultivated land, on average potato and tomato cover 0.115ha and 0.087 ha respectively. From the selected districts, households in Ejersa Lafo allocative more of their lands for potato and tomato production than households in other districts. As survey, data in Table 2 indicate the average vegetable farm experience of the sampled farm households is 24.992 years, and Abuna Gindabarat has the highest vegetable farm experience than others districts.

Table 2: Farm characteristics and land allocation of sample households

Variable	Mean	A/G/beret	D/Inchini	E/lafo	F-test
Potato yield(kg)	981.09	886.462	739.583	1741.356	0.33
Tomato yield (kg)	841.12	198.490	548.142	1743.875	0.00
Cultivated land(ha)	0.922	1.413	1.630	2.205	7.46 *
Land for potato(ha)	0.115	0.076	0.185	0.114	2.20*
Land for tomato(ha)	0.087	0.061	0.019	0.092	0.64
farming experience (year)	24.992	26.934	23.125	20.566	7.73*

Not: * indicate the level of significance at less than or equal to 10 percent
Source: own surveyed data of 2018

3.1.3 Institutional Service and Availability of Infrastructure

Availability of infrastructure usually plays a great role in the economic development of any country while, institutional service improve the production and productivity of the farmers. As indicated in Table 3, only 84 (21.82 percent) of farm households obtained credit for their vegetable production while the remaining 78.18 percent are non-credit users. 117 (32.96 percent) of the farm households had extension contact five times per year and 92 (25.92 percent) of them gain only one time extension contact throughout a year. The average walking distance from farm household residence to development agent office is 0.69hr with standard deviation of 0.458 and the average distance of the farm households' residence to that of nearest market is 0.74hr with standard deviation of 0.540. These show that extension service more close to the farmer than nearest market. Moreover, extension contact, distance from major town and distance from all-weather condition (road) were found to be significantly different among the districts at less than or equal to five percent significance levels respectively (Table 3).

Table 3 also showed that about 28.57 percent of the sampled farm households are cooperative members. Being cooperative member helps the farm household to share more information about production as well as about market of the product.

Table 3: Institutional service and availability of infrastructure

Variable	[Frequency]/ mean	[Percent]/stnd.	A/G/beret	D/Inchini	E/lafo	F-test
Credit access	[84]	[21.82]	0.192	0.125	0.466	0.04
Extension contact /year	[5]	[32.96]	2.873	3.593	2.500	5.98**
Cooperative membership	[110]	[28.57]	0.436	0.093	0.016	0.06
Distance to development agent office (hr)	0.694	0.458	0.686	0.629	0.891	1.70
Walking distance from the nearest market(hr)	0.741	0.540	0.791	0.634	1.013	0.02
Walking distance from major town(hr)	1.872	0.987	1.524	2.793	1.724	4.24**
Walking distance to all weather condition road(hr)	0.609	0.602	0.602	0.494	0.879	5.92**

Not: numbers in [ ] indicate frequency and percent and ** stands for 5 percent significances

Source: own survey data of 2018

3.1.4 Soil Management and Agronomic Practice of Vegetable Production

Vegetable growers must specify the types of vegetable produced from their farms, identify the potential critical hazards and establish and monitor appropriate measures during all phases of farm production (GAP--VF, 2005). In addition to using adaptation, improved agricultural technology, appropriate soil management lead to enhance potential vegetable production. Sampled farm household in the study area were asked whether they used 'good' agricultural practice during the production season or not. These practices are farmyard manure, crop rotation, fallowing, using composite and inter-cropping system, weed and disease control mechanism. The results on farmers' use of recommended soil management and agronomic practices of vegetable production in the study areas during 2017/2018 cropping season presented in Table 4 below.

- **Farmyard Manure**: Farmyard manure is one of the good practices of soil fertility management, which improve the productivity of land. Application of the farmyard manure contributes to sustainability of the farm (Ranogajec, *et al.*, 2015). As shown in Table 4 above, 240 (67.04 percent) of sampled farm households applied farm yard manure while the remaining 110 (32.96 percent) of the respondents did not.
- **Crop Rotation**: Crop rotation shows producing different crops in different cropping season on the same land. It is the old traditional system, which was used to reduce damage from insect pests, to limit the development of vegetable diseases, and to manage soil fertility. As indicated in the Table 4, 299 (86.17 percent) of sampled farm households practiced crop rotation during 2017/2018 production season.
- **Fallowing**: It is cultivating land that is not seeded for one or more growing season**.** It is the system in which, farmers can improve their soil fertility to increase the productivity of their land. As explained in

Table 4, out of total number of the respondents 159 (44.79perecent) of them used fallowing in 2017/2018 cropping season.

- **Compost**: Compost fertilizer is the main organic type of fertilizer which prepared from animal west (often from slaughterhouses) and from different plants. It is the means in which farmers can maintain their land fertility to increase the yield per hectare. As showed in Table 4, 143 (39.83 percent) of the sampled farm households used compost in 2017/2018 cropping season.
- **Intercropping**: Intercropping is the mixed planting method of growing one crop alongside another (Mousavi and Eskandari, 2014; Smith and Liburd, 2012). The purpose behind intercropping is to extend yields by doubling up on available growing area. Intercropping creates multifariousness that attracts a range of useful and predatory insects that is uphill with monoculture horticulture. As showed in Table 4, about 63 (17.75 percent) of sampled farm households applied intercropping farming system in 2017/2018 cropping season.

Table 4: Soil management and agronomic practice of vegetable production

Agricultural Practices	Frequency	Percent	A/G/beret	D/Inchini	E/lafo	F-test
Farmyard manure	240	67.61	66.04	13.96	20.00	3.20*
Crop rotation	299	86.17	55.48	35.48	9.03	0.35
fallowing	159	44.79	71.43	12.57	16.00	0.81
Compost	141	39.83	16.17	25.45	58.38	0.01
Inter cropping	63	17.75	46.97	13.64	39.39	0.01

Source: own survey data of 2018

3.1.5. Weed Management System

Appropriate weed control measure undertaken to improve quality and quantity of grain production. Weeds infestation reduces yields of the crop (yield), deteriorate the quality of farm produce, and trim down the market value of production. Effective weed control not achieved without appropriate control measure should be undertaken attain good grain harvest and quality grain production (Sareta, 2016). As showed in Table 5, 4.94 percent sampled farm households applied mulching, while 9.61 percent spread of wood ash and 100 percent of the respondents used hand weeding in 2017/2018 cropping season

Table 5: weed management system

Variable	Frequency	Percent	A/G/beret	D/Inchini	E/lafo	F-test
Mulching	19	4.94	27.03	54.05	18.92	0.21
Spread of wood ash	37	9.61	100.00	0	0	0.02
Hand weeding	385	100	59.48	24.94	15.58	-

Source: own survey data of 2018

3.1.6. Technology Adoption

The contribution of technology to economic growth can only be realized when and if the technology is widely applied by the users (Samy, 2016). The increasing rate of technological advancement in the agricultural sector, has resulted in increased efficiency and productivity (Ugochukwu, 2018). As the result explained in Table 6, about 315 (81.82 percent) of sampled farm households used chemical fertilizer in 2017/2018 cropping season. The result also showed that 96 (24.94 percent) of the sampled farm households applied improved seed of tomato while 243 (63.12 percent) of them applied improved potato seed in 2017/2018 cropping season. Moreover, fertilizer application and improved seed use for tomato and potato production of the farm households were significantly different at less than or equal to one percent significance level among sampled districts in 2017/2018 cropping season.

The result in Table 6 showed that on average sampled household invest 571.12 Birr with standard deviation of 240.75 to purchase NPSb fertilizer and 600.08 Birr with standard deviation of 270.35 for tomato and potato production in 2017/2018 cropping season. This implies that, the sampled farm households use 0.5quintal of fertilizer in the study area. As shown in Table 6, sampled farm households invested on average 382 Birr and 377 Birr with standard deviation of 261.1 and 211.01 to purchase herbicide and pesticide for tomato and potato production in 2017/2018 cropping season, respectively.

Table 6: Technology adoption

Variable	[yes]/ mean	[Percent]/stnd. dev.	A/G/beret	D/Inchini	E/lafo	F-test
Fertilizer	[315]	[81.82]	60.95	22.86	16.19	2.09***
Improved seed (T)	[96]	[24.94]	1.45	15.98	23.15	2.93***
Improved seed (P)	[243]	[63.12]	53.74	16.76	24.94	2.11***
NPSb	571.12	240.75	59.38	25.00	15.63	1.42
UREA	600.08	270.35	15.57	34.54	67.54	1.57
Herbicide	377.48	211.01	59.48	24.94	15.58	0.01
pesticide	382.8	261.10	15.00	1.78	25.89	2.35

Source: own survey data of 2018

3.1.7. Reasons for Not Adopting Agricultural Technology

In addition to technology adoption, the study report identifies sampled farm household who did not use improved seed for vegetable production and the reason behind depicted in figure 5. As shown in figure 5, 25.8 percent of the sampled households did refuse improved seed because of high price and 23.09percent did refuse because of lack of transportation. The other section of sampled households, 10.55 percent did not use improved seed because of credit arrangement while 40.7percent of them did not use because of lack of supply in improved seed of tomato and potato for production in 2017/2018 cropping season.

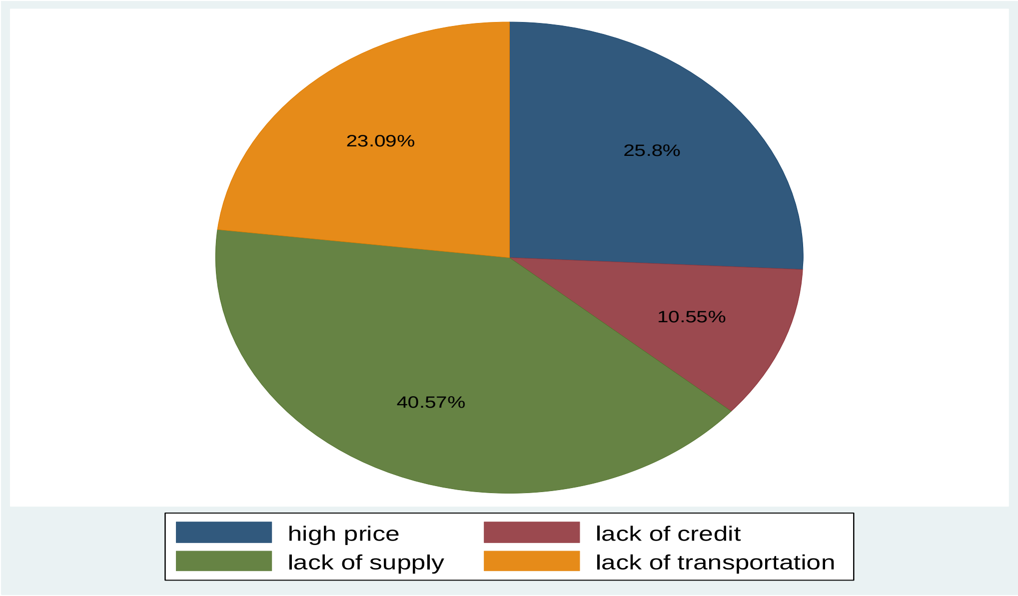

Figure 1: Main reason of not using improved seed

3.2. Efficiency Analysis Using Data Envelopment (DEA) Method

This section assesses the efficiency of vegetables production by households in terms of TE, AE, and EE. Remembering the generally acknowledged method for doing DEA in efficiency analysis, it was settled on executing different input and, output kept away from the likelihood of experiencing issues related with useful structure misspecifications. The output factors were vegetable production characterized as amount of potato and tomato harvested in kilograms. The inputs used were land, labor, oxen seed, fertilizer and agrochemicals.

The DEA technique used in the estimation of relative efficiency of DMUs was checked for potential problems such as sample size and outliers that can seriously affect the efficiency scores. Data Envelopment Analysis Program (DEAP) Version 2.1 was applied to compute the efficiency of vegetable (tomato and potato) production. Even though, data collected had zero value it is difficult to use zero in the DEAP therefore, In order to solve such hardle we employed the method of substituting small no recommended by (George, 1997; Battese, 1991).

Since DEA is an intense factor technique, noise (even symmetrical noise with zero mean) such as measurement error can cause massive problems. The tests for the affectability of DEA effectiveness scores to enter yield anomalies are, hence, urgent to check the heartiness of the productivity results. Primarily, Z score and box plot strategy were utilized and confirmed the information is generally appropriated. Further, to confirm heartiness of effectiveness after effects of DEA model to input-output anomalies, we utilized, among others, the strategy utilized by (Yang *et al.,* 2009). In the wake of tackling the DEA issues utilizing each of the perceptions creating for example, all homestead farms that were completely productive were excluded and DEA issues were addressed.

Using DEAP 2.1 version result, there is the existence of difference in efficiency score level among the three efficiencies TE, AE and EE with score ranging the lowest from 3.8 %, 5.5% and 0.9% to 100%, respectively. From the total sampled households 20.5%, of them were technically efficient while, 0.78% of them were both allocative and economically efficient. This indicates that 79.5% of the respondents were technically Vs in efficient while, 99.22% of the respondents were allocative and economically inefficient. Therefore, as the result implies that there is a room to households to improve their vegetable production with the current level of technology. Data envelopment analysis package result revealed that, the average TE of the households' were 49.5 percent indicating farm households are producing 50.5% much less of achievable output given their prevailing degree of technological know-how and input use. Under the assumption of CRS, the efficiency ratings continue to be identical in each input orientation (input minimization) and output orientation (output maximization). Thus, if we had chosen to maintain inputs constant and measure efficiency in output growing path the efficiency rating is additionally indicating that outputs improved by 50.5% to come to be efficient.

The mean allocative efficiency and economic efficiency showed that, there was a significant difference in the level of inefficiency in production process. As DEA result indicated the mean AE of farm households was 33.7 percent, this indicate that AE of the farm households' shown 66.3% growth in output by improving AE, with current technology. As identified in DEA the average EE of farm households was 17.4 percent. This quit end result indicated that if the commonplace farm household in the pattern end up to advantage the EE degree of his/her most efficient complement, then the not unusual farm household might also moreover need to experience a 82.6% increase in output by using way of improving each EE, with the winning era. Therefore, this stop surrender stop quit result suggests the life of big technical, allocative and economic inefficiency in vegetable production amongst smallholder farmers within the study area.

As featured within the writing detail, the uses of DEA approach had some negative aspects. The primary issue is that the DEA approaches anticipate all DMUs are homogenous and indistinguishable of their responsibilities. Inside the event that the heterogeneous DMUs are surveyed by using DEA without an adjustment, the DEA yields a one-sided act rankings and wrong investigations. Therefore, to clear up such trouble we hired hierarchical cluster efficiency analysis, which is comprised of agglomerative techniques and divisive techniques that find clusters of observations within a data set. The divisive techniques begin with all of the observations in one cluster and then proceeds to split (partition) them into smaller clusters while, the agglomerative methods begin with every observation being considered as separate clusters and then proceeds to mix them till all observations belong to one cluster (Cimiano *et al.*, 2001).

Four of the highly acknowledged algorithms for hierarchical clustering are average linkage, whole linkage, single linkage and ward's linkage. Average linkage clustering makes use of the common similarity of observations between two groups as the measure between the two groups (Yildirim and Birant, 2017). Complete linkage clustering makes use of the farthest pair of observations between two groups to decide the similarity of the two groups (Camiz, 2007). Single linkage clustering, on the other hand, computes the similarity between two groups as the similarity of the closest pair of observations between the two groups (Mohbey, 2016; Stuetzle and Nugent, 2007).Ward's linkage is distinct from all the other methods due to the fact it uses an analysis of variance approach to evaluate the distances between clusters. In short, this method attempts to minimize the Sum of Squares (SS) of any two (hypothetical) clusters that can be formed at each step (Murtagh, 2014; Singh 2008). In general, this method was very efficient; however, it tends to create clusters of small size. At each clustering step, the cluster recognized for combination is the best that minimizes the sum of squared distance over all devices. The dendrogram is generally represented in squared distances as the following figure 2.

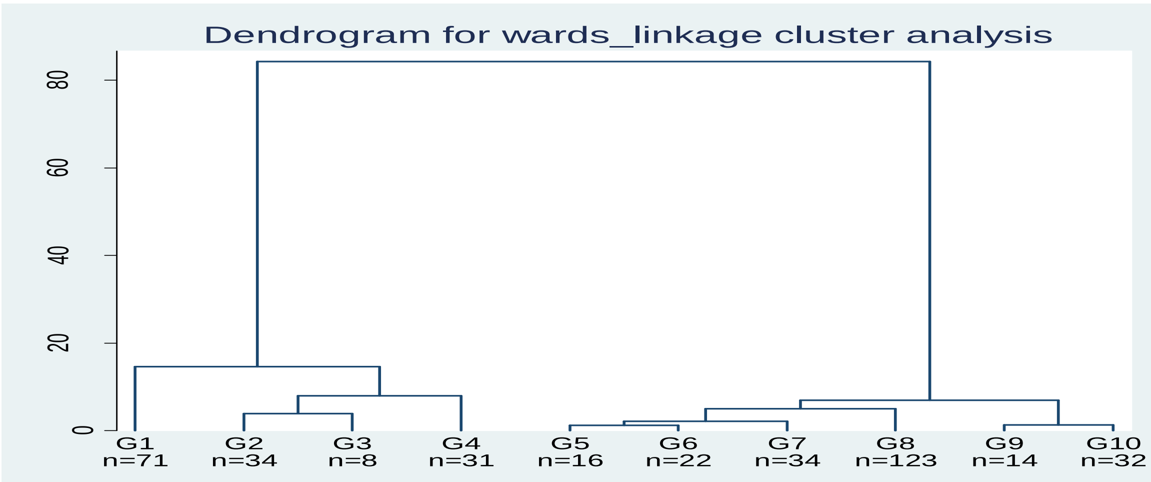

Figure 2: Dendrograms for Ward's linkage hierarchical cluster analysis of efficiency scores

Source: Own computation from efficiency scores of the survey data (2018)

Reading the dendrogram from the bottom to the top, we see that clusters G5 to G8 are merged in quick succession while G2 to G3 and G9 to G10 were merged at about the same distance and G1 and G4 were initially separate. These five clusters remain stable until, at a much higher distance, G1 merges with the second cluster. This result clearly suggests a five-cluster solution. Increasing the number of clusters appears unreasonable, as many mergers take place at about the same distance. Looking at appendix (1), it is shown that the Duda/Hart (Je(2)/Je(1)) index yields the highest value for four clusters (0.6718), followed by a seven-cluster solution (0.5481). Conversely, the lowest pseudo T-squared value (53.64) occurs for ten clusters.

Comparing the variable means across the five clusters, we find that respondents in the second cluster were very strong TE (0.97), but AE (0.59) and EE (0.58) moderate. Respondents in the fourth and fifth cluster have extremely high expectations regarding all five-performance features, as evidenced in average values below average. Finally, respondents in the first cluster do not express high expectations in general, except TE in terms of efficiency Table 7.

Table 7: Mean value of efficiency scores

Mean of efficiency level				
Cluster	Households	TE	AE	EE
1	71(18.44%)	0.96	0.23	0.22
2	42 (10.91%)	0.97	0.59	0.58
3	31 (8.05%)	0 .58	0.54	0.32
4	195(50.65%)	0.28	0.24	0.06
5	46 (11.95%)	0.18	0.53	0.10

Source: Own surveyed data (2018)

3.3 Assessment of Sources of Inefficiency

After identifying each efficiency level, finding out the source of inefficiency of farm household is the primary objective of the study. To see this, the technical, allocative and economic inefficiency of the household was analyzed using Tobit model given in Table 8. To illustrate this, socio-economic, demographic and institutional factors that affect vegetable production efficiency of the households were observed. Before explaining the model, multicollinearity test was carried out and the mean VIF was 1.26 and a maximum VIF of 1.76. This shows that there is no problem of multicollinearity in the data set (Appendix Table 2).For interpretation purposes; the marginal effects of explanatory variables from Tobit regression model were used. In other words, the derived values for the significant explanatory variables indicated that the effects of a unit change in those variables on the expected unconditional value of TE, AE and EE conditional up on between 0 and 1, and probability of being between 0 and 1. Tobit model result showed that, age of household head, education level of the household, land size, access to irrigation, extension contact, access to information and pesticide use significantly affected TE of vegetable production, while age of the household, land size, access to irrigation, extension contact, access to information and pesticide use affect, allocative efficiency of the farm households. Finally economic efficiency of the farm households were affected by age of the households, education level of household head, land size, access to irrigation, access to information and pesticide use.

As Tobit output in Table 8 shows age of household head affect significantly and negatively AE and EE of vegetable production. This implies that, as household head get older and older his/her AE and EE decreases. This is because of young people can easily get familiar with different technology and allocates their resources effectively and efficiently. In other words, younger people were more efficient in vegetable production than older people. As the study by Li and Sicular (2015) indicated technical efficiency of farm labour decreased after the age of 45. The study by Li and Sicular (2015) and Mutz *et al.(*2017) confirmed that as households get older their vegetable production efficiency level decreased.

The Tobit regression result revealed that, education level of household head affect technical efficiency and economic efficiency negatively vegetables production. This implied that when education level of household head increases the opportunity of off farm income increase, which in contrast decreases farm management of the households. This is why increasing the level of education lead to decrease in technical efficiency and economic efficiency of vegetable production of farm households. The study by Thi and Dao (2013) confirmed that the fact that an individual gets more education he/she perform less in vegetable production.

Land size had significant and positive relationship with TE, AE and EE of vegetable production. This indicates that farmers with large land size had more opportunity to allocate his/her land for different production activities to improve the productivity of their land. The results of this work indicate the importance of crop diversification. Farms favoring market-oriented products, such as vegetable production, have greater efficiency than farms focusing on staple crops such as teff, wheat and maize. This result was agreed with the study of (Mokgalabone 2015).

As the Tobit output in Table 8 details, access to irrigation affected AE and EE of vegetable production significantly and negatively. This variable hypothesized to influence vegetable production positively. Nevertheless, in this result it influences vegetable production efficiency negatively. This is for the reason why farmers in the study area were used traditional irrigation system, which needs more of labor force, and difficult to use mechanized agricultural input. Irrigated production regarded as either high input-low input or high input high output depending on the area and form of irrigation. Irrigation costs are used as a proxy for the quantity of water used for production because the irrigation water has been chargeon each unit of the cultivated area, making it difficult to quantify the quantity of water entering the farm. The study was agree with the studies by (Nwauwa *et al.*, 2015 and Puozaa, 2015).

As Table 8 identified extension contact affected TE and AE of vegetable production positively and significantly. This implies that as frequency of extension contact to vegetable producer increases farm households TE and AE were increased. The result revealed that, as frequency of extension contact increase farmers ability to apply input for their vegetable production as well as allocating cost of production during production process in good position because they gained necessary information from extension agents. This result is in line with the studies by (Awotide, 2018; Mokgalabone, 2015). The study also revealed that, access to information affected TE, AE and EE of farm households' vegetable production positively and significantly. This implies that farmers with better access to information were in better position in terms of TE, AE and EE of vegetable production. This indicates that, farm households having access to information were more efficient than others were. This result in lined with the study by (Abdul-salam and Phimister, 2015).

Table showed that pesticide use affected TE, AE and EE of vegetable production of farm households positively and significantly. The positive marginal effect revealed that, as farmer increase the use of pesticide, vegetable production efficiency was also increased. This implies that farmers with pesticide use were more efficient in vegetable production than others were. This result is agreed with the studies by (Jha and Regmi, 2009; Rahman, 2018).

Table 8: Tobit Model for Sources of Inefficiency Analysis

variable	Technical inefficiency		Allocative inefficiency		Economic inefficiency	
	Marginal effect	Std. Err	Marginal effect	Std. Err	Marginal effect	Std. Err
Sex of HH	-0.111	0.074	0.016	0.028	-0.027	0.031
Age of HH	0.002	0.001	0.001***	0.000	0.001*	0.000
Education level of household head	0.019***	0.006	-0.009	0.002	0.004*	0.002
Land size	-0.499***	0.143	-0.457***	0.053	-0.386***	0.058
Access to irrigation	-0.010	0.058	0.104***	0.022	0.073***	0.024
Extension contact	-0.028**	0.012	-0.010**	0.004	0.003	0.005
Fertilizer use	-0.009	0.049	-0.009	0.019	-0.016	0.020
Access to information	-0.258***	0.071	-0.075***	0.027	-0.114***	0.030
Amount of credit used	0.005	0.009	0.006	0.003	0.003	0.004
Off/non-farm income	-0.003	0.004	0.001	0.001	-0.001	0.001
Improved seed	-0.027	0.047	-0.024	0.018	-0.020	0.019
Pesticide use	-0.091*	0.049	-0.097***	0.018	-0.065***	0.020

Note: ***, *** and * showed 1%, 5% and 10% significant level

Source: survey data of 2018

4. Conclusion and Policy Implications

The study identifies the factors that determine vegetable production efficiency (tomato and potato) using DEA and Tobit model. DEA estimation employed to identify the overall TE, AE and EE of farm households' vegetable production efficiency. Accordingly, the overall TE, AE and EE were 49.5%, 33.7% and 17.4%, respectively. The result showed that, even though, it is below average TE is better than AE and EE. The result also indicated that if the households operate at full efficiency level, on average the farm household could reduce the cost of production by 82.6% while producing the same amount of output.

The study also revealed the sources of Technical, Allocative and Economic inefficiency using Tobit regression model. Accordingly, technical inefficiency of the farm households' significantly affected by education level, land size, extension contact, access to information and pesticide use. Furthermore, allocative efficiency significantly affected by age of the household, access to irrigation, land size, extension contact, access to market information and pesticide use. And economic efficiency significantly influenced by age of the household, education level, land size, access to irrigation, access to information and pesticide use.

Acknowledgements

The authors gratefully acknowledge the Ethiopian ministry of science and higher education and Ambo University.

References

Abdul-salam, Yakubu, and Euan Phimister. 2015. “Efficiency Effects of Access to Information on Small Scale Agriculture : Empirical Evidence from Uganda.”

Andrew W., Shepherd. 2007. “Approaches to Linking Producers to Markets,Food And Agriculture Organization Of The United Nations Rome, 2007.”

Antoci, Angelo, Pier Luigi Sacco, and Paolo Vanin. 2009. “Social Capital in a Homogeneous Society,” no. 13661.

Asfaw Zeleke. 2015. *Production And Management Of Major Vegetable Crops In Ethiopia Volume I*. Vol. I.

Awotide, Diran Olawale. 2018. “Analysis Of Production Efficiency Of Food Crop Farmers In Ogun Analysis Of Production Efficiency Of Food Crop,” no. September 2012.

Banjaw Td. 2017. “IMedPub Journals Review of Post-Harvest Loss of Horticultural Crops in Ethiopia , Its Causes and Mitigation Strategies of Post-Harvest Loss Horticultural Crops in Ethiopia In,” 1–4.

Barrett, Christopher B, Maren E Bachke, F Marc, and Thomas F Walker. 2011. “Smallholder Participation in Agricultural Value Chains: Comparative Evidence from Three Continents,” no. 27829.

Battese, George E. 1991. “Frontier Production Functions and Technical Efficiency: A Survey of Empirical Applications In Agricultural Economics,” no. 50.

Brook, Keith. 2005. “Labour Market Participation : The Influence of Social Capital,” no. March: 113–23.

BV, Triodos Facet. 2013. “Country Report Ethiopia.”

Byron. 2014. “Determinants of Soybean Market Participation by Smallholder Farmers in Zimbabwe.” *Journal of Development and Agricultural Economics* 6 (2): 49–58. https://doi.org/10.5897/JDAE2013.0446.

Camiz, Sergio. 2007. “Comparison of Single and Complete Linkage Clustering with the Hierarchical Factor Classification of Variables Comparison of Single and Complete Linkage Clustering with the Hierarchical Factor Classification of Variables,” no. June. https://doi.org/10.1556/ComEc.8.2007.1.4.

Chala, Hailu, and Chalchisa Fana. 2017. “Determinants of Market Outlet Choice for Major Vegetables Crop : Evidence from Smallholder Farmers ’ of Ambo and Toke-Kutaye Districts , West Shewa ,” 4 (2): 161–69.

Christopher, E P. 2009. *Introductory Horticulture*.

Cimiano, Philipp, Andreas Hotho, and Steffen Staab. 2001. “Comparing Conceptual , Divisive and Agglomerative Clustering for Learning Taxonomies from Text.”

Damalas, Christos A. 2017. “Farmers ’ Training on Pesticide Use Is Associated with Elevated Safety Behavior.” https://doi.org/10.3390/toxics5030019.

Fanos, Tadele. 2015. “A Review on Production Status and Consumption Pattern of Vegetable in Ethiopia” 5 (21): 82–93.

Fufa, Nimona. 2017. “Opportunity , Problems and Production Status of Vegetables in Ethiopia : A Review” 4 (2): 1–13.

Gani, B S, and A I Adeoti. 2011. “Analysis of Market Participation and Rural Poverty among Farmers in Northern Part of Taraba State , Nigeria” 2 (1): 23–36.

George E. Bathe. 1997. “A Note On The Estimation Of Cobb-Douglas Production Functions When Some Explanatory Variables Have Zero Values” 48 (2): 250–52.

Girma Kebbede. n.d. “Farmers in the City : The Case of Addis Abeba,” 1–15.

Hailu Gebru, Kebede W/Tsadik2, and Tamado Tana. 2015. “Evaluation of Tomato (Lycopersicon Esculentum Mill) and Maize (Zea Mays L .) Intercropping System for Profitability of the Crops in Wolaita Zone , Southern Ethiopia” 5 (1): 132–41.

Jha, Ratna Kumar, and Adhrit Prasad Regmi. 2009. “Productivity of Pesticides in Vegetable Farming in Nepal,” no. 43.

Li, Min, and Terry Sicular. 2015. “Aging of the Labor Force and Technical Efficiency in Crop Production Evidence from Liaoning Province , China,” no. August 2013. https://doi.org/10.1108/CAER-01-2012-0001.

Maponya P, Venter Sl, Du Plooy Cp, Modise Sd, and Van Den Heever. 2016. “An Evaluation of Market Participation Challenges of Small Holder Farmers in Zululand District, Kwazulu Natal, South Africa.” *African Journal of Business and Economic Research* 11 (1): 117–42.

Mohamedl, Abdi. 2014. “Determinants Of Participation In Milk Marketing Of Small Holders In Jijiga Woreda, Ethiopia."

Mohbey, Krishna K. 2016. "An Experimental Survey on Single Linkage Clustering An Experimental Survey on Single Linkage Clustering," no. November. https://doi.org/10.5120/13337-0327.

Mokgalabone, Maria Sylvia. 2015. "Analyzing The Technical And Allocative Efficiency Of Small-Scale Maize Farmers In Tzaneen Municipality Of Mopani District."

Murtagh, Fionn. 2014. "Ward's Hierarchical Clustering Method: Clustering Criterion and Agglomerative Algorithm," no. May.

Musah, Abu Benjamin, Osei-asare Yaw Bonsu, and Wayo Seini. 2014. "Market Participation of Smallholder Maize Farmers in the Upper West Region of Ghana" 9 (31): 2427–35. https://doi.org/10.5897/AJAR2014.8545.

Mutz, Rüdiger, Lutz Bornmann, and Hans-dieter Daniel. 2017. "Are There Any Frontiers of Research Performance ? Efficiency Measurement of Funded Research Projects with the Bayesian Stochastic Frontier Analysis for Count Data." *Journal of Informetrics* 11 (3): 613–28. https://doi.org/10.1016/j.joi.2017.04.009.

Nwauwa, Linus Onyeka Ezealaji and Omonona, Bola T . *. 2015. "Efficiency of Vegetable Production under Irrigation System in Ilorin Metropolis : A Case Study of Fluted Pumpkin (Telferia Occidentalis)," no. September.

Omiti, John M, and Ellen Mccullough. 2009. "Factors Influencing the Intensity of Market Participation by Smallholder Farmers : A Case Study of Rural and Peri-Urban Areas of Kenya" 3 (1): 57–82.

Osmani, Ataul Gani, and Elias Hossain. 2015. "Market Participation Decision Of Smallholder Farmers And Its Determinants In Bangladesh" 3 (62).

Po, Rung-wei, Yuh-yuan Guh, and Miin-shen Yang. 2009. "A New Clustering Approach Using Data Envelopment Analysis." *European Journal of Operational Research* 199 (1): 276–84. https://doi.org/10.1016/j.ejor.2008.10.022.

Puozaa, Frederick Z. 2015. "Allocative Efficiency Of Irrigated Tomato Production In The Upper East Region , Ghana ."

Rahiel, Hagos Abraha, Abraha Kahsay Zenebe, and Gebreslassie Woldegiorgis Leake. 2018. "Assessment of Production Potential and Post - Harvest Losses of Fruits and Vegetables in Northern Region of Ethiopia." *Agriculture & Food Security*, 1–13. https://doi.org/10.1186/s40066-018-0181-5.

Rahman, Sanzidur. 2018. "Determinants of Pesticide Use in Food Crop Production in Southeastern Nigeria," 1–14. https://doi.org/10.3390/agriculture8030035.

Singh, Warsha. 2008. "Robustness of Three Hierarchical Agglomerative Clustering Techniques for Ecological Data," no. October.

Stuetzle, Werner, and Rebecca Nugent. 2007. "A Generalized Single Linkage Method for Estimating the Cluster Tree of a Density."

Thi, Giang, and Ngan Dao. 2013. "An Analysis of Technical Efficiency of Crop Farms In The Northern Region of Vietnam By," No. September.

Usid. 2005. "Global Horticulture Assessment."

Welderufael, Alemayehu Hailu. 2016. "Assessment of Horticultural Crops (Vegetables , Tubers & Fruits) Production Constraints and Opportunities in West and Southwest Shewa Zones of Oromia Region , Ethiopia" 1 (3): 84–90. https://doi.org/10.11648/j.ijae.20160103.16.

Yildirim, Pelin, and Derya Birant. 2017. "K-Linkage : A New Agglomerative Approach for Hierarchical Clustering" 17 (4): 77–88.