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Impacts of migration on agricultural productivity in Osun state, Nigeria

Ogunleye Ayodeji Sunday*, R. Adeyemo, A. S. Bamire and S. O. Binuomote

Department of Agricultural Economics, Faculty of Agriculture, Obafemi Awolowo University, Ile Ife, Osun State, Nigeria.

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ABSTRACT

This study investigated the effects of migration on agricultural productivity in Osun State, with a view to compare the socioeconomic characteristics and farm-level efficiency of migrant and indigenous farmers in the State. A multistage sampling procedure was used to select a total of 360 arable crops farmers. Data were collected of farmers' socio-economic characteristics, migration indices as well as items of costs and returns to production. Using descriptive statistics, stochastic frontier analysis (SFA) and data envelopment analysis (DEA), the study revealed that there were no significant differences among the socioeconomic characteristics of migrant and indigenous farmers. The result further showed that indigenous farmers were more efficient (SFA-73.40%; DEA-42.6%) than the migrant farmers (SFA-60.20%; DEA-35.8%) and that the observed differences in the level of efficiencies among the two groups were statistically significant ($p<0.05$). It was concluded that indigenous farmers were more efficient than the migrant farmers in the study area.

Introduction

Migration has been described as a form of spatial mobility from one geographical unit to another involving a permanent change of residence. It has also been defined as the movement of people or animals from one place to another and can be classified broadly into four main categories which include intercontinental, international, interregional and internal migrations (UNDP, 1958; Todaros *et al.*, 2009). Internal migration can be classified further into four major types; these include urban to urban, urban to rural, rural to rural and rural to urban migrations (Sada, 1984). Migratory movement can be involuntary resulting from war, natural disasters or voluntary such as in the case with search for better opportunities. According to Deshingkar (2004), migration may be engendered by either economic or non-economic factors (demographic, political, and socio-cultural, among others). However, general models of migration have discovered that economic motivation for migration prevailed over other forms of reasons (Da Haan, 2008). Economic factors may include the search for good jobs, better salary, new pastures, arable land and other production activities.

Migration and economic development are closely connected. A new theory of labour migration (NTLM) has viewed migration as a family's strategy to spread the risks between the destination and the source, thus focusing on the functions of remittances from migrants to smoothing family consumption and financing household investment at the source communities (Taylor *et al*, 1996 and Tomaya *et al*, 2006). The workforce of poorer households and of poorer regions migrates for better employment and productive opportunities in other regions through which they generate income sufficient enough to cater for their family members at home.

Migration and Agricultural Productivity

Migration is radically changing the socio-economic, demographic and development profile of developing countries like Nigeria. This has a far-reaching implication on farming system, agricultural productivity and farm level efficiency (POPIN, 1995). Studies (Tomaya *et al*, 2006 and Iheke, 2008) have shown that socio-economic factors were significant determinants in migration decision. Interestingly, studies by Deshingkar (2004) and Simfer (2008) argued that migrants were set of poor, less educated and unemployed people driven by worse economic conditions in their origin while other literature (Lipton, 1980 and Zachariah, 2001) argued that in practice, the poor rarely migrate. They claimed that migrants were the already employed, more entrepreneurial, open-minded and relatively better educated people. These differences in view require a further investigation of the socio-economic characteristics of migrant and indigenous farm households especially in the study area.

Migration can aid economic growth and development of both the regions of origin and destination. Capital, skills and knowledge transferred by migrants can help both the source and destination communities in their development take-off especially form the point of view of farming activities, agricultural productivity and efficiency (De Haan, 2008). According to Ogbonnaya (2005), the in-flux of migrant farmers to Kwara State in 2004 has helped to jump-start economics development in the State through commercial farming system, agricultural productivity and increased market networks. However, it is important to note that indigenous farmers were displaced from their landed properties for migrant farmers, and compensated by government. The reasons for such actions were not clear. The possible reasons were either for lack of skills, poor productivity and/or inefficiency but were not stated. Therefore, comparing the productivity of migrant and indigenous farm households might be of empirical interest. This study therefore examined the socio-economic characteristics of migrant and indigenous households; and compared the productivity of migrant and indigenous farm households in the study area. Although past studies (POPIN, 1995 and Iheke, 2008) have examined the role of migrations and gender on the agricultural productivity of the farm households at the point of origin, there is no known study on the impact of migration on

Tele:

E-mail addresses: ogunleyedeji@yahoo.co.uk

the agricultural productivity and farmers' efficiency especially at the point of destination. These were the gaps identified and filled by this study.

Methodology

This study was carried out in Osun State because migration and migrant farming activities were common features in the State. The farmers considered in this study were the arable crop farmers. Crops output were limited to four for ease of analysis. The crops considered include maize, cassava, yam and vegetables. A multistage sampling technique was employed in this study. The first stage involved purposive selection of three local government areas (LGAs) noted for good migrant farming activities within the State. The second stage included the use of proportionate sampling procedure to select four villages in each LGA to make a total of 12 villages. In the final stage, random sampling was used to select farm households to make a total of 60 migrant and 60 indigenous farm households per LGA. In all, 180 migrant and 180 indigenous farm households were interviewed to make a total of 360 respondents for this study.

The data were collected using a set of pre-tested structured questionnaire to increase its reliability. Information sought include respondent's socio-economic characteristics such as age, gender, years of education, marital status, farm size, as well as quantities and prices of various inputs used and outputs produced. Descriptive statistics were used to describe and compare the socio-economic characteristics of farmers, while both parametric and nonparametric measures of efficiency were used to compare productivity and farm level efficiency among the farmers in the study area. The parametric measure employed the use of stochastic frontier analysis (SFA) while data envelopment analysis (DEA) was used as non-parametric measure.

Parametric stochastic frontier production function

The stochastic frontier production function was used to measure the technical efficiency of the farmers. The empirical model is as specified in equation (i):

$$\ln Y_i = \beta_0 + \sum_{j=i}^{n} \beta_j \ln \mathbf{X_{ji}} + \mathbf{v_i} - \mathbf{u_i} \qquad \text{.................. (i)}$$

The less restrictive translog model was employed because the normal Cobb-Douglas (CD) is admittedly restrictive with respect to the maintained properties of the underlying production technology (Coelli and Perelman, 1999).

The translog model is as specified in equation (ii):

$$\ln Y_i = \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + 1/2(\beta_1 \ln \mathbf{X}_1^2) + \beta_{12} \ln X_1 \ln X_2 + \beta_{13} \ln X_1 \ln X_3 + \beta_{14} \ln X_1 \ln X_4 + 1/2(\beta_2 \ln \mathbf{X}_2^2) + \beta_{23} \ln X_2 \ln X_3 + \beta_{24} \ln X_2 \ln X_4 + 1/2(\beta_3 \ln \mathbf{X}_3^2) + \beta_{34} \ln X_3 \ln X_4 + 1/2(\beta_4 \ln X_4^2) + V_i - U \text{.......................(ii)}$$

Where, Y_i was the aggregate observed output of the famers (since the output were more than one and were of different measures.). The method of aggregation used is in Table I in appendix A. X_j was the j-th input quantity for i-th farmer which included farm size, labour, chemicals and cost of other inputs. β_0 and β_j were unknown parameters estimated. V_i was a random variation in outputs values that were beyond the farmers' control. It was assumed to be independently and identically distributed ($V_1 \sim [0, \sigma^2]$) independent of U_i, and U_i was the non-negative variable associated with technical inefficiency in production. It was assumed to be independently and identically distributed as half normal, ($U_1 \sim [0, \sigma^2]$).

Given the distributional assumptions, the values of the unknown parameters could be estimated by the maximum likelihood method. Following, Betsey and Coelli (1995), the input-orientated technical efficiency (TE) scores could be predicted using the conditional expectation predictor specified in equation (iii):

$$TE_i = \alpha_0 + \alpha_1 Z_1 + \alpha_2 Z_2 + \alpha_3 Z_3 + \ldots + \alpha_9 Z_9 \text{..............(iii)}$$

Where TE_i was the technical efficiency score of i-th farm and Z_j (j=9) was the inefficiency factor(s) considered which include age, family size, farming experience, years of education, access to credit, extension contact, membership of association, off-farm income and rent paid. $\alpha_0 - \alpha_9$ were the parameters estimated.

Non-parametric, data envelopment analysis (DEA)

In computing technical efficiency using non-parametric approach, constant returns-to-scale (CRS) was assumed for each farm j out of N farms producing y_j output (aggregate) with x_j inputs. Efficiency scores were then computed by running linear programming model for each farm in the data set. The DEA model for the present study was developed for the case of a single aggregated output and multiple inputs. Assuming that there were N farms which produced a single output using M different inputs and the i-th farm produces *i y* units of output applying *ki x* units of k-th input, the M × N input matrix, *X* , and the 1 × N output matrix, *Y* , represented the data for all N farms in the sample.

The linear programming model is specified in equation (iv):

$$\begin{aligned} & min_{\theta,\lambda}\ \theta, \\ \text{st}\quad & -y_i + Y\lambda \geq 0 \\ & \theta x_{ki} - X\lambda \geq 0 \\ & \lambda \geq 0, \text{................ ....(iv)} \end{aligned}$$

Where, θ was the input technical efficiency measure having a value $0 \leq \theta \leq 1$. The resultant efficiency measure depicted the distance of each farm unit from the frontier. If the score was equal to one, it would then imply that the farmer was on the frontier. The vector λ was an N × 1 vector of weights which defined the linear combination of the peers of the i-th farmer. $X\lambda$ and $Y\lambda$ were efficient projections on the frontier. $N\mathbf{1}'$ was an N × 1 vector of ones. The linear programming problem would be solved N times, thereby providing a value for each farmer in the sample.

Result and Discussion

The result of the socioeconomic characteristics of the migrant and indigenous farm households is presented in Table 1.The result showed that there were no significant differences in most of the socioeconomic characteristics (like age, years of education, households size and farming experience) between the migrant and the indigenous farm households. This contradicted the arguments of Deshingkar (2004) and Simfer (2008) that migrants were set of poor, less educated and unemployed people. However, there were expected significant differences (*ab-initio*) in farm sizes, access to credit and membership of association.

The maximum likelihood estimates (MLE) of the stochastic frontier analysis (SFA) are shown in Table 2. For the entire sample, result showed that not all independent variables (Xs) were significant (except for farm size) at 5% level and most variables have expected signs (except farm size, cost, chemical, age, and farming experience). However, the results were different between groups. For migrant farmers, the independent variables like cost of other inputs and farm size were significant at 5%, but these parameters were significant and negative.

Table 1. Socioeconomic characteristics of migrant and indigenous farm households

Variables	Pool	Migrant Farmers	Indigenous Farmers	t-test
Age	48.28	47.05 (13.88)	49.51 (13.60)	-1.70
Education/Years of Schooling	6.87	6.52 (4.95)	7.21 (4.89)	-1.33
Access to Credit	0.54	0.47 (0.50)	0.60 (0.49)	-2.49**
Membership of Association (Yrs)	3.42	3.08 (2.87)	3.76 (3.60)	-1.98**
Extension Visit	0.04	0.02 (0.15)	0.05 (0.22)	-1.51
Household Size	7.38	6.94 (3.99)	7.82 (5.32)	-1.78
Areas of Land Cultivated (Ha)	4.02	3.46 (2.74)	4.59 (3.78)	-3.25*
Farming Experience (Years)	18.41	18.97 (12.44)	17.86 (9.01)	0.97

Note: () figures in parentheses are standard deviations, *and ** indicate significance at 1% and 5%.

Table 2. The MLE estimate of the production frontiers

Variable	Migrant Farmers (N=180)	Indigenous Farmers (N=180)
	Coefficient	Coefficient
Constant	18.076 (14.404)*	5.631 (5.782)*
$\ln X_1$	1.130 (1.169)	-0.962 (-1.133)
$\ln X_2$	-1.465 (-2.203)*	1.271 (2.325)*
$\ln X_3$	-4.787 (-5.834)*	-3.392 (-7.652)*
$\ln X_4$	-0.713 (-0.916)	-0.713 (-2.850)*
$(\ln X_1)^2$	0.498 (4.032)*	0.023 (0.218)
$\ln X_1 \ln X_2$	-0.299 (-2.988)*	0.098 (1.331)
$\ln X_1 \ln X_3$	0.508 (13.721)*	0.561 (21.592)*
$\ln X_1 \ln X_4$	0.080 (0.848)	-0.031 (-0.061)
$(\ln X_2)^2$	0.169 (1.339)	-0.158 (-2.878)*
$\ln X_2 \ln X_3$	0.033 (0.450)	-0.240 (-3.957)*
$\ln X_2 \ln X_4$	0.048 (0.555)	0.036 (1.234)
$(\ln X_3)^2$	0.138 (1.612)**	0.022 (0.312)
$\ln X_3 \ln X^4$	0.040 (0.504)	0.214 (4.356)*
$(\ln X_4)^2$	-0.016 (-0.151)	-0.018 (0.032)
Inefficiency function		
Intercept	-2.582 (-1.138)	0.362 (1.797)**
Age	-0.098 (-1.724)**	-0.028 (-0.480)
Family size	-0.330 (-1.987)*	0.043 (0.481)
Farming experience	-0.056 (-1.482)	-0.002 (-0.189)
Years of education	0.167 (1.834)**	-0.030 (-1.965)*
Access to credit	0.296 (0.382)	-0.088 (-0.735)
Farmers' association	1.101 (1.265)	-0.028 (-0.208)
Extension contact	-2.814 (-1.297)	0.543 (2.033)*
Off-farm employment	0.349 (0.440)	-0.044 (-0.437)
Land Rent	-0.0002 (-1.902)*	-0.00002 (-0.393)
Diagnosis statistics		
Sigma-square	9.416 (1.917)*	0.302 (5.684)*
Gamma	0.980 (78.221)*	0.070 (0.198)
Average TE	0.6016	0.7344

Note: figures in parentheses are t-ratios, * and ** indicate significance at 5% and 10%.

Table 3. Frequency distribution, summary and hypothesis of TE measures

SFPF Result			
Technical Efficiency Index (%)	Pool (N=360)	Migrants (N=180)	Indigenous (N=180)
	Percentage	Percentage	Percentage
<20	6.7	8.3	0.0
21-40	7.8	8.9	0.6
41-60	13.1	16.1	9.4
61-80	61.7	58.9	58.3
81-100	10.8	7.8	31.7
Total	100.0	100.0	100.0
Mean	0.6328	0.6016	0.7344
Standard Deviation	0.1960	0.2097	0.4811
Minimum	0.0092	0.0078	0.3586
Maximum	0.9194	0.9102	0.9860
DEA Result			
Technical Efficiency Index (%)	Pool (N=360)	Migrants (N=180)	Indigenous (N=180)
	Percentage	Percentage	Percentage
<20	44.2	36.1	20.0
21-40	28.1	36.7	36.7
41-60	12.8	12.2	15.6
61-80	6.4	7.8	15.0
81-100	8.6	12.2	12.8
Total	100.0	100.0	100.0
Mean	0.315	0.358	0.426
Standard Deviation	0.2583	0.2806	0.2681
Minimum	0.0210	0,0140	0.0100
Maximum	0.9200	0.9400	0.9890

Table 4. Test of statistical difference between the TE scores of migrant and indigenous farmers.

Analysis	Variables	Migrant Farmers	Indigenous farmers	T-Value
SFA	Mean	0.6016	0.7344	8.496*
	Std Deviation	0.2097	0.4811	
DEA	Mean	0.3580	0.44360	2.351*
	Std Deviation	0.2806	0.2681	

Note: SD represent standard deviation and * indicates that vale is significant at 5%.

Appendix 1

Table I. Conversion Table of Average Crop Price per Kilogram in the Study Area

Crops/LGAs	Price per Kilogram (₦/kg)		
	Ayedaade	Ife-East	Ife-South
Maize	90.00	80.05	85.15
Cassava	65.05	60.09	60.00
Yam	80.50	75.06	70.70
Tomato	60.09	60.00	65.02
Mellon	89.01	72.08	75.01
Ewedu	80.00	50.00	60.00
Pepper	120.06	120.00	115.00
Okra	30.16	25.55	20.73

Source: Market survey 2011.

This was contrary to the a priori expectation and the reason for this, according to the farmers, was bad weather condition experienced during the production season. On the contrary, cost of other inputs, farm size and chemicals were significant and positive for the indigenous farmers. Cost of other input was positively significant probably because as land owners, most of the indigenous farmers did not have to pay rent for land used like many other migrant farmers. However, farm size and chemicals were significant and negative for the same reason given by migrant farmers since the two groups operated within the same weather condition.

The inefficiency factors considered were age, farming experience, households' size, and years of education, access to credit, membership of association, extension contact, off-farm employment, and rent paid on land. For migrant farmers, only family size, farming experience, years of education, and rent paid on land, were significant. The implied that these factors actually affected the farm level efficiency of migrant farm household. The result was entirely different among the indigenous farm households. Only years of education and extension contacts were significant. The gamma diagnosis was also significant at 5% for the migrant farmers (0.98) but not significant for indigenous farmers (0.07). This implied that 98% and 7% of the total variation in output (inefficiency) of the migrant and indigenous farmers (respectively) were due to the inefficiency factors considered. The mean efficiency values (TE) for migrant and indigenous farmers were 0.60 and 0.73. This indicated that the efficiency level of the indigenous farmers

(74%) was higher than that of the migrant farmers (60%). This evidently showed that the farmers were operating below the frontier and there were still rooms for improvement.

Comparison of efficiency scores and distribution

The result of the efficiency scores and distribution from parametric SFA and non-parametric DEA models for migrant and indigenous farm households are presented in Table 3. For the SFA, technical efficiency (TE) of migrant farm households ranged from 0.01-91.9 with a mean of 60.2%. The result implied that the average migrant farm household lost 38.8% of its output for not operating on the frontier. In other words, the migrant farmers could improve their technical efficiency by 38.8% through appropriate measures. The technical efficiency (TE) of indigenous farm households (SFA result) ranged from 35.9-98.6 with a mean of 73.4%. The result also implied that the average indigenous farm household lost 26.6 percent of its output for not operating on the frontier. Considering the DEA result, the technical efficiency (TE) of migrant farmers ranged from 1.40-94.0 with a mean of 35.8%. This implied that an average migrant farmer could still increase his technical efficiency by 64.2%. The technical efficiency (TE) score for indigenous farmers (DEA result) ranged from 1.00-98.9 with a mean of 42.6%. Although the technical efficiency (average value) of all the farmers were very low, It is however important to note that both the SFA and DEA analysis showed that indigenous farmers were more efficient than the migrant farmers in the study area. This result supported the findings by Iheke (2008) and Syed (2010)

Test of statistical difference in technical efficiency

In order to ascertain the consistency between the results of SFPF and DEA, the statistical significance of the different between the efficiency scores of the migrant and indigenous farmers was evaluated using the student t-test. The result of this test is presented in Table 4. The t-test showed that the differences between the migrant and indigenous farmers (SFPF and DEA) were statistically significant at a confidence interval of 95% and indigenous farmers were more efficient than the migrant farmers.

Conclusion and Policy implications

The study examined and compared socioeconomic characteristics; and compare efficiency differentials between the migrant and indigenous farm households in Osun State, Nigeria. Generally, findings showed that the socioeconomic characteristics of migrant farmers were not significantly different from those of indigenous farmers in the study area. Furthermore, farmers in the study area were generally inefficient irrespective of their migration status. It was concluded that the indigenous farmers were more efficient than the migrant farmers and that land rent, household size and farm size were the major determinants of efficiency among the migrant farmer households in the area. Therefore, an enduring 'Land Use Act' that would aid migrant access to land for agricultural purposes should be put in place in order to increase the level of agricultural production and farm level efficiency among farm households in Osun State, Nigeria.

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