Economics Bulletin

Volume 42, Issue 2

Impact of non-farm work on agricultural productivity: Empirical evidence from rural smallholder

Yevessé Dandonougbo
University of Lome

Abstract

The issue of this paper is to analyse the determinants of smallholder participation in non-farm work and the impact of participation on smallholder total productivity, using survey data from 4,542 rural households in Southern Togo. Based on an endogenous switching regression (ESR) model, the findings show that participation in non-farm work can be attributed to the head of household socio-demographic characteristics and their farm characteristics. The result also shows that participation in non-farm work improves total household productivity by an average of about 221,040 CFA francs. There is also an improvement in the productivity of male-headed households participating in non-farm activities, whereas that of women is declining. With regard to the type of non-farm activity, only those engaged in trade have increased productivity. Income diversification should be encouraged as a strategy among smallholders to improve their productivity.

The author would like to acknowledge the Community-Based Monitoring System program of the Partnership for Economic Policy (PEP), the Department for International Development (DFID) and the International Development Research Centre (IDRC)-Canada.
Citation: Yevessé Dandonougbo, (2022) "Impact of non-farm work on agricultural productivity: Empirical evidence from rural smallholder", *Economics Bulletin*, Volume 42, Issue 2, pages 458-475
Contact: Yevessé Dandonougbo - ydandonougbo@univ-lome.tg.
Submitted: August 10, 2020. **Published:** June 30, 2022.

1. Introduction

In most developing countries, especially those in sub-Saharan Africa, the productivity of farming households remains low despite the abundant agricultural technologies developed in this sector to boost crop yields (Silva et al., 2019). With production essentially intended for on-farm consumption, the low productivity recorded could be attributed to low soil fertility and low availability of nutrients (Vanlauwe et al., 2014; Tittonell and Giller, 2013). It is therefore necessary to adopt new production techniques to boost production. The main resources available to smallholders are their land, labour force and capacity to invest in technology, which largely depends on access to capital (Silva et al., 2019). However, most of them lack resources and have limited financing for their activities, given the virtual lack of credit and insurance markets as well as fluctuating yields (Reardon, Delgado and Matlon, 1992). Low productivity may be more pronounced among women, who were reported to be poorer than men and were faced with problems of access to land and farm inputs (Quisumbing, 1996).

Rural households in developing countries, which are made up mainly of poor households (Seidu et al., 2019), depend on agriculture for their food, income and means of subsistence (Minten and Barrett, 2008). As a result, developing the agricultural sector is considered to be the main way out of poverty and food insecurity for these populations (Collier and Dercon, 2014; Dawson, Perryman and Osborne, 2016). Farm and non-farm activities are therefore practised together, such that labour is reallocated between farm and non-farm income-generating activities. In sub-Saharan Africa and especially Togo, the National Agricultural Census (RNA, 2013) showed that among the 95.8% of rural farming households, 53% were involved in non-farm activities. Trade was the main non-farm activity and was practised by 67.3% of women. Despite this high proportion of households involved in non-farm activities, the 2010 - 2017 period showed a downward trend in main cereal crop yields, from 1.22 to 1.14 tons/ha, and 7.40 to 5.22 tons/ha in tubers (DSID, 2018).

The literature shows that non-farm activity provides a risk management tool to reduce income variability and fill the gap between agricultural income and household consumption (El-Osta, Mishra and Morehart, 2008). Thus, diversification of non-farm income in an attempt to ensure stability for farmers is one of the best risk management strategies in agriculture, among many others. (Velandia et al., 2009). Anríquez and Daidone, (2010) and Oseni and Winters, (2009), have shown that income from non-farm activities contributes to improving agricultural production by providing producers with more resources to adopt productivity-enhancing agricultural technologies such as improved seeds, fertilizers, machinery and labour hire. Also, De Janvry and Sadoulet, (2001) have shown that non-farm activities reduce the burden on agriculture by indirectly improving food security at the household level through better management of fluctuations in food consumption. Additionally, the reallocation of resources from farming activities and the absorption of agricultural labour by the agricultural sector can negatively affect agricultural production (Amare and Shiferaw, 2017). Likewise, participation in a non-farm activity could negatively affect agricultural production when the non-farm income is used for consumption or for other investments in non-farm activities (Pfeiffer, López-Feldman and Taylor, 2009).

While various authors have highlighted the importance of the non-farm sector in providing income to rural households in sub-Saharan Africa (Barrett, Reardon and Webb, 2001), there is little research on the subject in West African countries. This paper therefore attempts to analyse the effect of the participation of farming households in non-farm activities on their productivity, taking gender disparity into account. The contribution of this paper in terms of methodology is that it takes into account the endogenous selection bias in the analysis of participation in non-farm activities. Thus, in addition to the research drawn from the literature and using various techniques, including sample selection models (Amare and Shiferaw, 2017), structural equations (Scharf and Rahut, 2014) and instrumental variables (Babatunde and Qaim, 2009; Kilic et al., 2009), we use the endogenous switching regression (ESR) method to correct possible selection bias. This study also highlights the gender disparity and the effect of participation depending on the type of non-farm activity.

The rest of the paper is organised in four sections. The following section presents the ESR method used to achieve the objectives of this paper and describes the data used. Section 3 presents the main descriptive results and econometric estimates. The results are discussed in Section 4, while the last section presents the conclusion and implications of economic policies.

2. Methodology

2.1. Theoretical framework

Following Huffman, (1991) and Owusu, Abdulai and Abdul-Rahman, (2011), let us take an agricultural model in which farmers also devote their time to non-farm activities. The farmer's objective is to maximize his total utility, subject to certain constraints. The utility function that the farmer seeks to optimize is expressed by U=U(Q,H), where Q is the consumption of household goods and H is leisure. This utility maximizing behaviour is subject to time, budget, production and non-negativity constraints. The time constraint of the farmer is expressed by:

$$T = L_1 + L_2 + H, \quad (1)$$

where T denotes the total time constraints of the household as an endowment, L_1 is the time allocated to farm activities, L_2 is the time allocated to non-farm activities, and H is the free time or time allocated to leisure.

The farmer faces a budgetary constraint in terms of income, which can be represented by the following equation:

$$PQ = p_1 y_1 - w_1 L_1 + w_2 L_2 + R \quad (2)$$

and non-negativity condition for labor allocation variables, where P denotes the price of goods purchased by the household, w_1 and w_2 denote returns to labor from farm work and non-farm work, respectively, y_1 is agricultural production, p_1 is the price of the farmer's agricultural production and R is the farmer's income outside of agricultural and non-agricultural works.

The first order condition for optimal time allocation for farm work, non-farm work and leisure is given as $\partial U/\partial L_i = w_i\, \partial U/\partial Q - \partial U/\partial L = 0$ (3)

By reorganizing equation (3), we can calculate the return of farm and non-farm activity in the following way:

$$w_i = (\partial U/\partial L)/(\partial U/\partial Q) \quad (4)$$

When farm households allocate their time to the three activities, the labor supply functions for farm work and non-farm work can be derived as:

$$L_1 = L_1(w_1, w_2, p_1, p_2; Z) \tag{5}$$

$$L_2 = L_2(w_1, w_2, p_1, p_2, R; Z) \tag{6}$$

where Z denotes the independent variables affecting the farmer's acceptance income and non-farm income. As noted by Huffman (1991), a positive number of non-farm hours will be observed for an individual i, if the potential market wage (w_i^m) is greater than the reservation wage (w_i^r). The reservation wage for non-farm activity is the marginal value of the individual's time when all of it is allocated to farm and leisure. Thus $L_i = 1$ if $w_i^m > w_i^r$, and $L_i = 0$ if $w_i^m \leq w_i^r$. The acceptance income and potential market income are not observable, but we can observe the decision to participate or not participate in non-farm activity. This decision can be specified as an index function, with unobserved variable.

2.2. Model specifications

Referring to the conceptual framework, endogenous switching regression (ESR) was used to analyse the effect of participation in non-farm activity on the productivity of smallholders. The ESR is suitable for situations where we are interested in the effect of two different systems (participation or non-participation) on a desired outcome. Thus, the two decision-making systems in this paper are the participation or non-participation of the household in a non-farm work, and the outcome of interest is agricultural productivity. Since the decision to participate in a non-farm activity is voluntary, farmers may choose to participate in non-farm wage activities, which results in a biased sample that makes it difficult to determine the causal link. For example, participants in a non-farm activity may systematically have different attributes from those of non-participants due to self-selection. In this regard, the use of the ESR method controls both observable and non-observable factors that could explain the tendency of farming households to engage in non-farm activity. Thus, the ESR method makes it possible to monitor the problem of selection bias.

The first step of the ESR method involves estimating the determinants of participation in non-farm activities using a probit model (Lokshin and Sajaia, 2004), defined as follows:

$$L_i^* = \alpha Z_i + u_i$$

$$L_i = \begin{cases} 1\ si\ L_i^* > 0 \\ 0\ for\ others \end{cases} \tag{7}$$

where L_i^* is the latent dependent variable of participation in a non-farm activity, which is observed by the choice to participate in this activity. The dichotomous choice observed through participation in a non-farm activity is denoted by L_i, which is equal to 1 for participants and 0 for non-participants. The Z_i vector represents all the characteristics of farms and sociodemographic characteristics of farmers that affect participation in non-farm activities, α is the vector of unknown parameters and μ_i is the random error term.

The second stage of the ESR method involves estimating distinct productivity functions for both groups of farmers. The productivity models are therefore presented as follows:

Participants: $\quad Y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i} \quad if\ L_i = 1 \quad (8)$

Non-participants : $\quad Y_{2i} = \beta_2 X_{2i} + \varepsilon_{2i} \quad if\ L_i = 0 \quad (9)$

Y_{1i} and Y_{2i} represent the dependent variables (productivity logarithm) respectively in the equation of productivity of participants and non-participants; X_{1i} and X_{2i} represent vectors of exogenous variables, β_1 and β_2 parameter vectors; and ε_{1i} and ε_{2i} are random disturbance terms.

In order to solve problems of selectivity bias in the sample, the ESR method is based on the common normality of the error terms in the binary participation and continuous productivity equations. Thus, error terms u_i, ε_{1i} and ε_{2i} are contemporaneously correlated and assumed to be jointly normally distributed with a zero mean vector and the following covariance matrix:

$$cov(u_i, \varepsilon_{1i}, \varepsilon_{2i}) = \Omega = \begin{bmatrix} \sigma_u^2 & \sigma_{1u} & \sigma_{2u} \\ \sigma_{1u} & \sigma_1^2 & \sigma_{12} \\ \sigma_{2u} & \sigma_{12} & \sigma_2^2 \end{bmatrix} \quad (10)$$

Where $var(u) = \sigma_u^2$, $var(\varepsilon_{1i}) = \sigma_1^2$, $var(\varepsilon_{2i}) = \sigma_2^2$, $cov(\varepsilon_{1i}, u) = \sigma_{1u}$, $cov(\varepsilon_{2i}, u) = \sigma_{2u}$, $cov(\varepsilon_{1i}, \varepsilon_{2i}) = \sigma_{12}$

The variance σ_u^2 is assumed to be 1 as α can be only estimated up to a scale factor (Maddala, Griliches, and Michael 1986; Rao and Qaim 2011). In addition, the covariance σ_{12} is equal to zero because Y_{1i} and Y_{2i} are not observed together. Note that in a cross-sectional sample, Y_{1i} and Y_{2i} are only partially observed, with the former being only observed for the subsample of nonfarm participants and the latter being only observed for the subsample of nonparticipants.

When there are unobserved effects, the error term u_i of the selection equation is correlated with the error terms $\varepsilon_{1i}$and ε_{2i} of the outcome equations. That is, the expected values of $\varepsilon_{1i}$and ε_{2i} would be nonzero conditional on regime selection. Therefore, endogeneity can be tested with estimates of the covariance terms σ_{1u} and σ_{2u}. If $\sigma_{1u} = \sigma_{2u} = 0$, the model exhibits exogenous switching; if either ε_{1i}or ε_{2i} is nonzero, the model shows endogenous switching (Maddala, Griliches, and Michael 1986). In this case, one needs to test for significant coefficients of the correlation between ε_{1i} and u_i ($\sigma_{1u} = \sigma_{1u}/\sigma_1\sigma_u$) and between ε_{2i} and u_i ($\sigma_{2u} = \sigma_{2u}/\sigma_2\sigma_u$) (Lokshin and Sajaia 2004). Using these correlations, the expected values of the error terms ε_{1i}or ε_{2i} conditional on regime selection can be written as:

$$E(\varepsilon_{1i}|L_i = 1, X_1) = E(\varepsilon_{1i}|u_i > -\alpha Z) = \sigma_{1u}\frac{\phi(Z\alpha)}{\Phi(Z\alpha)} \quad (11)$$

$$= \sigma_{1u}\lambda_1$$

$$E(\varepsilon_{2i}|L_i = 0, X_2) = E(\varepsilon_{2i}|u_i > -\alpha Z) = \sigma_{2u}\frac{-\phi(Z\alpha)}{1-\Phi(Z\alpha)} \quad (12)$$

$$= \sigma_{2u}\lambda_2$$

where ϕ is the standard normal probability density function and Φ is the cumulative distribution function of the standard normal distribution. λ_1 and λ_2 are the Inverse Mills Ratios (IMRs) predicted at $Z\alpha$ for participants and nonparticipants, respectively (Greene 2008).

In addition to the endogeneity test, σ_{1u} and σ_{2u} allow economic interpretations based on their signs. If the coefficients σ_{1u} and σ_{2u} have opposite signs, farmers decide whether to participate in nonfarm activities based on the comparative advantage (Maddala 1983; Fuglie and Bosch 1995; Roa and Qaim 2011). That is, participants enjoy above-average productivity levels once they participate in nonfarm activities if $\sigma_{1u} < 0$, whereas nonparticipants enjoy above-average productivity levels when they do not participate if $\sigma_{2u} < 0$. Alternately, if σ_{1u} and σ_{2u}have the same signs, 'hierarchical sorting' is evidenced (Fuglie and Bosch 1995), suggesting that the productivity of participants above-average levels regardless of whether they participate in nonfarm activities but they are better off participating than not participating. Similarly, the productivity of nonparticipants is below average levels in either case but they are better off choosing not to participate in nonfarm activities. Furthermore, the coefficients σ_{1u} and σ_{2u} can indicate model consistency under the condition $\sigma_{1u} < \sigma_{2u}$ (Trost 1981). This condition also implies that the participants' productivity levels are above what they otherwise would be if they did not participate in nonfarm activities.

2.3. Estimation approach

Once either σ_{1u} and σ_{2u}takes a nonzero value, one can estimate the model by using a two-stage procedure. In the first stage, a probit model of regime choice is estimated, providing the estimates of α on which the IMRs λ_1 and λ_2 can be predicted according to Equations (10) and (11). In the second stage, the outcome equations are estimated by including the predicted IMRs as regressors. The estimated coefficients of IMRs yield the estimates of σ_{1u} and σ_{2u} . However, due to the estimation of the IMRs, the residuals $\varepsilon_{1i}$and ε_{2i} cannot be employed to compute the standard errors of estimates in the second stage (Maddala 1983; Fuglie and Bosch 1995).

The particular interest of the current study is to quantify the effects of nonfarm activities on farm productivity. To do this, one needs to compare the participants' conditional expected productivity derived from the endogenous switching regression model with the counterfactual case that the same participants have chosen not to participate. The conditional expected value of productivity by a farm household with characteristics $X\ and\ Z$ that participates in nonfarm activities is derived as follows (Maddala 1983):

$$E(Y_{1i}|L_i = 1, X_{1i}) = \beta_1 X_{1i} + \sigma_{1u}\lambda_1 \quad (13)$$

Wheres $\sigma_{1u}\lambda_1$ accounts for sample selection arising from the fact that farmer participating in nonfarm activities differs from other farmer with characteristics X and Z because of unobserved characteristics (Fuglie and Bosch 1995). The conditional expected value of agricultural productivity that the same farmer would enjoy without participation is derived from the following (Maddala 1983):

$$E(Y_{2i}|L_i = 0, X_2) = \beta_2 X_{1i} + \sigma_{2u}\lambda_1 \quad (14)$$

The productivity gain, which is defined as the change in productivity due to nonfarm participation, can then be computed as follows (Maddala 1983):

$$E(Y_{1i}|L_i = 1) - E(Y_{2i}|L_i = 1) = (\beta_1 - \beta_2)X_{1i} + (\sigma_{1u} - \sigma_{2u})\lambda_1 \quad (15)$$

In the literature on impact assessment, this productivity gain is called the average treatment effect on the treated (ATT), which accounts for all factors potentially leading to productivity differences. This treatment effect on the treated results from the differences in the coefficients in Equations (13) and (14) ($\beta_1 - \beta_2$ and $\sigma_{1u} - \sigma_{2u}$). If a farmer self-selects to participate in nonfarm activities or not participate based on the comparative advantage, ($\sigma_{1u} - \sigma_{2u}$) would be positive, and participation in nonfarm activities would produce bigger benefits in terms of productivity under self-selection than under random assignment (Maddala 1983; Rao and Qaim 2011). In this case, a simple comparison between mean productivity in the participant group $E(Y_{1i}|L_i = 1)$ and that in the nonparticipant group $E(Y_{2i}|L_i = 1)$ would result in an upward bias of the treatment effect, which is accounted for in Equation (15).

2.4. Data and sources

The data used in this paper comes from a survey of farming households in Southern Togo, namely, four cantons located in the maritime and plateau regions where 55% of the cropped land is devoted to food crops (RNA, 2013). This data was collected in collaboration with the Community-Based Monitoring System (CBMS) network by the Economic Policy Partnership (PEP), in partnership with the Department for International Development (DFID) of the United Kingdom (UK Aid) and the International Development Research Centre (IDRC) of Canada. The main objective of the project was to set up a local system to monitor the different dimensions of poverty in rural areas in Togo, in order to study and define strategies to support rural households in their efforts to increase their productivity and reduce the productivity gap between men and women.

The data was collected in January and February 2018 from all households in the target localities. In total, 4542 households were counted but 2.55% of the households were not included due to their absence at the time of data collection or refusal to respond to the questionnaires. The data was gathered by interviewers from the same regions in order to facilitate the administration of the questionnaires in the local languages in case the respondents were illiterate. The final questionnaires were first prepared in French and then translated into local languages during the training of the data collection officers.

Three survey questionnaires were distributed to the respondents: one on household profiles (HPQ), one on individuals (individual questionnaire), and one on community profile (CPQ). The household questionnaire was designed to gather information on the characteristics of the household/household member such as education, health and nutrition, housing, water sources and sanitation, etc. The individual questionnaire was aimed at gathering additional information on the characteristics of farms, production and investments in the agricultural sector. Lastly, the community questionnaire was to be completed by chiefs or representatives of districts or zones as well as key persons in fields such as health and education. However, the lack of data on soil quality to take into account its effect on productivity is a limitation in this work.

Table 1 summarises the descriptive statistics of the variables used in the econometric analysis. It shows that around 26.17% of farming households were also involved in non-farm activities, and that on average, 67.64% of households were headed by men. The average area cultivated area was 7.9 ha and most household heads (40.76%) had secondary-level education, while

34.62% had primary schooling. Their average age was 47 years and only 3.3 % of them had access to agricultural credit.

2.4.1. Dependent variables

The dependent variable in the selection equation is a binary variable for participation in nonfarm activities. In the literature on the non-farm economy, there are several approaches about the concept and definition of 'non-farm'. According to a recent review by Feder and Lanjouw (2000), the non-farm sector includes all economic activities in rural areas with the exception of agriculture, livestock, fishing and hunting. Adams (1994) points out that the rural non-farm sector includes activities as diverse as administration, trade, manufacturing and services. In this paper, we focus on the occupational aspect and definite the farm sector as self-employed farmers plus the self-employed working in livestock and agricultural services. We define non-agricultural work as wage and salary work (including wage and salary work on farms and self-employment in any non-agricultural activity. It equals 1 for a farm household that engages in at least one nonfarm work activity and 0 for a farm household that does not engage in any nonfarm work activities.

The dependent variable in the outcome equations is agricultural productivity. It can be defined as production per unit of input (Yabi and Afari- Sefa, 2009). Thus, inputs can be labour, land or capital. The total productivity with both inputs (crop area and labor) is the ratio of farmer output value to total crop area and labor factors used in farm production. Agricultural productivity depends on the quality of inputs and how these inputs are integrated into the production process. For example, land productivity depends strongly on the location of the land and its physical characteristics. However, in this study the data was collected in the same locality. This is a census of households in the township. Thus, the risk of having different land types from one household to another is low. Furthermore, the lack of data on land physical characteristics does not allow to take into account the quality of land in this study. Moreover, the quality of the labour factor could influence the farmers' productivity. Thus, years of schooling is often taken as a proxy for the quality of labour (and stock of human capital). In the case of the productivity measure based on land and labor factor, the effect of education becomes unnecessarily confounded with productivity.

2.4.2. Explanatory variables

The explanatory variables consist of household characteristics, farm characteristics, availability of irrigation infrastructure in the village, availability of public transportation in the village and agroecological risks. These variables are summarized in Table 1.

Table I: Descriptive statistics and definitions of variables

Variables	Definitions	Mean	Standard deviation
Productivity	Monetary value of total production per unit of labour input and area utilised	1057435	1251435
Age	Age of the household head (in years)	46.73	13.60
Dependency ratio	Proportion of household members aged over 65 years and under 15	0.45	0.52
Farm size	Total area cultivated by the household (in ha)	7.90	52.21

Income	Household income (in CFA francs)	313568.5	339662.7

Variables	Definition	Modality	Proportions (in %)
Non-farm household	Household participating in a non-farm activity (0. Farming; 1. Non-farm)	Farmer	73,83
		Non farmer	26,17
Sex	Sex of household head (0. Female; 1. Male)	Female	32,36
		Male	67,64
Educational level	Educational level of household head (0. None; 1. Primary; 2. Secondary; 3. University)	None	23.81
		Primary	34.62
		Secondary	40.76
		University	0.81
Access to Credit	Household with access to agricultural credit (0. No; 1. Yes)	Not access	96.7
		Access	3.3
Migrant remittance	Household receiving remittances from a migrant (0. Non; 1. Yes)	Not receive	99.13
		Receive	0.87
Locality	Locality of the household residence (0. Danyi; 1. Tsévié)	Danyi	83.13
		Tsévié	16.87
Distance to market	Distance of household residence to closest produce market (0; over 5 km; 1 less than 5km)	More than 5Km	34.95
		Less than 5Km	65.05

3. Results

This section begins with an analysis of the differences in averages between farming households whose heads practised only agriculture and those who participated in non-farm activities as well. The second part analyses the results of the econometric estimations. The section concludes with a discussion of the results presented.

Table 2 presents the differences in averages between essentially farming households and those involved in other, non-farm activities. The statistics in the table point to noticeable differences between the two household categories, that are confirmed by simple statistical tests for differences in averages. Thus, as the analysis of the table indicates, there was a significant statistical difference between the two household groups in terms of productivity. On average the agricultural productivity of households involved solely in agriculture was higher than those of farming households participating in other activities such as trade or crafts as well. Compared to non-farm heads of households, heads of farming households were older and their households had, on average, a higher dependence ratio. In addition, non-farm heads of households had a higher educational level and greater cultivated farm size than farming households. On average, households participating in non-farm activities also had greater access to agricultural credits and received more migrant remittances than farming households.

Table II: Difference in average

Variables	Non-Participants	Participants	Mean difference	Standard deviation
Productivity	1120488.	987297.7	133190*	(2.54)
Age	47.892	44.283	3.608***	(7.53)
Sex	0.685	0.654	0.0308	(1.85)
Educational level	1.890	2.112	-0.222***	(-5.31)
Dependency ratio	0.462	0.423	0.0394*	(2.12)
Farm size	6.704	10.510	-3.805*	(-2.09)
Access to Credit	0.029	0.044	-0.0155*	(-2.45)
Income	312227.8	302180	10047.7	(0.84)
Migrant remittance	0.006	0.017	-0.0105**	(-3.12)
Locality	1.899	1.731	0.168***	(5.29)
Distance to market	0.598	0.795	-0.197***	(-11.78)

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1. Determinants of participation in non-farm activities

The descriptive analysis indicates significant differences in total productivity between households involved mainly in farming and those involved in non-farm activities. However, in order to carry out a proper assessment of the effects of the participation of farming households in non-farm activities, we used an ESR model. Productivity equations were estimated jointly with the selection equation, explaining the participation of farming households in non-farm activities.

Table 3 presents the results of the determinants of participation in a non-farm activity and highlights participation by gender (columns 2 and 3) and also type of non-farm activity (columns 4 and 5). The analysis of the determinants of household participation in non-farm activities shows that a high level of education and residence within five kilometres of a market increase the probability of farming households engaging in non-farm activity. The same effects can be observed when considering gender disparity and the diversification of household activities to include trade or other non-farm activities. These findings are similar to those reported by Lanjouw and Shariff, (2004) and of De Janvry, Sadoulet and Zhu, (2005), who argue that education can help farming households adapt better to the demands of the non-farm labour market, thus increasing the probability of educated household heads participating in farm activities. It was also observed that the further away the farming household is from the product market, the less entrepreneurial it will be because of the operational costs and lack of information regarding opportunities.

The total area cultivated was significant and negatively correlated with participation in non-farm activities. This demonstrates that farming households with larger cultivated areas were more likely to prefer agricultural work to diversification into non-farm activities. These findings are consistent with those of Benjamin et al., (1994) and Mishra and Goodwin, (1997), who maintain that a large farming household is unlikely to engage in non-farm activities.

Table III: Probit estimation of the determinants of participation in non-farm activities

Variables	**participation in non-farm activities**				
	All household	Male	Female	Trade	Other activity
Sex	-0.142***			-0.565***	0.574***
	(-3.22)			(-10.54)	(7.14)
Educational level	0.101***	0.098***	0.082**	0.068***	0.135***
	(5.41)	(4.22)	(2.24)	(3.02)	(4.67)
Dependency ratio	0.029	0.039	-0.161**	0.118**	-0.005
	(0.73)	(0.74)	(-2.04)	(2.50)	(-0.07)
Access to Credit	-0.031	-0.024	0.071	0.181	-0.248
	(-0.28)	(-0.18)	(0.31)	(1.48)	(-1.38)
Farm size	-0.002***	-0.002***	0.002***	-0.004***	0.002***
	(-4.55)	(-3.79)	(2.64)	(-9.33)	(4.29)
Locality	0.001	0.034	-0.086**	-0.133***	0.165***
	(0.05)	(1.08)	(-1.97)	(-4.18)	(4.92)
Distance to market	0.237***	0.216***	0.437***	0.179***	0.505***
	(5.58)	(4.24)	(5.08)	(3.16)	(8.23)
Age	-0.002***	-0.003**	-0.005**	-0.000	-0.006***
	(-2.90)	(-2.56)	(-2.55)	(-0.33)	(-4.44)
Migrant remittance	-0.023	-0.082	0.020		
	(-0.18)	(-0.45)	(0.17)		
Income	-0.036**	-0.044***	0.107***		
	(-2.56)	(-2.58)	(5.17)		
_cons	-0.212	-0.275	-1.779***	-0.638***	-2.152***
	(-1.09)	(-1.13)	(-5.91)	(-5.69)	(-14.73)

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2. Determinants of household productivity

The estimates for the productivity equations of the model are reported in Table 4. Considering each of the models (All household, male, female, trade and other activities), the likelihood ratio test for joint independence of the three equations and the significance of the σ covariance coefficients indicating self-selection (Lokshin and Sajaia 2004) are reported at the bottom of the table 4. The likelihood ratio test result suggests that the three equations are jointly dependent, providing evidence of endogeneity that needs to be controlled in the model specification of productivity equations. The model also shows that σ_{1u} and σ_{2u} have alternative signs, with the former being statistically significant and negative but the latter being positive and statistically significant, suggesting that farm households decide whether to participate in nonfarm activities based on the comparative advantage. Moreover, the statistically significant negative sign of σ_{1u} indicates that the productivity of households participating in non-farm activities was higher than the average productivity of rural households once they participate in non-farm activities. These results confirm that the endogenous switching regression is an appropriate model for controlling for self-selection and inherent differences between the nonfarm participants and the nonparticipants, with the model consistency condition being satisfied (σ_{1u} , σ_{2u}).

Considering both households managed by men and women, the results show that the productivity of participants increased when the household was headed by a male farmer, but decreased with the formal education level, farm size and distance to market. For the non-participants in non-farm work, productivity was affected by the formal education of the household head, farm size, and distance to market. The productivity of non-participants in non-farm work increased with the household head education level and distance to market, but decreased with farm size.

In terms of the gender estimate for male-headed households, the columns (3) and (4) in table 4 show that the productivity of participants decreased with their formal education level, farm size and distance to market. Considering non-participants in non-farm work, their productivity is positively correlated with the formal education of the household head and the farm size, but negatively affected by the farm size. Among female-headed households, the productivity of participants and non-participants are negatively affected by the farm size, access to credit and the distance to the market.

Furthermore, considering the estimates by type of activity, the results in columns (7) and (8) reveal that the productivity of participants increased when the household was headed by a male farmer, but decreased with the formal education level, dependency ratio, farm size and distance to market, but increase with the urban location. For the non-participants, their productivity was positively associated to the household head formal education, and negatively by farm activity.

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Table IV: Determinants of productivity

	All		Man		Woman		Trade		Other activities	
	Part	Non Part	Part	Non Part	Part	Non Part	Part	Non Part	Part	Non Part
Sex	1.033***	-0.032	-	-	-	-	2.415***	-0.407***	-0.786**	0.267***
	(6.01)	(-0.30)	-	-	-	-	(10.77)	(-4.14)	(-2.04)	(2.74)
Educational level	-0.382***	0.238***	-0.452***	0.224***	-0.260*	0.098	-0.201**	0.147***	-0.621***	0.150***
	(-5.12)	(5.34)	(-4.89)	(4.00)	(-1.95)	(1.50)	(-2.30)	(3.57)	(-4.84)	(3.78)
Dependency ratio	-0.136	-0.170*	-0.140	-0.040	0.384	-0.071	-0.697***	-0.059	0.379	0.016
	(-0.85)	(-1.89)	(-0.68)	(-0.35)	(1.37)	(-0.58)	(-3.83)	(-0.72)	(1.45)	(0.21)
Access to Credit	0.169	0.096	-0.101	0.291	-0.104	-1.148**	-0.522	0.107	-0.448	-0.532**
	(0.40)	(0.36)	(-0.20)	(0.93)	(-0.13)	(-2.34)	(-1.16)	(0.44)	(-0.57)	(-2.19)
Farm size	-0.014***	-0.018***	-0.013***	-0.017***	-0.031***	-0.026***	-0.006***	-0.022***	-0.026***	-0.022***
	(-9.58)	(-19.08)	(-8.03)	(-15.17)	(-10.44)	(-17.31)	(-3.02)	(-25.40)	(-15.03)	(-27.10)
Locality	-0.018	0.068	-0.105	0.119	0.383**	0.159**	0.699***	-0.097*	-0.689***	0.081*
	(-0.18)	(1.17)	(-0.82)	(1.56)	(2.27)	(2.13)	(5.02)	(-1.84)	(-4.65)	(1.65)
Distance to market	-1.044***	0.368***	-0.954***	0.374***	-1.818***	-0.381**	-0.769***	0.067	-2.314***	-0.319***
	(-5.94)	(3.80)	(-4.44)	(3.19)	(-5.51)	(-2.52)	(-3.19)	(0.75)	(-8.26)	(-3.73)
_cons	17.712***	13.319***	18.957***	13.174***	17.266***	12.268***	16.788***	13.597***	23.600***	12.510***
	(50.51)	(70.23)	(42.92)	(56.26)	(29.32)	(47.48)	(37.16)	(77.58)	(29.70)	(75.50)
$ln\sigma_{u1\ v}$	1.318***		1.310***		1.271***		1.256***		1.409***	
	(43.69)		(35.59)		(24.91)		(25.56)		(31.08)	
$ln\sigma_{u0\ v}$	0.989***		1.001***		0.708***		0.872***		0.755***	
	(64.79)		(55.76)		(22.79)		(61.39)		(55.96)	
$\sigma_{u1\ v}$	-2.629***		-2.616***		-2.946***		-2.743***		-2.671***	
	(-22.86)		(-20.70)		(-10.56)		(-14.88)		(-17.86)	
$\sigma_{u0\ v}$	2.378***		2.516***		-0.383***		2.249***		-0.075	
	(34.99)		(29.59)		(-3.73)		(26.02)		(-1.10)	
N	3682.000		2514.000		1168.000		3210.000		3295.000	
LR test of indep. eqns.	1881.23		112.822		156.342		172.945		321.834	
p	0.000		0.000		0.000		0.000		0.000	

Note: Part=Participant; Non Part=Non-participant ; t statistics in parentheses ; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.3. Effects of participation in non-farm activity on household productivity

To assess the effects of participation in a non-farm activity on the productivity of rural households, we compared the expected contingent productivity of households participating in non-farm activities with the productivity they would have achieved if they had not participated in these activities. This was done using the average treatment effect on treated (ATT) measure presented in Table 5.

According to the findings from all farming households, the participation of farming households in non-farm activities helped them to achieve productivity gains of about 221,040 CFA francs on average per ha. In terms of gender disparity, if the head of the household was male, participating in a non-farm activity improved the household's productivity by 315,316 CFA francs per ha. On the other hand, the household productivity declined when the household head was a woman. Moreover, in terms of type of non-farm activity, households involved in trade had increased productivity, while there was a decline in the productivity of households participating in activities other than trade.

Table V: Effects of participation in non-farm activities on productivity

Groupe	**ATT**	**t-stat**
All	221040***	(50.43)
Man	315316***	(58.11)
Woman	-287958***	(-47.17)
Trade	357321***	(29.56)
Other activities	-213750***	(-28.80)

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4. Discussion

The findings of this study highlight education, farm size and distance from a market as key variables in the economic literature that influence participation in non-farm work and total household productivity in Southern Togo. Educated farmers had a high opportunity cost of labour and were therefore more likely to trade their labour in the non-farm labour market. The closer farming households lived to markets, the more they benefit from agricultural policies and comparative advantages generated by the market (Sheahan and Barrett, 2014). The results presented in Table 4 show an inverse relationship between farm size and total farmer productivity. This result could be explained by the fact that smallholders are generally poor and often do not have access to other resources for production, and are limited in managing their farms if farms become larger. Furthermore, the results reveal a negative correlation between education level and non-participants' productivity. This suggests that, higher education of farmer is associated with less productivity, but more non-farm productivity. This effect is fairly strong. Better-educated are more productive in nonfarm work; they respond to this by reallocating their time away from less productive to more productive activities. On the other hand, the low level of education of farmers limits their ability to manage large farms. This explains the inverse relationship between farm size and agricultural productivity observed in the results.

From the findings of the average treatment effect, we can conclude that there is a positive association between non-farm work and agricultural productivity. This is consistent with findings from various literature (Nasir and Hundie, 2014; Mathenge and Tschirley, 2009; Gebregziabher et al., 2012). Indeed, since non-farm works generates additional household income, it can provide participants with additional capital to invest in agricultural technologies, which helps to boost productivity. In addition to generating income, the involvement of farming households in non-farm employment can reduce the possibility of disguised work resulting from excessive on-farm labour, thus improving farm productivity. Income from non-farm activities can also help to mitigate the effects of liquidity shortage and reduce financial constraints in terms of investment in order to contribute to productivity growth (Gebregziabher et al., 2012). On the other hand, participation in non-farm activities can negatively affect household productivity if it deprives farming activities of labour and significantly reduces the amount of time that the household devotes to farming (Wang, Wang and Pan, 2011). Thus, the participation of households in non-farm activities (other than trade) on their total productivity negatively affects their total productivity and that of female household heads. This can be explained by the fact that non-farm activities generally take up more time and most often lead to detachment from farming activities for a number of periods during the farming season. Furthermore, the negative impact on the productivity of female-headed households can be attributed to gender-related barriers such as women's limited access to land, credit, agricultural inputs, extension services, technology, information and markets, which affect their productivity and entrepreneurial potential in rural areas.

5. Conclusion

This article analyses the effects of rural household involvement in non-farm activities on agricultural productivity using data collected in four cantons in Southern Togo in 2018. The endogenous switching regression model was used, explaining the productivity of farming households and taking into account the selection bias and systematic differences between participants in non-farm activities and non-participants. The findings confirm that the decision to participate in non-farm activity and household productivity are influenced by unobserved characteristics of farming households. Taking into account the self-selection bias and the inherent differences between the two types of households, participants in non-farm activities can earn, on average, about 221,040 CFA francs through their participation. Moreover, in terms of the type of non-farm activity, only those who participate in trade achieve productivity gains. Therefore, by engaging in non-agricultural activities as an income diversification strategy, rural farm households are likely to improve their productivity. This shows the need to focus on the rural non-farm economy as a way of improving the well-being of rural farm households.

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