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Contract Farming and Smallholder Farmer Productivity in Northern Ghana: Does Farm Size Matter?

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ABSTRACT

Data seems to suggest that smallholder's share of area under cultivation in Ghana and Africa in general, is declining while medium-scale farms are increasing rapidly. Without any empirical evidence, there is a perception that the steady rise in the share of farms in the medium-scale category would usher in an Asia-like green revolution, where technology revolution expanded access to modern inputs and led to a dramatic increase in farm productivity and food production. This study explored the question of whether changes in the scale of farm operations, from small to medium-sized farms led to an increase in farm productivity. The study used data from 420 maize farmers in Northern Ghana, and the estimation of naïve, semi-log, and stochastic frontier models, the paper tested the farm-size-productivity hypothesis and explored the factors that influence farm output and input use efficiency. The study found the presence of an inverse farm-productivity relationship in maize farming. While the value of farm output increased with farm size, input use efficiency followed a quadratic pattern where farms in the range of 1-10 acres (smallholder farms) were found to be more efficient in terms of output per unit input than medium-sized farms in the ranges of 11-50 acres. It can be concluded that smallholder farmers were not able to transfer their productive efficiency to medium-sized farms. This reality needs to be considered in the government's agricultural modernisation policy.

Key Words: *Agricultural productivity; Agricultural commercialisation; Inverse farm size relationship; Contract farming*

INTRODUCTION

In 2018, the World Bank extended a US$50 million facility to support Ghana lay a foundation for inclusive and sustainable growth in the agricultural sector (World Bank, 2018). According to the report, the additional funding was to support the country to increase its area under irrigation and improve the livelihood of close to 15000 farm households in the Northern Development Authority area).

Agriculture in Ghana is is dominated by smallholder farmers who contribute close to 20 percent of the country's GDP (IFAD, 2019). Even though Ghana has experienced positive agricultural growth in recent times, much of this growth especially in staple crops has resulted from area expansion rather than increased yield (Akudugu et al, 2013). Some scholars have argued that, increasing agricultural performance would require targeting smallholder farmers with improved service delivery and new pathways for inclusion of smallholders in efficient value chains (Fan and Rue, 2020; IFPRI, 2007).

Agricultural transformation in Africa does not appear to follow the trajectories experienced in

other continents where exit from the agricultural sector were associated with farm size expansions. Rapsomanikis (2015) observed that, the rapid urbanisation in Africa, characterised by exits from the agricultural sector has not resulted in the expansion of farm sizes. The reverse, where the decline in farmer populations has been associated with declines in farm sizes and low agricultural labour productivity has occurred.

Some scholars and actors in the development arena have been unanimous on the need for farm size upscaling if Africa is to meet Sustainable Development Goal two which aims to end hunger. Jayne et al. (2016) and Collier (2008) have argued that, the realisation of SDG-2 in Africa may require a shift from small-scale farming to large-scale commercial farming.

In effect, commercial agriculture which is increasingly seen as a necessary condition for higher productivity, has become synonymous with large-scale farms, while agricultural commercialisation is largely (mis)-perceived as the process of creating large-scale farms. As a consequence, smallholder farmers who dominate African agriculture are increasingly seen as incapable of producing outputs at the levels of efficiency required to end hunger.

While some scholars (Jayne et al. 2016; Collier, 2008) stress the need for policy to facilitate and support farm size expansions, others such as Rapsomanikis (2015) have found that farm sizes in Africa are not increasing and have been declining as more and more farmers exit the agricultural sector due to urbanisation. While not discounting the importance of farm size expansions, it is necessary to test the strength for statistical significance of large farm size as a precursor of productivity. The questions this paper poses are twofold:

i. does farm size matter in productivity?

ii. do farmers who cultivate relatively smaller farms (smallholders) less efficient than those who cultivate large farms?

Quite a few studies (Rada and Fuglie, 2019; Fan et al., 2013; Eastwood et al., 2010) have established various forms of inverse farm size-productivity relationships, with some offering counter-intuitive explanations for their findings such as, smallholder farms having lower labour transaction costs, being more inputs-intensive, and farmers having specialised skills and knowledge (Larson et.al.,2012; Barrett et.al., 2010).

The inverse farm size hypothesis remains a contentious issue among agricultural economists even though the phenomenon has continued to influence agricultural policy discourse and design in many developing countries (Larson et al. 2014; Larson et al. 2016). Fan et al. (2013) criticised the lumping of small-scale farms as a homogenous group describing them as inefficient. Smallholder farmers are not a homogenous group. Just as some large-scale farmers are not efficient, some smallholder farmers are able to achieve higher levels of productivity. There is therefore the need for some distinction and in-depth interrogation of farm productivity in smallholder farmers before conclusions can be drawn.

This paper examines productivity in maize farms with an emphasis on farm size. The paper also examines the factors that drive productivity in maize farms in Northern Ghana, with emphasis on the role of farm size expansion. An understanding of the drivers of farm productivity inter alia including the role of farm size, would enrich the farm-size productivity debate and contribute to policies on agricultural commercialisation.

This paper is presented in five sections. Section two discusses the literature on productivity and the inverse farm size hypothesis. The methods and material employed are presented in section 3. The findings of the paper are discussed in section 4 while the conclusion and policy implications are outlined in the final section 5.

Contract Farming, Farm Size and Productivity

Over the years, contract farming schemes have been employed in government policies to support smallholder farmers to improve productivity. Contract farming is basically an agreement between a buyer and a farmer for a certain amount, quality, and delivery date of agricultural goods under predetermined pricing terms.

Under contract farming arrangements, a farmer commits to deliver some predetermined quantity and quality of a particular agricultural product to the buyer in the predetermined timeframe. In exchange, the buyer agrees to buy the product under the predetermined terms of pricing. In some instances, the buyer commits to support farmers with inputs, technology and in the performance of certain farm operations including land preparation (FAO, 2016).

The assumption is that the incentives provided under contract farming arrangements would encourage farmers to increase land under cultivation (farm size), as well as time and skill in the production processes, and thus lead to increased productivity. Contract farming is also perceived to have other benefits such as linking smallholder farmers to markets. Smallholders and medium-scale farmers across Africa face several layers of market constraints, including, limited access to credit, insurance, agricultural inputs, and technology. Contract farming is touted as viable means of removing these constraints and market barriers (Ncube, 2020).

The inverse relationship between farm size and productivity was first observed by John Stuart Mills in 1848 (Lipton, 2009). Since then, several other studies have documented similar observations in different locations (Larson, et al., 2014; Carletto, et al., 2015; Wineman and Jayne, 2018; Helfand and Taylor, 2020).

The causes of this inverse relationship have baffled scholars, with justifications ranging from differences in the quality of land (Barrett, Bellemare, and Hou 2010) to errors of measurement (Carletto et al., 2013; Dillon et al., 2019; Gourlay et al., 2019); to market imperfections (Sen, 1966; Feder, 1985), and phenomenon known as "edge effect" (Bevis and Barrett, 2017).

The dual labour market hypothesis (Sen, 1966), and the model of moral hazard and costly monitoring of hired labour (Feder, 1985), Risk aversion (Barrett, 1996), household endowment with credit constraints (Eswaran and Kotwal, 1986) and agronomic and behavioural issues at plot-level (Bevis and Barrett, 2020) offer alternative justifications to this relationship. However, agreement among agricultural economists on the reasons for the inverse relationship puzzle remains vague.

Knowledge of the effects of contract farming on smallholder productivity is still largely vague. Also, the perception that farm productivity increases with farm size requires further testing in northern Ghana. This paper will highlight the combined effects of contract farming and farm size on farm productivity.

Literature on the scope of farm size expansion in Africa has been growing steadily. In countries like Ghana, Kenya and Rwanda, Jayne *et al.* (2016) observes that, there is a decline in the share of smallholder farms and an increase in the percentage of medium-scale farms. The paper estimates that medium-scale farms now constitute about about 32% in Ghana.

Regarding productivity between different scales of farm operation, Masters et al. (2013) observed that, farm size expansions arising out of demographic transitioning in Africa has led to less land and a corresponding shift of labour into the nonfarm sector. Debonne et al. (2020), found no difference in yield between small-scale farms and medium-scale farms in Kenya.

MATERIALS AND METHODS

There is no clear-cut approach to measuring the productivity-farm size relationship. Helfand and Taylor (2020) report that, various measure of productivity have been used to explore the inverse farm-productivity relationship. Productivity, measured as output per unit land has been employed by some scholars to test inverse farm size-productivity relationship (Deininger et al., 2018; Dillon et al., 2019). An alternative measure of performance commonly employed is by conditioning land productivity on input use and estimated a production function (Barrett et al., 2010; Ali and Deininger, 2015). Value added per unit of land, profit per unit land, profit as well as technical efficiency (TE) are also employed (Carletto et al., 2013; Henderson, 2015; Foster and Rosenzweig, 2017; Ali and Deininger, 2015; Kagin et al., 2016; Ateka et al., 2021).

This paper employed a combination of measures, including technical efficiency (TE) and production function to test the relationship between farm size and factor productivity in maize farm operations in northern Ghana. The paper perceives TE as a better indicator of productivity than the raw measures of output per land area, which is perceived as biased towards small farms (Ateka, et al., 2021). Others such as Helfand and Levine (2004) have argued that the use of more efficient measures of productivity could reduce inverse farm relationship or altogether reverse it. The use of the translog production function and stochastic frontier analysis is intended to strengthen the measurement of farm size-productivity relationship by comparing TE (output per unit input) and not just the nominal output per land area.

Estimation

Theoretically, the econometric testing of the farm-size-productivity hypotheses is done by estimating a production function. Let Y_{ijk} represent output on maize plot i cultivated by the household j in village k. Let us also assume that X_{ijk} represent observable predictor variables such as inputs and characteristics of the farm household that can plausibly be assumed to exert some effect production. Since the emphasis is on maize, let A_{ijk} be the size of land cultivated to maize. The X_{ijk} vector includes labour (family and hired) and purchased inputs (fertiliser and weedicides) as well as household demographic characteristics such age, sex, household size, household experience in maize farming and regional dummies. If constant returns to scale is assumed, all variables can be converted into per acre terms, with Y_{ijk} signifying on plot *i* and X_{ijk} symbolizing the rate of input applied to plot *i* (Barrett et al., 2010). Below is the specified production function.

$$Y_{ijk} = \beta_1 X_{ijk} + \gamma_1 A_{ijk} + \varepsilon_{ijk} \quad \text{……………………………………(1)}$$

γ_1 explains the yield-farm size relationship and is the parameter of interest, β_1 represents coefficients to be estimated ε_{ijk} is the error term.

The empirical approach has been to estimate a naive regression using semi-log regression functional form with only farm size and its quadratic term as the predictor variables using equation (1). This approach allows for the testing of the hypothesis of no inverse relationship between maize farm size and maize yield ($H_0 : \gamma_1 > 0$) against the alternate hypothesis the presence of inverse farm size relationship ($H_1 : \gamma_1 < 0$). The null hypothesis will be accepted if the coefficient of farm size is positive, indicating a direct relationship between farm size and productivity. The alternate hypothesis, $(H_1: \gamma_1 < 0)$ indicating the presence of inverse farm size productivity relationship is accepted if γ_1 is negative. The second strategy was to add households' socio-economic characteristics to estimation model and re-estimated the semi-log model looking to see if $\gamma_1$moves towards zero and the results confirmed this.

The stochastic frontier approach
To estimate household-level technical efficiency, the paper employed the Stochastic Production Frontier (SPF) technique. The SPF allows for the estimation of two distinct components of overall farm-level productivity: the productivity of the production process itself and technical inefficiency in production. An ordinary production function would mix the two, without accounting for the inefficiency component, thus leading to skewed and inconsistent parameter estimates (Kumbhakar and Lovell, 2000). Estimating the association between maize farm size and technical efficiency could provide evidence of some correlation between farm size and productivity in maize cultivation in northern Ghana.

The stochastic frontier paradigm is distinguished from the standard average production model paradigm by its non-symmetric two-component error, which consists of a regular idiosyncratic disturbance and an additional one-sided non-negative error component. The former takes into account issues such as measurement error, misspecification, and the randomness of the manufacturing process, whereas the latter attempts to depict technological inefficiency that reduces real output from its maximum practicable level. The SPF techniques have been widely used in a variety of situations, including agriculture, to model correlations between input and output and to compute individual farmers' technical efficiency. Following Gautam and Ahmed (2018), the SPF is specified as below:

$$\ln\left(\frac{Y_i}{A_i}\right) = \alpha_0 + \beta_\alpha \ln(A_i) + \beta_x \ln\left(\frac{x_i}{A_i}\right) + v_i - u_i \quad \ldots\ldots(2)$$

$\left(\frac{Y_i}{A_i}\right)$ is the value of maize output per acre, $A_i$is maize farm area cultivated measured in acres and $\frac{x_i}{A_i}$ denotes set of inputs use per acre (labour, fertiliser and weedicides).

The effect of farm size on technical efficiency was investigated using the fractional regression model (FRM) proposed by Papke and Wooldridge (2008) based on the TE scores predicted. This approach was also adopted by Ateka et al. (2021) to analyse the inverse farm size-productivity relationship among Kenyan tea farmers.

Data and sampling process
The study was conducted in two regions of northern Ghana namely, the Upper West and Northern regions. These regions were purposively selected after a scoping survey because they exhibited similarities in agro-ecological potential as well as being contract farming intensive areas thus allowing for the capture of impact of contract farming on both farm size expansion and productivity. Two Districts (Tolon and Kumbungu) were chosen in the Northern region while one, Wa West was chosen in the Upper West Region. The districts were selected in a manner that allowed for the inclusion of communities in which farmers engaged in grains contract farming. Contract farming was important because it was a key driver of farm expansion especially from small to medium and large-scale farms.
Each selected District was divided into two clusters, each containing 10 communities yielding two clusters of 20 communities in the Upper West region and four (4) clusters of 40 communities in the Northern Region. Seven (7) households were then randomly selected in each community leading to a

sample of 140 households in the Upper West Region and 280 farm households in the Northern Region.

The study collected data on crop yield, land use, labour (family and hired labour) and household demographic variables that would allow us to undertake comparative analysis of productivity at different levels of farm operation.

RESULTS AND DISCUSSIONS

Descriptive statistics

Table 1 presents summary statistics of variable used in the models. Out of 420 farmers who participated in the survey, 349 constituting 83 percent were small-scale, cultivating between 1-10 acres of land. About 52 farmers or slightly over 12 percent cultivated medium-scale farms of between 11-50 acres. Only 19 farmers or four percent of farmers cultivated more than 50 acres.

Milu et al. (2017) defines medium-scale farms as famers who cultivate between 5 to 100 ha. The categorization by Milu et al. (2017) means small-scale farmers are those who cultivate farms that range from 1 ha up to 4.9 ha. This paper approximates small-scale farms as farms in the range of 1 acre to 10 acres; medium-scale farms as farms in the range of 11acres -50 acres and above 50 acres as large-scale farms.

The average value of maize output per acre was estimated at 1,207 Ghana cedis (US$201). Family labour used per acre was approximately 39 days per acre while the use of hired labour was estimated at five days per acre. Maize farmers in the study area applied 2.4 bags of fertiliser which is lower than the recommended rate of 3 bags per acre by the Ministry of Food and Agriculture while weedicides application was about 5.4 litres per acre.

Table 1: Descriptive farm statistics of sample households

Variable	Description	Mean	Std Dev
Age	Number of years	31.142	19.231
Farming experience	0 = less than 20 years, 1 = above 20 years	0.213	0.415
Sex	1 – male; 0 =female	0.810	0.28
Formal education	1= yes; 0 = no	0.344	0.477
Value of crop per acre	Amount in Ghana Cedis	1205.0	1738.8
Farm size	Acres	9.840	6.782
Family labour	Man days	38.743	22.449
Hire labour	Man-days	5.247	2.260
Fertiliser applied	quantity of fertiliser 50kg bag	2.338	1.503
Weedicides applied	Kilograms applied	5.337	9.469
Contract farming participant	1= yes; 0 = no	0.267	0.341
Land ownership status	1= owner; 0 = tenured	0.512	0.488

Source: Author, from Field Data, (2021)

In testing for the presence of inverse farm size effect, the sample of farmers was divided into three categories based on farm size. Small-scale farmers cultivated farms in the size range of 1 – 10 acres; medium-scale 11 – 50 acres and large-scale, above 50 acres. This categorisation allowed for the assessment of input intensity of different levels of operation.

Table 2 presents the results of the technical efficiency-farm size relationship analysis as well as the descriptive statistics of per acre output and inputs use intensity. The output variable is the Ghana Cedi value of all maize produced per acre evaluated at the current market price at each location. Table 2 shows that the average value of maize produced by farmers in the small-scale category was GHS 1,091.9 (US$182) per acre, GHS 1,162.8 (US$193.8) for medium-scale category and GHS 1,637.8 (US$273) for large-scale typology farmers. The average value of maize output increased with farm size. This was somehow anticipated since we expect *inter alia,* the volume of maize production in large farms to be relatively higher than in small farms *ceteris paribus*. Even though the result in Table 2 implies there is a direct relationship between maize output and farm size, the relationship does not capture the full extent of productivity or returns to inputs.

A more robust comparative analysis of productivity between the different categories of farm size operation is to use a measure that captures returns to input. Technical efficiency allows for this type of analysis. Also presented in Table 2, is technical efficiency estimates in the three farm size categories. The average technical efficiency was highest in the large farm size type. The TE estimate of 0.9554 means large-farm size typology farmers were able to produce at about 96 percent efficient. This is followed by small farm size category with estimated efficiency of 0.7369, implying that farmers who cultivated between 1-10 acres of land were able to produce at about 74 percent efficiency. Farmers in the medium farm size category were the least efficient with technical efficiency of 0.6809 or 68 percent technical efficiency. Table 2 shows that the inverse farm size hypothesis may be present in maize farming in Northern Ghana to a certain degree. Smaller farms (1-10 acres) are about 6 percent more efficient that medium farm size operations. This means this means small farms lose efficiency (6%) as the size typology changes from small to medium. While medium-sized farms gain efficiency of about 28 percent as size changes from the medium to large-farm size category.

As anticipated, results in table 2 show that labour input, expressed as total number of labour days per acre of both family and hired labour used was relatively higher (than the both medium and large farm size categories) in the small-scale operations. The data also shows that the relative portion of family labour was also highest in the small farm typology. This finding is in tandem with Verschelde et al. (2011) who found that the level of labour use per unit land tended to be higher among smallholder farmers.

In terms of fertilizers use, the study found that farmers in the large farm size category used about 175.3kg per acre as compared to 115.35 kg per acre for medium scale farm size and 130.1 kg per acre for the small farm size category. It was only in the large farm size category that the study found fertilizer use rates consistent with the rates recommended by the Ministry of Food and Agriculture. In terms weedicides application, small farmers used an average of 1.248 litres per acre, medium farmers 1.458 litres per acre while large farmers used about 1.428 litres of weedicides on their maize farms.

The little difference between small and medium farm operations in terms per acre fertiliser and weedicide consumptions perhaps explains why efficiency in small-scale farms is higher than what is observed in medium-scale farms. One of the arguments in favour of farm size expansions is the perception that expansion of farm sizes is mostly associated with complementary input intensification. Per he finds of this paper, while there is significant input intensification in the large-scale category, the difference between small and medium land operations is limited.

Table 2: Comparison of mean productivity and inputs across farm size

	Farm size Operation					
	Small		Medium		Large	
	1 – 10 (acres) (n = 370)		11 – 50 (acres) (n = 31)		>50 (acres) (n = 19)	
Variable	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Measure of productivity						
Value of crop per acre (Ghana cedis)	1091.9	1566.6	1162.8	608.8	1637.8	183.1
Technical efficiency	0.7369	0.2331	0 .6809	0.2276	0.9554	0.0149
Input intensity						
Family labour (man-days per acre)	39.6	22.3	7.4	5.8	2.3	1.3
Hire labour (man-days per acre	0.0589	0.7752	25.6	20.5	34.0	20.6
Fertiliser used per acre (50kg bag)	2.307	1.502	2.602	1.640	3.506	0.941
Weedicides used per acre (litres)	1.248	0.971	1.485	0.848	1.428	0.272

Source: Author, from Field Data, (2021)

Table 3 presents the results of regression analysis of total output per acre, labour use (family labour) and cost of input per acre with respect to farm size. The results show that the coefficients of total output per acre, labour days and cost of input per acre with respect to farm size are statistically significant with different signs. The coefficients of farm size with respect to output per acre and input cost per acre were positive, suggesting increases in output per acre and input cost per acre as farm size increases. However, the square of farm size with respect to the two outcome variables showed an inverse relationship, which implies that there is a point at which output per acre and input cost reduces as farm size expand.

The coefficient of farm size exerted an inverse and significant relationship with labour days which implies declining man-days of family labour used as farm size increases. These results support the argument that small farms use labour especially family labour intensively. This finding suggests that imperfect labour market may be widespread in northern Ghana.

The effect of the square term of farm size was positive, signaling that at a certain point, labour days begin to increase as farm size increases.

Table 3: Semi-log regression results of output per acre, labour days per acre and input cost per acre with maize land area cultivated.

Independent variable	Dependent variables		
	Log of output per acre	Log labour per acre	Log of input cost
Farm size	0.0601***	-0.12769***	0.0512**
	(0.0196)	(0.0117)	(0.0202)
Farm size square	-0.0007**	0.0023***	-0.0008*
	(0.0004)	(0.0003)	(0.0005)
Constant	1.8684***	3.9228***	5.5104***
	(0.0584)	(0.0418)	(0.0723)
R^2	0.0625	0.2597	0.0232
$R_{(2, 417)}$	13.90	73.16	4.95
No. observations	420	420	420

***significant at 1% level, **significant at 5% level and *significant at 10% level, standard errors are in backets. Source: Author, from Field Data, 2021

The study also estimated an extended semi-log regression model by including socio-economic variables such as household age, sex of household head, household size and household experience. These socioeconomic variables serve as proxies for access to resources (access to extension, land, credit and technology). The reason for including these variables is that the inverse relationship may not be plausible if households have better access to resources. The coefficients of the regressions of both output per acre and cost of input per acre with respect to maize farmland are positive and significant at one percent and 10 percent levels respectively. In the case of labour days per acre, the coefficient of farm size was negative. Even though the direction of the coefficient remain the same as in table 3, the magnitude of the coefficients change slightly. This is an indication that the proxy variables do not change had little impact on the productivity-farm size relationship in maize farming.

The coefficients of farmer experience with respect to output per acre and cost of input per acre are significant with negative signs, suggesting that farm productivity and cost of input per acre may be relatively low, if households are more experience maize production. The coefficient of labour days with respect to maize farm size is positive but was not statistically significant. The coefficient of household size is significant with positive signs with respect to output per acre and cost of input per acre, suggesting that farm output per acre and cost of input per acre may relatively be high, if household size increase. The significant and negative sign of region dummies highlights the existence of regional level factors that influence the productivity in maize farming.

Participation in contract farming schemes, which was an important parameter in sampling was found to exert significant and positive effects on log of output per acre, log of labour used per acre and log of other inputs used per acre. The strong influence of participation in contract farming scheme is indicative of the importance of support programmes that improve farmer's access to resources and technology.

Table 4: Results of extended semi-log estimating model

Independent variable	Dependent variable		
	Log of output per acre	Log of labour per acre	Log of input value
Farm size	0.0811***	-0.1370***	0.0344*
	(0.0141)	(0.0121)	(0.0197)
Farm size square	-0.0012***	0.0024***	-0.0006
	(0.0003)	(0.0003)	(0.0005)
Experience	-0.0192***	0.0013	-0.0117*
	(0.0049)	(0.0042)	(0.0068)
Age	0.0044	-0.0017	0.0022
	(0.0030)	(0.0025)	(0.0042)
Sex	-0.3358***	0.1011	1.1638***
	(0.1015)	(0.0865)	(0.1411)
Household size	0.0034	0.0243***	0.0209***
	(0.0055)	(0.0047)	(0.0077)
Region	0.6210***	0.0137	0.1362
	(0.0647)	(0.0552)	(0.0901)
Contract farming	0.2477*	0.1127***	0.0139 ***
	(0.280)	(0.027)	(0.015)
Ownership of Land	1.018	0.645	0.102
	(0.409)**	(0.555	(0.305)
Constant	1.7709***	3.6759***	4.2654***
	(0.1373)	(0.1170)	(0.1910)
R^2	0.3867	0.3136	0.1921
$R_{(2, 412)}$	37.12	26.89	14.00
No. observations	420	420	420

***significant at 1% level, **significant at 5% level, and *significant at 10% level, standard errors are in brackets. Source: Author, from Field Data, (2021)

Effect of farm size on technical efficiency

Table 5 shows the results of fractional regression and semi-log models. The effects of farm size on productivity in maize farming were examined with the fractional FRM and TE scores from the stochastic frontier model.

To account for heteroskedasticity, all specifications report robust standard errors. The semi-log model results serve as a check of robustness in the fractional regression model. Maize farm size is the major variable of importance in this model since it is its coefficient that represents the farm size–productivity link. A negative coefficient of the farm size variable suggests the existence of some form of inverse association. Farm size was found to exert a positive effect on technical efficiency and was significant at the one percent level. However, the coefficient of the square farm size exerted a negative and statistically significant at the 1 percent level on productivity, indicating that the positive effect of farm size on productivity is non-linear, with TE initially increasing (as farm size grows) and subsequently decreasing. It is assumed that farm households that cultivate large farms also adopt new and improved farming techniques, which may boost production and technical efficiency. The findings imply that, at the small farm size level, increasing farm size leads to increased productivity but there exists a threshold beyond which increasing farm size leads to a declining productivity.

Apart from farm size, additional factors influencing TE include family labour, fertilizer quantity, weedicide quantity, experience in maize growing, sex of home, household size, and region (as indicated in Table 5). In both fractional regression and semi-log models contract farming was found to be a significant determinant of technical efficiency and value of output per acre.

The findings highlight the importance of improving input distribution and market functioning to successfully serve geographically distributed smallholders (Ateka et al., 2019; Mbeche et al., 2021). The coefficient of family labour (man days) was negative and statistically significant at the 5 percent level. Because it is a residual claimant of the output, family labour has stronger incentives to work extensively than hired labour. This fact is examined in relation to the elimination of unequal landholding distributions, with the assumption that land redistribution will have a positive influence on farm productivity.

Table 5: Regression results of farm size and productivity (TE and Value of maize per acre)

Variable	**Fractional model**	**regression**	**Semi-log model**	**regression**
Farm size	0.0575**	0.1155***	0.0470**	0.0757***
	(0 .0224)	(0.0095)	(0.0195)	(0.0173)
Farm size square	0.0003	-0.0012***	-0.0006	-0.0012***
	(0.0009)	(0.0002)	(0.0005)	(0.0004)
Family labour (man-days)		-0.0008**		0.0054***
		(0.0004)		(0.0016)
Hire-labour (man-days)		-0.0004		-0.1096**
		(0.0064)		(0.0436)
Quantity of fertiliser (50kg bag)		0.0097*		0.0816***
		(0.0052)		(0.0250)
quantity of weedicides (litres)		0.0359***		-0.0111
		(0.0090)		(0.0360)
Quantity of seed (kg)		0.0002		0.0016
		(0.0001)		(0.0031)
Experience		-0.0152***		-0-.0118**
		(0.0014)		(0.0056)
Age		0.0005		0 .0010
		(0.0008)		(0.0034)
Sex		-0.0435*		-0.1992*
		(0.0256)		(0.1151)
Household size		-0.0041***		0.0032
		(0.0015)		(0.0064)
Contract farming participant		0.0172**		0.3526***
		(0.0101)		(0.1315)
Region		1.1865***		0.8621***
		(0.0199)		(0.0771)
Constant		-0.4971***		5.7788***
		(0 .0455)		(0.1785)

***significant at 1% level, **significant at 5% level and *significant at 10% level, standard errors are in brackets. Source: Author, from Field Data, 2021

The number of years a farmer has cultivated maize was used as a proxy for experience and had a negative and significant impact on the technical efficiency of the farm households. This meant that households with a longer history of maize farming were less technically efficient. This could be attributed to the fact that households with more years of maize farming experience have older members, who may be less efficient. The coefficient of household size is significant with a negative sign, suggesting that farm productivity may be relatively low, if households use more labour from the household. The variable area coefficient has a direct relationship with the level of technological efficiency. The variable region is a dummy that indicates 0 for the Northern area and 1 for the Upper West region. The sign of the coefficient indicates that farm households in the upper west region outperformed farm households in the north. Muyanga and Jayne (2019) observed that, on the other hand, that disparity in productivity across farm sizes were unrelated to location or distance to markets. The fundamental assumption is that households in one region confront the same set of market issues. In practice, however, farmers from the same location incur different transaction costs. For the robustness of the finding, the level of technical efficiency and the log value of crops per acre was regressed with only farm size and square of farm size. The study found that, farm size shows a significant and positive correlation both in technical efficiency and the log value of crop per acre, suggesting that the results were robust.

CONCLUSIONS AND POLICY IMPLICATION

Using data from 420 maize households in northern Ghana, this study examined the farm size productivity relationship. The paper found that an inverse farm size-productivity relationship exists in maize farming in northern Ghana but only to a certain degree. Small maize farm operations (1-10 acres) are relatively more efficient (returns to input) up until farm sizes reach the medium farm size operation category (11-50 acres) when efficiency drops from 74 percent to 68 percent. Input-use efficiency again rises to about 95 percent as farm sizes grow beyond the medium size range to the large farm sizes category (above 50 acres). The detection of inverse farm size- productivity relationship in maize farming in small-scale and not medium-scale farms has implications for agricultural commercialisation and modernisation.

We observed that large-scale farms in the study area did not occur as a result of the consolidation of medium- or small-scale farms into large farms. Most of the large-scale farms were created by urban elites and absentee businessmen in cities. In the case of medium-scale farms, many of them expanded from small-scale operations. It is therefore evident that farmers who were efficient at the small-scale farm level are not able to transfer this efficiency into medium-scale farm operations. While increasing farm size increased the nominal value of output, it did not improve productivity across all categories of farm operations. Small farms were found operating at TE levels over and above medium scales.

The gamut of farm technologies required for medium-scale farm operations as well as the knowledge and capacity to implement these technologies may not be present at the smallholder level. Medium-size farm operations may require a specific gamut of technology to enable them to operate efficiently. Policy efforts to encourage farm size expansions should be complemented by size-to-type technology.

Without significant changes to the production systems of smallholder farmers, smallholders are better-off as smallholder farmers. The government’s agricultural commercialization efforts that focus on nudging smallholder farmers towards medium-scale farms come at a cost in terms of loss of technical efficiency and this reality must be taken into consideration by policymakers.

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COMPETING INTEREST
To the best of my knowledge, there is no issue of competing interest associated with the conduct of the research and subsequently, the writing of this paper.

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