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Impact of Off-farm Income on Agricultural Technology Adoption Intensity and Productivity

Evidence from Rural Maize Farmers in Uganda

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This study analyzed the impact of off-farm earnings on the intensity of adoption of improved maize varieties and the productivity of maize farming in Uganda in the years 2005/06 and 2009/10. Summary statistics show significantly higher adoption intensity and expenditure on purchased inputs among households with off-farm income relative to their counterparts without off-farm income. Households with off-farm income allocated about 15.9 percent of their land to improved maize varieties, and spent UShs 32,048 annually on input purchases compared to an adoption intensity of 13.8 percent of land allocated to improved maize and input expenditure of UShs 12,270 for those without off-farm income. The results of the random effects Tobit model show a positive and significant association between off-farm income and the proportion of land planted with improved maize varieties. We, however, find farm households without off-farm work to be more efficient maize producers than those with off-farm income. The mean level of the technical efficiency score was 0.43 for those without off-farm work compared to the 0.39 for an average farmer with off-farm income. In addition, the cumulative distribution function (CDF) for the farmers without off-farm income stochastically dominated the CDF for farmers with off-farm income. This suggests that off-farm opportunities, while inducing increased use of improved seed, due to competition for labor time, may undermine the productivity gains from adoption of improved seed. The findings from this study support diversification of household income as a strategy for increasing capital availability to increase uptake of the modern purchased inputs

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INTRODUCTION

Off-farm income opportunities have been widely documented as an important strategy for overcoming credit constraints faced by the rural households in many developing countries (e.g., De Janvry and Sadoulet, 2001; Iiyama et al., 2007; Barrett et al., 2001; Reardon et al., 2007). In Uganda, about 60 percent of rural households engage in some form of off-farm income generating activity, and the proportion of those with positive off-farm earnings increased from 49 percent in 2003 to 53 percent in 2005 (Kijima et al., 2006). While some studies in Uganda have linked off-farm income to poverty reduction (Ellis and Bahiigwa, 2003; Kijima et al., 2006), there is limited empirical information on the linkage between the farm and the off-farm sectors. Worldwide, the literature on the effect of off-farm income on the farm sector presents mixed conclusions. One strand of literature shows that off-farm income is a substitute for borrowed capital in rural economies where credit markets are either missing or dysfunctional (Collier and Lal, 1984; Reardon, 1997; Ellis and Freeman, 2004). In addition, off-farm work may serve as collateral to facilitate access to credit by small-scale farmers (Reardon et al., 1994; and Barrett et al., 2001). In summary, off-farm income is expected to provide farmers with liquid capital for purchasing productivity enhancing inputs such as improved seed and fertilizers. On the other hand, pursuit of off-farm income by farmers may undermine their adoption of modern technologies (especially labor intensive technologies) by reducing the amount of household labor allocated to farming enterprises (McNally, 2002; Goodwin and Mishra, 2004).

The present study analyzes the premise that off-farm income for Uganda smallholder farmers increases the intensity of adoption of improved technologies, translating into increased productivity. We use maize production as a case study. To determine the productivity effects of off-farm earnings, the study establishes the effect of off-farm earnings on technical efficiency[1]. It is hypothesized that investment of off-farm income in crop yield-enhancing inputs leads to crop productivity gains through improved production efficiency.

SIGNIFICANCE OF THE MAIZE SUBSECTOR IN UGANDA

This study focuses on maize to explore the linkage between farm and non-farm sectors in Uganda. Maize is one of the most important non-traditional agricultural export commodities and is the most widely cultivated cereal crop in Uganda. Maize is cultivated by 86 percent of Uganda's rural households accounting for about 46 percent of the area under cereal crops in the country (UBOS, 2006). It is estimated that 59 percent of maize farmers in Uganda produce surplus for the market every season (UBOS, 2005/06), and the household marketed share of maize has increased by 38 percent between 2000 and 2007 (UBOS, 1999/00; PMA, 2007).

Substantial technological improvements have occurred in Uganda's maize subsector, especially through the increased use of improved seed varieties. The National Agricultural Research Organization has generated and disseminated new maize varieties, among which are the Longe series 1 through 12, which have been bred for disease resistance and high yields. In 2007, the proportion of farmers planting improved maize seed varieties in Uganda was estimated at 59 percent, and about 84 percent of the land opened up that year for maize was planted with improved maize varieties (UNHS, 2005/06).

[1] Technical efficiency measures a producer's ability to achieve output relative to a defined maximum from a given set of inputs and technology (Chavas et al., 2005).

MODEL SPECIFICATION

Causal effects of off-farm earnings on technology adoption

The effect of off-farm income on technology adoption is estimated by examining its influence on the proportion of maize area a farmer planted with improved seed. The dependent variable thus, has a censored distribution since there is a cluster of households (non-adopters) with zero land allocation to the improved technology. This study adopts a Tobit model to correct for the non-normality of the distribution of the censored dependent variable. In this case, estimation done using ordinary least squares would result in biased results. We use a panel regression approach to control for the unobserved heterogeneity of households with respect to off-farm income, posited as one of the drivers of adoption intensity.

In reduced form, the random effects Tobit model of adoption is specified as follows.

$$y^* = \alpha_0 + \alpha_x X^o + \alpha_z Z + \lambda + \tau + \varepsilon \tag{1}$$

where y^* is a latent variable representing the proportion of land planted with improved varieties; X^o is farmer's annual off-farm income; Z is a vector of household level exogenous factors, λ is a term capturing unobserved household heterogeneity; τ is a time dummy (1 if 2010, 0 if 2006) is included to capture the time-varying shocks common to all households, and $\alpha_0, \alpha_z, \alpha_x$ are parameters to be estimated. The impact of off-farm income on adoption of improved seed is captured by α_x and is identified after controlling for other sources of financial capital in the household – the household cash farm earnings and a dummy for household access to credit. The effect of human capital on intensity of adoption is captured by education of the head of the household (1 if household head acquired some form of formal education, 0 otherwise), sex of the head of the household (1=male), the proportion of prime age members of the household (between 18 and 45 years of age), and the age of the household head (years). Regional dummies representing the northern, central, western, and eastern parts of the country are included to capture heterogeneous effects due to locational and agro-ecological related characteristics of the study households.

Model for estimating the impact of off-farm earnings on maize productivity

This paper investigates the possibility of productivity gains from investing off-farm income in better maize technologies by examining the technical efficiency of maize farmers. Following Aigner et al. (1977), Battese (1992) and Rahman (2003), we specify the stochastic production function for a given farmer as:

$$Q = f(X; \beta) + v - u \tag{2}$$

where Q, X and β are vectors of maize output (in kilograms), input levels used in maize production and estimated parameters, respectively. The inputs include land (in hectares), labor (hours) and capital (in Uganda shillings). The term v is a two-sided ($-\infty < v < \infty$) normally distributed random error [$v \approx N(0, \sigma_V^2)$] that captures the stochastic effects outside the farmer's control, measurement errors, and other statistical noise. The term u is a one-sided ($u \geq 0$) efficiency component that captures the technical inefficiency of the farmer. Thus, u measures the shortfall in output Q from its maximum value given by the stochastic frontier $f(X_{ik}; \beta_k) + v_i$. We study assume that u follows a half-normal distribution [$u \approx N(0, \sigma_U^2)$]. The two components v and u are also assumed to be independent of each other. In both cases v_i and u_i cause actual production to deviate from the frontier. Following Bravo-Ureta and Pinheiro (1997), technical efficiency of a farm is empirically measured using adjusted output as

$$Q_i^* = f(X_{ik,} B_k) - u_i \tag{3}$$

where the conditional mean of u_i, given $\varepsilon_i = v_i - u_i$, is calculated as

$$E(u_i / \varepsilon_i) = \frac{\sigma_i \gamma_i}{1 + \gamma_i^2} \left[\frac{f^*(\varepsilon_i \lambda_i / \sigma_i)}{1 - F^*(\varepsilon_i \lambda_i / \sigma_i)} - \frac{\varepsilon_i \lambda_i}{\sigma_i} \right]. \tag{4}$$

In (4) $f^*(.)$ and $F^*(.)$ are the standard normal density and cumulative distribution functions, respectively, $\gamma = \sigma^2/\sigma^2_v$, and $\sigma^2 = \sigma^2_u + \sigma^2_v$. Q^* is observed output, adjusted for statistical noise. Technical efficiency (TE) of an individual farm is, thus, the ratio of the observed output Q^*, to corresponding frontier output, Q_i, both in original units (Equation 5):

$$TE_i = \frac{Q_i}{Q_i^*} = \frac{f(X_{ik};\beta_k)\exp(v_i - u_i)}{f(X_{ik};\beta_k)\exp(v_i)} = \exp(u_i). \tag{5}$$

To generate TE efficiency estimates for maize farm households, we adopt a second-order flexible form of the stochastic production frontier in (Equation 6). In this case the trans-log specification, for the ith household is:

$$\ln Q = \beta_o + \sum_j B_j \ln X_j + \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln X_j \ln X_k + v_i - u_i. \tag{6}$$

The production function coefficients (β) together with variance parameters (σ^2 and γ) are estimated by maximum likelihood. The predicted farm level TE scores were then examined with respect to off-farm income in two ways. First, we compared the technical efficiency levels between farmers with off-farm income and those without off-farm income using the stochastic dominance (SD) criterion as applied by Chang and Yen (2010). The SD criterion compares cumulative density functions (CDF) to identify the most efficient set. Let F and G denote the CDFs of technical efficiency (TE) for farmers with off-farm income and without off-farm income, respectively. First degree stochastic dominance (FDSD) is obtained if technical efficiency of farmers with off-farm work dominates its counterpart if and only if G ≥ F for all levels of technical efficiency. Thus, the cumulative density curve of F always lies below and to the right of G, when, F is the choice. Second degree stochastic distribution (SDSD) criterion is obtained if the stochastic outcomes from off farm income and the lack of tradeoff do not always have the FDSD relationship i.e. if the cumulative density curves cross each other. According to the SDSD rule, F stochastically dominates G if the integral of G is not less than that of F for any outcome level, i.e., $\int_{-\infty}^{TE}(G-F)d)(TE) \geq 0$.

For, the SDSD criterion to hold, the area under F is always smaller than that under G.

Second, we analyze the effect of off-farm earnings on technical efficiency using panel regression methods. We estimate and compare the results derived using pooled OLS with those from the random effects and fixed effects models. In our econometric model of mean efficiency, we control for other household and institutional variables that influence technical efficiency (equation 7).

$$TE = \varphi_0 + \varphi_x X^o + \varphi_k H + \lambda + \tau + \varepsilon \tag{7}$$

where TE is the level of technical efficiency of maize production for a household X^o is the level of off-farm income; H is a vector of technical, institutional and other exogenous household variables that influence technical efficiency. These variables include:

- a dummy variable for household interaction with service providers;
- education of household head, included to capture the effect of human capital on efficiency,
- sex of the household head (1 if male; 0 otherwise),
- age (in years) of household head,
- the size of household (number of persons) to capture labor availability and resource endowment in the household,
- area cultivated with maize (in hectares) to account for economies of scale,
- dummy for weather shocks (1if household experienced long dry spells during the production year, 0 otherwise),
- regional dummies to capture heterogeneity due to agro-ecological conditions,
- a dummy variable for use of improved maize seed varieties to capture the effect of technological progress on technical efficiency.

The parameters $\varphi_0, \varphi_k, \varphi_x$ are to be estimated. The rest of the variables are as defined earlier.

Data sources

The study utilises two waves of data collected by the Uganda Bureau of Statistics (UBOS). These include the Uganda National Household Survey (UNHS) III collected in the 2005/06 production year, and the first round of the Uganda National Panel Survey (UNPS) dataset collected in 2009/10. The UNPS is a follow up survey covering 3123 households from the UNHS III sample. We constructed a sample that has 1102 maize-producing households that responded to the questions on off-farm work participation in both rounds of data collection.[2]

Off-farm employment has become increasingly important to farm families of Uganda. About 90 percent of the sample of maize farmers reported receiving earnings from off-farm work. In this paper we define off-farm earnings as income generated by households from any non-agricultural income generating enterprises such as artisanal activities, metalwork, transportation or any other informal businesses, as well as transfers and remittances. Agricultural production inputs reported in the data include family and hired labor measured by the hours spent on maize production, land allocated to maize and expenditures on other variable inputs, including seed, fertilizer and pesticides, which we use as proxies for capital.

Table 1 summarizes the characteristics of the study households, contrasting between farmers with and without off-farm income. The summary statistics show a significantly larger proportion of land allocated to improved maize varieties and higher expenditures on purchased inputs among farmers with off-farm income compared to those without off-farm income. A larger proportion of farmers with off-farm income had received formal education and interacted with extension agents, and had access to credit compared to their counterparts without off-farm income. However, maize yields are significantly higher among farmers without off-farm income.

[2] We dropped farmers with missing data on the area cultivated with maize.

Table 1: Household Level Summary Statistics

	All households (n=2204)	With no off-farm income (n=220)	With off-farm income (n=1984)	t-statistic
Expenditure on purchased inputs (UShs)/year	29,975 (225,598)	12,270 (44,828)	32,048 (237,867)	-1.26
Land allocated to maize (hectares)	0.620 (0.889)	0.338 (0.449)	0.654 (0.921)	-5.13***
Adoption of improved maize variety (yes=1; otherwise=0)	0.200 (0.400)	0.169 (0.375)	0.204 (0.403)	-1.25
Proportion of land allocated to improved maize varieties	0.157 (0.338)	0.138 (0.326)	0.159 (0.340)	-0.89
Maize output (kg)	809 (2,945)	1,004 (4,344)	786 (2,736)	1.07
Total annual farm income ('0,000 UShs)	518 (1,820)	89 (617)	568 (1,910)	-3.79***
Dummy for access to agriculture extension services (1=interacted with a service provider)	0.107 (0.309)	0.091 (0.288)	0.109 (0.312)	-0.84
Dummy for education level of head (1=attained some formal education)	0.814 (0.390)	0.736 (0.442)	0.823 (0.382)	-3.21***
Age of head of household (years)	45.9 (14.9)	45.6 (15.6)	45.9 (14.8)	-0.36
Male head of household dummy	0.744 (0.437)	0.844 (0.363)	0.732 (0.443)	3.71***
Household size	6.7 (3.2)	6.3 (3.0)	6.8 (3.2)	-1.90**
Agricultural credit dummy (1=farmer allocated credit to farming)	0.120 (0.325)	0.048 (0.213)	0.129 (0.335)	-3.60***
Household experienced severe drought during production dummy	0.525 (0.500)	0.502 (0.501)	0.527 (0.499)	-0.72***
Proportion of prime age (18-45 years old) members in the household	0.349 (0.229)	0.453 (0.230)	0.337 (0.226)	7.39
Central region	0.235 (0.424)	0.173 (0.379)	0.242 (0.429)	-2.35***
Eastern region	0.337 (0.473)	0.342 (0.475)	0.336 (0.472)	0.18
Northern region	0.223 (0.417)	0.208 (0.407)	0.225 (0.418)	-0.60
Western region	0.205 (0.009)	0.277 (0.030)	0.197 (0.009)	2.87***
Total labor (hours)	254 (9.2)	110 (7.4)	271 (10.2)	-5.38***

Note: ***, ** and * indicate significance level at 1%, 5% and 10%, respectively; standard error in parentheses

EMPIRICAL FINDINGS AND DISCUSSION

Estimations for the effect of off-farm earnings on adoption of improved seed

The results of the random effects Tobit model for the causal effects of off-farm income on the level and intensity of adoption of improved maize varieties in Uganda are presented in Table 2. The estimated model and its associated error components (σ_u and σ_e) are statistically significant at the 1 percent level. Significance of σ_u suggests that unobserved heterogeneity is important in the estimated regression. Column (1) of Table 2 presents the estimated parameters of the Tobit regression model whereas the rest of the columns report the marginal effects. These include the marginal probabilities for being observed (column 2), the expected values of the dependent variable conditional on being observed – the change in intensity of adoption with respect to a unit change of the independent variable(column 3), and the marginal effects for the unconditional expected value of the observed dependent variable (column 4).

The results show a positive and significant effect (at 10 percent level) of household off-farm income on adoption of improved maize varieties. A one percent increase in off-farm income earned increased the probability of adopting improved maize varieties by about 0.4 percent. The intensity of adoption is about 0.003, implying that the number of hectares planted with improved seed increased by about 0.3 percent due to a one percent increase in off-farm income among the adopters.

The positive effect of off-farm income suggests that off-farm earnings may induce technology adoption by providing farmers with capital for purchasing the improved maize technologies. Promoting off-farm income generating activities in the rural areas could thus be an important policy strategy that can be used to encourage increased uptake of yield enhancing technologies.

Table 2: Marginal Effects of the Intensity of Adoption

Dependent variable: proportion of maize area allocated to improved seed				
Variable	**Coefficients**	**Marginal Effects**		
	(1)	**(2)**	**(3)**	**(4)**
Log of annual off-farm earnings (UShs)	0.015* (0.008)	0.004* (0.002)	0.003* (0.002)	0.003* (0.001)
Agricultural credit access dummy (1=farmer allocated credit to farming)	0.060 (0.102)	0.015 (0.025)	0.013 (0.022)	0.011 (0.020)
Male head of household dummy	0.241*** (0.091)	0.055*** (0.020)	0.049*** (0.018)	0.041*** (0.014)
Access to agriculture extension services dummy (1=interacted with a service provider)	0.499*** (0.097)	0.138*** (0.030)	0.117*** (0.025)	0.117*** (0.028)
Proportion of prime age (18-45 years old) members in the household	0.122 (0.184)	0.029 (0.044)	0.026 (0.039)	0.022 (0.034)
ln(annual farm revenue in UShs)	0.017 (0.018)	0.004 (0.004)	0.004 (0.004)	0.003 (0.003)
ln(years of formal education of household head)	0.044 (0.036)	0.011 (0.009)	0.009 (0.007)	0.008 (0.007)
ln (age of head of household in years)	-0.028 (0.111)	-0.007 (0.027)	-0.006 (0.023)	-0.005 (0.020)
Central region	0.740*** (0.132)	0.204*** (0.039)	0.175*** (0.034)	0.176*** (0.038)
Eastern region	1.286*** (0.126)	0.351*** (0.033)	0.310*** (0.033)	0.321*** (0.037)
Northern region	0.649*** (0.134)	0.177*** (0.039)	0.152*** (0.034)	0.151*** (0.037)
Year dummy (1=2010;0=2006)	0.073 (0.103)	0.018 (0.025)	0.015 (0.022)	0.013 (0.019)
Constant	-2.46 (0.509)	-	-	-
σ_u	0.402	-	-	-
σ_e	0.099	-	-	-
Wald chi^2	169.69***			-
Rho	0.133 (0.064)	-	-	-
Likelihood-ratio	-1260.9	-	-	-

Note: ***, ** and * indicate significance level at 1%, 5% and 10%, respectively; standard error in parenthesis. Dependent variable is proportion of maize area allocated to improved seed.
Column (1) presents the estimated parameters of the Tobit regression model.
Column (2) presents the expected values of the dependent variable conditional on being uncensored.
Column (3) presents the change in intensity of adoption with respect to a unit change of the independent variable.
Column (4) presents marginal effects for the unconditional expected value of the dependent variable.

Other significant determinants of the intensity of adoption of improved maize include household access to agriculture extension service and sex of household head (Table 2). In particular, farmer interaction with extension services providers increased the probability of land allocated to improved seed by 13.8 percent. Adopters who interacted with an agricultural extension services provider increased the land allocated to improved maize production by 0.117 hectares. Access to extension and advisory service is an important ingredient for diffusion of new and modern agricultural innovations. The main agriculture extension and advisory services providers in Uganda include the National Agricultural and Advisory Services (NAADS) program, the local government extension system, and other private non-governmental organizations. The positive and statistically significant effect of the extension and advisory services underscores the important role played by extension and advisory services in increasing diffusion and dissemination of improved agricultural production technologies in farming systems in the country. We also found that household with male heads had a higher probability of allocating land to improved maize varieties than those with either female heads or headed by children. Male farmers are relatively endowed with production resources, especially land, and have more sources of finances for farm investments.

Although not significant, household access to agricultural credit exhibited a positive relationship with the intensity of adoption. The non-significant effect of credit could arise due to the small proportion of the credit actually invested in farming. Some households received credit but invested none in the farming, citing uncertain returns associated with farming[3]. Farmers decided to invest all the credit that they obtained in off-farm activities that they judged economically more certain than farming.

All the three regional dummies included in the model are positive and significant, implying high likelihood to adopt and increase the use of improved varieties in these agro-ecological zones, as compared to the western region (the base region for the model). These results imply that regionally-specific factors, whether agro-ecological or due to other locational characteristics, play a significant role in the decision by farmers to adopt and increase the use of improved maize varieties.

The effect of off-farm earnings on productivity

In this sub-section, we present the results of the two step estimation approach employed to investigate the relationship between off-farm income and technical efficiency among smallholder farmers in Uganda. The results of the first step, the stochastic production frontier models, are presented in Table 3. The second step estimations (technical efficiency model) are reported in Tables 4 and 5 and in Figures 1 and 2, where specific comparisons of the distribution of the technical efficiency scores between the two farmer categories are made.

STOCHASTIC FRONTIER ANALYSIS (SFA)

The maximum-likelihood estimates for the parameters in the translog (TL) and the Cobb-Douglas (CD) stochastic frontier production functions for maize farmers in Uganda are presented in Table 3. The estimate of the parameter, associated with the variability of the technical inefficiency effects, is relatively close to the maximum value of one for both the TL and the CD models. These results indicate that technical inefficiency is high in the production of maize by smallholder farmers in Uganda. The variance of the random error terms is significant for both models, and, hence, the stochastic frontier model may be significantly different from the corresponding deterministic frontier model. This is not surprising for a production frontier model for farm-level data, as random errors associated with measurement of output and the effects of excluded variables are expected to be relatively large.

We reject the null hypothesis that the coefficients of the second-order variables in the TL model are zero, implying that the Cobb-Douglas function specification may not be an adequate representation of the data used by the current study. The discussion in the rest of this section therefore focuses on the results derived using the TL model. All the coefficients of the three inputs in the production function are positive, but only labor is statistically significant at the 10 percent level (Table 3). It is not surprising that labor is the most significant input in the production of maize, since most farmers in Uganda, including maize farmers, rely heavily on family labor for agricultural production. The observed lack of significance of the coefficients for capital and land could result from low levels of utilization of these inputs in maize production.

The coefficients for all the squared terms of the inputs used in maize production are positive and significantly associated with maize output, suggesting that maize farmers can increase productivity of the crop by increasing the level of inputs used. Furthermore, two input pairs, land and capital, and land and labor exhibit a positive and significant association with maize output. This means that farmers can reduce production inefficiency in maize production by jointly increasing these paired combinations of inputs. On the other hand, the interaction effect for capital and labor is negative and significant suggesting that the more capital and labor an average farmer employs in a pair; the more inefficient it is to produce maize. The negative effect could be as a result of a case that households with a lot of capital hire many farm laborers who may not have adequate knowledge required for proper application of purchased inputs such as fertilizers and pesticides.

[3] Not all households without access to credit are actually credit-constrained. This effect is not isolated by this study.

Table 3: Maximum Likelihood Estimates of the Stochastic Frontier Analysis Models (TL & CD) in Uganda (2005/06-2009/10)

Variable	Trans-log	Cobb-Douglas
ln(capital)	0.009 (0.020)	0.016*** (0.004)
ln(land)	0.227 (0.182)	0.478*** (0.034)
ln(labor)	0.109* (0.054)	0.193*** (0.028)
½ ln(capital)^2	0.015*** (0.002)	-
½ ln(land)^2	0.023*** (0.006)	-
½ ln(labor)^2	0.051** (0.023)	-
labor-capital interaction	-0.012* (0.007)	-
capital-land interaction	0.017** (0.008)	-
labor-land interaction	0.091 (0.057)	-
year dummy (1=2001, 0=2006)	-1.001*** (0.086)	-0.737 (0.080)
constant	5.593*** (0.270)	6.786 (0.145)
Variance parameters		
/lnsig2v	-0.287*** (0.053)	-0.202*** (0.053)
/lnsig2u	1.046*** (0.056)	1.104*** (0.057)
$\ln \sigma_v^2$	-0.287*** (0.053)	-0.202*** (0.053)
$\ln \sigma_u^2$	1.046*** (0.056)	1.104*** (0.057)
σ_s^2	3.596 (0.158)	3.833 (0.169)
γ	0.791 (-0.015)	0.787 (-0.014)
Log likelihood ratio	-4291.5	-4365.6
Chi-square(10)	497.3	372.3

Note: ***, ** and * indicate significance level at 1%, 5% and 10%, respectively; standard error in parenthesis.

COMPARING THE DISTRIBUTIONS OF EFFICIENCY

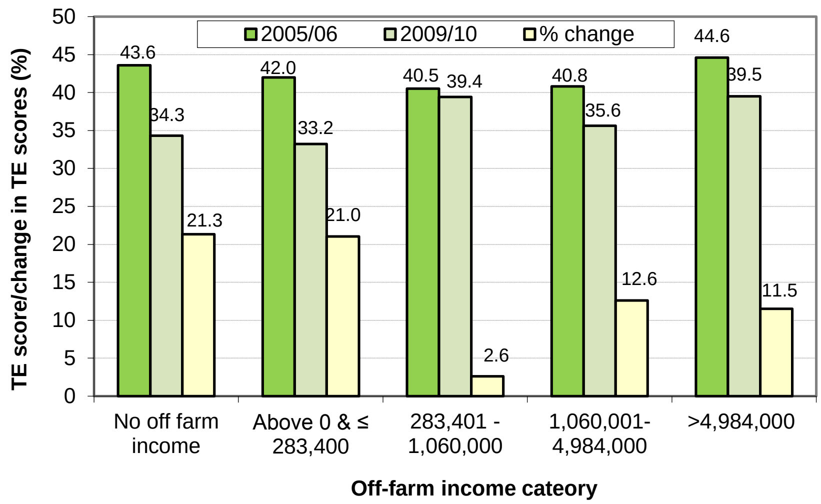
Table 4 presents the summary statistics of technical efficiency scores in terms of means and selected percentiles for farmers who fall in the categories of those with off-farm income and those without off-farm income. The results show that farmers without off-farm income were slightly more efficient relative to their counterparts with off-farm income. The mean level of technical efficiency is about 0.43 for farmers without off-farm income compared to 0.39 for farmers with off-farm income. In addition, farmers without off-farm earnings have a relatively higher level of technical efficiency in most of the percentiles relative to their counterparts.

Table 4: Predicted Farm-level Technical Efficiency and Off-farm Income

Parameter	No off-farm income	Category of farmers with off-farm income (Uganda shillings) ≤ 283,400	283,401 to 1,060,000	1,060,001 to 4,984,000	> 4,984,000
Mean score	0.429 (0.166)	0.380 (0.780)	0.398 (0.196)	0.377 (0.208)	0.415 (0.203)
1 percent	0.038	0.000	0.000	0.000	0.000
5 percent	0.149	0.029	0.000	0.000	0.000
10 percent	0.213	0.124	0.097	0.049	0.127
25 percent	0.318	0.283	0.272	0.225	0.278
50 percent	0.420	0.416	0.420	0.403	0.443
75 percent	0.542	0.508	0.536	0.524	0.556
90 percent	0.661	0.603	0.653	0.647	0.684
95 percent	0.710	0.656	0.705	0.693	0.734
99 percent	0.810	0.731	0.801	0.764	0.780

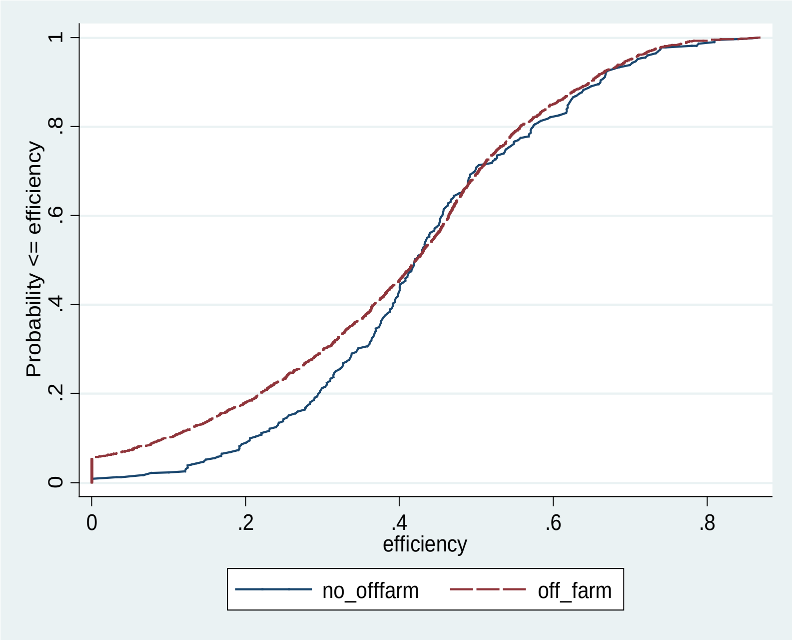
The results further show a decline in technical efficiency (TE) between 2005/06 and 2009/10 (Figure 1). The decline is substantially higher among farmers without off-farm income (21.3percent) and among those with low levels of off-farm income (21.0 percent) compared to the farmers with higher income from off-farm activities. The decline in efficiency can be attributed to economic factors such as high input prices caused by inflation. The high cost of inputs inhibits uptake of improved technologies such as use of certified seed varieties and chemical fertilizers. In the case of seed, resource-poor farmers who cannot afford to buy certified improved seed resort to saving seed from their own production and plant recycled seed, foregoing the higher yields they could get when certified single-cross hybrid seed is used. Productivity of single-cross hybrid maize is predicted to decrease upon recycling.

Figure 1: Change in mean Technical Efficiency scores, 2005/06 – 2009/10



We further examined the relationship between farmers with off-farm income and those without off-farm income by comparing their cumulative distribution functions (CDF) for technical efficiency scores (Figure 2). In general, the CDF for farmers without off-farm income stochastically dominates that for their counterparts with off-farm income, suggesting lower technical efficiency among maize farmers with off-farm income. This may arise from the competition within household for available labor between off-farm economic activities and farm activities. This results in reduced time allocation to farming by farm households that have off-farm work. These results suggests that although off-farm earnings may induce adoption of improved technologies, efficiency gains from adoption may be undermined by the more limited time that farmers with off-farm income sources allocate to farm enterprises. Given the relatively certain returns from off-farm activities, farmers with off farm income also may rely on hired farm labor, which may be lower labor quality than the farmer's own labor. Farmers without off-farm work benefit from the more efficient labor of family members who pay more attention to the quality of their own labor inputs to household farm production.

Figure 2: Cumulative Distribution Functions (CDFs)



THE EFFECT OF OFF-FARM INCOME ON TECHNICAL EFFICIENCY

We estimate the effect of off-farm income by regressing the amount of household off-farm income on the level of technical efficiency predicted from the SFA. The estimated results are based on pooled OLS, random effects (RE) and fixed effects (FE) regressions (Table 5). The standard errors are adjusted for potential heteroskedastic disturbances by adopting the White's standard errors. All three models show a negative association between off-farm income and farm TE. These results corroborate the earlier results analyzed using stochastic dominance. The effect is weakly significant in the fixed-effects model but not significant in the OLS and the RE model.

Table 5: Panel Regression Estimates of Technical Efficiency, 2005/06 and 2009/10

Variable	Pooled OLS	Random effects	Fixed effects
ln (total off-farm income earned x10^{-2})	-0.030 (0.080)	-0.060 (0.080)	-0.230* (0.130)
Use of agricultural extension dummy (1=household interacted with service providers)	0.016 (0.014)	0.014 (0.014)	-0.010 (0.020)
ln(education of household head (years of formal schooling) x 10^{-2})	0.94** (0.43)	0.96** (0.45)	0.960 (1.040)
Planted improved maize seed variety dummy(1=yes)	0.009 (0.011)	0.007 (0.011)	-0.014 (0.014)
Male head of household dummy	0.026*** (0.010)	0.025** (0.012)	-0.030 (0.032)
ln(farm size (hectares))	-0.0102** (0.005)	-0.012** (0.005)	-0.030*** (0.007)
ln(household size (persons))	0.021** (0.008)	0.023*** (0.008)	0.049** (0.020)
Household experienced severe drought during production dummy	-0.019** (0.009)	-0.0185** (0.008)	-0.015 (0.012)
ln (age of head of household (years))	-0.028 (0.013)	-0.0284** (0.014)	0.0138 (0.0638)
Year dummy (1=2010,0= 2006)	-0.036*** (0.009)	-0.034*** (0.009)	-0.0170 (0.0132)
Central region	-0.021 (0.013)	-0.020 (0.014)	-
Eastern region	0.013 (0.012)	0.015 (0.013)	-
Northern region	-0.033** (0.0128)	-0.032** (0.013)	-
Constant	0.456*** (0.055)	0.452*** (0.057)	0.282 (0.231)
Log likelihood ratio	9.07	10584.59	7.55
σ_e	-	0.066	0.150
σ_u	-	0.177	0.177
Rho	-	0.121	0.417
Within R-sq	0.048	-	-
Between R-sq		0.058	0.000
Overall R-sq	0.053	0.053	0.013

Note: ***, ** and * indicate significance level at 1%, 5% and 10%, respectively; standard error in parenthesis.

Our findings, however, show a relatively strong effect of human capital variables on technical efficiency. For example, the coefficient of education is positive and statistically significant (5 percent), suggesting that farmers with some level of formal schooling produce more efficiently compared to less-educated farmers. Formal education enables farmers to make informed production decisions, such as optimal input mixing. We also find that male-headed households are more efficient. Household size exhibited a positive effect on technical efficiency, which is expected because households with many members are expected to be more endowed with higher quality family labor for agriculture production. Farm size has a negative and significant effect on technical efficiency, implying that farmers who have relatively large maize farms are less efficient relative to their counterparts with smaller farms. The result is contrary, however, to the prior theoretical expectations that large farms benefit from increased economies of scale and hence are more efficient. We further find that weather shocks, particularly the drought significantly reduce technical efficiency. Drought spells experienced by farmers during production season results in lower yields, causing lower levels of maize technical efficiency.

CONCLUSIONS AND RECOMMENDATIONS

We utilize two waves of data (UNHS 2005/06 and UNPS 2009/10) collected by the Uganda National Bureau of Statistics (UBOS) to analyze the effects of off-farm earnings on farm-level adoption of improved maize seed and on the productivity of maize farming in Uganda. Our analytical results demonstrate that off-farm earnings are important for adoption of improved seed among smallholder farmers in Uganda. Institutional frameworks that promote and facilitate rural off-farm income generating enterprises to increase availability of capital to farming households are important for increasing farm investment in modern technologies. Another important factor that increases adoption is interaction with extension service providers.

Our analysis also reveals that farmers without off-farm income are generally more efficient than those with off-farm income, implying that productivity gains from increased adoption of improved seed may be undermined by reduction in quality time allocated to farm management because of off-farm opportunities competing for household labor. There is thus need design and implement extension trainings programs aimed at farm labor, whether family or hired-in, more productive. Furthermore, farm mechanisation need to be promoted so that physical capital can substitute for farmer's labor.

Although our study reveals some interesting findings, more research work is needed to address some of the issues that we were not able to deal with in this study. A more sophisticated model is needed to account for the potential endogeneity between off-farm work, adoption and farm productivity. In addition, further related studies need to isolate the effect of off-farm income from various categories of off-farm work – wage earnings, self-employment and household transfers received by the households – while accounting for intra-household labor decisions.

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