Efficiency Effects of Access to Information on Small Scale Agriculture: Empirical Evidence from Uganda

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Abstract

To test the effects of access to information on efficiency in small scale agriculture, we formulate a standard stochastic frontier (SF) model which is augmented with a technical efficiency model that allows for an index which captures farmers' *ability to access information*. The index is constructed as a 2-parameter Rasch model. Panel data on small scale agricultural production in Uganda is used in the construction of the index and the estimation of the SF model. We find empirical evidence of a significant and positive relationship between farmer *ability to access information* and farm efficiency. Mean efficiency for farmers with greater access to information is 90%, about 33% higher than efficiency of farmers with lower access to information. Our findings underscore the need for greater access to ICT equipment and agriculture related information services for small scale farmers in developing countries.

Keywords: Access to Information, Efficiency, Small Scale Farming

JEL code: Agricultural and Natural Resource Economics Q1; Economic Development, Technological Change and Growth (O1, O2, O3)

1 Introduction

Economists have long established that for markets to function efficiently, access to information by agents is critical[1]. Access to price information for example underpins two of the most well-known results in economics, i.e. the First Fundamental Theorem of Welfare Economics and the Law of One Price (Jensen, 2007). At the same time however, access to information can often be costly and/or limited (Stigler, 1961). Nowhere is this truer than in developing countries, where vast populations live in rural areas and are subject to highly inefficient and information asymmetric markets, marked in particular by multiple market failures (e.g. insurance, credit, labour). As Geertz (1978) succinctly wrote of isolated rural economies in developing countries, 'information is poor, scarce, mal-distributed, inefficiently communicated and intensely valued…''.

For much of the developing world, small scale farming is an important source of the livelihoods of peoples particularly those in rural communities which so often lag in access to basic infrastructure. For policymakers, knowing whether farm efficiency effects due to access to information exist is important for a number of reasons. Firstly it provides a justification for directing more resources towards the improvement of access to ICT and related infrastructure (e.g. roads, electricity, etc.) for rural communities. In so doing, other broader policy objectives could be addressed indirectly. For example, the rural-urban drift which sees the (undesirable) mass migration of rural populations to urban locations for jobs. Secondly, improved access to information amongst farmers could provide the medium needed by agricultural policymakers to disseminate information regarding best farming practices and to encourage farmer participation in competitive markets outside their local rural economies.

Thirdly, small scale farmers in low income countries are known to resist adoption of yield enhancing farm technologies (Kelsey, 2011). Improved access to information could provide the conduit needed by policymakers to provide information regarding new technologies (e.g. crop varieties) in the hope of persuading farmers to adopt and in so doing improving their incomes and livelihoods. Indeed non-adoption of technologies could in part be explained by lack of farmer access to credit and risk markets, a situation that is fostered by large information asymmetries between farmers and financial institutions (Kelsey, 2011). With improved access to information, these asymmetries could be further lessened through low cost monitoring and communication channels between financial institutions and the farmers (via mobile telephony for example), hence making it possible for credit access needed by farmers to invest in new technologies.

There is now a body of evidence which supports the view that access to information has significant and positive efficiency and productivity effects on small scale farming in low income countries. For example, Aker and Fafchamps (2010) find in Niger that use of mobile phones have an impact on price dispersion particularly where travel costs are high, while (Overå, 2006) showed evidence in Ghana of mobile phones helping increase the effectiveness of trade networks. Similarly, the World Bank (2012) finds that access to the internet raises

[1] Among other elements needed for efficient markets are property rights, trust, enforceable laws and contracts, competition, etc.

the efficiency of existing processes and makes new production processes possible, whilst Zavale et al. (2005) find that access to electricity enhances efficiency of maize growing farms in Mozambique. Improved access to information could also have more direct efficiency effects associated with cost effective access to agricultural inputs as well as improved managerial practices and farm coordination. For example, De Silva and Ratnadiwakara, (2008) show that access to mobile phones significantly helped gherkin farmers in Sri Lanka reduce waste while Jensen (2007) finds that the adoption of mobile phones significantly decreased price dispersion and wastage for Kerari fishermen in India, hence making markets more efficient and further enhancing both consumer and producer welfare[2].

Whilst there's much empirical evidence of the impact of access to information on efficiency at the macro level, much of the micro-level evidence has been anecdotal (Jensen, 2007). In this paper, we seek to empirically examine the effects of access to information on efficiency in small scale farming by testing this relationship for farmers in Uganda. To accomplish our empirical goal, we formulate a standard parametric stochastic frontier (SF) model which is augmented with a technical efficiency model that allows for an index which captures farmers' *ability to access information*. The novelty of the index is that it is constructed as a 2-parameter Rasch model using data on farmers' access to 6 ICT equipment and services. The assumption is that access to these ICT equipment/services is an indication of farmers' *ability to access information*. We find evidence that farmers' *ability to access information* significantly determines efficiency of small scale agricultural outputs in Uganda. We conclude that more needs to be done to improve access to ICT equipment and agriculture related ICT services for small scale farmers in developing countries as this would improve their livelihoods and grow their rural economies.

The remainder of this paper proceeds as follows: In Section 2, we discuss our empirical strategy. In particular, we discuss the specification of the full SF model as well as the Rasch model used in the construction of the *ability to access information* index. In Section 3, we introduce our data. In Section 4, we discuss our results. The paper concludes in Section 5.

2 Empirical Strategy

2.1 SF model

SF models are motivated by the theoretical idea that no economic agent can achieve efficiencies beyond the ideal efficiency frontier and the deviations from this frontier represent an agent's inefficiency. We index our variables and observations on farm land parcel i and time period t. Following Dawson et al. (1991), we define a SF model as follows;

$$q_{it} = f\left(x_{kit}, \hat{\theta}\right)\exp\left(\varepsilon_{it}\right), \quad i = 1,...,N, \quad t = 2,...,T \tag{1}$$

[2] Mittal, Gandhi, and Tripathi (2010) provide an excellent review of the literature on the impact of mobile phone use in developing countries.

where the $k-th$ index denotes the $k-th$ production input. q_{it} denotes realised farm income[3] (Ugandan Shillings) on a parcel of farm land, x_{kit} is the vector of k farm inputs, $\hat{\theta}$ is a vector of estimated model parameters and ε_{it} is a composite error term that decomposes as the sum of two independent elements; a term v_{it}, representing measurement and specification error; and a term u_{it} representing technical inefficiency relative to the technical frontier i.e.

$$\varepsilon_{it} = v_{it} - u_{it} \tag{2}$$

The inefficiency term u_{it} is fundamental to SF analysis as it represents the inefficiency realised with the technology embodied in the production function $f(.)$. Substituting equation (2) into equation (1) and taking natural logarithms of both sides of equation (1) yields

$$y_{it} = \ln\left\{ f\left(x_{kit}, \hat{\theta}\right)\right\} + v_{it} - u_{it} \tag{3}$$

$$v_{it} \sim J \tag{4}$$

$$u_{it} \sim F \tag{5}$$

where $y_{it} = \ln\left(q_{it}\right)$, J and F are the assumed distributions of the error term v_{it} and inefficiency term u_{it} respectively. The main object of SF analysis is the estimation of u_{it}. Point estimates are however not directly recoverable from model (3)-(5). A strategy for disentangling u_{it} is therefore needed. Typically, this would involve two sequential steps. In the first step, estimates of the model parameters $\hat{\theta}$ are derived. In a second step, estimated $\hat{u}_{it}$ is derived by exploiting its conditional distribution given the predicted composite error term $\hat{\varepsilon}_{it}$, where

$$\hat{\varepsilon}_{it} = y_{it} - \ln\left\{ f\left(x_{kit}, \hat{\theta}\right)\right\} \tag{6}$$

Having obtained point estimates of inefficiency $\hat{u}_{it}$, estimates of the efficiency, $\hat{\eta}_{it}$ realised on the $i-th$ parcel can be obtained as follows

$$\hat{\eta}_{it} = \exp\left(-\hat{u}_{it}\right) \tag{7}$$

Assumptions about the time dependence of the error term v_{it} and inefficiency term u_{it} as well as their respective distributions J and F are needed to make model (3)-(5) efficiently estimable by Maximum Likelihood method (Belotti et al. 2012). As such, these considerations have received significant attention and have motivated different specifications in the SF analysis literature (e.g. Lee and Schmidt, 1993; Kumbhakar, 1990; Battese and

[3] 'Income' is used interchangeably with 'output'.

Coelli, 1992; Battese and Coelli, 1995; Greene, 2005). We adopt the specification proposed by Battese and Coelli (1995). Accordingly the model we estimate is presented as follows;

$$
\begin{aligned}
& y_{it} = \ln\left\{ f\left(x_{kit}, \hat{\theta}\right)\right\} + v_{it} - u_{it} \\
& v_{it} \sim N\left(0, \sigma_v^2\right) \\
& u_{it} \sim N^{+}\left(\mu_{it}, \sigma_u^2\right)
\end{aligned} \tag{8}
$$

where N and N^{+} denote normal and truncated-normal distributions respectively for the measurement error and inefficiency terms, σ_v^2 and σ_u^2 are the variances of the respective distributions; and μ_{it} is the mean of the technical inefficiency distribution. Both distributions are independent and identically distributed.

2.1.1 Functional form for production technology

We have deliberately not specified the functional form for the production technology, $f(.)$ in our SF model (8). As Michler and Shively (2015) point out, debate exists around what is the most appropriate functional form for production technology with numerous early studies adopting the less flexible Cobb-Douglas production function largely due to empirical difficulties with otherwise more flexible functional forms. Recent computational and econometric advancements however have enabled use of the flexible functional forms such as the translog form. Following Michler and Shively (2015), we adopt a translog production function and accordingly expand production technology $f(.)$ in model (8) as follows;

$$
\begin{aligned}
\ln\left\{ f(.)\right\} = & \sum_{h}^{4} \beta_h \ln\left(X_{hit}\right) + \frac{1}{2}\sum_{h}^{4}\sum_{l}^{4} \beta_{hl} \ln X_{hit} \ln X_{lit} \\
& + \sum_{j}^{9} \gamma_j D_{jit} + \frac{1}{2}\sum_{h}^{4}\sum_{j}^{9} \phi_{hj} \ln X_{hit} D_{jit}
\end{aligned} \tag{9}
$$

In the above specification, there are $h=4$ quantitative production inputs X_{hit}, and $j=9$ qualitative variables D_{jit}, for a total of $k=13$ variables. The quantitative inputs for the $i-th$ farm parcel are parcel size $(prclSize)$ measured in acres; farm labour (lab) measured in the number of days worked; value of land parcel $(valOfLand)$ measured in the monetary value of a parcel per acre[4]; and total monetary cost of pesticide $(pest)$ used on a parcel. Six of the nine qualitative variables are binary indicators capturing each of the $T=6$ production periods in our panel dataset. These are named $D_{1,it}, D_{2,it}, \ldots, D_{6,it}$ respectively. For example, $D_{1,it}=1$ for $t=1$ and $D_{1,it}=0$ for $t \neq 1$. To avoid perfect collinearity, the first period $D_{1,it}$ is marked as the reference period. The remaining three qualitative variables are binary

[4] This variable is a proxy for the farm land quality.

indicators *tractor*, *oxen*[5] and *rainfed* indicating whether parcel is farmed with tractor or oxen and whether the main source of water on a parcel is rain. Use of *tractor* and/or *oxen* is expected to increase the capital labour ratio for a parcel and thus is expected to increase efficiency. For computational reasons, we do not include a constant term, as doing so introduces numerical problems in the estimation.

Following Michler and Shively (2015), we do not include interaction terms between qualitative inputs in (9) for three reasons. First, it is difficult to construct a theoretical argument regarding how these terms should interact. Secondly, such interaction terms are likely to introduce a substantial degree of collinearity. Thirdly, the model is more parsimonious without the inclusion of such terms. Equation (9) is substituted into model (8) to carry out the SF model estimation via Maximum Likelihood method.

2.1.2 Technical efficiency model

The issue of interest in this paper is the degree to which access to information affects efficiency of farm outputs. Accordingly, let $infoIndex_{it}$ denote an index indicating the ability of the farmer or household managing parcel i in period t to access information. Whilst $infoIndex_{it}$ is not a direct farm input and so does not appear in equation (9)[6], it nonetheless affects the output of the $i-th$ parcel as farmers with more access to information are more likely to adopt better farming practices hence realise higher efficiency. $infoIndex_{it}$ and similar variables which are neither the inputs nor outputs of the production process but affect (in)efficiency are known as 'exogenous inefficiency determinants' (Belotti et al., 2012).

Typically, researchers would examine the effects of the exogenous inefficiency determinants on efficiency by using a two-step SF procedure (Belotti et al., 2012). Wang and Schmidt (2002) however show that this approach can lead to severely biased results. A number of approaches have been proposed which simultaneously estimate the coefficients of the production function as well as the exogenous inefficiency determinants by introducing a technical efficiency model to augment the SF model. Among these are the approaches proposed by Kumbhakar et al. (1991), Huang and Liu (1994) and Battese and Coelli (1995). As noted above, we adopt the approach by Battese and Coelli (1995). They propose simultaneous estimation of the coefficients of the inefficiency determinants by introducing heterogeneity in the location parameter μ_{it} of the truncated inefficiency distribution $N^{+}\left(\mu_{it},\sigma_u^2\right)$. We accordingly augment our SF model (8) with the following technical efficiency model;

[5] Tractor and oxen ownership is not available for period 1 and period 2 in our data. Ownership of such farm capital is however persistent over time. We therefore assume a household has ownership of a tractor and oxen in periods 1 and 2 if it has ownership in any subsequent period. This assumption prevents huge loss of usable data.

[6] Period variables $D_{1,it}, D_{2,it}, \ldots, D_{6,it}$ are not farm inputs either. However, they are included in the translog production function to capture intertemporal effects.

$$\mu_{it} = \alpha_1 \cdot infoIndex_{it} + \alpha_2 \cdot maleHead_{it} + \alpha_3 \cdot ageHead_{it} + \alpha_4 \cdot propEduc_{it} \qquad (10)$$

where $maleHead_{it}$ is a binary variable indicator showing whether head of household managing parcel i is male (=1) or female (=0), $ageHead_{it}$ is the age of the head farmer managing parcel i and $propEduc_{it}$ is the proportion of educated residents in the household managing parcel i. The four exogenous inefficiency determinants in (10) are proxies for ability and/or experience of the farmer or household managing parcel i and hence affect the (in)efficiency realised on the parcel. A positive (negative) coefficient $\alpha_p \left(p = 1,...,4 \right)$ in (10) increases (decreases) inefficiency by increasing (decreasing) the mean inefficiency μ_{it} of the truncated normal inefficiency distribution $N^+\left(\mu_{it}, \sigma_u^2\right)$ in model (8). A negative and significant coefficient of $infoIndex_{it}$ (i.e. α_1) is therefore prima facie evidence of the positive effects of access to information on farm efficiency. We reiterate that in model (8), the parameter vector in (9) and (10) are simultaneously estimated.

2.1.3 Estimation issues

A potential econometric issue is that persistent unobserved heterogeneity at the farmer or parcel level may bias estimation of our model. A solution to this problem would be to exploit the panel nature of our data to control for unobservable farmer or parcel characteristics. An advantage of adopting the Battese and Coelli (1995) specification for panel data estimation of SF models is that it controls for potential unobserved heterogeneity in order to obtain unbiased estimates. We therefore expect our results to be unbiased. A disadvantage to this method however is that it assumes technical inefficiency distribution to be monotonic i.e. technical inefficiency is either increasing or decreasing for all farmers/parcels in the panel at all times. This assumption could be unrealistic because some farmers in the data may become more technically efficient at the same time as others become less efficient (Belotti et al., 2012).

2.2 Rasch model: Quantifying '*ability to access information*' index

As noted in our introductory discussion, much of the micro-level evidence in the literature on the effects of access to information in developing countries has been ***anecdotal*** (Jensen, 2007). A key to our ***empirical*** approach to examine these effects is to construct a variable that objectively captures and quantifies subjects' *ability to access information*. The novelty of our approach is that we achieve this variable by constructing it as an index ($infoIndex_{it}$) using a 2-parameter Rasch model on Ugandan farmers' access to 6 ICT equipment and services. The assumption is that access to these ICT equipment/services is an indication of farmers' *ability to access information*. The variables are $electricity_{it}$, $radio_{it}$, $phone_{it}$, PC_{it}, $internet_{it}$ and $extension_{it}$, each indicating whether farm parcel i in period t is managed by a farmer or household with access to electricity, radio, mobile phone, personal computer, the internet and/or government extension service respectively.

Rasch models are a type of Item Response Theory (IRT) models where responses are binary (1 = have access; 0 = have no access) as is the case with our 6 access to ICT equipment/service variables. Rasch models concern models in which responses to questionnaire variables reveal latent traits of respondents, usually conceptualised as the respondent's *ability* (Bond and Christine, 2013). They have been used to index latent traits such as intelligence (Rasch, 1993), pain tolerance (Tennant and Conaghan, 2007) and anxiety (Pallant and Tennant, 2007). In our case the latent trait being measured is farmers' *ability to access information*. The link between the binary variables and the latent trait is non-linear. It is assumed that this link is a logistic distribution hence the use of the logistic function to fit Rasch models. We formally estimate the 6-item information-access index $infoIndex_{it}$ using the following 2-parameter Rasch model;

$$\pi_{1ij} = \frac{\exp\left[a_j\left(infoIndex_i - b_j\right)\right]}{1+\exp\left[a_j\left(infoIndex_i - b_j\right)\right]} \tag{11}$$

where π_{1ij} is probability that farmer managing parcel i has access to equipment/service item j, a_j is the level of *'discrimination'* in access to equipment/service item j and b_j is *'difficulty'* of access to equipment/service item j.[7]

$infoIndex_i$, a_j, b_j and π_{1ij} are all endogenously determined, where a_j, b_j and $infoIndex_i$ are continuous and unbounded whilst π_{1ij} being a probability is continuous but bounded between 0 and 1. *Difficult* items would typically be the more expensive and less common ones and would typically accord greater access to information. Ownership of *difficult* items (e.g. the internet) would therefore give greater ranking in the index ($infoIndex_i$). The more *discriminatory* an item, the more sharply it differentiates between respondents' *ability to access information* ($infoIndex_i$). This means that the ranking on the index ($infoIndex_i$) of a subject with access to a very *discriminatory* item can be sharply higher than that of a subject with access to a low *discriminatory* item.

We may construct a *naïve* index by simply counting the *'number'* of ICT equipment/service a farmer has access to as an indication of their *ability to access information*. This would mean that a farmer scores say 2 if he has access to any 2 of the 6 ICT equipment/services mentioned. Since our variables are indexed at the parcel i and period t level, all parcels managed by this farmer would have a score of 2 on the *ability to access information* index. An example of such a simple index is the ICT-usage index in (Esselaar et al., 2006). Such an index however does not consider the *'type'* of ICT equipment/service involved. It therefore does not reflect the difficulty of access to the equipment/services involved, or their differences in terms of the level of useful farm related information gained from access to them. For example, take the case of two farmers who each have access to 2 of the 6 ICT variables above;

[7] For a fuller discussion of the definitions of these terms, see 'http://www.rasch-analysis.com' (accessed April, 2015)

	electricity	*radio*	*phone*	*PC*	*internet*	*extension*
Farmer I	1	1	0	0	0	0
Farmer II	1	0	0	0	1	0

Table 1: Capturing *number* and *type* of equipment/service accessed in the information index

In a simple index, both farmers would score 2 by way of the number of ICT equipment/services they have access to. Surely however, Farmer II should have a higher ranking due to the potentially higher level of useful farm related information sourced from access to the internet rather than a radio set. A more appropriate index would therefore reflect and weigh the *number* as well as the item *types* (i.e. items' *difficulty* and *discrimination*) a subject has access to. This is what the Rasch model does in constructing the *ability to access information* index, $infoIndex_i$.

3 Data

We use the Ugandan National panel Survey (UNPS) which is an annual panel survey of a nationally representative sample of Ugandan households. There are two rounds to each annual wave. These rounds are conducted at 6 month intervals in order to 'better capture agricultural outcomes associated with the two cropping seasons of the country' (UNPS, 2012). The survey started in 2009 with data collected for some 2,975 households. Subsequent waves were carried out for 2010/11 with some 2,716 households surveyed and 2011/12 for 2,277 households.

We first undertook data transformation of the UNPS dataset to achieve a secondary panel. In doing so, we define time period t as a half-year. We therefore construct a 6-period secondary panel[8] from the 3-year UNPS dataset. Each period in the secondary panel represents a whole farming season with a planting session at the beginning and a harvesting session at the end of the sixth month. This data transformation, along with indexing our observations at the parcel level (rather than household level), presents an econometric advantage because a longer panel is likely to increase the precision of our empirical estimates.

After data processing of all relevant variables, we attained 2,562 unique farm households and 7,944 unique parcels of farm land over the 6 periods (3 years) of the panel, though the panel is unbalanced[9].

Table 2 presents parcel level summary statistics for variables used in the SF analysis, differentiated by the *ability to access information* index, *infoIndex*[10]. As expected mean farm income, parcel size, yield, pesticide use and proportion of educated household residents are significantly higher for parcels managed by farmers with high *ability to access information*.

[8] Period 1 and 2 are derived from UNPS 2009/10, Period 3 and 4 from UNPS 2010/11 and Period 5 and 6 from UNPS 2011/12

[9] See supplementary material to this paper for more information on data and variable construction

[10] Low and high ability to access information are defined in Section 4.2.1

Perhaps unexpectedly, mean land parcel value is higher for parcels managed by households with low access to information. Ability to access information does not seem to significantly differentiate the distribution of parcels in terms of source of irrigation (i.e. *rainfed*) or the age of the farmers managing the parcels.

	low *infoIndex* (*N*=15,340)		**high *infoIndex*** (*N*=12,626)	
	Mean	Std. Dev.	Mean	Std. Dev.
Farm income (U. Sh million)	0.34	7.84	0.82	31.99
Parcel size (acres)	2.73	32.44	4.15	65.15
Yield (U. Sh. million /acre)	1.65	36.01	9.15	382.06
Labour (No. of days/acre)	13.16	87.04	17.47	138.85
Land value (U. Sh. thousand /acre)	5.02	525.40	1.79	131.16
Pesticide (U. Sh. thousand /acre)	8.00	223.07	72.00	2519.05
Tractor	0.00	0.04	0.00	0.07
Oxen	0.08	0.26	0.11	0.32
Rain fed	0.52	0.50	0.52	0.50
Male head	0.67	0.47	0.82	0.39
Age head	47.95	15.35	44.82	13.06
Proportion educated	0.47	0.32	0.67	0.26

Table 2: Parcel characteristics, differentiated by access to information index

Table 3 reports the percentage of farm parcels which have the managing farmer or household having access to the corresponding equipment/service used in the construction of the *ability to access* information index. Most parcels are managed by farmers with access to radios and to some extent, mobile phones. The internet is the least accessible service, with very few or no parcels managed by a farmer with access to it in periods 1 and 2. Access to or ownership of the 6 access variables tends to be persistent over time hence the variation in percentages across periods is minimal, with any variations likely to be caused by attrition in the data.

	2009/10		**2010/11**		**2011/12**	
Variable	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
electricity	4.06%	4.09%	3.23%	2.96%	3.40%	3.35%
radio	67.59%	67.56%	67.45%	69.45%	67.25%	69.18%
phone	46.85%	46.88%	51.66%	52.52%	58.81%	60.92%
PC	1.23%	1.22%	0.44%	0.43%	0.48%	0.44%
internet	0.00%	0.00%	0.09%	0.08%	0.31%	0.28%
extension	12.98%	12.96%	8.93%	8.84%	14.14%	13.58%

Table 3: Percentage of farm parcels managed by farmers or households with access to ICT equipment/service

4 Results

As the SF model uses results from the Rasch model, we first present the results of the Rasch model, and then proceed to present results from the SF model.

4.1 Rasch model

We implement the Rasch model in equation (11) as a logit structural equation model. The variance of the latent information-access index $infoIndex_i$ is constrained to 1 to aid interpretation (Stata, 2012). This way the distribution of $infoIndex_i$ is normally distributed with 0 mean and unit variance i.e. $N(0,1)$. The resulting difficulty and discrimination of the 6 items in the model are presented in Table 4 below;

N = 27,966
Log Likelihood = -50437.061

Item *j*	***electricity***	***radio***	***phone***	***PC***	***internet***	***extension***
a_j (discrimination)	2.03***	1.53***	2.39***	1.29***	3.28***	0.44***
	(0.098)	(0.065)	(0.158)	(0.101)	(0.431)	(0.027)
Rank a_j	4	3	5	2	6	1
b_j (difficulty)	2.41***	-0.70***	-0.07***	4.37***	3.59***	4.68***
	(0.136)	(0.028)	(0.024)	(0.142)	(1.124)	(0.021)
Rank, b_j	3	1	2	5	4	6

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Table 4: Rasch model results for the information-access index

Consistent with Table 3, *radio* and *phone* are the least ranked *difficult* items to access, with over 50% ownership of these items on average across periods. However, our expectations on the ranking of the remaining items in terms of *difficulty* are not met. For example, we a priori expected *internet* to be the most *difficult* item because access to this service is lowest across periods as seen in Table 3. The estimates suggest that *internet* is only the fourth most *difficult* item. However, consistent with our expectation, *internet* is the highest ranked *discriminatory* item, meaning that the ability of an individual to access information (i.e. their *infoIndex* ranking) given that they have access to the internet, can be sharply higher than the ability of another without access, ceteris paribus. Table 5 reports the estimated information-access index for various combinations of the 6 items in the Rasch model.

Household access to item (s)	**Information-access index,** $infoIndex_i$
None	-1.043675
extension only	-0.8329193
PC only	-0.4603853
radio only	-0.3657558
radio, extension only	-0.1877102
electricity only	-0.1632907
phone only	-0.018712
radio, PC only	0.1576323
phone, extension only	0.1596604
radio, PC, extension only	0.3402535
internet only	0.3422879
electricity, radio only	0.4642835
radio, phone only	0.622498
electricity, radio, extension only	0.6584128
radio, phone, extension only	0.823343
electricity, phone only	0.851728
electricity, radio, PC only	1.058908
electricity, phone, extension only	1.061303
radio, phone, PC only	1.234261
electricity, radio, PC, extension only	1.273496
radio, phone, PC, extension only	1.449975
electricity, radio, phone only	1.591306
electricity, radio, phone, extension only	1.801035
radio, phone, internet only	2.163455
electricity, radio, phone, PC only	2.186368
radio, phone, internet, extension only	2.348181
radio, phone, PC, internet only	2.676018
radio, phone, PC, internet, extension only	2.82913
electricity, radio, phone, PC, internet only	3.319669
electricity, radio, phone, PC, internet, extension only	3.446725

Table 5: Information-access index, $infoIndex_i$

Table 5 above shows that the farmer managing parcel i who has access to all ICT equipment/service ranks highest on the information-access index with an *ability to access information* score of nearly 3.45 whilst a farmer with no access to any equipment or service ranks lowest with an ability of about -1.04.

4.2 SF model

Two functions make up our SF model; the translog production function in equation (9) and the technical efficiency function of equation (10). We reiterate that coefficients for both functions are simultaneously estimated. Our main interest is with the estimated coefficients of the technical efficiency function, which shows the effect of *ability to access information* (*infoIndex*) on inefficiency. We however first report coefficients for the translog production function as these estimates would provide information about the production characteristics of

Ugandan farm households. Moreover, the plausibility of the estimates for the translog function would also point to the tenability of our composite SF model.

4.2.1 Production function estimates

We subjectively defined low ability to access information (i.e. low *infoIndex*) as having a negative *infoIndex* value, and high ability to access information (i.e. high *infoIndex*) as otherwise. We think this is a reasonable classification, given that six out of the seven instances of negative *infoIndex* correspond with ownership or access to one equipment/service only.

Table 6 below reports coefficients of the translog production function in the SF model. Only significant variables and interactions terms are reported. For brevity and relevance to discussion, we do not report estimates for period variables (i.e. $D_{1,it}, D_{2,it}, ..., D_{6,it}$) and their interactions with other variables, though some of these terms are significant. The coefficients of parcel size, labour use and use of pesticide are positive and statistically different from zero suggesting that increased use of these variables significantly increases output. We a priori expected coefficients for value of land parcels and use of oxen to be positive. We also expected variable *rainfed* to have a negative coefficient because rainfed parcels are without irrigation for much of non-rainy farming seasons. Somewhat surprisingly, the signs of the coefficients for these variables are reversed, hence contradicting our expectations. As suggested by Michler and Shively (2015) in a different context, a possible explanation for the unexpected negative coefficients is that the coefficient of the interaction of the subject variables (i.e. *valOfLand* and *oxen*) with other variables in the translog specification account for their expected positive marginal products hence reducing the coefficient of the single variables to the extent that they become negative.

In the case of variable *rainfed*, the unexpected positive coefficient suggests that rainfed parcels are more productive than irrigated parcels. A possible explanation for this result is that irrigated parcels are not optimally watered hence making the marginal product of rainfed parcels positive. This line of argument has been advanced by Mignouna et al., (2010) in the context of fertiliser use, where it was found that fertiliser use impacted negatively on farm output due to sub-optimal application. The same argument could also be advanced as a second explanation for the negative impact of *oxen*, where use of oxen for traction is sub-optimally applied.

Production function			Technical efficiency function		
	Coefficient	Std. Err.		Coefficient	Std. Err.
ln (*prclSize*)	0.711***	0.160	*infoIndex*	-2.188***	0.253
ln (*lab*)	0.173***	0.064	*maleHead*	-0.338	0.194
ln (*pest*)	0.268***	0.053	*ageHead*	-0.004	0.005
ln (*valOfLand*)	-4.305***	0.134	*propEduc*	-4.104***	0.789
oxen	-2.001***	0.415			
rainfed	8.029***	0.287			
ln (*prclSize*) * ln (*valOfLand*)	0.180**	0.084			
ln (*prclSize*) * ln (*lab*)	-0.153***	0.015			
ln (*prclSize*) * ln (*pest*)	-0.081***	0.014			
ln (*lab*) * ln (*pest*)	-0.037***	0.007			
oxen * ln (*lab*)	0.537***	0.069			
oxen * ln (*valOfLand*)	-0.709**	0.342			
rainfed * ln (*lab*)	0.514***	0.064			
rainfed * ln (*prclSize*)	0.850***	0.248			
rainfed * ln (*valOfLand*)	7.667***	0.350			
rainfed * ln (*pest*)	0.291***	0.063			
Log likelihood = - 8836					
N = 27,966					

Note: $^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$

Table 6: SF model estimates

Negative interaction between continuous variables suggests the constituent variables are substitutes for one another. For example, the interaction between parcel size and labour is negative suggesting labour is a substitute for parcel size. Smaller parcels are therefore more labour intensive. Positive interactions between continuous variables suggest complementary impact on output, as found for parcel size and parcel value. Significant interactions between categorical variables (*oxen* and *rainfed*) with continuous variables mean the effect of the continuous variable on output is dependent on the categorical variable. For example, the positive and significant interaction between oxen and labour use means that labour is more effective on parcels that are ploughed by oxen.

4.2.2 Technical efficiency distribution estimates

Coefficients for the technical efficiency model are also listed in Table 6. A negative coefficient implies the associated variable reduces inefficiency (i.e. increases efficiency). For this study, we are most interested in the effect of farmer *ability to access information* (*infoIndex*) on technical efficiency. Coefficient for *infoIndex* is negative and significantly different from zero, suggesting that parcels of farm land managed by farmers with higher access to information are more efficient and closer to the ideal stochastic frontier. This finding is consistent with our a priori expectation, and corroborates the literature cited in our introductory discussion. For further analyses, we recovered technical efficiency estimates from the inefficiency predictions in equation (10) using equation (7). The distribution of technical efficiency by *infoIndex* is given in Table 7.

Variable	*N*	Mean	Std. Dev.	Min	Max
Technical efficiency	27,966	0.72	0.24	0.03	0.96
by High *infoIndex*	12,626	0.90	0.05	0.59	0.96
by Low *infoIndex*	15,340	0.57	0.24	0.03	0.91

Table 7: Summary statistics of technical efficiency, by *infoIndex*

Average technical efficiency is about 0.72 across parcels. The average for parcels managed by households with higher ability to access to information is however 0.90, about 33% higher than efficiency on parcels that are managed by households with lower ability to access information. The standard deviation of efficiency is also much lower for parcels managed by households with higher ability to access information, perhaps indicating that they have more stable farm outputs and hence farm incomes. This suggests that ability to access information has implications for volatility of farm incomes. Figure 1 below graphically illustrates the relationship between ability to access information and technical efficiency. Consistent with our observations thus far, efficiency looks to increase with higher ability to access information.

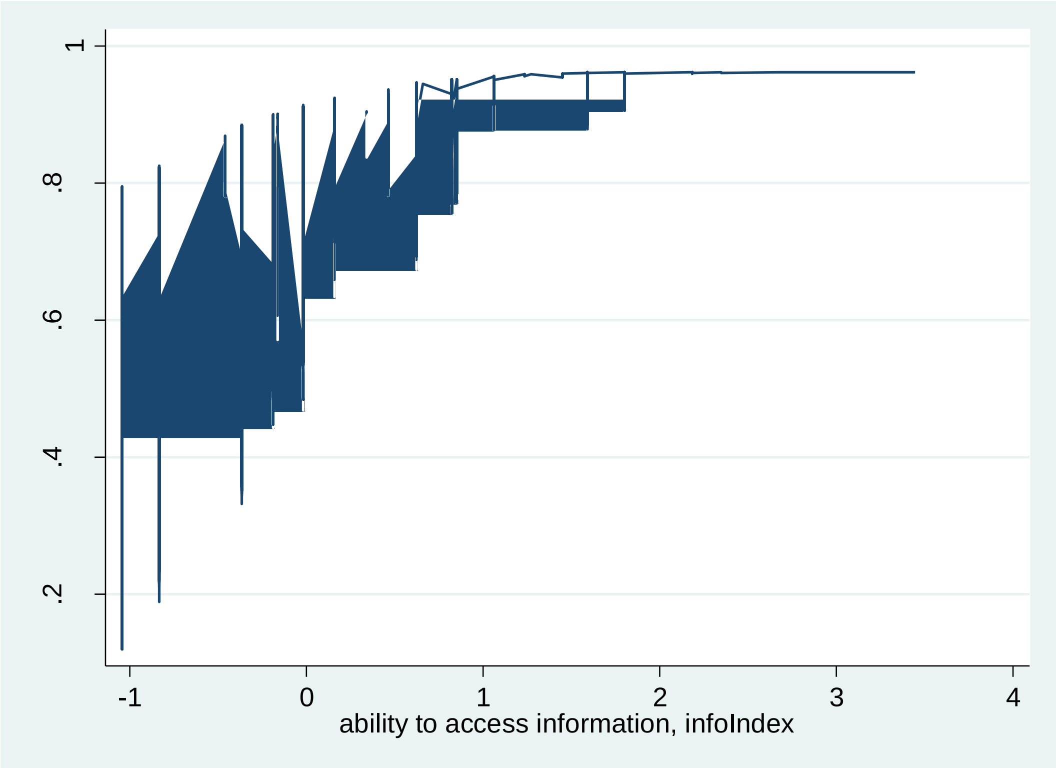

Figure 1: The relationship between efficiency and ability to access information (*infoIndex*)

Among the additional variables in the technical efficiency model, coefficient for age of the household head managing a parcel (*ageHead*) is not significantly different from zero suggesting that age, a proxy for experience, does not determine farm efficiency. Similarly, coefficient for parcels managed by male household heads (*maleHead*) does not significantly affect efficiency, suggesting that gender of a farmer is irrelevant to efficiency realised on a parcel. However, the coefficient of the proportion of educated residents in a household managing a farm parcel (*propEduc*) is negative and significantly different from zero suggesting that literacy significantly increases the efficiency realised on a parcel. In a way, *propEduc* is related to *infoIndex* as households with higher levels of education and literacy are likely to have greater capacity to 'receive, decode and understand information'. The coefficient for *propEduc* could therefore be regarded as further evidence of the significant impact of farmer *ability to access information* (*infoIndex*) on farm efficiency.

5 Conclusions

We have empirically tested the relationship between farmers' ability to access information and farm efficiency. We find evidence of a significant and negative (positive) relationship between farm inefficiency (efficiency) and farmers' ability to access information. Farmers with greater access to information therefore realise greater efficiencies in their farming activities. This finding corroborates a number of empirical and anecdotal evidences in the literature as cited in our introductory text. It has significant implications for policy making geared towards poverty reduction in developing countries where farming is an important source of livelihood particularly in rural communities. This significance is further crystallised by a finding of the World Bank (2008) which points to the fact that growth in agriculture is on average at least twice as effective in reducing poverty as growth outside agriculture. For this reason, opportunities to improve efficiency in agriculture through improved access to information should be taken seriously. Improved farm efficiencies due to improved access to information could reduce poverty directly through enhanced farm incomes, and indirectly by enabling profit based farming that supports livelihoods beyond the subsistence level. It would also help reduce prices of food which constitutes a significant portion of the budgetary allocations of the rural poor, further reducing poverty.

Whereas general access to information on farming best practices, market information (e.g. prices, logistics, spatial demand distribution, etc.) and contextual information (e.g. weather, village specific farm features, etc.) are important, the promptness and relevance of the information as well as its credibility are important features that need to be ensured to enable farmers leverage the full potential of information in enhancing farm efficiencies. These characteristics may require significant improvements in ICT infrastructure and capacity building by governments as well as information service providers. For example, investments in roads, mobile mapping technologies, telephone and internet infrastructure, etc. Government research in agriculture should be promoted and the role of agricultural extension officers in disseminating relevant research outputs to often isolated rural communities should be supported.

We acknowledge the position of critics who argue that investments in ICT infrastructure and services should not be a priority for developing countries, given the inadequacies in infrastructure for health, education, etc. Microsoft's Bill Gates (Gates, 2000) is among the most prominent of such critics. This position however neglects the evidence in the literature, corroborated by this study, that access to information enabled by investments in ICT infrastructure and services can significantly raise the incomes of a significant fraction of the poor in developing countries. This has the potential of raising their living standards which enhances access to health, education, etc.

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