DETERMINANTS OF USE OF KENYA AGRICULTURAL COMMODITY EXCHANGE ICT: THE CASE OF SMALLHOLDER FARMERS IN BUNGOMA COUNTY, KENYA

Wawire, A.W., Okello, J. and Wangia, S.M.
Department of Agricultural Economics, University of Nairobi, P. O. Box 30197-00100, Nairobi
Dept of Agricultural Resource Economics and Extension, Karatina University, P. O. Box, 1957-10101, Karatina
Email: wanjamos@gmail.com, Tel.: +254720282813

Citation: *Wawire, A.W., Okello, J. and Wangia, S.M.(2014)* Determinants of use of Kenya agricultural commodity exchange ict: the case of smallholder farmers in Bungoma county, Kenya. In: Isutsa, D.K. and Githae, E.W. *Proceedings of the Second Chuka University International Research Conference held in Chuka University, Chuka, Kenya from 28th to 30th October, 2015*

ABSTRACT
Smallholder farmers' access to markets has traditionally been constrained by lack of market information. Efforts to strengthen access of farmers to markets has triggered the mushrooming of a number of projects that embrace ICT tools in promoting access to competitive market information. Nevertheless, most farmers still lack access to accurate market information such as commodity prices. This study examines the determinants of the use of ICT tools by Kenya Agricultural Commodity Exchange (KACE) among smallholder farmers for agricultural transactions. The data used for this study were collected in 2011 from smallholder farmers in Bungoma South and Central Sub-Counties. The two Sub-Counties were purposively selected because of being the hub of KACE activities. Multi-stage sampling was used to select 136 households for interview using pre-tested semi-structured questionnaire. Farmer characteristics, farm and capital endowment factors affected use of ICT tools, particularly mobile phones. Occupation, farming experience, age, literacy and crop income explained use of tools. Household size, crop income, gender, level of literacy, owning a mobile phone, nearness to output market, level of literacy and crop income explained intensity of use of the mobile phones. The paper further discusses the policy implications of the findings.

Keywords: ICT, market, Mobile phones, Agriculture, Market access

INTRODUCTION
Agricultural information is a critical ingredient to improving small-scale agricultural production and linking farmers to profitable markets. This will translate to better rural livelihoods in terms of food security at both household and national level, and overall enhanced national economies. Improved productivity in agriculture will be realized when farmers are linked to market information (Rogaly, et al, 199). However, in most rural regions, the smallholder farmers and small-scale entrepreneurs are consistently incapacitated

by lack of information on prevailing market prices before they travel to the market. This is due to poor communication facilities forcing farmers to often rely on middlemen who take advantage to exploit them. Poorly organized marketing activities coupled with inadequate marketing experience, and poor access to farm capital, have further exacerbated farmers' woes (Munyua, 2007).

This scenario has necessitated the emergence of ICT-based marketing information systems especially in developing countries, which target small-scale producers. Some of these include and not limited to, the Kenya Agricultural Commodity Exchange (KACE) and DrumNet in Kenya; TradeNet in Ghana; Malawi Agricultural commodity Exchange in Malawi; Songhai Centre in Benin, and women of Uganda Network (WOUGNET) in Uganda (Ferris et.al, 2006). Others include Govi Gnana Seva (DDEC) in Sri-Lanka; D-Net1's Community-based Technology Centre (CTC) and Grameenphone and Katalyst2's Grameenphone Community Information Centre (GPCIC in Bangladesh (Dey 2008). These initiatives to resolve the problem of poor access to better performing markets by smallholder farmers have thus focused on supporting information transfer through ICT-based innovations (Tollens, 2006; Aker, 2008). These innovations include mobile telephony, internet/web-based means, and interactive video and CD-ROM programs as well as older ICT-based technologies namely the radio and television (Munyua, 2007). The promotion of these mostly new generation ICT tools especially the mobile phones stems from its rapid penetration in Africa and increased ownership by rural population (Okello et al., 2010).

The increased focus on modern ICT methods of information provision is because they can play a critical role in: i) communicating knowledge and information to smallholder farmers, ii) providing educative and training components to farmers at affordable rates, iii) improving rural producers' access to remunerative markets and farm credit, iv) endowing smallholders to effectively bargain for profitable prices, and v) mobilizing, promoting and enhancing networking among smallholder farmers.

Despite the proliferation of ICT Information Systems, capable of addressing farmers' marketing information needs, numerous challenges still prevail, such as low prices for farm produce and poor access to agricultural inputs, attributed to poor bargaining power. The problem has been blamed to such factors as low literacy among the target users, complexity of some tools, and lack of electricity in the rural areas, and so, the awareness and level of utilization of the services offered by these initiatives among farming communities is reportedly low (Munyua, 2007). Owing to the reality that little is known about the application of these tools for agricultural transactions has further undermined their usage.

This study examines the factors that determine the use of ICT tools for agricultural transactions by assessing the factors that affect the use of mobile phones, which is undoubtedly the most popularly owned and adopted new generation ICT tool among farm households, for agricultural purposes. Principally, the study focuses on smallholder farmers in Bungoma County. It uses data collected in 2011 from smallholder farmers stratified by participation in Kenya Agricultural Commodity exchange, an ICT-based Market Information Service project. The rest of this paper is organized as follows: Section 2 presents the conceptual framework used for study. This is followed by Section 3, which presents and discusses the study results. The conclusion of the study is presented in section 4.

CONCEPTUAL AND EMPIRICAL METHODS

Knowledge is becoming an increasingly significant factor in production and marketing for small-scale agriculture. Timely knowledge about what and when to plant; where and who is buying the farm produce, the price on offer, who are the potential buyers are and what the important expected costs, such as transport, is critical for the decision making by the producers.

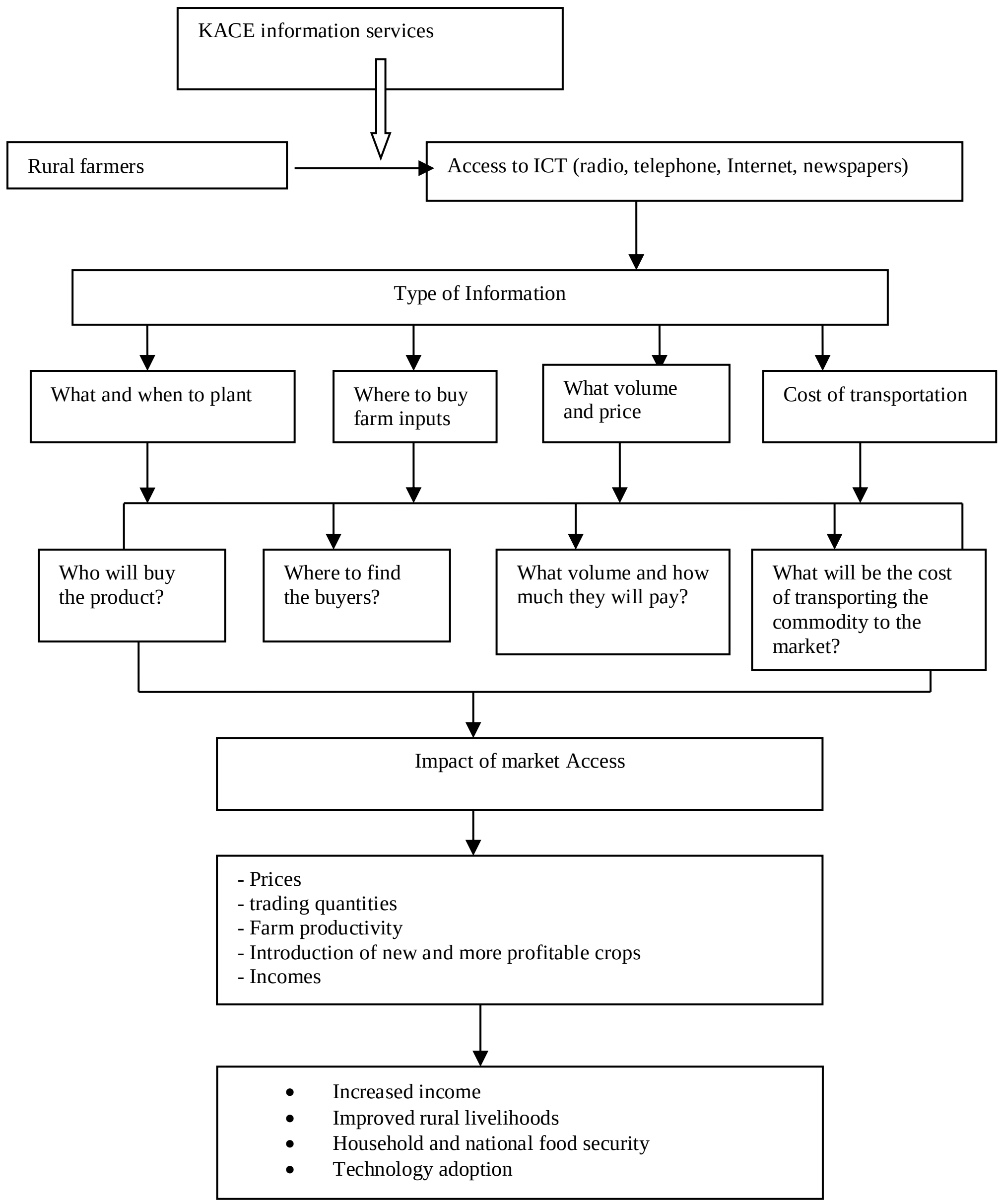

Figure 1: Conceptual framework for Market information access impact on rural livelihoods

In this study agricultural information (production and marketing) is expected to be accessed through ICT such as the internet, radio, telephone, television, newspapers, and magazines (Figure 1). It is expected that access to agricultural information through ICT and particularly mobile phones, are expected to influence on farmers' adoption of new crops and new technologies, the quantity marketed, prices and incomes. Access to timely market information via ICT tools is expected lead to increased income among the rural farmers, overall improvement of livelihoods of rural households, improved national food security and a motivation increased technology adoption.

A layout of the empirical methods used in analyzing the determinants of use of ICT tools are presented. Factors affecting the use and intensity of use of mobile phones by small farm households for agricultural transactions are examined. Lastly, the sampling procedure and data are described.

Determinants of Use of ICT Tools (Mobile Phones) in Agriculture

To realize the stated study objectives, both qualitative and quantitative methods of data analysis were used in interpretation of the results. Descriptive analysis was used to assess the awareness and usage of KACE information services. Logit regression model was used to separately examine the factors that condition awareness and use of KACE information services. In a logistic regression model, the probability, p, that a household will use (be aware of) KACE Information Services is given by the reduced form of a logit model below:

$$P = e^z/1+e^z \quad (1)$$

The significance to using logistic regression is primarily the logit transformation of p given by Z

$$Z = ln(p/1-p) \quad (2)$$

Where;

$$Z = X\beta + \varepsilon \quad (3)$$

β represents the vector of regression parameters, while X represents the explanatory variables' vector, and ε represents the stochastic term, which is assumed to have a logistic distribution. For this study, the vector X encompasses demographic characteristics of farmers, physical, capital, social and human endowments. Z represents a latent variable that assumes the value of 1 if the farmer has knowledge or uses KACE ICT services and 0 if otherwise.

Assessing Intensity of Use of KACE ICT Tools

Intensity of use of KACE ICT tools in this study refers to the number of tools a farmer used, to access information from Kenya Agricultural Commodity Exchange (KACE). The number of tools a given farmer uses to access information assumes integer values of discrete nature and is therefore a non-negative count variable. According to Maddala (2001), count data are non-normal and hence are not well estimated by Ordinary Least Squares (OLS) regression.

The most preferred models in analyzing count data include the Poisson Regression Model (PRM), the Negative Binomial Regression Model (NBRM), the Zero Inflated Negative Binomial (ZINB) and the Zero Inflated Poisson (ZIP). Some authors have pointed that Poisson and negative binomial regression models are the most popular models for analyzing response variables with nonnegative integer (Winkelmann and Zimmermann, 1995; Greene, 2008). The remaining two models, ZIP and ZINB, are particularly used in accounting for the frequency of zero counts (in cases where more zeros are recorded, than expected, in either PRM or NBRM). However, that is not the scenario in the case of this study. The response variables in this study were nonnegative integers and with not many zero counts. Hence a discussion of PRM and NBRM was undertaken.

According to Greene (2003) both PRM and NBRM models (for analyzing count data) are closely related to Ordinary Least Squares (OLS) regression model more than any other discrete choice models. As in the case of OLS, the optimality conditions can be derived from the PRM models and that violation of variance assumptions in the models does not essentially lead to inconsistent estimators, instead the coefficient estimates are inefficient and standards errors are potentially biased (Wooldridge, 2002). However, OLS regression models rest on particular assumptions which oftentimes are not satisfied (Maxfield and Babbie, 2001). OLS assumes that the dependent variable is a continuous value, normally distributed and with linearly related to the independent variables (McClendon, 1994)

Poisson and negative binomial regression models are primarily designed to analyze count data. The occurrence nature of counts is controlled for in the formulas of both Poisson and negative binomial regression. However, Poisson and negative binomial regression models differ in regards to their assumptions of the conditional mean and variance of the dependent variable. The Poisson model is based on assumption that the variance of the distribution and the conditional mean are equal. According to Osgood, (2000), Patemoster and Brame, (1997), Negative binomial regression does not assume an equal mean and variance and particularly correct for over-dispersion in the data, which is when the variance is greater than the conditional mean.

Poisson regression is a modeling method that overcomes some of the problems of traditional normal regression in which the errors are assumed to be normally distributed (Cameron and Trivedi, 1998). The Poisson model analyses is normally the first form of analysis in many count data analyses (Areal et al., 2008). The model rests on assumption that the dependent variable $\boldsymbol{y}$ given vector of predictor variables $\boldsymbol{x}$ has a Poisson distribution. Given x, the probability density function of $\boldsymbol{y}$ is completely determined by the conditional mean as presented by the log linear expression 4 and 5 below. PRM specifies that each observation $\boldsymbol{y_i}$ is drawn from a Poisson distribution with parameter λ_i which is related to a ray of predictor variables X\` (Greene, 2003; 2008). The model is derived from the Poisson distribution by introducing parameters into the relationship between the mean parameter $\lambda_i$ and predictor variables X\`.

$$\lambda(x) = E(y \mid x) \tag{4}$$

$$f(y_i|x_i) = \frac{e^{-\lambda(x)}\lambda_i(x)^y}{\Gamma(1+y_i)} \tag{5}$$

Where $\lambda_i = \exp(\alpha + X'\beta)$ *and* $y_i = 0,1,\ldots.,i$ is the number/count of tools/services used (in our case); X = a vector of predictor variables.

Wooldridge (2002) and Greene (2003; 2008) have demonstrated that the expected number of events, y_i , (in this case, number of tools used for accessing information via KACE ICT tools) is given as below:

$$E(y_i|x_i) = \mathrm{var}[y_i|x_i] = \lambda_i = \exp(\alpha + X'\beta) \quad \text{for } i = 1,2,\ldots.,n \tag{6}$$

The log-linear conditional mean function $e(y_i|x_i) = \lambda_i$ and its equi-dispersion $var(y_i|x_i) = \lambda_i$ assumptions are the main features of Poisson regression model (Greene, 2008). As pointed out by Winkelmann and Zimmermann (1995), the log-linear regression models accounts for the non-negative constraint imposed on the dependent variable by Poisson. The Poisson distribution is often used to model information on *counts* of numerous kinds, predominantly in situations where the natural "denominator", is missing, implying the absence of limit or upper bound on how big observed counts can be. The Binomial distribution, on the other hand, emphasizes on observed proportions.

The Poisson model has the advantages of overcoming some of the normal model's weaknesses. Foremost, its minimum value is zero. This implies that, it cannot predict negative values. It is therefore ideal for a distribution in which the mean or the most typical value is close to zero. Secondly, the Poisson is a primarily skewed model; meaning, its data is characterized with a long 'right tail'. Further, the model is mostly applicable in events with rare counts, for instance, crime occurrences. Additionally, this model is approximated by a maximum likelihood method, the estimates are adapted to the real data. This implies that when the predicted values are summed up, they are essentially equal to the input values summed up, apart from a minor error due to rounding off. The other advantage of normal model lies in its ability to yield a better count approximation for every record. Poisson model reduces the over-(under) estimation of incident counts. Essentially, the Poisson model presents a lesser total error compared to the normal model in calculating the residual errors.

Conclusively, the Poisson model has some desirable statistical properties that make it very useful for predicting incidents. The PRM has been applied in quite a number of disciplines. The model has been used in agriculture by Ramirez and Shultz (2000, cited in Kirui, 2010) to explain the adoption of agricultural and natural resource management technologies by small farmers in Central American countries. Another application of the model has been in the study of hidden health costs of pesticide use among Zimbabwe's smallholder cotton growers by Maumbe and Swinton (2003). In another study by Okello (2005), the model was used to examine the drivers of the number of pesticide that induced acute illnesses and the count of gear items used to prevent exposure to pesticides. Despite its strengths over normal models, the Poisson model has its shortcomings that render it not perfect. The major weakness is that count data are usually *over-dispersed* (Wooldridge, 2002; Greene, 2008). Over-dispersion refers to excess variation when the systematic structure of the model is correct (Berk and MacDonald, 2007).

SAMPLING PROCEDURE AND DATA

This study used data collected from smallholder farmers located in Bungoma South and Bungoma Central sub-counties of Bungoma County. Personal interviews were conducted among a total of 136 respondents. To determine the sample size used for this study, Cochran's (1963) formula was used. For large populations, Cochran developed the following equation:

$$n_0 = \frac{Z^2 \text{ pq}}{e^2}$$

Where n_0 is the sample size, Z^2 is the abscissa of the normal curve that cuts off an area at the tails (1- equals the desired confidence level, e.g. 95%, e is the desired level of precision, while p represents the proportion estimate of an attribute that is present in the population, and q is 1-p. The value Z is found in statistical tables which contains the area under the normal curve. For this study, assuming, P = 0.5 (maximum variability), desired confidence level of 90% and ±10% precision:

$$n_0 = \frac{(1.96)^2\ (.5)(.5)}{(.01)^2} = 96\ farmers$$

To compensate for the farmers that may not be possible to reach, a 10% was added. Similarly, to compensate for the likely non-responses, it requires a further 30% (Vehovar et al., 2002). A total of 136 farmers were hence interviewed during the study. The target populations for this study were farmers in Bungoma South and Bungoma Central Districts. These two districts are principally the hub of KACE operations, popularly known for technology-driven innovations of linking producers and buyers. Two divisions were purposively selected from each of the two districts. All the locations in the selected divisions were listed, from which one was randomly selected. Sub-locations from the chosen locations were listed and one from each randomly picked. Random sampling was used to select two villages from the chosen sub-locations. Using the list of the villages at the selected sub-location, the first and second village was selected from each sub-location based on the distance to the nearest main market. Village one was closer to the market while village 2 was further away from the market. The major reason for this was the observed heterogeneity in socio-economic characteristics of the households across the villages. While households near the market tended to be settled on tiny pieces of land, mostly purchased, their counterparts in villages away from the market were practicing farming on ancestral pieces of land. A total of 17 farmers from each of the eight villages were randomly selected and interviewed. This translated to a sample of 136 respondents.

RESULTS AND DISCUSSION

Determinants of Use of KACE Information Services

In addition to examining farmers' knowledge, the study also sought to measure rural households' use of KACE ICT tools. Farmers' use of ICT tools, was measured using a dichotomous (binary) choice variable of "Yes" or "No" type signifying farmers' use (Yes) or non-use (No) of KACE ICT tools. Among the variables included in the model were respondents' contact with extension; farmers' perception on service relevance and affordability. Respondents were asked on whether they thought information services offered by KACE were affordable in terms of premiums attached, or otherwise.

Table 1: Estimation results for the Logit Regression model on Use of KACE ICT project

Independent variable definition	Logit regression	Marginal effect

Variable	Coefficient	Std. Error	*P*-value	Coeff	*P*-value
Gender	2.2	0.65	0.000	1.230	0.000
Age	-1.53	0.03	0.001	-0.34	0.001
Education	1.17	0.1	0.000	0.26	0.000
Main occupation	0.6	0.93	0.876	0.74	0.875
Family size	-1.14	0.1	0.599	-0.82	0.599
Farm size	-0.01	0.22	0.149	-0.21	0.148
Farm ownership	0.54	0.52	0.298	0.06	0.298
Farm income	0.2	0.23	0.663	0.03	0.663
Contact with Extension	0.05	0.94	0.104	0.005	0.940
KACE Importance	1.48	0.56	0.376	0.463	0.376
Affordability	1.32	0.65	2.030	1.08	0.650
Mobile ownership	0.32	0.81	0.146	0.065	0.146
Group membership	1.48	0.56	0.009	0.236	0.008
Radio listenership	0.4	19.4	0.566	0.023	0.566
Radio farm program listenership	1.97	0.78	0.012	0.875	0.012
_cons	-2.43	1.559	0.438		

Log likelihood= -47.65

Pseudo R^2= 0.46 LR χ^2 (14)= 84.14 Prob>χ^2=0.000

Number of observations=136

The regression results (presented in Table 1), from the model were significant for farmers' perception on the importance of KACE services, and affordability. From the results, an increase in education level by one year is expected to increase adoption by 0.26. Men are 1.23 times more expected to use KACE ICT tools than women. The results of the model suggest that increased perception of usefulness and affordability of the services increases the propensity of farmers to use ICT services, which corroborates with the theoretical adoption literature. Perceived usefulness has been considered an important influence in technology adoption. However, the respondent's contact with extension workers was not statistically significant, showing lack of impact of extension on farmer's decision to use the technology. The reason to this could be attributed to the rather erratic contact between extension workers and the farmers. In fact, studies have demonstrated that stagnation in public investment and the breakdown of extension services has widened gaps between the yield from experimental farms and the yield from farmers' fields. Further, deficiency of extension staff and poor access to information has impeded the transfer of technology at the farm level (Mittal 2010).

Determinants of Intensity of Use of KACE Information Tools

To assess the factors determining the extent to which smallholder farmers use KACE information tools, the study used Poisson regression techniques. This count variable model was chosen because of its suitability for dependent variables that are countable finite such as the number of tools a farmer uses a service (Gitonga, 2009). Results for the Poisson regression model are presented in Table 2.

The independent variable used is the number of KACE tools used by the respondent to obtain market information. The results for age, gender, education and group membership were statistically significant, suggesting their link on the farmers' use of the KACE information. The expected number of ICT tools used is 0.75 times higher among men than female farmers, other factors held constant. This could be explained by most cultural practices which assign most of the domestic chores to women, leaving them with almost no extra time to allow them to seek such services.

Table 2: Poisson model of the intensity of the use of KACE ICT tools by farmers

Independent Variables	Poisson regression	
Unit	Coef.	P-value
Gender	0.75	0.001***
Age	-1.53	0.012**
Education	1.21	0.005***
Main occupation	0.64	0.181
Family size	-0.14	0.432
Farm size	-0.01	0.149
Farm ownership	0.45	0.145
Farm income	0.09	0.129
Contact with Extension	0.05	0.163
KACE Importance	1.68	0.003***
Affordability	1.32	0.005***
Mobile ownership	1.32	0.004***
Group membership	1.48	0.008***
Radio listenership	0.4	0.14
Radio farm program listenership	1.79	0.078*
Distance to the nearest center that has electricity (km)	-0.006	0.009***
Distance the produce and livestock market (km)	0.37	0.067*
_cons	-2.43	19.6
Log likelihood= -57.25; Psedo R^2= 0.26; LR χ^2 (14)= 89.14; Prob>χ^2=0.000 Number of observations=136		

Significance at 1%, 5%, and 10% levels is denoted respectively by ***, **, *.

The findings corroborates past studies which argue that culture among the rural communities places the responsibility of purchasing inputs and arrangements to sale farm output on men, may have a bearing on use of ICT tools (Okello, et al., 2011)Increase in age of the respondent by one year reduces the expected number of KACE ICT tools used by 27%. The inverse relationship between age and use of KACE ICT to access market information, which upholds the findings by past studies, suggest that this group of farmers are more literate and well equipped to use ICT tools (Okello, et al., 2011). Being a member of a farmers group is also expected to have a positive effect on use of KACE information services.

Results of the Poisson regression model estimates that among the farmer-specific variables, gender and age, affects the intensity of use of KACE ICT tools. The expected number of tools used is 0.75 times higher among the males than female farmers, ceteris paribus. This finding corroborates earlier research which argued that culture among rural farmers which entrusts the responsibilities of purchasing inputs and planning for output sale on men, affects the use of ICT tools such as mobile phones.

The results further demonstrate that among farm-specific factors, distance to the nearest market connected with electricity, affect the extent of use of ICT tools for agricultural transactions. An increase in distance to the market with electricity source by one kilometer is likely to reduce the expected number of ICT tools used by about 0.8 times. This could be explained by the fact that mobile phones need to be recharged. Rural farmers have difficulties making frequent trips to the market centre, due to huge transport costs. Similarly, distance to the main produce market has also been found to influence the number of ICT tools by farmers in accessing market information. An increase in the distance of the homestead to the market by one kilometre decreases the expected number of KACE ICT tools used by eight%. This finding contradicts past research that suggests an inverse relationship between distance to the market and number of mobile phone calls by farmers for agricultural transaction purposes (Okello et al., 2011). This could be due to the fact that this study was based on different ICT tools, some of which were to be accessed at KACE's merchandize shops.

The study also suggests that increase in the size of a household decreases the intensity of use of ICT tools by the family for agricultural activities by 15%. Putting in mind of the large average family size of about seven members per household, in the area of study, the finding is not surprising, as large households have many mouths to feed, and therefore have little surplus to take to the market, as a result will be less interested in market related information. Among capital endowment variables, education, literacy and mobile ownership, condition the extent of using ICT tools. Farmers who are literate will use more tools to access market information than their illiterate counterparts. One unit increase in education is expected to increases the expected number of KACE ICT tools used by 0.32. Literacy plays a big role in technology adoption, as the use of some of these tools require some basic knowledge.

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

The study examines the use of KACE information tools and services among the smallholder farmers in Bungoma County of Kenya. It uses a Logit regression model to examine the factors conditioning use of ICT tools and a Poisson regression model to assess the conditioners of use and intensity of use of the mobile phones for agricultural transactions. This study finds that there is a fairly low awareness and usage of this project among the farmers. The study further finds that age, literacy level and gender (cultural backgrounds of rural communities), as well as a lack of motivation stemming from the farmers' perception of the scant usefulness of ICTs and their limited digital skills, affect awareness of KACE information services among smallholder farmers. Young farmers, considered more educated, are more outgoing and willing to know what is going on in their environment as compared to their older counterparts, otherwise viewed as conservative (stuck on the past). More men compared to women have an opportunity to interact with the outside world and therefore more placed to be aware of the technology in the market.

Using the logit regression model to examine the use KACE ICT tools, the study found that the decision to use KACE tools was determined by age, gender and education and explain the usage of KACE information services. As expected, youthful farmers were more likely to adopt KACE ICT tools as compared to the older counterparts. This could be attributed to their high literacy level and ability to use modern technologies. More men than women were found to use KACE tools. This is because of the culture, which allocates women to non-financial responsibilities, while leaving financial obligations (which may require seeking of information) to men. Farmer's perception of affordability and importance of the services provided by KACE was also found to influence the usage decision.

Poisson regression model was used to examine factors that determine the intensity of use of KACE ICT tools by farmers in accessing marketing information. Age and gender were the farmer-specific factors found to influence the number of tools used by farmers. Capital endowment factors such as literacy and ownership of mobile phones also affected the use of KACE ICT tools. Further, number of ICT tools used were influenced by group membership (social capital), with number of KACE ICT tools expected to increase for farmers belonging to groups.

The role of information for efficient functioning of markets has been a major concern for many researchers. Application of ICT-based technologies have been touted as having the potential to empower farmers with market and other agricultural information to help them make informed decisions on where to sell their produce at profitable prices. Although, there has been a massive rollout of such initiatives aimed at addressing the problem of information asymmetry to ensure market efficiency, research shows that farmers in sub-Saharan Africa still face challenges in accessing profitable markets.

The implication of the findings of this study is that there is need to sensitize smallholder farmers on the KACE information services and other ICT-based market information platforms. Application of ICT in agriculture present a potential opportunity of resolving the asymmetry in market information, responsible for market failures, resulting in farmers receiving minimal returns for their agricultural commodities, a scenario that traps them in a poverty cycle. Further, there is need to support the emerging ICT applications, while ensuring an enabling environment and infrastructures, such as electricity (this is a major constraint in most rural homes, where one has to trek quite a long distance to charge their mobile phones). The findings of this study identify priorities for policymakers and other stakeholders, including the private sector to invest in projects that aim at linking farmers to market and other agricultural information. Efforts should also be made to empower the farmers with knowledge on how to use the facilities; since most of the farmers are either illiterate or semi-illiterate. The study indicates the importance of improving the general literacy standards of the rural community. Farmers' organization groups (collective action), which have been found to play a significant role in technology adoption, should be key priority areas.

Age is likely to be a hindrance in technology adoption, with young people being more likely than older people to embrace new ways of doing things. There is need to design technologies that takes care of the interest of the older people. This group constitutes a significant number of the users of commercial services. Understanding the needs of older adults is more urgent than ever, coupled with addressing these needs will present a major market opportunity for new ICT products and services. At the same time, ICT literacy is critical for the older generation to enable them take advantage of emerging technologies.

Results also indicate that gender variable has a significant impact on adoption; being a woman decreases the probability of ICT tools ownership. Women empowerment is therefore necessary in effort to improve production and enhance the living conditions of the rural population (Okello et al., 2010, FAO 1994).
Addressing of Social access issues must extend beyond gender. This calls for a comprehensive understanding of the agricultural economy at the local, national, and regional level, which is important for ensuring that ICT interventions do not restrict poor producers' participation to the low end of agricultural value chains like other technologies have. The ICT does not guarantee inclusion of all social groups per se. full participation can be realized by focusing on the full range of capacities and resources that small-scale producers will need to benefit from an intervention. Results demonstrate a significant relationship between education and awareness as well as adoption. Increased investment in education to improve its quality is therefore key to boosting adoption of new technologies. Education should also be further extended to organized farmers groups to increase their uptake of the new technologies. The groups should also be supported to ensure their sustainable operations.

To take advantage of ICTs to reverse the unequal development of agriculture, national as well as regional policies must be implemented to overcome the barriers to adoption in the most underdeveloped segments. Perhaps one possible mechanism would be the exchange of successful stories between areas, or countries in the region, which share fairly similar realities in terms of the importance of agriculture in the economy and the origin of sectorial asymmetries. The most extensive experience in the region in terms of facilitating farmers' access to ICTs has been with telecentres and computer-supply and connectivity programmes for rural schools. Policy on its own, however, cannot guarantee access to and use of ICTs in these areas. Motivational and educational strategies aimed at overcoming resistance, demonstrating the usefulness of the technologies and developing digital skills and content are necessary.

Questions of social access should be raised when using ICT to improve rural livelihoods. Do socio-cultural norms or divisions prevent certain groups from using these technologies? Will the groups which are better-off reap more benefits than the already less privileged? Broad-based rural development must be accompanied with monitoring and evaluation of outcomes while making necessary adjustments.

ACKNOWLEDGEMENTS
I am highly indebted to the National Council for Science and Technology for funding this research. There are not enough words to describe the council's excellent work of providing grants for research at all levels. You are truly the heart and soul of research and innovations in this country.

This work is a product of collaborative efforts from numerous people of good will. First and foremost I wish to register my sincerest gratitude to my academic mentors: Dr Sabina Wangia and Dr. Julius Okello for their abundant help and their inexhaustible suggestions. I attribute this work to their encouragement and effort and without which, execution of this research would not have been possible.

Much gratitude to the following people for having contributed to the success of this work in one way or the other: Ms. Beatrice Wafula, office of the District commissioner, Bungoma South district for providing me with the current Geographical map of the area. Thanks to Mr. Kirui Stanley, the District Agricultural Officer (DAO), Bungoma Central and Adelaide Waswa, the Divisional Agricultural Extension Officer (DAEO), Chwele Division for their assistance during the field survey. My Special thanks go to Kenya Agricultural Commodity Exchange (KACE), staff; Pius Wamalwa, and Alex Wasari, who is the managing director, Chwele Market resource Centre.

REFERENCES
Aker, J. C. 2008. Does digital divide or provide? The impact of cell phones on grain markets in Niger, Mimeo, University of California, Berkeley.

Areal, F. J., Touza, J., Mcleod, A., Dehnen-schumtz, K., Perrings, C., Palmieri, M. G. and Spence N. J. 2008. Integrating drivers influencing the detection of plant pests carried in the ionternational cut flower trade. Journal of Environmental Management, 89:300-307. http://dx.doi.org/10.1016/j.jenvunam.2007.06.017.

Cameron, A. and Trivedi, P. 1998. Regression analysis of count data, Cambridge University Press, Cambridge.

Dey, Bidit Lal., Prendergast, R. and Newman, David. 2008. How can ICTs be used and appropriated to address agricultural information needs of Bangladeshi farmers? GlobDev 2008. Paper 21. http://aisel.aisnet.org/globdev2008/21.

Ferris, S., Engoru, P. and Kanganzi, K. 2006. Making market information services work better for the poor in Uganda. A paper presented at Research Workshop on Collective Action and Market Access for Smallholder Farmers, Cali, Columbia. ICT to substantially reduce agricultural costs to farmers (2008). Financial Times, 2(40), March 2. Financial Sector Deepening (Kenya) Annual report, 2007

Gitonga, Z. 2009. Economic assessment of leafmine Invasion and control strategies in Kenya's snow pea industry: The case of Nyeri North and South Imenti Districts. University of Nairobi

Greene, H.W. 2003. Econometric analysis: Pearson Education Inc. New York University.

Greene, W. 2008. Functional forms for the negative binomial model for count data. Economics Letters, 99, 585–590. http://dx.doi.org/10.1016/j.econlet.2007.10.015

Kirui, O.K., Okello, J.J. and Nyikal, R.A. 2010. Awareness and use of m-banking services in agriculture: The case of smallholder farmers in Kenya.

Maddalla, G.S. 2001. limited dependent and quantitative variables in econometrics. Cambridge: Cambridge University Press.

Maumbe, B.M. and S.M. Swinton 2003. Adoption of Cotton I.P.M. in Zimbabwe. The role of technology awareness and pesticide-related health risks. Journal of Sustainable Development in Africa

Maxfield, M. and Babbie, E. 2001. Research methods for criminal justice and criminology. Third edition. Wadsworth/Thompson Learning: Belmont, CA

McClendon, M. 1994. Multiple regression and causal analysis. Itasca, IL: F.E. Peacock Publishers.

Mittal, A. K. and Mukherjee, R.P 2010. Comparison of generalized competitive modes and return maps for characterizing different types of chaotic attractors in the Chen system. International Journal of Bifurcation and Chaos. 20(3):735–748. doi: 10.1142/S0218127410026022

Munyua, H. 2007. ICTs and small-scale agriculture in Africa: a scoping study. Unpublished Report 1, Submitted to International Development Research Center.

Okello, J.J. 2005. Compliance with international food safety standards. The case of green bean production in Kenyan Family Farms. PhD Dissertation, Michigan State University

Okello, J., Kirui, O., Njiraini, G. and Gitonga, Z. 2011. Drivers of use of information and communication technologies by farm households: The case of smallholder farmers in Kenya

Okello, J., Ruth, M. and Adera O. Edith 2010. Awareness and use of mobile phones for market linkage by smallholder farmers in Kenya.

Osgood, W. 2000. Poisson-based regression analysis of aggregate crime rates. Journal of Quantitative Criminology

Paternoster, R. and Brame, R. 1997. Multiple routes to delinquency? a test of developmental and general theories of crime. Criminology 35: 45-84

Tollens, E. F. 2006. Market information systems in sub-Sahara Africa challenges and opportunities. Posterpaper prepared for presentation at the International Association of Agricultural Economists Conference, Gold Coast, Australia August 12-18, 2006.

Vehovar, V., Batagelj, Z., Manfreda, K.L. and Zaletel, M. 2002. Nonresponse in web surveys. In: R. Groves, D.. Dillman, J. Eltinge, and R. J. Little (Eds.). Survey nonresponse (pp. 229-242). New York: John Wiley and Sons

Winkelman, R. and Zimmerman, K. 1995. Recent developments in count data modeling: Theory and applications," Journal of economic surveys, 9:1-24 http://dx.doi.org/10.1111/j.1467-6419.1995.tb00108.x