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Impact of Information and Communication Technology-based Market Information Services on Smallholder Farm Input Use and Productivity: The Case of Kenya

By:

Sylvester O. Ochieng, Julius J. Okello, David J. Otieno

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65- Impact of Information and Communication
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Services on Smallholder Farm Input Use and
Productivity: The Case of Kenya

Sylvester O. Ochieng^{a*}

^aUniversity of Nairobi, Department of
Agricultural Economics, P.O. Box 29053,
Nairobi, Kenya

*Corresponding Author, e-mail:
syloch2000@yahoo.co.uk
Tel: +254 720-771-605

Julius J. Okello^a

^aUniversity of Nairobi, Department of
Agricultural Economics, P.O. Box 29053,
Nairobi, Kenya
Email: jjokello@gmail.com

David J. Otieno^a

^aUniversity of Nairobi, Department of
Agricultural Economics, P.O. Box 29053,
Nairobi, Kenya
Email: Jakinda1@yahoo.com

Abstract

Information asymmetry has traditionally constrained smallholder farmers' access to markets. Past studies indicate that it inhibits adoption of modern technologies that have the capacity to enhance productivity of smallholder farms. Hence, farm productivity and agricultural transformation is stifled, leaving smallholder farmers in grinding poverty. Improved smallholder farmers' access to markets via an Information and Communication Technology (ICT) platforms could reverse this scenario. This study evaluates the impact of participation in ICT-based market information services (MIS) on farm input use and land productivity in Kenya, using Propensity Score Matching technique. It finds that participation in ICT-based MIS project has a positive and significant impact on the use of seeds and fertilizers and improves land and labour productivity, but has a negative and significant impact on the usage of hired and family labour. These findings highlight the need for scaling up of the coverage of ICT-based MIS to enhance smallholder productivity and market access.

Key words: ICT, Impact assessment, Market access, Productivity

1. Introduction

The importance of information for adequate functioning of markets has been a prominent concern in economic theory, tracing back to the seminal work of Stigler (1961) on the economics of information. Moreover, in the late 1980s to early 1990s, many developing countries assisted by donors and or development partners, invested in Market Information Services (MIS) and other reforms to improve market linkage and subsequently, rural household incomes (Kizito, 2009). Various forms of MIS mainly emerged as accompanying measures to the Structural Adjustment Programs (SAPs) that targeted the liberalization of agricultural markets. Such interventions eliminated some of the barriers that curtailed the private sector from providing agricultural services. Private sector participation in the agricultural markets was expected to address smallholder farmers' problems of access to input and output markets (Okello and Ndirangu, 2010).

Nevertheless, situations of information asymmetry still prevail in most developing countries (Svensson and Yanagizawa, 2008). As a result, there have been information related problems such as moral hazard and adverse selection (see Akerlof (1970), Quiggin et al., (1993) and Horowitz and Lichtenberg (1993)) that in turn increases transaction costs, hence limiting market participation by some farmers (Okello et al., 2012). Although smallholder farmers play a vital role in the economies of most developing countries, they face significant challenges in accessing agricultural markets. In Kenya for instance, smallholder farmers account for about 75 percent of the total agricultural output and provide virtually all the domestic food requirements of the nation (Kuyiah et al., 2006). However, these farmers are resource poor and face substantial constraints in accessing inputs and high-end markets for their products (Okello, 2010).

Some of the factors considered to have contributed to the failure of input and output markets comprise: high transactions costs by the farmers in the input markets, illiteracy, distance to information sources and absence of the type of information the farmers need to produce their choice crop (Okello and Ndirangu, 2010). Consequently, these challenges often dampen farmers' incentives to use better production techniques such as yield augmenting

inputs that have the potential to increase productivity of their land holdings and enhance their access to high value markets. The low use of inputs in turn results in lower farm productivity, and curtails the transition from subsistence to commercial agriculture, hence perpetuating the confinement of smallholder farmers in the low-equilibrium poverty trap (Barrett, 2008). Such is the case in Kenya where productivity levels for most crops are below optimal due to poor market access, extension services and low application of modern agricultural technologies (Kenya Vision 2030).

The enhancement of agricultural productivity has, therefore, drawn the attention of policy makers in Kenya due to the significant role of the agricultural sector in the country's economic development (Odhiambo and Nyangito, 2003). Thus, Information and Communication Technology (ICT)-based projects have been recently introduced as part of the strategies to overcome the low farm productivity and improve agricultural performance among smallholder farm households. Such projects include: DrumNet, Kenya Agricultural Commodity Exchange (KACE), Regional Agricultural Trade Intelligence Network (RATIN), National Livestock Market Information System (NLMIS), and M-farm. Similar initiatives elsewhere comprise the Malawi Agricultural Commodity Exchange (MACE), Busoga Rural Open Source Development Initiative (BROSDI), and Women of Uganda Network (WOUGNET). Theoretically, it is expected that farmers who participate in such projects will tend to use the technical information acquired through them to adopt superior techniques of production, hence realize higher outputs.

In spite of the expected gains from ICT-based MIS projects in theory, few studies have provided empirical evidence of the impact of such projects, particularly in the developing country context. Notable exceptions include: Jensen (2007), Aker (2008), Svensson and Yanagizawa (2008), Houghton (2009) and Okello (2010). Specifically, there is a dearth of empirical evidence of the impact of such projects on farm input use and productivity. The few studies that have attempted to provide empirical evidence of the impact of ICT-based MIS on agricultural productivity are limited and comprise: Lio and Liu (2006), that was conducted at macro-level and applied Ordinary Least Squares (OLS) approach, that failed to control for selection bias. Additionally, Houghton (2009)

assessed the impact of mobile phones on agricultural productivity by employing micro-level data using Heckman two-stage regression. That study used cattle ownership as the proxy for measuring productivity gains, hence distinct from the present study. Finally, Kiiza et al., (2011) evaluated the impact of ICT-based market information on prices received by farmers and the intensity of adoption of improved maize seed in rural Uganda. This study is similar in some aspects to that of Kiiza et al., (2011), but extends it by evaluating the impact of ICT-based MIS projects on the use of fertilizer, pesticides, farm manure, besides improved seed. Furthermore, it examines the impact of ICT-based MIS on land and labour productivity.

The rest of the paper is organized as follows. The next section presents the theoretical framework of the study. The results are presented in section three followed by discussion in section four. Finally, some imperative conclusions and policy insights are offered in section five.

2. Theoretical framework

2.1 Participation decision and household welfare

Following Ali and Abdulai (2010), it can be assumed that the decision to participate in an ICT-based MIS project is dichotomous, where participation only occurs when the expected utility with participation (U_{ip}) is greater than without participation (U_{iN}) i.e. $(U_{ip}) > (U_{iN})$. The difference between the utility with and without participation may be denoted as a latent variable R_i^* , such that $R_i^* = (U_{ip}) - (U_{iN}) > 0$ indicates that the utility with participation exceeds that without participation. The decision by a farmer to participate or not to participate in the new ICT-based MIS project is dependent on the farm, as well as farmer characteristics; hence, it relies on each farmer's self-selection rather than random assignment. Assuming a risk neutral farmer who bases his or her production decisions on the criterion of maximizing the expected return of his or her monetary income, the index function to assess participation in an ICT-based MIS project can be expressed as:

$$R_i^* = \gamma X_i + \varepsilon_i \quad (1)$$

where R_i^* is a latent variable signifying the difference between the utility derived from participation in an ICT-based MIS project and the utility from failure to participate in an ICT-based MIS project. The term γX_i represents an estimate of the difference in utility derived from participating in an ICT-based MIS project by employing the household and farm-level characteristics (X_i) as explanatory variables, whereas ε_i is an error term. Theoretically, participation in ICT-based MIS projects is expected to affect the demand for agricultural inputs such as fertilizer, purchased seed, manure, pesticides, herbicides, labour, as well as yields and net returns (π). To link the participation decision with these potential outcomes of participation in an ICT-based MIS project, we still consider a risk neutral farmer that maximizes profits (π) subject to a competitive output and input market and a single output technology that is quasi-concave in the vector of variable inputs, w . It is however noteworthy that this is a strong assumption which might not hold in imperfect markets which are prominent in Kenya. The profit maximization equation may be expressed as:

$$Max\pi = pq(w, x) - vw \quad (2)$$

where p is output price, q is the quantity of output, v is a vector of factor prices, while w is a vector of input quantities and x is a vector of farm level and household characteristics. The farmer's net returns or profits can be expressed as a function of participation (r), variable inputs (v), output price (p) and household characteristics (x) as follows:

$$\pi = \pi(r, v, p, x) \quad (3)$$

Application of Hotelling's Lemma to equation (2) with respect to factor price and output price yields reduced form equations for negative input demand and output supply, respectively;

$$\frac{d\pi}{dv} = -w = w(r, v, p, x) \quad (4)$$

$$\frac{d\pi}{dp} = q = q(r, v, p, x) \quad (5)$$

The specifications in equations (4) and (5) show that the decision to participate, input and output prices, as well as farm and household characteristics tend to affect a farm household's net returns, demand for inputs and output level.

2.2 Impact evaluation

The fundamental approach to consider when evaluating the impact of participation in an ICT-based MIS project on smallholder farm productivity would be to include a dummy variable equal to one in the outcome equation if the household participated in ICT-based MIS project and zero otherwise, and then apply an Ordinary Least Squares (OLS) regression. That basic relationship is a linear function of vector explanatory variables (X_i) and a participation dummy variable (D_i) specified as follows:

$$Y_i = \alpha X_i + \beta D_i + \mu_i \quad (6)$$

where Y_i is the mean outcome of the target variable for household i , D_i is a dummy variable, $D_i = 1$ for participation in an ICT-based MIS project and $D_i = 0$ otherwise. X_i is a vector representing household and farm level characteristics. μ_i is the normal stochastic term reflecting unobserved characteristics that also affect Y .

Equation (6) reflects an approach commonly used in impact evaluations (such as in Lio and Liu, 2006), which is to measure the direct effect of the program D on outcomes Y . This approach, however, is likely to generate biased estimates because it assumes that participation in an ICT-based MIS project is exogenously determined while it is potentially endogenous. The treatment assignment is not often random due to either purposive program placement or self-selection into the program. That is, programs being placed according to the need of the communities or individuals who in turn self-select based on program design and placement. Self-selection can be based on observed characteristics, unobserved factors, or both (Khandker et al., 2010).

Selection bias specifically occurs if unobservable factors influence both error terms of the participation equation (1) ε_i , and the outcome equation (6) μ_i , resulting in the correlation of the error

terms of the participation decision and the outcome specification. In other words, the correlation between the two stochastic terms is greater than zero. In this case, ordinary least squares (OLS) will lead to biased estimates, including estimates of the program effect (Becerril and Abdulai, 2010). This may lead to over estimation of the project's effect.

To address the problem of selection bias, most empirical studies employ Heckman two-step estimation. This method has the advantage of controlling for the differences in both the observed, besides the unobserved attributes between the treated and control groups by the inclusion of the inverse of mills ratio as an extra regressor in the outcome equation. However, the main drawback of this method is that selection estimators are dependent on a strong assumption that the hidden variables are normally distributed. This has resulted to the questioning of the robustness of their results in literature employing both actual and simulated data (Ali and Abdulai, 2010; Kiiza et al., 2011).

Selection bias can also be controlled by Instrumental Variable (IV) method. This technique yields unbiased and consistent estimates in the presence of hidden bias. The main drawback of the IV method, however, is that it will often be difficult to find at least one variable in the selection model to serve as a suitable 'instrument' that should influence the probability of treatment, without itself being determined by any confounding factors affecting outcome, i.e. without being correlated to the error term (Wooldridge, 2002). Since this last condition is difficult to test, the choice of a valid instrument largely depends on intuition and economic reasoning. In addition, the IV approach typically reduces the precision of the causal estimates and introduces new uncertainty, besides the difficulty in testing the assumptions (DiPrete and Gangl, 2004; Kiiza et al., 2011).

Double Difference (DD) methods can also be used. They are advantageous in the sense that they relax the assumption of conditional exogeneity or self-selection on observed characteristics. Moreover, they provide an appealing and intuitive way to account for selection based on unobserved characteristics. Their main shortcoming, however, rests precisely with this assumption: the concept of time-invariant selection bias is unlikely

for many target programs in developing countries (Khandker et al., 2010). Furthermore, DD methods are limited to studies with baseline survey data. To overcome the drawbacks of the mentioned methods, this study employs Propensity Score-Matching (PSM) technique to control for selection bias. The method does not depend on the functional form and distribution assumptions and is intuitively attractive since it compares the observed outcomes of adopters (participants) and non-adopters (non-participants) of technology (Asfaw, 2010). The matching technique has heavy data requirement. However, in the absence of such data, experimental treatment effect results can still be obtained.

2.3 Impact evaluation problem and the propensity score matching method

The main challenge of impact evaluation in this study is to determine the outcome of the ICT-based MIS project participants if the project had not existed. A participant's outcome in the absence of the intervention would be its counterfactual. The PSM approach provides unbiased estimation of treatment effects and can be used to draw causal-effect inference and control for simple selection bias in non-experimental settings. It does this by attempting to construct a proper counterfactual of the outcome of participants conditional on non-participation. According to Rosenbaum and Rubin (1983), the average treatment effect (Δ_i) in a counterfactual framework can be specified as:

$$\Delta_i = Y_1 - Y_0 \quad (7)$$

Where Y_1 and Y_0 denotes the outcomes of household i that participates in an ICT-based MIS project and one that does not participate, respectively. Estimating the impact of project participation on the i^{th} household from equation (7) would be misleading due to the problem of missing data. Normally either outcome Y_1 or Y_0 is observed for household i at a time, but not both. That observed outcome can be expressed as:

$$Y_i = D_i Y_1 + (1 - D_i) Y_0 \quad (8)$$

where D denotes a dummy = 1 or 0 for participant and non-participant, respectively. The average treatment effect on the

treated (ATT) households which is the parameter of interest in empirical research, as noted by Rosenbaum and Rubin (1983), Caliendo and Kopeinig (2008) and Kiiza et al., (2011) is written as follows:

$$ATT = E(Y_1 - Y_0 | D=1) = E(Y_1 | D=1) - E(Y_0 | D=1) \quad (9)$$

Since $E(Y_0 | D=1)$ which is the counterfactual outcome is not observed for a given household, it implies that although ATT may be estimated, it is likely to be biased. Therefore, it is noteworthy that the central focus of impact evaluation lies in estimating $E(Y_0 | D=1)$ and not $E(Y_0 | D=0)$. The problem of using $E(Y_0 | D=0)$ is that the participating and non-participating households may not be similar before the intervention; hence the expected difference between these households may not entirely be due to program intervention. The PSM technique attempts to capture the effects of various observed covariates X on participation in a single propensity score. The propensity score in this study's context can be defined as the conditional probability that a household will participate in an ICT-based MIS project, given its pre-participation characteristics. Consequently, the program effects can be obtained by comparing the outcomes of participating and non-participating households with similar propensity scores.

According to Ali and Abdulai (2010), the PSM technique creates conditions of a randomized experiment by employing two assumptions namely, unconfoundedness assumption also referred to as conditional independence assumption (CIA) and common support assumption (CSA). The CIA implies that once X , vector of pre-participation characteristics is controlled for, participation in an ICT-based MIS project will be random and uncorrelated with the outcome variables. In other words, selection into group will be solely based or explained by the observable characteristics. The propensity score under the CIA is given by:

$$p(X) = pr(D=1 | X) = E(D | X) \quad (10)$$

Where $D = 1$ or 0 is the indicator for participation and X is the vector of pre-participation characteristics. The conditional distribution of X , given $p(X)$ is similar in both groups of

participants and non-participants. The core objective of estimating the propensity score is to balance the observed distribution of covariates across groups of participants in ICT-based MIS projects and non-participants.

On the other hand, the CSA helps in ensuring that every individual has a positive probability of being either a participant or a non-participant in an ICT-based MIS project, hence ruling out perfect predictability. The CSA is expressed as:

$$0 < pr(D=1 | X) < 1 \quad (11)$$

Under the assumptions (10) and (11), the ATT be expressed as follows:

$$ATT = E(Y_1 - Y_0 | D=1)$$

$$ATT = E[E(Y_1 - Y_0 | D=1, p(X))]$$

$$ATT = E[E\{Y_1 | D=1, p(X)\} - E\{Y_0 | D=0, p(X)\} | D=1] \quad (12)$$

The propensity scores can be generated using either a binary probit or logit model. The probit model assumes a normal distribution of the stochastic term, whereas the logit assumes a logistic distribution. Since we cannot determine that the random term has a normal distribution a priori, a logit model is estimated to generate the propensity scores for participation in an ICT-based MIS project. This is then succeeded by matching. Various matching methods have been employed in literature, however, this study uses the most commonly used nearest neighbor matching (NNM), Radius matching (RM) and Kernel-based matching (KBM). The three matching methods are used to check the robustness of the results.

2.4 Test for robustness and unobserved heterogeneity

Since matching is not conditioned on all covariates, but on the estimated propensity score, it is essential after matching to check if all the relevant covariates are balanced in both treatment and control groups (Caliendo and Kopeinig 2008, Becceril and Abdulai, 2010). The quality of the resulting matches are inherently tested by examining the situation before and after matching to

check if there remains any difference after conditioning on the propensity score (Caliendo and Kopeinig 2008). Furthermore, Sianesi (2004), Caliendo and Kopeinig (2008) and Becceril and Abdulai (2010) suggest the re-estimation of propensity score on the matched sample, i.e. on participants and matched non-participants, and subsequent comparison of pseudo- R^2 before and after matching. Pseudo- R^2 indicates how well the predictors X predict the probability of participation. The pseudo- R^2 after matching should be fairly low, indicating that there are no systematic differences in the distribution of observed covariates between treatment and control groups. In addition, one can also perform a likelihood ratio test on the joint significance of all predictors in the probit or logit models. The test should not be rejected before, but should be rejected after matching.

Given that with PSM ‘hidden bias’ may arise if there are unobserved covariates that simultaneously influence participation and the welfare outcomes of households, it is essential to check for the presence of hidden bias after matching. In order to test the extent to which an assignment on unobserved covariates may bias the results or inferences, this study employs Rosenbaum bounds sensitivity analysis to ascertain how strongly an unmeasured variable must influence the selection process so that it could undermine the findings of the matching analysis. Rosenbaum bounds take the difference in the response variable between treatment and control cases, and give the critical levels of gamma γ at which the causal inference of a significant impact of treatment may be questioned. By considering the lowest critical value of sensitivity analysis, we can conclude the level at which unobserved heterogeneity would alter the inference about the estimated effects of treatment (Kiiza et al., 2011).

2.5 Sampling procedure and data

This study used data collected from smallholder farmers located in Kirinyaga, Bungoma and Migori districts. The districts were selected for the survey because they hosted an ICT-based MIS project, namely the DrumNet project, between 2004 and 2007. They were therefore likely to have benefited from the demonstration effects of the project. The districts were also selected to capture diverse social and economic backgrounds.

Kirinyaga district has export-oriented agriculture with several export crops (French beans, various Asian vegetables and baby corn) being produced by the farmers that were targeted by the project. Smallholder farmers in Bungoma district mainly planted maize (a lower value crop) and some sugarcane, while in Migori district; the main crops were maize and tobacco (for some farmers). The study targeted smallholder farmers including those who participated in ICT-based projects that used ICT-based tools and those who did not. The respondents in this study were therefore stratified by participation in such an ICT-based MIS agricultural project.

The sampling procedure entailed three stages. First, in each district, an area with an ICT-based MIS project was identified. Second, for each such area, a list of all farmers registered to participate in the ICT-based MIS project was drawn with the help of project staff and farmers' leaders. A second list of farmers that did not participate in the ICT-based projects was also obtained with the help of local administration (village elders and area agricultural extension officers) and verified by project staff and farmers' leaders as non-project members. Third, the respondents were sampled from the two lists using probability proportionate to size sampling method. That is, more farmers were sampled from the list with more names. This procedure resulted in 144 farmers who had participated in ICT-based MIS projects and 231 non-participants, giving a total sample of 375 farmers comprising 130, 127 and 118 respondents from Bungoma, Kirinyaga and Migori districts, respectively. The data was collected through personal interviews using a pre-tested questionnaire. Important information collected included farmer-specific characteristics, farm-specific characteristics, household capital/asset endowments, and location characteristics. The household survey was conducted in April and May 2010.

Definition of the variables collected during the study and applied in the econometric models is given in Table 1, while Table 2 presents the test of mean differences in some characteristics of participants and non-participants in ICT-based MIS projects.

3. Results and Discussion

The descriptive statistics reveal that 35 per cent of the farmers interviewed in Kirinyaga participated in ICT-based MIS projects, compared to 55 per cent and 25 per cent in Bungoma and Migori districts, respectively. Contrary to expectation (see Okello et al., 2012, who suggest that farmers in Kirinyaga district have a higher likelihood of using ICT tools for agricultural transaction due to their production of market-oriented export vegetables), the proportion of participants in the ICT-based MIS project is highest in Bungoma relative to other districts. This was possibly due to awareness created by the existence of an ICT-based MIS provider, KACE, in the region. Overall, the sample mean indicates that only 38 per cent of the all the farmers interviewed participated in ICT-based projects, probably due to lack of awareness of the existence of the projects and or their possible benefits.

<Table 1>

The results in Table 2 indicate that there are significant differences between participants and non-participants in an ICT-based MIS project with respect to use (or value) of farm inputs. In particular, participants have higher values of purchased seed per acre, fertilizer per acre and aggregate non-labour inputs per than non-participants. However, the results indicate that participants use less hired labour per acre and total labour per acre than non-participants. The *t* values suggest that there are significant differences in some of the variables used in the empirical analysis namely farm, farmer and asset endowment variables. Specifically, participants have higher average figures for age, household size, adult equivalent, distance to nearest local market, number of crop enterprises, market participation and membership to farmer organization than non-participants.

<Table 2>

3.1 Impact of ICT-based MIS projects on farm input use and productivity

The impact analysis is preceded by the estimation of propensity scores for the treatment variables using the logit model presented in Table 3. Propensity scores, as noted by Lee (2008), are useful for balancing the distribution of observed covariates across the treated and the untreated groups. Generally, most of the variables in the model have the expected signs.

<Table 3>

Figure 1 presents the distribution of the estimated propensity scores and the region of common support. A visual analysis of the density distributions for the two groups as suggested by Caliendo and Kopeinig (2008) reveals that all the treated and the untreated individuals were within the region of common support. That is, each individual had a positive probability of being either a participant or a non-participant in the ICT-based MIS project, thus implying that the Common Support Assumption (CSA) which requires each treated household to have a corresponding untreated household as a match was satisfied.

<Figure 1>

The empirical results of the impact of ICT-based MIS projects on farm input use and productivity estimated with NNM, RM and KBM are presented in Table 4.

<Table 4>

The three matching methods indicate that participation in ICT-based MIS projects has a positive and significant impact on the use (or value) of purchased seed per acre, purchased fertilizer per acre and total purchased non-labour inputs per acre. The average treatment effect on the treated (ATT) for the value of purchased seed per acre was Kshs 285.41 in Radius Matching (RM), Kshs 285.45 in Kernel Based Matching (KBM) and Kshs 359.21 in Nearest Neighbour Matching (NNM) and was significantly different from zero at 5 percent in all the matching methods. This implies that participation in the ICT-based MIS project increased the use of improved seeds by between Kshs 285.41 and Kshs 359.21. Furthermore, the ATT for the value of purchased fertilizer per acre was Kshs 1,009.86 in RM, Kshs 952.67 in KBM and Kshs 1,035.10 in NNM and was significantly different from zero at 5 percent with KBM, but at 1 percent for both NNM and RM. This result is consistent with the finding by Kiiza et al., (2011) that revealed that access to ICT-based MIS improves the intensity of adoption of improved maize seed. Additionally, the ATT for the total value of purchased non-labour inputs per acre was Kshs 1,171.86 in RM, Kshs 1,129 in KBM and Kshs 1,363.59 in NNM and was significantly different at 1 percent in all the matching methods, except in KBM where it was significant at 5 percent. These results suggest that participation in the ICT-based MIS

project increased the aggregate use of non-labour inputs per acre by Kshs 1,171.86 in RM, Kshs 1,129 in KBM and Kshs 1,363.59 in NNM.

However, the ATT for hired labour per acre was - 6.10 in NNM, - 6.11 in RM and - 6.46 in KBM and was significantly different from zero at 5 percent in all the matching methods, except in NNM where it was significant at 10 percent. Similarly, the ATT for family labour man-days per acre was -13.49 in NNM, - 6.99 in RM and - 7.95 in KBM, while that of total labour man-days per acre was - 21.96 in NNM, - 15.68 and - 16.94 in KBM. The ATT for family labour was significantly different from zero at 5 percent in all the methods, except in NNM where it was 1 percent, while the ATT for total labour man-days per acre was significantly different from zero at 1 percent in all the matching methods. These results imply that, participation in the ICT-based MIS project reduced the use of hired labour man-days per acre by 6.10 in NNM, 6.11 in RM and 6.46 in KBM. Participation also reduced the use of family labour man-days per acre by 13.49 in NNM, 6.99 in RM and 7.95 in KBM, while the aggregate labour man-days used per acre was reduced by 21.96 in NNM, 15.68 in RM and 16.94 in KBM.

Following the results in Table 4, it can be argued that access to ICT-based MIS projects enhances the use of non-labour improved inputs, but conversely, reduces the use of labour in farm households. Improved access to the right information on inputs via an ICT-based MIS project reduces information asymmetries and transaction costs, hence facilitating increased smallholder farmers' participation in input markets. Households with sufficient information are likely to use less labour in negotiating for contracts and searching for information on production inputs such as certified seeds, fertilizer, hired labour etc, hence use less labour. Additionally, the negative but significant impact of ICT-based MIS projects on labour use is perhaps due to the "induced innovation hypothesis" (Hayami and Ruttan, 1971) which postulates that as resources become scarcer or expensive, individuals invest in technologies that facilitate the substitution of the less expensive factors for the more expensive factors of production. Thus, better access and use of improved inputs is argued to be substituting for less-skilled labour use among ICT-based MIS project participants.

Table 4 further shows that participation in the ICT-based MIS project increased the value of output per man-day by Kshs 367.46 in RM, 374.85 in KBM and Kshs 406.95 in NNM. The increments were significant at 1 percent in all the matching methods. These results suggest that participation in the ICT-based MIS project had a positive and significant effect on labour productivity. Finally, participation in an ICT-based MIS project also increases the value of output per acre (land productivity). As shown in Table 4, the ATT for the value of output per acre was Kshs 7,007.14 in RM, Kshs 7,160.28 in KBM and Kshs 8,605.84 in NNM and was and is significantly different from zero at 1 percent in all the matching methods. Participation in the ICT-based MIS project, therefore, increased land productivity by between Kshs 7,007.14 and 8,605.84. These findings possibly suggest that the higher levels of labour and land productivity among participants were stimulated by the expanded use of improved agricultural inputs such as seed and fertilizer, due to better access to agricultural information. This is particularly noteworthy because increased use of non-labour inputs spurs productivity and subsequently leads to increased commercialization as farm households participate more in the market economy.

3.2 Test for robustness of results

Table 5 presents results of covariate balancing tests and sensitivity analysis for assessing the quality of the matches and robustness of the results.

<Table 5>

As shown, there is a substantial reduction in bias as a consequence of matching. The estimates show that the standardized mean bias before matching is 29.60 percent, while the standardized mean bias after matching is reduced to between 5.11 percent and 12.93 percent. The percentage reduction in the absolute bias is 82.7, 56.31 and 64.48, with NNM, RM and KBM matching methods, respectively. Since the percentage reduction in bias by all the three matching methods is greater than 20 percent, a value suggested by Rosenbaum and Rubin (1985) as sufficiently large enough reduction in standardized bias, it is deduced that matching substantially reduced selection bias.

The second diagnostic statistic employed is the pseudo- R^2 from the logit estimation of the conditional probabilities of participation. The results in Table 5 indicate that the pseudo- R^2 after matching is lower than before matching for all matching algorithms. This implies that after matching there are no systematic differences in the distribution of covariates between the participants and non-participants in ICT-based MIS projects. After matching, the predictors in the vector X have extremely low or no explanatory power for assignment into treatment. The p -values of the likelihood ratio tests indicate that the joint significance of the regressors could not be rejected at any level of significance before matching. However, after matching the joint significance of the regressors is rejected. This suggests that there was no systematic difference in the distribution of covariates between participants and non-participants in ICT-based MIS projects after matching.

The results of the sensitivity analysis of hidden bias, which show the critical levels of gamma γ at which the causal inference of a significant impact of participation in an ICT-based MIS project may be questioned, are also presented in the last column of Table 5. Since sensitivity analysis for insignificant effects is not meaningful, Rosenbaum bounds (rbounds) are calculated only for treatment effects that are significantly different from zero (Hujer et al., 2004). The results show that robustness to hidden bias varies across different outcomes. Specifically, the value of gamma γ vary from 1.15 to 1.35, 3.65 to 4.25, 1.35 to 2.00 and 2.95 to 6.00 for values of total non-labour inputs per acre, total labour man-days per acre, value of output per acre and value of output per man-day, respectively. For instance, for the impact of participation in ICT-based MIS project on the value of output per acre (land productivity), the critical value of gamma γ with NNM is between 1.95 and 2.00. This suggests that the unobserved variable would have to increase the odds ratio of participation by 95 to 100 percent before it would bias the estimated impact.

The lowest critical value of gamma γ is 1.15 to 1.20, whereas the largest critical value is 5.95 to 6.00. Some of the empirical studies that have reported critical values of gamma γ close to this study's (in the lower range of 1.15 to 1.20) comprise: Becceril and Abdulai (2010), Ali and Abdulai (2010) and Kiiza et al., (2011), while in the

upper range, Kiiza et al.,(2011) and Clement (2011). This study therefore concludes that the estimated average treatment effects of participation in the ICT-based MIS project on input use, labour and land productivity remain robust even in the presence of substantial amounts of unobserved heterogeneity. Thus, the CIA requirement for the PSM was satisfied.

4. Discussion

It is noteworthy that a clear understanding of farmer, farm-specific, capital-asset endowment and institutional factors is crucial prior to the dissemination of technologies that target the improvement of agricultural performance at the farm level. Moreover, it is essential to subsequently evaluate the impact of such technologies in order to ensure that they achieve their target objectives. As shown in Tables 3 and 4, this study presents the effect of some variables on the decision to participate in an ICT-based MIS, besides impact of participation on farm input use, labour and land productivity.

The avenues for policy discussed in this section are based on the results presented above (see section three). Briefly, this study finds that participation in an ICT-based MIS project has a positive and significant effect on the level of use of farm inputs (seed and fertilizer). However, participation in an ICT-based MIS project has a negative and significant impact on the use of hired, family and total labour. Additionally, participation in an ICT-based MIS project also increases labour and land productivity.

These findings highlight the need to expand the coverage of ICT-based MIS projects in rural areas, since they enhance smallholder farmers' participation in agricultural input markets, subsequently improving their labour and land productivity. Furthermore, the findings imply that programs aiming to improve food security and farm incomes should consider both the promotion of yield-augmenting agricultural technologies as well as improved access to ICT-based market information. The positive correlation between ownership and use of mobile phones (ICT device) and participation in an ICT-based MIS project suggests the importance of improving the infrastructure for ICT usage (especially mobile phones which are essential tools for delivering the benefits) in rural areas. The results also highlight the need for expansion of rural

electrification programs to allow access to power (electricity) for charging mobile phone batteries and powering other ICT devices. Besides, the need for expansion of mobile phone network coverage in farming areas where mobile phone network is still poor is also brought to the fore.

5. Conclusion

Smallholder farmers, particularly in developing countries face challenges in accessing input and output markets. Such challenges include lack of adequate information about the right quality and quantity of inputs, besides other yield-augmenting technologies. This study evaluates the impact of participation in an ICT-based MIS project on farm inputs use, labour and land productivity among smallholder farmers in Kenya using PSM technique. The results reveal that participation in an ICT-based MIS project increases the use of farm inputs (i.e., seed and fertilizer), but reduces the use of hired, family and total labour. Participation in an ICT-based MIS project also increases labour and land productivity. It is argued that access to market information either from an ICT-based project or via an ICT tool e.g. mobile phone, reduces information asymmetry and transactions costs among the beneficiaries. Subsequently, this increases access and use of purchased inputs which in turn improve labour and land productivity. These findings highlight the vital role that ICT-based MIS can play in enhancing smallholder farmers' access to markets, hence providing avenues for policy making.

In light of this study's findings, future work should focus on quantifying the effects of access to ICT-based market information services on other key outcome variables such as output price, food security status and poverty in Kenya and other developing countries. Additionally, a comparison of the benefits of participation in an ICT-based MIS project such as improved labour and land productivity, with the cost of participation in such a project is worth investigating.

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Table 1: Summary of descriptive statistics

District	Kirinyaga n =127		Bungoma n =130		Migori n =118		Pooled n =375	
Dependent Variables	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
ICT-based MIS project (1 = participant 0 = Non-participant)	0.35	0.47	0.55	0.50	0.25	0.43	0.38	0.49
Value of purchased seed per acre (Kshs)	1,660.05	1,470.66	984.82	603.22	599.39	599.31	1,092	1,075.51
Value of purchased fertilizer per acre (Kshs)	3,672.28	2,994.03	3,613.99	2,660.78	914.41	1706.85	2,784.26	2,825.52
Value of purchased manure per acre (Kshs)	104.35	471.21	18.27	146.93	0.28	3.07	41.76	290.38
Value of purchased herbicides or pesticides per acre	454.83	747.98	9.86	69.45	1.59	17.26	157.95	485.29
Total value of purchased inputs per acre (Kshs)	6,290.65	5,131.50	4,626.93	2,930.68	1,515.67	1,932.27	4,155.37	3,913.28
Value of household output per acre (Kshs)	29,952.63	23,062.32	25,826.00	16,818.12	16,151.62	11,398.74	24,179.35	18,707.94
Value of household output per man-day	709.61	748.75	546.44	482.24	469.60	474.94	577.52	591.26
Hired labour man-days per acre	30.14	35.1	10.82	16.3	10.68	16.01	17.32	25.91
Family labour man-days per acre	29.98	32.15	46.21	31.87	33.63	26.7	36.76	31.16
Total labour man-days per acre	57.30	38.5	57.41	31.58	45.45	25.7	53.61	32.88
Farm specific variables								
Age (Years)	43.78	12.46	43.7	13.12	42.75	16.04	43.43	13.87
Gender (1=Male 0=Female)	0.54	0.50	0.49	0.50	0.48	0.50	0.50	0.50
Farming experience (years of farming)	18.09	10.49	16.22	11.01	18.87	13.19	17.69	11.6
Household size (count)	4.41	1.28	6.87	2.23	5.93	2.11	5.74	2.17
Household adult equivalent (count)	2.42	0.62	3.27	0.92	2.97	0.94	2.89	0.91
Farm specific variables								
Distance to the local market (km)	3.07	1.93	2.12	1.45	1.81	1.58	2.89	0.91
Distance to the nearest local market for inputs (Km)	4.04	3.10	4.13	2.59	4.69	5.39	4.27	3.84
Number of crop enterprises (count)	3.11	1.43	3.08	1.74	3.08	1.74	2.91	1.52
Market participation (1=yes 0=No)	0.77	0.42	0.58	0.49	0.58	0.49	0.65	0.48
Asset endowment variables								
Education (years)	8.96	3.44	8.85	3.49	7.34	3.84	8.41	3.66
Cultivated land area in 2009 (acre)	2.32	1.80	1.53	1.25	1.53	1.25	2.20	1.91
Group membership (1=Member 0=Non-member)	0.63	0.49	0.72	0.45	0.25	0.43	0.62	0.49
District of Survey: Kirinyaga	1= Kirinyaga, 0=Otherwise						0.34	0.47
Bungoma	1= Bungoma, 0=Otherwise						0.33	0.48
Migori	1= Migori, 0=Otherwise						0.31	0.47

The exchange rate at the time of the survey was 1 US dollar = Kshs 78

Table 2: Differences in means of participants and nonparticipants

Characteristic	Participants n = 144	Nonparticipants n = 231	Mean Difference	t values	p values
Dependent variables					
Value of purchased seed per acre (Kshs)	1,297.25	964.4	332.85 ^a	2.73	0.007
Value of purchased fertilizer per acre (Kshs)	3,582.90	2286.41	1296.48 ^a	4.13	0.000
Value of purchased manure per acre (Kshs)	52.37	35.15	17.22	0.53	0.600
Value of purchased herbicide or pesticide per acre	140.66	168.73	-28.08	-0.57	0.568
Total value of purchased inputs per acre(Kshs)	5,073.16	3583.23	1489.93 ^a	3.52	0.001
Family labour man-days per acre	34.32	38.28	-3.96	-1.22	0.225
Hired labour man-days per acre	14.25	19.23	- 4.98 ^c	-1.91	0.057
Total labour man-days per acre	46.38	58.11	- 11.73 ^a	-3.59	0.000
Value of household output per man-day (Kshs)	793.82	442.69	351.13 ^a	5.12	0.000
Value of household output per acre (Kshs)	28,905.47	21,233.20	7,672.28 ^a	3.83	0.000
Farmer specific variables					
Age (years)	46.68	41.4	5.28 ^a	3.74	0.000
Gender (1= Male , 0= female)	0.54	0.48	0.06	1.15	0.251
Farming experience (years of farming)	19.52	16.55	2.98	2.47	0.014
Household size (number)	6.10	5.52	0.59 ^b	2.52	0.012
Household size (adult equivalent)	3.10	2.76	0.33 ^a	3.46	0.001
Farm specific variables					
Distance to the nearest local market (Km)	2.56	2.21	0.35 ^c	1.86	0.064
Market participation (1=yes, 0= No)	0.74	0.59	0.15 ^a	3.16	0.002
Number of crop enterprises	3.31	2.67	0.64 ^a	3.89	0.000
Asset endowment variables					
Education (years of formal education)	8.75	8.2	0.55	1.41	0.160
Cultivated land area in 2009 (acre)	2.17	2.22	-0.05	-0.27	0.787
Membership to farmer organization (1=yes, 0=No)	1.00	0.39	0.61 ^a	18.98	0.001

^a Significant at 1 % level, ^b Significant at 5 % level and ^c Significant at 10 % level

Source: Authors' calculation based on eARN Project data (2010)

Table 3: Logistic regression estimates of propensity scores for participation in ICT-based market information service projects

^a Significant at 1 % level, ^b Significant at 5 % level and ^c Significant at 10 % level

Variable definition	coefficient	p-value
Dependent variable = Participation in ICT-based MIS project		
Farmer specific variables		
Age	0.12 ^b	0.035
Age-squared	- 0.00 ^c	0.096
Gender	- 0.01	0.984
Farming experience	0.00	0.957
Farm specific variables		
Household size	- 0.03	0.690
Distance to the local market	0.10	0.184
Number of Crops	0.22 ^a	0.007
Asset endowment variables		
Mobile phone user (ICT tool user)	1.01 ^a	0.008
Education	0.01	0.760
Group Membership prior to project	0.58 ^b	0.041
Land size owned prior to project	0.12 ^b	0.034
Regional variables		
Bungoma	1.27 ^a	0.000
Migori	- 0.14	0.696
Constant	- 6.30 ^a	0.000
No. of observations: 375 Pseudo R ² : 0.15 p-value : 0.000 Log Likelihood: -211.07 Hosmer-Lemeshow χ^2 (8) = 5.77 Prob > χ^2 = 0.6729		

Source: Authors' calculation based on eARN Project data (2010)

Table 4: Impact of participation in ICT-based market information services on input use and productivity

Matching Algorithm	Nearest Neighbor Matching		Radius Matching		Kernel Based Matching	
Outcome Variable	ATT	T-stat	ATT	T-stat	ATT	T-stat
Value of purchased seed per acre	359.21 ^b	2.35	285.41 ^b	2.25	285.45 ^b	2.17
Value of purchased fertilizer per acre	1,035.10 ^a	2.61	1,009.86 ^b	3.08	952.67 ^a	2.84
Value of purchased manure per acre	33.79	1.01	20.12	0.59	19.92	0.57
Value of purchased Herbicides per acre	-9.85	-0.14	-58.68	-1.10	-50.83	-0.91
Value of total purchased non-labour inputs per acre	1,363.59 ^a	2.61	1,171.82 ^a	2.62	1,129.33 ^b	2.45
Hired labour man-days per acre	- 6.10 ^c	- 1.68	- 6.11 ^b	-2.16	- 6.46 ^b	-2.19
Family labour man-days per acre	-13.49 ^a	-2.99	- 6.99 ^b	-2.00	-7.95 ^b	-2.19
Total labour man-days per acre	-21.96 ^a	-4.62	-15.68 ^a	- 4.43	-16.94 ^a	-4.58
Value of output per man-day	406.95 ^a	5.25	367.46 ^a	5.22	374.85 ^a	5.24
Value of output per acre	8,605.84 ^a	3.30	7,007.14 ^a	3.31	7,160.28 ^a	3.28

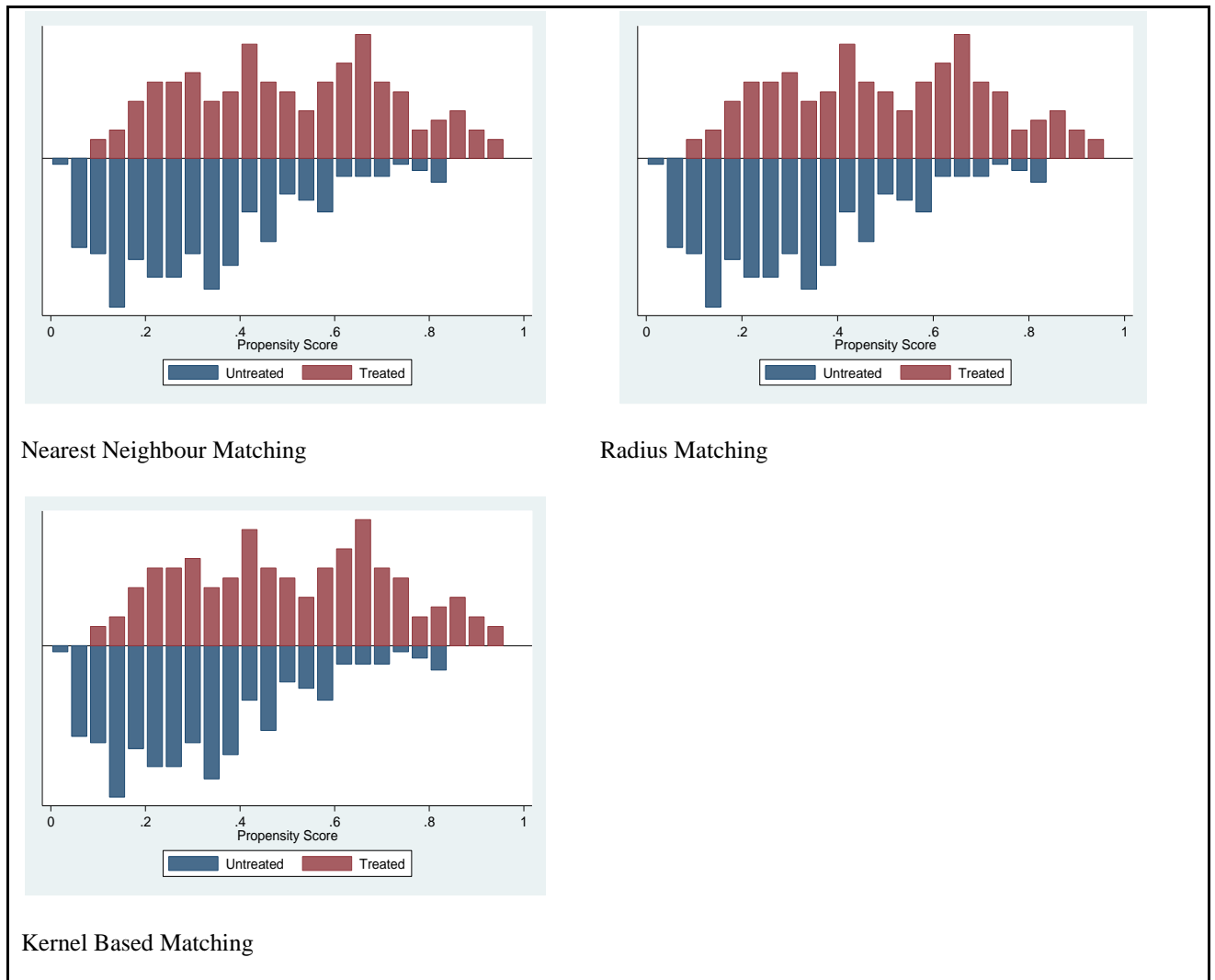
Significant at 1 % level, ^b Significant at 5 % level and ^c Significant at 10 % level

Source: Authors' calculation based on eARN Project data (2010)

Table 5: Covariate balancing tests, PSM quality indicators before and after matching with NNM, RM & KBM, and sensitivity analysis

Matching algorithm	Mean bias before matching	Mean std bias after matching	% bias reduction	Pseudo – R ² unmatched	Pseudo –R ² matched	P-value of LRChi2 unmatched	P-value of LRChi2 matched	Outcome	Critical level of hidden bias (γ)
Nearest Neighbour Matching	29.60	5.11	82.7	0.156	0.011	0.000	0.978	Value of purchased seed per acre	1.15 – 1.20
								Value of fertilizer per acre	1.35 – 1.40
								Value of total non-labor inputs/acre	1.30 – 1.35
								Hired labor man-days per acre	1.70 – 1.75
								Family labour man-days per acre	2.45 – 2.50
								Total labour man-days per acre	4.20 – 4.25
								Value of output per man-day	3.65 – 3.70
								Value of output per acre	1.95 – 2.00
Radius Matching	29.60	12.93	56.31	0.156	0.038	0.000	0.287	Value of purchased seed per acre	1.15 – 1.20
								Value of fertilizer per acre	1.30 – 1.35
								Value of total non-labor inputs/acre	1.15 – 1.20
								Hired labour man-days per acre	2.75 – 2.80
								Family labour man-days per acre	2.25 – 2.30
								Total labour man-days per acre	3.85 – 3.90
								Value of output per man-day	5.95 – 6.00
								Value of output per acre	1.35 – 1.40
Kernel Based Matching	29.60	9.33	64.48	0.156	0.022	0.000	0.803	Value of purchased seed per acre	1.15 – 1.20
								Value of fertilizer per acre	1.25 – 1.30
								Value of total non-labour inputs/acre	1.15 – 1.20
								Hired labour man-days per acre	2.85 – 2.90
								Family labour man-days per acre	2.35 – 2.40
								Total labour man-days per acre	4.20 – 4.25
								Value of output per man-day	2.95 – 3.00
								Value of output per acre	1.40 – 1.45

Figure 1: Distribution of the estimated propensity scores and the region of common support.



Source: Authors' calculation based on eARN Project data (2010)