IMPACT OF ICT-BASED MARKET INFORMATION SERVICE PROJECTS ON SMALLHOLDER FARM INPUT USE AND PRODUCTIVITY: THE CASE OF KENYA

A thesis submitted in partial fulfillment of the requirements for the award of a Master of Science Degree in Agricultural and Applied Economics.

It has already been done

By

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DECLARATION AND APPROVAL

DECLARATION

This thesis is my original work and has not been previously presented for an award of a degree in this or any other university.

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APPROVAL

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DEDICATION

To my dearly loved sister, Anne.

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ABSTRACT

Information asymmetry has traditionally constrained smallholder farmers' access to markets. Past studies indicate that it contributes to low adoption of modern agricultural technologies that have the capacity to enhance the productivity of smallholder farms. Low use of inputs results in low farm productivity, which curtails the transformation from subsistence to commercial agriculture, hence perpetuating the detention of smallholder farmers in the low equilibrium poverty trap. In Kenya, information and communication technology (ICT) based projects have been introduced as part of the strategies to overcome the low farm productivity 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), M-farm and Arid Lands Information Network (ALIN).

Theoretically, these projects are expected to improve the performance of the targeted farmers. Specifically, 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. However, there is still a dearth of empirical evidence of the impact of such interventions on farm input use and productivity in Kenya. This study evaluated the impact of participation in ICT-based MIS projects on the use of purchased farm inputs, labour and land productivity in Kirinyaga, Migori and Bungoma districts in Kenya.

The study focused on the DrumNet project which sought to reduce agricultural information asymmetries by linking smallholder farmers to interlinked credit scheme, agro-input dealers, and produce buyers in order to improve their productivity. The DrumNet project's transactions were mainly performed via an ICT-based platform. The study employed Propensity Score-Matching

(PSM) technique on cross-sectional data collected from 375 farmers to evaluate the impact of participation in the DrumNet project on smallholder farm input use and on land and labour productivity.

The study found that participation in the ICT-based market information service (MIS) project had a positive and significant effect on the usage farm inputs such as seed and fertilizer. Participation in the ICT-based MIS project also increased labour productivity and land productivity. Conversely, participation in the ICT-based MIS project had a negative and significant impact on the usage of hired, family and total labour. The study concluded that participation in ICT-based projects improves the use of non-labour inputs such as seed and fertilizer, but reduces the use of hired, family and total labour. Furthermore, it concluded that participation in ICT-based projects increases both labour and land productivity.

The implication of these findings is that there is 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. Moreover, programs aiming to improve food security and farm incomes should consider the promotion of yield-augmenting agricultural technologies as well as improved access to ICT-based MIS. The study findings also suggest the need for expansion of mobile phone network coverage in farming areas where mobile phone network is still poor, since mobile phone usage was crucial in delivering the benefits.

Key words: Impact evaluation, ICT-based projects, propensity-score matching, smallholder farmers, productivity, Kenya.

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List of Acronyms

ALIN	Arid Lands Information Network
ASDS	Agricultural Sector Development Strategy
ATE	Average Treatment Effect
ATT	Average Treatment effect on the Treated
CIA	Conditional Independence Assumption
CSA	Common Support Assumption
DD	Double Difference or Difference-in-difference
eARN	Electronic Agricultural Research Network
ICT	Information and Communication Technology
IV	Instrumental Variable
KACE	Kenya Agricultural Commodity Exchange
KBM	Kernel Based Matching
MDGs	Millennium Development Goals
MIS	Market Information Service
NIE	New Institutional Economics
NNM	Nearest Neighbour Matching
OLS	Ordinary Least Squares
PFP	Partial Factor Productivity
PSM	Propensity Score Matching
RD	Regression Discontinuity
RM	Radius Matching
SAPs	Structural Adjustment Programs
SSA	sub-Sahara Africa
TCE	Transaction Cost Economics
TFP	Total Factor Productivity

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CHAPTER ONE: INTRODUCTION

1.1 Background Information

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. In the late 1980s to early 1990s, many developing countries assisted by donors or development partners, invested in Market Information Services (MIS) and other reforms to improve market linkage and subsequently, rural household incomes (Kizito, 2009).

The 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 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; Horowitz and Litchenberg, 1993 for examples) 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, 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 challenges 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 farmers in accessing the 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).

In spite of the vital role of agriculture in Kenyan economy, the sector is constrained by setbacks relating to productivity. Productivity levels for most crops are below optimal levels (ASDS, 2010-2020). Agricultural productivity growth has been curtailed by various factors which include: high cost of agricultural inputs, limited extension services, poor livestock husbandry, overreliance on rain fed agriculture, limited market access and low application of agricultural technology and innovation. Inefficiencies in the supply chain also constrain productivity, whereas exploitation by market intermediaries creates distortions in the market (Kenya Vision 2030).

Consequently, the enhancement of agricultural productivity has drawn the attention of policy makers in Kenya due to the significant role of the agricultural sector in economic development (Odhiambo and Nyangito, 2003). It has been observed that in order to grow the sector, Kenya must increase its farm productivity, due to its limited arable land area and low irrigation capacity. Undoubtedly, focus must shift to yield improvement rather than land area expansion for future increases in crop production (Karanja *et al.*, 1998). Limited use of farm inputs by smallholder farmers in sub-Sahara Africa (SSA) relative to other developing countries partly explains the gap between the actual and the potential yields at the farm level (Chianu *et al.*, 2008).

The development of agriculture in Kenya is regarded to be of utmost importance in poverty alleviation through employment creation, foreign exchange earnings and reduced food insecurity

(Kuyiah *et al.*, 2006). It has been noted that emerging technologies are key success factors in addressing the challenges of smallholder farmers. These technologies, particularly Information and Communication Technologies (ICTs), have caused substantial excitement over their role in economic development (Okello, 2010). Improved access to information can play a vital role in ensuring food security and sustainable development (Munyua, 2007).

In Kenya, several ICT-based MIS projects have and continue to be implemented with the objective of correcting the long-standing problem of information asymmetries. The ICT-based MIS projects that have been implemented include: the Kenya Agricultural Commodity Exchange (KACE), Livestock Information Network and Knowledge System (LINKS) and DrumNet. KACE uses ICTs such as internet and mobile phones to supply farmers with low-cost reliable market information to improve their bargaining power for better market prices for their produce. KACE also has an established market resource center to supply farmers with genuine farm inputs (Mukhebi *et al.*, 2007).

LINKS which has been recently integrated into the National Livestock Marketing Information System (NLMIS) facilitates the dissemination of information on livestock prices and volumes traded in the markets via cell phones. Whereas DrumNet sought to reduce agricultural information asymmetries by linking smallholder farmers to an interlinked credit scheme for input purchase, agro-input dealers to improve ready access to quality seed and fertilizer, and produce buyers who also provided technical advice in order to enhance their market access and productivity. These transactions were performed via an ICT-based platform, mainly mobile phone (Gine, 2005). Other ICT-based MIS projects include: Regional Agricultural Trade Intelligence Network (RATIN), M-farm and Arid Lands Information Network (ALIN).

1.2 Problem Statement

Lack of adequate market information stifles the growth of smallholder farms due to several factors. Mukhebi *et al.*, (2007) argue that information asymmetry increases transaction costs and reduces market efficiency. It creates a situation where both farmers and buyers lack awareness about input and commodity quality and quantities. Consequently, this dampens farmers' incentive to use better production techniques such as yield enhancing inputs that have the potential to increase the productivity of their land holdings and enhance their access to high value markets.

The low use of inputs in turn results in low farm productivity and perpetuates the detention of smallholder farmers in the low-equilibrium poverty trap (Barrett, 2008). Imperfect market information among smallholder farmers also leads to absence of market transparency, weak bargaining power, highly volatile input and output prices, weak spatial integration of markets and limited production to satisfy consumer demands (Tollens, 2006). These challenges constrain smallholder farmers in sub-Sahara Africa (SSA) in general and Kenya in particular, limiting the transition from subsistence, to commercial agriculture as envisaged by Kenya's Vision 2030 development plan.

The introduction of ICT-based MIS projects was motivated by their potential capacity to enhance market efficiency, raise prices received by farmers and stimulate higher levels of production (Tollens, 2006). This expectation is logically consistent with Todaro (2000) who argues that commercialization in agriculture requires technological and price incentives to spur the productivity of smallholder farms. Okello (2010) also argues that the use of ICT-based MIS is expected to reduce agricultural transaction costs and increase smallholder commercialization.

However, despite 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 ICT-based MIS projects on farm input use and productivity.

The few previous studies that have attempted to provide empirical evidence of the impact of ICT-based MIS on agricultural productivity are limited and comprise a study by Lio and Liu (2006), which was conducted at a macro-level using cross-country data to assess the impact of ICT on agricultural productivity. The study used an Ordinary Least Squares (OLS) regression, which failed to control for selection bias. Houghton (2009) also assessed the impact of mobile phones on agricultural productivity by employing micro-level data from Cambodia, Honduras and Swaziland using Heckman two-stage regression. The study used cattle ownership as the proxy for measuring productivity gains. In these studies, either the outcome variables of focus were different from the present study's or the methodologies used were flawed.

Lastly, 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. The present 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. It also examines the impact of ICT-based MIS projects on land and labour productivity in an attempt to fill the gap in knowledge on the impact of ICTs.

1.3 Purpose of the study

The purpose of the study was to evaluate the impact of ICT-based market information service projects on smallholder farm input use and productivity in Kenya.

1.3.1 Specific Objectives

The specific objectives of the study were:

(1) To assess the impact of participation in ICT-based market information service projects on the use of agricultural inputs in smallholder farms in Kenya.

(2) To assess the impact of participation in ICT-based market information service projects on labour and land productivity in smallholder farms in Kenya.

1.4 Hypotheses

The tested hypotheses were that:

(1) Participation in ICT-based market information service projects has no effect on the use of agricultural inputs in smallholder farms in Kenya.

(2) Participation in ICT-based market information service projects has no effect on the productivity of labour in smallholder farms in Kenya.

(3) Participation in ICT-based market information service projects has no effect on the productivity of land in smallholder farms in Kenya.

1.5 Justification

This study contributes to the pioneering literature on the impact of ICT-based MIS projects in Kenyan agriculture. It also provides policymakers with information regarding the vital role of ICT-based MIS in stimulating a rural agriculture-reliant economy. The use of ICTs such as telephones, cell phones, personal computers and internet has been highlighted under the Millennium Development Goals (MDGs) in target eighteen as one of the strategies likely to play a vital role in the achievement of MDG eight, which aims to develop global partnerships for development (United Nations, 2000). Hence, it is vital to understand how to tap the benefits of ICTs in marketing in order to increase Kenya's bargaining power in global agricultural markets.

The achievement of Kenya's Vision 2030 requires a consistent economic growth rate of at least 10 per cent for a given time period, for the country to graduate from a low-income nation to a middle-income country by the year 2030. Enhanced total factor productivity amidst prudent monetary, fiscal and exchange rate policies are a recipe for the achievement of the target economic growth rate. Additionally, a dynamic ICT infrastructure is considered as a key element towards the improvement of productivity levels (Kenya Vision 2030).

Due to limited off-farm employment opportunities, particularly in developing countries, increases in household income for improvement of food security must come from gains in agricultural productivity through the use of better technology. The use of ICTs can enhance agricultural productivity through the mechanism of information symmetry by promoting effective dissemination of input and output information (Lio and Liu, 2006). Furthermore, impact evaluation of programs is crucial for ensuring that the limited resources available are used efficiently to achieve the program's set objectives.

CHAPTER TWO: LITERATURE REVIEW

2.1 The concept of productivity

There exists no conventional definition of the term productivity. Bluntly put, the definition of productivity is complex because it is both a technical, as well as a managerial concept. The concept has, until now, been widely used in three fields namely: Economics, Administration and Industrial engineering. These fields have made the search for a precise definition of the concept of productivity complex. Hence, productivity means many things to different people. Perhaps the least controversial definition among economists is that, it is a quantitative relationship between output and input (Antle and Capalbo, 1988; Oyeranti, 2000). Oyeranti (2000) argues that this definition has gained wide acceptability due to two reasons. First, the definition captures productivity in the context of an enterprise, as well as an industry or an entire economy. Secondly, this definition of productivity remains the same regardless of the existing production, political or economic system.

Among business managers, productivity is defined as a measure of efficiency, but with additional meaning of effectiveness and performance of individual organizations. To the managers, productivity would comprise quality of output, workmanship and customer satisfaction (Mulwa *et al.*, 2006). Furthermore, the authors argue that productivity may as well be interpreted as a measure of efficiency in which scarce resources are transformed into output. Improved levels of productivity therefore imply that, either more output is obtained from the same level of input or the same level of output is achieved with less input

Productivity remains the fundamental problem of economic progress, as it is required at both the initial stages of development, as well as in the sustenance of the permanent process. The key to economic growth therefore lies in increased productivity. The study assumed the definition of productivity as the quantitative relationship between output and input. Precisely, economic literature (see Owuor, 1998; Oyeranti, 2000; Mulwa *et al.*, 2006) defines productivity as output per unit of inputs employed in the production process. Owuor (1998) notes that there are two sub-concepts of productivity namely: Partial Factor Productivity (PFP) and Total Factor Productivity (TFP).

PFP is estimated as a ratio of the total output to a single factor input. This implies that there will be as many definitions of productivity as there will be the number of inputs involved in the production process. Oyeranti (2000) notes that most economic studies present productivity to be synonymous with labour productivity. The author argues that emphasis is usually placed on labour productivity because it is the only factor of production that the farmer manager has conscious control over its contribution to output. Among economists, apart from being an indicator of the state of development of a nation, labour productivity can also act as a measure of economic efficiency. Besides, labour is universally a key resource which is easy to quantify and theoretically has a connection with the per capita income of an economy (Oyeranti, 2000).

Labour productivity can for instance be expressed as: output per man-hour or output per unit of labour. This is a partial measure of productivity since it considers labour as the only input. Nevertheless, it is noteworthy that productivity is not a function of labour or one input alone, but a function of other factors too e.g. land, capital, technology, etc. This remains to be the only weakness of using PFP index, notwithstanding that, it is a vital index for measuring the contribution of a single input on the output. PFP measure simply divides physical output by the physical factor input.

TFP on the other hand, is expressed as a ratio of output to the aggregate amount of all inputs applied in production. Theoretically, this is the true measure of productivity since it considers the contribution of all the factor inputs. It is, however, difficult to compute TFP index due to challenges of input valuation, say summing up the hours done by labour or valuing the contribution of land and technology. This is the case particularly where the markets are not well functioning as is always the case in most SSA countries (Owuor, 1998; Mulwa *et al.*, 2006). Following the challenges arising with the computation of TFP index, the study adopted the partial factor measurement of productivity (PFP), where value of output was divided by a single physical factor input, *ceteris paribus*.

2.2 Agricultural productivity and input use in Kenya

Agriculture remains the fundamental vehicle for enhanced food security, poverty alleviation and sustainable development, particularly in Africa. Agricultural productivity growth therefore plays a key role in stimulating growth in other sectors of the economy. Yet, agricultural productivity has been declining over the years, culminating to increased poverty levels (Olwande *et al.*, 2009). At the moment, agricultural productivity growth in SSA lags behind that of other regions of the world and is clearly below the requisite levels for attaining food security and poverty targets (Olwande *et al.*, 2009). Hence, increasing agricultural productivity in Africa continues to be an urgent necessity.

In Kenya, the improvement of agricultural productivity has attracted the interest of policy makers and development practitioners due to two main reasons. First, Kenya relies heavily on the agricultural sector for employment creation, export earnings and economic growth. The sector employs 70 percent of the country's labour force, provides 75 percent of raw materials for industry, generates 60 percent of the foreign exchange, and provides about 45 percent of the total government revenue. Second, indications in Kenya, as well as numerous other SSA countries, are that agriculture is increasingly becoming less productive (Odhiambo and Nyangito, 2003). Kimuyu (2005) also shows that labour productivity in Kenya is on the decline. According to Odhiambo and Nyangito (2003), a declining trend in both land and labour productivity comprises a major challenge and indicates lower living standards at both farm and macro-level.

Literature both in Kenya and other developing countries consider the following factors as the key determinants of agricultural productivity: agricultural research, education, extension, relative factor-product prices, input use and market access (ASDS 2010-2020; Vision 2030). The current study focuses more on the last two factors. Other factors constitute: weather, land ownership patterns, farm production policies and the legal and the regulatory environment. In an effort to remove the constraints associated with the highlighted factors, many development programs have been introduced to provide: infrastructure, marketing networks, information, credit, farm inputs and education. It is believed that the removal of these constraints is likely to culminate in increased agricultural productivity and incomes at farm level. This is vital for poverty alleviation, increase in household food security and stimulating growth in non-farm activities (Odhiambo and Nyangito, 2003).

The achievement of growth in agricultural productivity will only be possible via the development, dissemination and use of productivity enhancing technologies, since it is no longer possible to increase agricultural output by expanding land area under production. For instance, the intensification of land use through fertilizer application is vital for enhancing yields. Chianu *et al.*, (2008) observed that fertilizer consumption rates are least in SSA relative to other regions of the world. Similar observations were made by Kidane *et al.*, (2006) and Olwande *et al.*, (2009).

In spite of the low fertilizer consumption rates in SSA relative to the rest of the world, Olwande *et al.*, (2009) revealed that Kenya's fertilizer consumption relative to other countries in the region has dramatically increased since the liberalization of the fertilizer market in the early 1990s. The authors also observed that Kenya is on record as the only country in SSA that has achieved at least 30 per cent growth in fertilizer use per cropped hectare over the last decade. However, the recent increases in world fertilizer prices, coupled with the civil upheavals of early 2008 are likely to disrupt the steady upward trend of fertilizer use in Kenya. Consequently, this highlights the need for continued promotion of fertilizer use in the country given its potential to increase productivity. It is noteworthy that although Kenya's fertilizer consumption rates rank highest in the region (Olwande *et al.*, 2009), this does not necessarily imply that the country has attained its optimal capacity of fertilizer use.

2.3 Empirical studies on the Impact of ICT-based market information services

There exists literature on the impact of ICT on the economies of developed countries. Nevertheless, most of such studies have been conducted at macro-level, mostly employing cross-country data. Furthermore, the literature providing empirical evidence on the impact of ICT-based MIS on agriculture becomes scanty as focus shifts from developed countries to developing countries in general and sub-Sahara Africa in particular. This sub-section provides a review of the empirical studies that have evaluated the impact of ICT-based MIS on agriculture or agricultural productivity.

Lio and Liu (2006) employed the Hayami and Ruttan model, with consideration of ICT adoption as an infrastructural input, in order to evaluate the effect of ICT on agricultural productivity. The study employed Cobb-Douglas production function estimations on cross-country data for the period 1995-2000 on 81 countries. It sought to provide empirical evidence on the relationship between ICT adoption and agricultural productivity. The Ordinary Least Square (OLS) regression results revealed that a positive and significant relationship exists between adoption of ICT and agricultural productivity. The basic equation used for estimating the effect of ICT, however, failed to control for selection bias. In contrast, the current study was conducted at micro-level and it evaluated the impact of ICT-based MIS using propensity score matching (PSM) approach, which attempts to provide unbiased estimation of treatment effects, by reducing selection bias.

Svensson and Yanagizawa (2008) conducted a study on the impact of ICT-based MIS in Uganda. The study was conducted at a micro-level and focused particularly on the impact of market information services disseminated via FM radio on the agricultural output prices received by smallholder farmers. The authors used the difference-in-difference model. Their findings were that farmers using MIS were able to negotiate for higher farm-gate prices on their surplus production. The current study evaluated the impact of ICT-based MIS projects on farm input use and productivity, and not farm-gate prices. The market environment faced by smallholder farmers in Kenya might not necessarily be same as in Uganda, hence the need for a study within Kenyan context. Generally, it can be argued that higher farm gate prices negotiated by farmers are likely to have spiral effects of increased incomes and purchase of agricultural inputs to enhance agricultural productivity.

Houghton (2009) assessed the impact of mobile phones on agricultural productivity by employing micro-data from Cambodia, Honduras and Swaziland. The author, using a two-stage regression, found that mobile phones improve agricultural productivity at the household level. In that study, cattle ownership was used as a proxy for measuring productivity gains, while in the current study, value of output per man-day and value of output per acre were used as proxies for labour and land productivity, respectively. The socio-economic characteristics of the respondents in their area of study may be different from the current study's context. Additionally, the Heckman two-step approach employed is based on the assumption that the unobserved variables are normally distributed and this has often raised doubts on the estimates they produce.

Mwakaje (2010) assessed the impact of ICT on market information access and its effects on incomes, trade volumes and adoption of new farming technologies in Tanzania. The study revealed that 23 percent of farmers used ICT to access market information. However, market information sources were still dominated by farmers, relatives and traders. The use of ICT was also found to be significantly related to quantity produced, income level, the type of crop marketed and gender. That study differs from the current study in the sense that it focused on revealing the extent to which ICT e.g. mobile phones and radio was used by famers to access market information and further conducted a regression analysis to determine the significance of the determinant factors influencing the use of ICT. The current study evaluated the impact of ICT-based MIS projects on smallholder farm input use and farm productivity in Kenya. It used propensity score-matching technique which attempts to reduce selection bias and provide average treatment effects of program participation.

Kiiza *et al.*, (2011) conducted a study that 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. The study employed propensity score-matching technique on cross-sectional data from maize farmers. The study findings revealed that ICT-based market information had a positive and significant impact on output prices received by smallholder farmers and the intensity of adoption of improved maize seed. The current study is similar, in some aspects, to that of Kiiza *et al.*, (2011), but extends it by assessing the impact of ICT-based market information service projects on the use of fertilizer, herbicides or pesticides, farm manure, besides improved seed. It also examines the impact of use of ICT-based MIS on land and labour productivity.

Okello (2010) conducted a study on the impact of ICT-based MIS projects on smallholder farmers in Kenya. The study applied transaction cost economics (TCE) theory approach and descriptive statistics in analysis. The study found out that smallholder farmers in ICT-based MIS projects were more food secure and had better access to medical health services compared to their counterparts. The study, based on the available literature, was the closest to assess the effects or impacts of ICT-based MIS in Kenya and provided vital insights for laying the platform for the current study. The critique to that study is that, the method used for analysis was not able to control for selection bias or self-selection. Furthermore, the study did not evaluate the impact of ICT-based MIS projects on farm inputs use.

2.4 The Theory of Impact Evaluation

Impact evaluation of programs and events such as adoption of technology or participation in projects are intended to provide policy makers with feedback regarding the net effects of such interventions on the target group or institutions (Baker, 2000). The resultant 'impacted' outcome is argued to be a function of various observed and unobserved 'impacting' factors. Nevertheless, the challenging task lies in determining the portion of the impacted outcome that is due to the specially chosen 'impacting factor' or 'treatment', i.e. problem of causal inference. This is mainly due to the unobserved or missing counterfactual outcome that makes the problem of impact evaluation one of missing data (Bryson *et al.*, 2002; Mendola, 2007). To effectively establish the impact of a program, the counterfactual outcome (outcome that would result without program participation, in the case of program participants, while the outcome with program participation would constitute the counterfactual outcome for non-participants) must therefore be obtained.

Similarly, Baker (2000) argues that determining the counterfactual outcome is the core of impact evaluation and it must be estimated to ensure methodological rigor. The determination of the counterfactual outcome can be accomplished by methodologies broadly falling into two categories namely experimental (randomized) and quasi-experimental (non-randomized) designs. The author argues further that it is, however, a demanding task to net out the impact of a program from the counterfactual conditions which are likely to be affected by history, selection bias and contamination.

Khandker *et al.*, (2010) also note that impact evaluation is basically a problem of missing data, since one cannot observe the simultaneous outcomes of program participants i.e. outcome with participation and outcome without participation. It is noteworthy that for non-participants, the factual outcome is the outcome without treatment; while the counterfactual outcome would be their outcome if they had received treatment. The authors also argue that due to the lack of information on the counterfactual, the next best alternative is to compare the outcomes of treated households with those of a comparison group that has not received treatment. By doing so, one attempts to pick a comparison group that has similar characteristics as the treated group, such that the treated group would have had similar outcomes to those in the comparison group in absence of treatment. A successful impact evaluation therefore depends on finding a good comparison group for estimation of the counterfactual outcome and the reduction of selection bias.

This study is also linked to the concept of Transaction Cost Economics (TCE) which is a strand of the New Institutional Economics (NIE) (Poulton *et al.*, 1998). Coase (1937) in "The nature of the firm" pioneered the concept of transaction cost which has been used extensively in studies addressing issues of bounded rationality and information asymmetry in agricultural economics and related fields (Fafchamps and Hill, 2005; Okello and Swinton, 2007 and Okello *et al.*, 2012). Transaction cost can be loosely defined as cost of doing business between or among various trading partners, in this case, farmers, agro-input dealers and buyers. The argument advanced in TCE is that information is not perfect; neither is it equally available nor distributed. Consequently, information search is necessary, but not costless and thus an important source of transaction cost. Coase (1937) argued that these costs include: cost of searching the buyer, negotiating a contract, screening the products, costs of monitoring and enforcing the terms of a contract, and costs of adapting to the changes in the environment. It is therefore expected that limited market information will increase the costs of exchange between various market actors. As a result, smallholder farmers who use market information services provided by ICT-based MIS projects are likely to face lower transaction costs in accessing input and output markets compared to their counterparts.

2.5 Prior Studies Utilizing Impact Evaluation Methods

There are various methods that have been employed in impact evaluation theory to help in estimating the unobserved counterfactual and subsequently reduce selection bias. Each of these methods carries its own assumptions about the nature of potential endogeneity or selection bias in program targeting or participation, and the assumptions are crucial for the development of appropriate models to determine program impacts. Among the methods employed in the literature include randomized evaluations and quasi-experimental or non-random methods.

Randomized evaluations are designed to address the problem of missing counterfactual outcome and selection bias by randomly generating an experimental group of individuals who would be willing to participate in a program, but are excluded from treatment. By so doing, success is recorded by using the randomly selected, but excluded group as control group and their responses are obtained as the desired counterfactual. Randomized experiments have the advantage of preventing selection bias at the level of randomization, hence providing a clear causal link between treatment and outcome. However, Randomized evaluations are limited to experimental studies, are costly and often encounter ethical challenges by denying the benefits of a program to otherwise eligible members of a population (Baker, 2000; Khandker *et al.*, 2010).

Quasi-experimental or non-random techniques, on the other hand, can be employed in impact evaluation when it is not possible to construct treatment and comparison groups via experimental design (Baker, 2000). Non-random techniques generate comparison groups that resemble the treatment group, at least in observed characteristics, through econometric methodologies, which comprise: double difference methods, matching methods and instrumental variables (IV) methods.

First, Double Difference (DD) techniques compare change in outcomes in the treatment group before and after the intervention to the change in outcomes in the control group. The difference in the outcomes of the treatment and control group gives the Average Treatment effect on the Treated (ATT). Comparison of the changes in outcomes between the two groups makes it possible to control for observed and unobserved time-invariant household characteristics that might be correlated with the participation decision as well as with outcome. The change in outcome of the control group is an estimate of the true counterfactual. Stated differently, the change in outcome in the treatment group controls for fixed characteristics, whereas the change in outcome in the control group controls for time varying factors that are common to both control and treatment groups (Galiani *et al.*, 2003).

DD methods 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. The main shortcoming, however, rests precisely on 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.

Second, Instrumental Variable (IV) approach identifies the exogenous variation in outcomes attributable to the program, recognizing that its placement is not random, but purposive. The "instrumental variables" are first used to predict program participation; then observation is made on how the outcome indicator varies with the predicted values. In this technique, selection bias on unobserved characteristics is corrected by finding a variable (instrument) that is correlated with participation, but is not correlated with unobserved characteristics affecting the outcome. This instrument is then used to predict participation (Baker, 2000).

The IV method comprises the estimation of a two-stage regression model. The method employs the use of an extra variable, referred to as 'instrument', in the second stage of the regression which introduces an element of randomness into the assignment. 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'. The instrument 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 difficult to test assumptions (DiPrete and Gangl, 2004; Kiiza *et al.*, 2011).

Third, is the Heckman two-step method which has been widely employed in empirical research to control for hidden or selection bias on unobserved variables. This method has the advantage of controlling for the differences in both the observed as well as the unobserved attributes of both 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 to this method is that selection estimators are dependent on the 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).

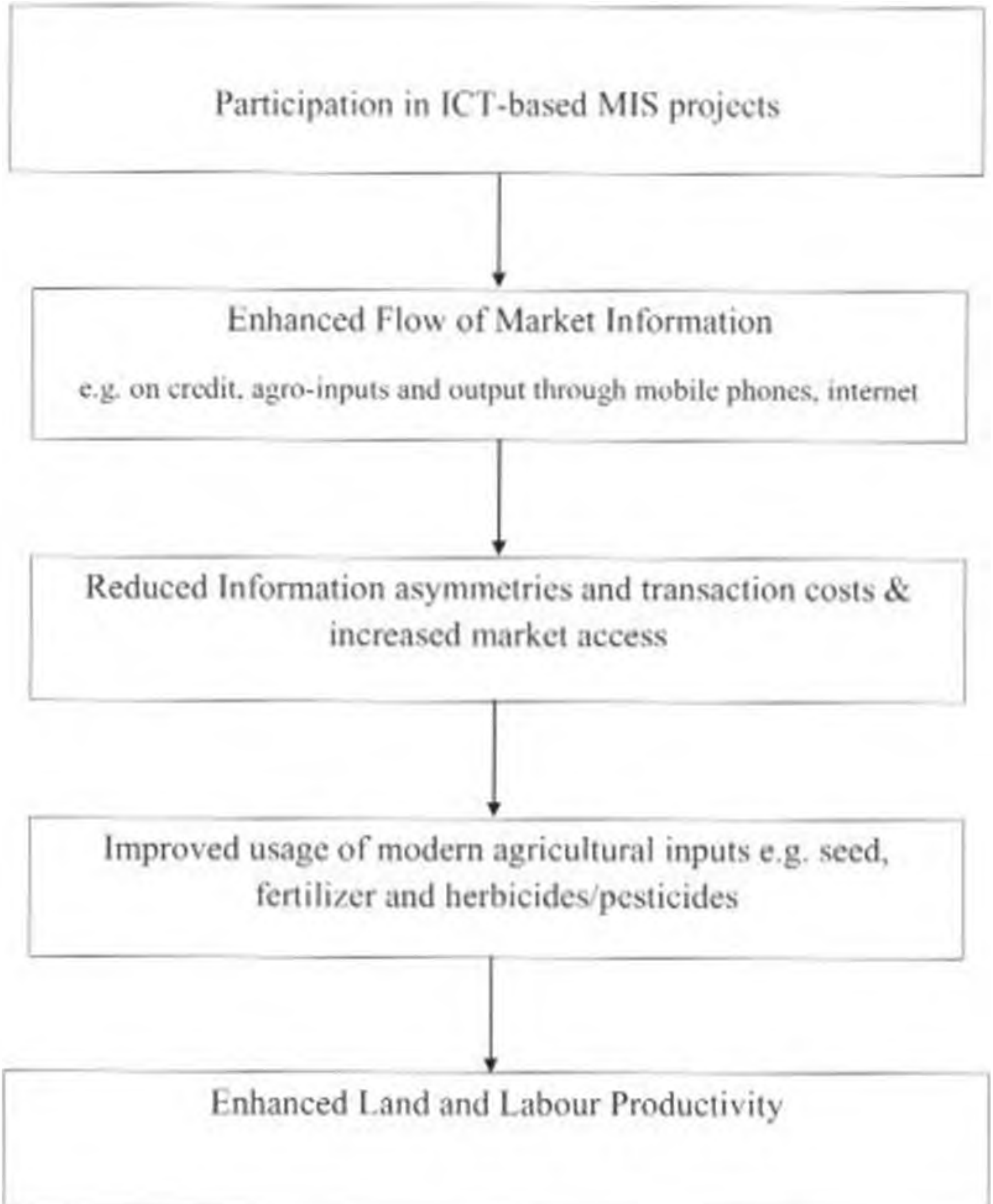
Finally, the non-parametric propensity score matching (PSM) technique, developed by Rosenbaum and Rubin (1983), can also be used to address the problem of selection bias. The method does not depend on functional form and distribution assumptions and is intuitively attractive since it compares the observed 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. PSM consists of matching treatment with control units (i.e., ICT-based MIS project participants versus non-participants) that are similar in their observed characteristics, according to the predicted propensity of participation (Rosebaum and Rubin 1983; Heckman *et al.*, 1998; Smith and Todd, 2005; Asfaw, 2010).

Due to the drawbacks of the previously highlighted methods, the current study employed the PSM technique to estimate the counterfactual outcomes and reduce selection bias in project participation. PSM has been extensively employed in previous empirical studies on impact assessment notably, Rosenbaum and Rubin (1983), Dehejia and Wahba (2002), Smith and Todd (2005), Mendola (2007), Caliendo and Kopeinig (2008), Becerril and Abdulai, (2010), Ali and Abdulai (2010), Kassie *et al.*, (2010), and Kriza, *et al.*, (2011).

CHAPTER THREE: METHODOLOGY

The figure below shows the link between the use of ICT-based MIS projects and their potential impact on farm input use and productivity.

Figure 3.1: Conceptual Framework for the Impact of ICT-based MIS Projects on Farm Input Use and Productivity in Kenya.



Source: Author's conceptualization

3.2 Theoretical framework

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 the utility without participation (U_{iN}) i.e. $(U_{ip}) > (U_{iN})$. The difference between the utility with participation 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 a 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:

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

where R_i* is a latent variable signifying the difference between the utility derived with participation in an ICT-based MIS project and without participation. The term γX represents an estimate of the difference in utility derived from participating in an ICT-based MIS project by employing household and farm-level characteristics (X) as explanatory variables, whereas ε_i is an error term. Theoretically, participation in an ICT-based MIS project 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, as already noted, we 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 most common in Kenya. The profit maximization equation may be expressed as:

$$Max\pi = P(Q|W, X) - VW \qquad (2)$$

where P is output price, Q is 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:

$$\pi = \pi(R, V, P, X) \qquad (3)$$

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:

$$\frac{d\pi}{dv} = -W = W(R, V, P, X) \qquad (4)$$

$$\frac{d\pi}{dp} = Q = Q(R, V, P, X) \qquad (5)$$

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

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 the ICT-based MIS project and zero otherwise, and then apply an Ordinary Least Squares (OLS) regression on it. That basic relationship is a linear function of vector explanatory variables (X_i) and a participation dummy variable (D_i) specified as follows:

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

where Y 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 is the normal stochastic term reflecting unobserved characteristics that also affect Y.

Equation (6) reflects an approach commonly used in impact evaluations (see Lio and Liu, 2006; Khandker *et al.*, 2010), 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 could be based on observed characteristics, unobserved factors, or both (Khandker *et al.*, 2010).

It is noteworthy that in the estimation of equations (1) and (6), the relationship between participation in an ICT-based MIS project and the outcome such as income could be correlated. Therefore, while participation in an ICT-based MIS project could increase output such as household income, wealthier households may have an advantage towards participation in an ICT-based MIS project. Thus, the assignment of treatment is not random, with the group of participating smallholder farmers being systematically different. This is likely to cause selection bias. Selection bias specifically occurs if unobservable factors influence the error terms of participation equation (1) – ε_i, and outcome equation (6) – μ, resulting in correlation of the error terms of participation decision and outcome specifications, i.e., the correlation between the two stochastic terms is greater than zero. In this case, application of OLS will lead to biased estimates (Becerril and Abdulai, 2010) which may result to over estimation of the program's effect, hence the adoption of PSM technique which reduces selection bias.

3.3 Impact Evaluation Using Propensity Score Matching

The PSM approach is more attractive in non-experimental situations, particularly when evaluating the impact of a program using cross sectional data. PSM 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) in a counterfactual framework can be specified as:

$$\Delta = Y_1 - Y_0 \qquad (7)$$

Where Y_i 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 the program participation on the i^{th} household from equation (7) would be misleading due to the problem of missing data. Normally either outcome Y_i or Y_0 is observed for a household i at a time, but not both. That observed outcome can be expressed as (Rosenbaum and Rubin, 1983):

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

where D denotes a dummy equal to one or zero for participant and non-participant, respectively. Bryson *et al.*, (2002) notes that the heterogeneity arising across individuals during impact evaluation raises two questions which evaluations might wish to solve. The first question concerns what impact a program would have on an individual randomly drawn from the population, i.e. the average treatment effect (ATE), whereas the second concerns what impact program participation would have on an individual who actually participated, i.e. the average effect of treatment on the treated (ATT). Both ATT and ATE estimates are of interest, while ATT can indicate the average benefit of receiving treatment, ATE is relevant where policy interest is focused on making a voluntary program compulsory.

The ATT of households, which is the parameter of interest in empirical research, as noted by Rosenbaum and Rubin (1983) and Caliendo and Kopeinig (2008) is written as follows:

$$ATT = E(Y_1 - Y_0 \mid D = 1) = E(Y_1 \mid D = 1) - E(Y_0 \mid D = 1) \qquad (9)$$

Since $E(Y_0 \mid D = 1)$ 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 $E(Y_0 \mid D = 1)$ and not $E(Y_0 \mid D = 0)$.

The problem of using $E(Y_0 \mid D=0)$ 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 approach attempts to capture the effects of various observed covariates X on participation in a single propensity score. The propensity score in our 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 effect can be obtained by comparing the outcomes of participating and non-participating households with similar propensity scores. Households for which no match is found are dropped since no basis exist for their comparison. The technique creates conditions of randomized experiment by employing the unconfoundedness assumption also referred to as Conditional Independence Assumption (CIA) and Common Support Assumption (CSA). The CIA implies that once X, a vector of pre-participation characteristics is controlled for, participation in the 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:

$$p(X) = pr(D=1 \mid X) = E(D \mid X) \qquad (10)$$

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 and non-participants in the ICT-based MIS project.

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 the ICT-based MIS project, hence ruling out perfect predictability. The CSA is expressed as (Rosenbaum and Rubin, 1983):

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

Under the assumptions (10) and (11), ATT can be expressed as follows (Rosenbaum and Rubin, 1983):

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

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

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

The following sub-section describes the model selection for generation propensity scores. Furthermore, it provides a description of the various matching methods that can be used in the implementation of the PSM technique. The estimation of the ATT using the PSM involves the generation of propensity scores which are subsequently used in matching or comparison of participants and non-participants in ICT-based MIS projects in order to net out a program's net effects.

3.4 Empirical Model

Khandker *et al.*, (2010) note that, to calculate program treatment effect, we must first calculate propensity score $P(X)$ on the basis of all observed covariates X that jointly affect participation and the outcome of interest. The aim of matching is to find the closest comparison group from a sample of non-participants to compare with the sample of program participants, in order to control for potential differences between participants and non-participants. In this case, the decision to participate or not to participate is dichotomous or binary.

Classical linear methods have been considered inappropriate for estimating probability response in binary decisions since they lead to heteroscedastic variances (Herath and Takeya, 2003). Linear probability models are also inappropriate as observed in Wooldridge (2004) who argues that although a linear probability model is easy to estimate, it has two key limitations: the resulting probabilities can be less than zero or greater than one, and that the partial effect of any explanatory variable is constant. Consequently, linear models are not often used in practice since logit and probit models are found more appealing.

The probit model assumes a normal distribution of the random term, while the logit model is founded on the assumption of a logistic distribution of the error term. Maddala (1992) notes that, since the cumulative normal distribution of the probit and the logistic distribution of the logit are very close to each other except at the tails, we are unlikely to obtain very different results, unless the samples are too large such that we have enough observations at the tails.

Similarly, Cameron *et al.*, (2005) observed that in empirical studies either a logit or a probit model can be used since there is often little difference between the predicted probabilities of the two models. The differences are noted to be greatest at the tails where the probabilities are close to one or zero. Herath and Takeya (2003) argue that under the standard assumptions about the error term, there is no *a priori* reason to prefer probit to logit, since in practice they don't have much difference. Following this reason, a logit model was estimated to obtain the observable covariates that determine project participation and to generate the propensity score.

According to the logit model, the probability of a household participating in an ICT-based MIS project $(iP|X) = P_i$, given the economic, social and physical characteristics can be specified as:

$$P(iP|X) = P_i = \frac{\exp(X\beta + \xi)}{1 + \exp(X\beta + \xi)} \qquad (13)$$

The probability of not participating in an ICT-based MIS project $P(iN|X) = 1 - P_i$ is therefore:

$$P(iN|X) = 1 - P_i = 1 - \left[\frac{\exp(X\beta + \xi)}{1 + \exp(X\beta + \xi)}\right]$$

$$= \frac{1}{1 + \exp(X\beta + \xi)} \qquad (14)$$

The relative odds of participating versus not participating in an ICT-based MIS project are given by:

$$\frac{P(iP|X)}{P(iN|X)} = \frac{P_i}{1 - P_i} = \frac{[\exp(X\beta + \xi)][1 + \exp(X\beta + \xi)]}{1 + \exp(X\beta + \xi)}$$

$$= \exp(X\beta + \xi) \qquad (15)$$

By taking the natural logarithms, the logit model can be obtained as:

$$ln\left[\frac{P(iP|X)}{P(iN|X)}\right] = ln\left[\frac{P_i}{1 - P_i}\right] = X\beta + \xi \qquad (16)$$

The maximum likelihood Estimation (MLE) approach can be employed to estimate the above equation, in order to generate the propensity scores.

3.4.1 Propensity Score Matching Algorithms

The subsequent stage after propensity score estimation is to match the treated households with households in the control group with similar propensity scores. Several matching algorithms have been previously applied. These include; Nearest Neighbour Matching (NNM), Kernel-based Matching (KBM), Radius Matching (RM) and Mahalanobis Matching methods. Asymptotically, all matching techniques should yield the same results. However, in practice, there are trade-offs in terms of bias reduction and efficiency with each matching method (Caliendo and Kopeinig, 2008).

The NNM is the most straightforward method. It consists of matching each treated individual with an individual from control group with the closest propensity score. NNM can be implemented either with replacement or without replacement. This implies that in the former case, an untreated individual can be used more than once as a match, whereas in the latter case such an individual is considered only once. Replacement increases the average quality of the matches and reduces bias. This is of great interest particularly with data where the propensity score distribution of the treated and the control group differs greatly (Caliendo and Kopeinig, 2008). However, although replacement provides a remedy in such a case, it reduces the number of distinct untreated individuals used to construct the counterfactual outcome and thereby increases the variance of the estimator (Smith and Todd, 2005).

Kernel-based Matching on the other hand, is a non-parametric estimator that matches each treated individual with a weighted average of all controls. It uses the weighted average of virtually all the individuals in the control group to construct the counterfactual outcome depending on the choice of the kernel function (Caliendo and Kopeinig, 2008). The weights used are inversely proportional to the distance between the propensity scores of the treatment group

3.4.2 Test for robustness and unobserved heterogeneity

Since matching technique 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, Becerril and Abdulai, 2010). According to Rosenbaum and Rubin (1983) and Kiiza *et al.*, (2011), the formation of matched pairs of observably comparable participants and non-participants eliminates the confounding effects of observable covariates. The object of matching, as argued earlier, is to restrict the non-participants sample in order to increase the resemblance of the sub-sample of non-participants cases that are directly comparable with the participants in order to estimate the project's effects.

The quality of the resulting matches are basically 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). Sianesi (2004), Caliendo and Kopeinig (2008) and Becerril and Abdulai (2010) also 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. Furthermore, one can also perform a likelihood ratio test *(F 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 unobserved heterogeneity or hidden bias after matching. Kiiza *et al.*, (2011) argued that an unobserved covariate that influences assignment to treatment, but does not affect the outcome beyond the variables already controlled does not challenge the robustness of the estimated results. In order to test the extent to which such an assignment on unobserved covariates may bias the results or inferences, the study employed 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 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. The cut-off point should be large enough to render the estimates robust against any unobserved selection bias (Kitza *et al.*, 2011).

3.5 Variables in the econometric model

The observed covariates hypothesized to influence participation are based on innovation diffusion theory and previous studies.

3.5.1 Dependent Variables

1. Participation in an ICT-based market information service project (MIS). This is a dichotomous choice variable (1 = project participant, 0 = non-participant).
2. Input use – measured as value of purchased seed, manure, pesticide and fertilizer in Kenya shillings (Kshs) per acre and hired labour, family labour and total labour in man-days per acre.
3. Land productivity – measured as the value of crop output in Kshs per acre.

and controls. The average places higher weight on controls close in terms of propensity score of a participant and lower weight on more distant observations. One major advantage of this approach is the lower variance, achieved mainly because more information is used (Heckman *et al.*, 1998). Kernel matching could thus be seen as a weighted regression of the counterfactual outcome on an intercept with weights given by the kernel weights (Smith and Todd, 2005).

In the radius matching approach, an individual from the control group is chosen as a matching partner for a treated individual that lies within a specified radius in terms of propensity score. Smaller radius usually results in better quality matching. Radius matching is normally faced with the risk of bad matches, particularly if the closest neighbour is far away. Caliper matching can provide a remedy to this problem. Caliper matching which is a variant of the nearest neighbor matching attempts to avoid 'bad matches' by imposing a tolerance on the maximum propensity score distance (caliper) allowed. The advantage of this approach is that it uses only as many comparison units as are available within the caliper and therefore allows for usage of extra (fewer) units when good matches are (not) available (Dehejia and Wahba, 2002; Caliendo and Kopeinig, 2008).

Finally, Mahalanobis matching technique randomly orders subjects and then calculates the distance between the first treated subject and all controls. The minimum distance between the treated subject and the controls is used as a match and the procedure is repeated for all the covariates. This technique is usually appropriate for panel data. The study employed NNM, RM and KBM methods to check the robustness of the results.

4. Labour productivity – measured as the value of crop output in Kshs per man day.

Maize, French beans, field beans, sunflower and baby corn were the selected crops considered in the computation of the above outcome or dependent variables. The selection of the crops was informed by the fact that the ICT-based MIS project studied targeted farmers that grew these crops and the availability of complete data on the same.

3.5.2 Independent Variables

According to Ngugi *et al.*, (2003), although age is a crucial factor in determining project participation, its influence cannot be determined a priori. As a measure of experience, older people may participate in projects due to previous losses as a result of failure to participate in projects early enough. On the contrary older farmers may be more risk averse and consequently be more reluctant to participate in projects. However, past adoption studies predict a negative correlation between age and technology adoption. For instance Walton *et al.*, (2010), argue that younger people are less risk averse and are more willing to make adjustments in their farming by adopting new technologies, unlike the older people. Given the nature of the project, a negative correlation between age and project participation was hypothesized.

Education was conceived to better enable farmers to visualize the benefits of participation in ICT-based projects. Findings in technology adoption studies e.g. Walton *et al.*, (2010), indicate that education improves the analytical ability of the decision makers, hence positively influencing adoption. It is noteworthy that, although the determinants of participation in projects and technology adoption may be different, there may be enough similarities to draw from the later. It was hypothesized that education has a positive influence on project participation.

Odendo *et al.*, (2010) argue that since previous research has documented evidence of inequalities in ownership and control of crucial resources between men and women, gender *per se* does not influence adoption patterns, but resource inequalities. Following this argument, it was hypothesized that male headed households were more likely to participate in the ICT-based MIS project relative to female headed households.

Herath and Takeya (2003) and Odendo *et al.*, (2010) observe that the effect of farming experience on technology adoption is ambiguous *a priori*. Many years of experience may reduce the time horizon for the realization of the benefits of participation in a project, and increase risk aversion. On the contrary, greater experience could lead to more accurate judgment of the benefits of participation. Hence, the effect of farming experience could not be determined *a priori*.

The influence of household size on participation cannot be determined *a priori* (Herath and Takeya, 2003). Project participation may depend on whether a household has a higher ratio of members who contribute to farm work implying more labour, hence more time for participation. On the other hand, it may depend on whether a household has a higher consumer-worker ratio raising the need for more labour for production; hence reducing time available for participation (Odendo *et al.*, 2010).The influence of household size was thus indeterminate *a priori*.

According to Odendo *et al.*, (2010), larger farm size (land area) is associated with greater wealth, increased availability of capital and high risk bearing ability which makes investment more feasible. Availability of capital may for instance promote the acquisition of the requisite ICT tools for project participation. A positive correlation between farm size and participation in an ICT-based MIS project was thus hypothesized. Similarly, membership to groups may enable farmers to learn about the benefits of a technology from other farmers or development agencies. Group membership was thus expected to increase the likelihood of participation in ICT-based MIS projects.

Living far from the market can create a barrier associated with limited information about distant marketing outlets and increased transaction costs (Odendo *et al.*, 2010). Based on this argument, it was hypothesized that distance to the local market is positively correlated with participation in an ICT-based MIS project. Farmers located far away from the market were perceived to have a higher likelihood of participating in an ICT-based MIS project to reduce their information asymmetries and transaction costs.

Other variables included in the model comprise: use of mobile phone and number of crop enterprises by a farmer. It was perceived that, since the project focused on the use of ICT tools in general, but mobile phone in particular, mobile phone usage by a farmer would increase the likelihood of project participation. Finally, it was hypothesized that the number of crop enterprises (proxy for risk aversion) would be negatively correlated with project participation. This hypothesis was informed by Ngugi *et al.*, (2003) who argued that risk aversion is negatively correlated with project participation and Okello *et al.*, (2012) who found a negative correlation between number of crop enterprises and use of ICT tools.

3.6 Data Collection and Sampling Procedure

The study used secondary data collected by the electronic Agricultural Research Network in Africa (eARN-Africa) project. The eARN-Africa project targeted smallholder farmers including those who participated in ICT-based projects that used ICT tools and those who did not. The respondents were therefore stratified by participation in such ICT-based agricultural projects.

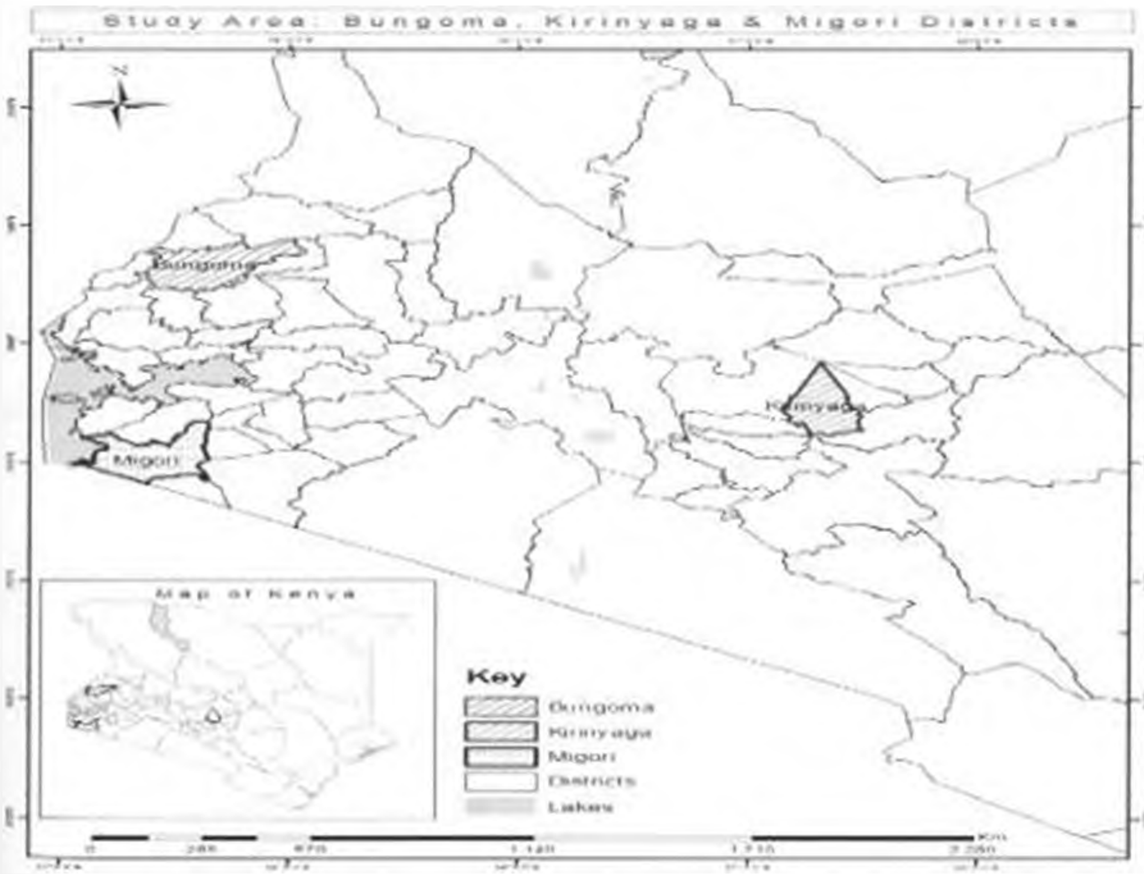
The data collection employed multi-stage sampling. The sampling procedure was conducted in three stages in the three districts i.e. Kirinyaga, Bungoma and Migori. First, in each district, an area with an ICT-based project was identified. Second, for each such area, a list of all farmers registered to participate in the ICT-based project was drawn with the help of project and farmers' leaders. A second list of farmers that did not participate in the ICT-based MIS project was also obtained with the help of local administration (village elders and area agricultural extension officers) and verified by project 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. A total of 375 farmers were therefore interviewed in this study. This comprised of 127, 130 and 118 respondents from Kirinyaga, Bungoma and Migori districts, respectively. The data was collected through personal interviews using a pre-tested questionnaire. The data 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. In addition, secondary time series data for the district level averages on inputs use and output for the focus crops in the study was collected from the agricultural offices in the districts.

3.7 Study area

The study was part of a project carried out by the Electronic Agricultural Research Network in Africa (eARN-Africa) in six countries including: Kenya, Ghana, Madagascar, Malawi, Benin and Uganda. The objective of the project was to evaluate the effectiveness of ICTs in linking smallholder farmers to markets. In Kenya the study area comprised Kirinyaga, Bungoma and

Migori districts. These districts are characterized by smallholder farmers with poor access to markets and reliance on agriculture. However, it is noteworthy that market access in Kirinyaga district is quite advanced relative to the other districts. The three districts were targeted by the study because some farmers in the districts had participated or were still participating in ICT-based projects aimed at facilitating the linkage of smallholder farmers to the markets through the use of new generation ICT tools. The three districts also provided some socio-economic diversity. In Kirinyaga district, farmers mainly produced French beans and baby corn for export market. Migori district had farmers in the project producing sunflower and maize, while in Bungoma district, farmers mainly produced maize and sugarcane.

Figure 3.2: Map of the study area



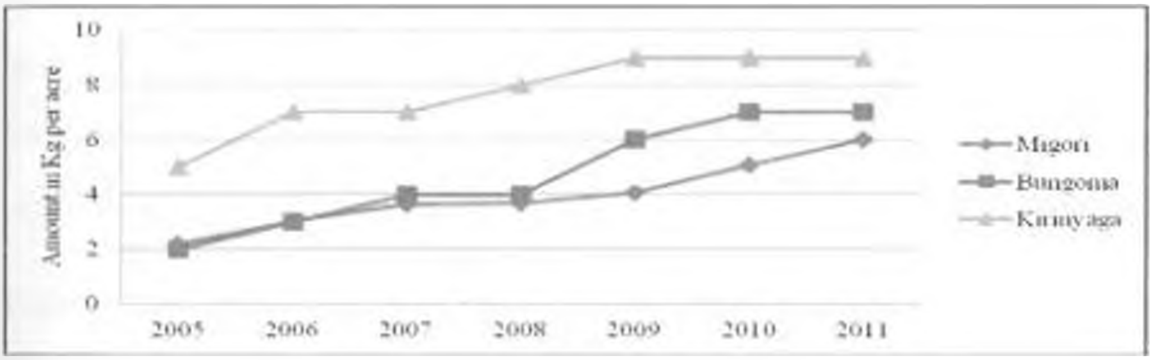
CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Descriptive results and summary statistics

4.1.1 Trends in output and inputs use

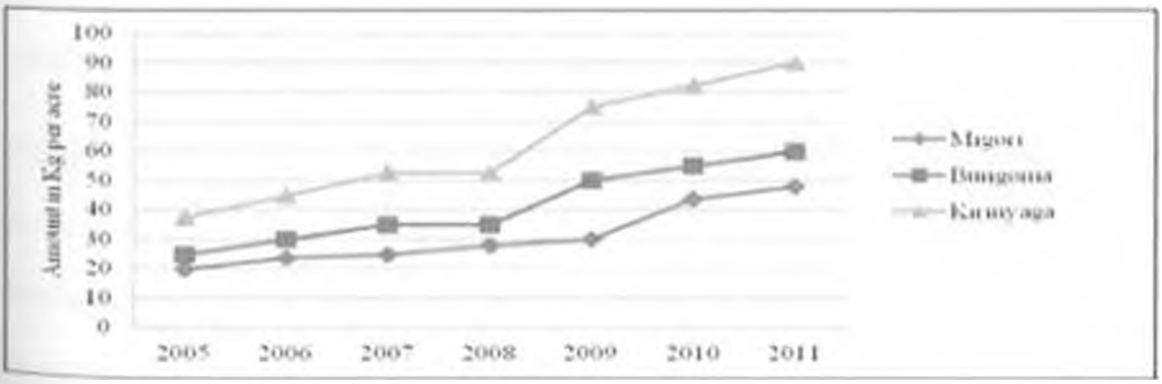
This sub-section examines the district level trends in agricultural output and input use for the period 2005 – 2011. Generally, the results indicate an upward trend in the quantity of purchased seeds per acre (Figure 4.1) and the quantity of purchased fertilizer per acre (Figure 4.2), in all the three districts.

Figure 4.1: Quantity of purchased seed per acre, 2005 – 2011



Source: Ministry of Agriculture (MoA) district level data, April 2012

Figure 4.2: Quantity of purchased fertilizer per acre, 2005 – 2011



Source: MoA district level data, April 2012

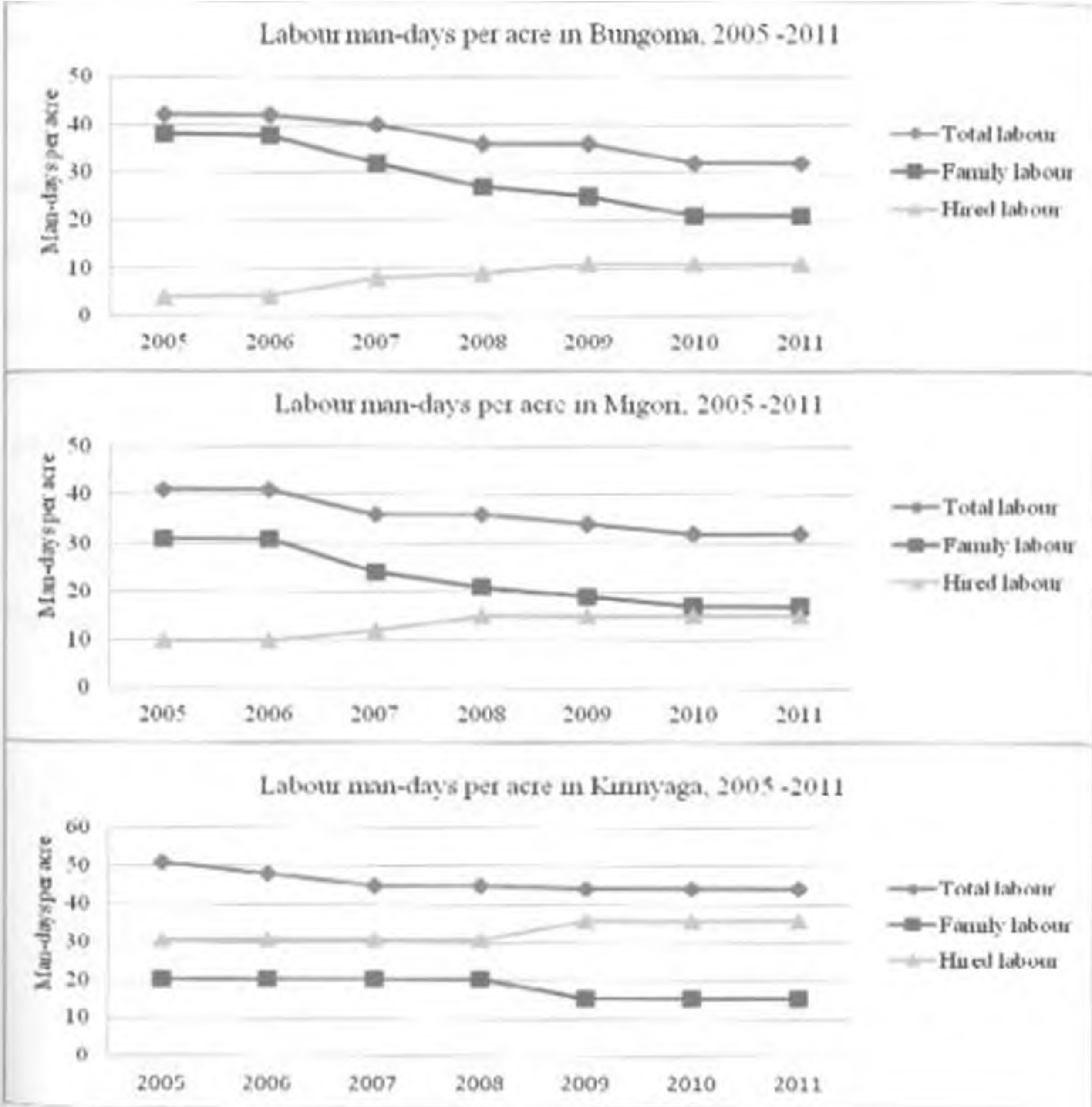
The findings in Figure 4.1 and 4.2 were consistent with the findings by Ariga *et al.*, (2008) who found an upward trend in fertilizer use from 1997 to 2007. The authors argued that the rising trend in fertilizer use over the period was due to stable input policy by the government which ensured elimination of fertilizer import restrictions, price controls and market uncertainties arising from large subsidy programs. Consequently, there were more market players leading to lower fertilizer prices and improved access of the inputs. That argument can be applied to this study. Furthermore, the results were consistent with the developments in the agricultural sector during the period. For instance, the existence of ICT-based MIS projects might have played a key role in facilitating smallholder farmers' access to input and output markets by increasing their awareness levels on inputs and output markets, hence promoting the use of improved seeds and fertilizer due to reduced transaction costs. Additionally, government initiatives such as the National Accelerated Agricultural Inputs Access Program (NAAIAP) might have also contributed to the rising trend in use of purchased seed and fertilizer during the period.

Figure 4.1 and Figure 4.2 also show that the quantity of purchased seed and fertilizer was highest in Kirinyaga district, but least in Migori district. This was attributed to the production of high value fresh export vegetables in Kirinyaga district that might have led to increased use of improved purchased inputs. Furthermore, Kirinyaga's proximity to Nairobi town was also considered as a possible explanation for the finding.

It is noteworthy that although pesticides, herbicides and manure are vital inputs in agricultural production, the study in analyzing the trends in input use focused on purchased seed and fertilizer only, due to secondary data limitations. However, the usage of manure and pesticides or herbicides was also evaluated in the econometric models where the cross-sectional data used was sufficient.

A key factor in agricultural production in Kenya is labour. Indeed, agricultural production has been and still remains labour intensive. The results in Figure 4.3 show a decline in the use of labour man-days per acre across all the three districts.

Figure 4.3: Labour man-days per acre in the study regions, 2005 – 2011



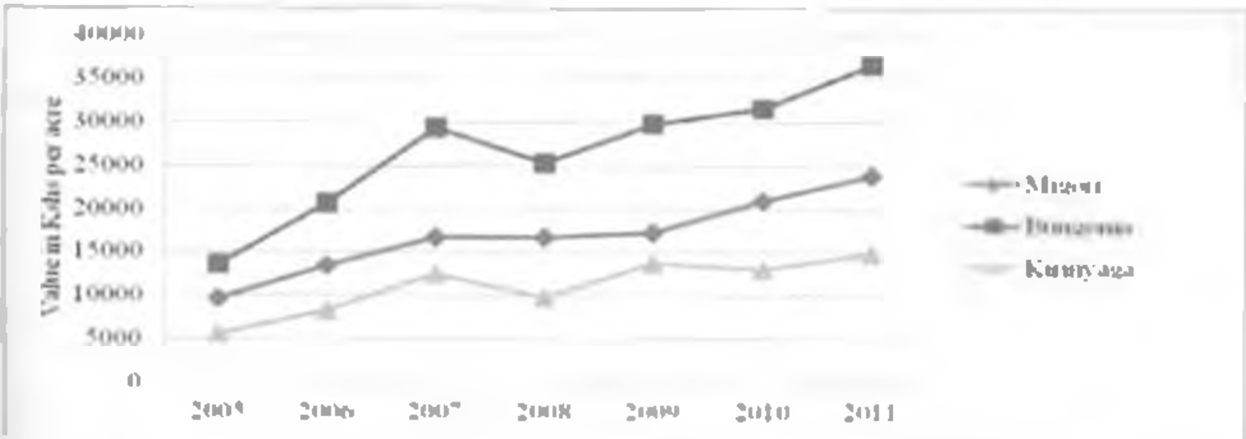
Source. MoA district level data, April 2012

This is a likely indication that labour was becoming a scarce resource, hence suggesting that the use of improved inputs was substituting for labour as indicated by the upward trend in use of improved inputs in Figure 4.1 and Figure 4.2. Furthermore, the traditionally predominant family labour source was declining as shown in Figure 4.3, while the use of hired labour was rising. This was probably due to decreasing household sizes and an increase in alternative sources of income in rural areas e.g. the thriving '*boda boda*' business in most rural areas.

In Bungoma and Migori districts, family labour was more predominant, unlike in Kirinyaga where hired labour was the key source of labour. It is argued that this finding was as a result of the differences in household size or household adult equivalent across the three districts as indicated in Table 4.1. Kirinyaga district had the lowest mean value of household sizes/household adult equivalent compared to other districts. This suggests that there was a lower ratio of family members contributing to farm work in Kirinyaga relative to other districts.

Figure 4.4 shows that land productivity has been trending upwards in all the three study areas.

Figure 4.4: Trend of the value of output per acre – land productivity, 2005 – 2011



Source: MoA district level data, April 2012

The upward trend in the value of output per acre over the period was consistent with the rising trend in the use of improved inputs observed earlier. Bungoma had the highest value of output per acre, while Kirinyaga had the least. The crops used in calculating the value of output per acre were maize and field beans. The low value of output per acre observed in Kirinyaga was thus expected due to the much attention given to fresh export vegetable crops in the region as opposed to maize and field beans which were used in the analysis.

4.1.2 Summary statistics of variables used in quantitative analysis

Table 4.1 presents a summary statistics of the farmers interviewed in Kirinyaga, Bungoma and Migori districts. It also provides information on pooled sample of the three districts surveyed.

The descriptive statistics reveal that 35 percent of the farmers interviewed in Kirinyaga participated in ICT-based MIS projects, compared to 55 percent and 25 percent 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 transactions due to their production of market-oriented export vegetables), the proportion of participants in the ICT-based project was highest in Bungoma. This may have been 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 percent of the farmers interviewed participated in ICT-based projects. This finding suggests a low rate of participation in ICT-projects, probably due to lack of awareness of the existence of the projects and or their possible benefits.

The mean farmer expenditure on purchased improved inputs that comprised seed, fertilizer, manure and herbicides or pesticides was Kshs 1,660.05, Kshs 3,672.28, Kshs 104.35 and Kshs 454.83 per acre, respectively in Kirinyaga district.

Table 4.1: 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
Farmer specific variables								
Age (Years)	43.78	12.46	43.7	13.12	42.75	16.04	43.43	13.87
Main occupation (1=farming 0=otherwise)	0.92	0.27	0.95	0.23	0.81	0.39	0.89	0.29
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
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
Districtof 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

Source: Author's computations based on eARN project survey data, 2010 Note: 1 US dollar = Kshs 78 in 2010

The corresponding expenditure on seed, fertilizer, manure and herbicides in Bungoma district was Kshs 984.82, Kshs 3,613.99, Kshs 18.27 and Kshs 9.86 per acre, respectively, while that in Migori was Kshs 599.39, Kshs 914.41, Kshs 0.28 and Kshs 11.59 per acre, respectively. In addition, the mean total expenditure on all purchased non-labour inputs in Kirinyaga, Bungoma and Migori districts was Kshs 6,290.65, Kshs 4,626.93 and Kshs 1,515.67 per acre, respectively, but with a wide variance as indicated by the standard deviation. The findings on the expenditure on non-labour purchased input use per acre, by district, ranked Kirinyaga highest, whereas Migori was the least ranked.

The relatively higher expenditure on non-labour inputs per acre in Kirinyaga might have been due to the high commercial orientation as well as market participation of farmers in the region. In Kirinyaga, 77 percent of the respondents participated in the market, while the corresponding figure on market participation for both Bungoma and Migori districts was 58 percent. As already noted, farmers in Kirinyaga produced market-oriented export vegetables such as French beans and baby corn, hence used more inputs than their counterparts in Bungoma and Migori districts. In Migori, farmers mainly produced crop for subsistence, hence the low use of non-labour inputs in the region.

The results of labour usage indicate that on average, a farmer in Kirinyaga used 30.14 and 29.98 man-days of hired and family labour per acre, respectively. The mean usage of labour in Bungoma was 10.21 and 46.21 man-days of hired and family labour per acre, respectively. On average, a farmer in Migori used 10.68 and 33.68 man-days of hired and family labour per acre, respectively. The pooled sample shows that on average, each farmer in the survey used 30.14 and 29.98 man-days of hired and family labour per acre, respectively. The mean total labour man-days used per acre was 57.3, 57.41, 45.45 and 53.61 in Kirinyaga, Bungoma, Migori and the pooled sample, respectively.

In addition, the results of labour usage indicate that Kirinyaga had the highest usage of hired labour man-days per acre, compared to other regions. This finding was in line with the study's *a priori* expectation since most of the farmers interviewed in Kirinyaga planted French beans which require intensive use of labour during weeding and picking harvesting. Furthermore, the finding suggests that family labour was most scarce in Kirinyaga relative to the other districts. This argument might be complemented by the lowest figure of household size adult equivalent observed in Kirinyaga compared to Migori and Bungoma[1].

Family labour was used most in Bungoma compared to Migori and Kirinyaga districts. This was perhaps due to the high household size adult equivalent, a likely indicator of family labour availability in the region relative to the other regions. Overall, the mean labour usage per acre was lowest in Migori, possibly due to the farmers' engagement in the cultivation of less labour demanding crops e.g. maize. Family labour dominated the labour input use, except in Kirinyaga, where family labour was most scarce. This finding was consistent with the earlier finding on the trend in labour use at the district level in Figure 4.3.

The mean value of output per man-day, the measure of labour productivity, was Kshs 709.61, Kshs 546.44 and Kshs 469.60 in Kirinyaga, Bungoma and Migori respectively. The results also show that the mean value of output per acre was Kshs 29,952.63, Kshs 25,826.00 and Kshs 16,151.62 in Kirinyaga, Bungoma and Migori districts respectively. These findings suggest that labour and land productivity rates were highest in Kirinyaga and lowest in Migori. It is argued

[1] The chi-square test results in appendix 3 indicate that, household size adult equivalent was significantly different across the three districts, with Bungoma having the highest figure and Kirinyaga the least

that the relatively higher levels of labour and land productivity in Kirinyaga were due to higher use of non-labour inputs and production of high value fresh export crops.

Generally, the results of the descriptive statistics consistently indicate that on average, farmers in Kirinyaga used more labour and non-labour inputs per acre relative to their counterparts in other districts, with farmers in Migori spending less. Moreover, value of output per man-day and value of output per acre also increase from Migori to Kirinyaga district.

Table 4.1 also provides additional information on of the farmers. The mean age, education, household size, household size equivalent, distance to local market, land size, years of farming experience and number of crop enterprises of the pooled sample were 43.43, 8.41, 5.74, 2.89, 2.89, 2.21, 17.61 and 2.91, respectively. Additionally, 50 percent of the cases were male, 62 percent had been members to a farmer group prior to the ICT-based MIS project and 65 percent were market participants[7].

Table 4.2 presents the test of difference in means of some characteristics between participants and non-participants in ICT-based MIS projects, along with their t-values. The results indicate that there were significant differences between ICT-based MIS project participants and non-participants with respect to age, main occupation, household size, distance to the nearest local market, number of crop enterprises – proxy for risk, and value of physical assets, group membership and crop income. ICT-based project participants were older in age, had higher household sizes, were located further from the local market, had more crop enterprises and had more proportions of individuals whose main occupation was farming and belonged to farmer groups prior to the ICT-based MIS project.

[7] The chi-square test results in appendix 3 present some of these variables that were significantly different across the three districts

Table 4.2: Differences in means of participants and non-participants

Characteristic	Participants n = 144	Non-participants n = 231	Mean Difference	t values	p values
Dependent variables					
Value of purchased seed per acre (Kshs)	1,297.25	964.4	332.85***	2.73	0.007
Value of purchased fertilizer per acre (Kshs)	3,582.90	2286.41	1296.48***	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***	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*	-1.91	0.057
Total labour man-days per acre	46.38	58.11	- 11.73**	-3.59	0.000
Value of household output per man-day (Kshs)	793.82	442.69	351.13***	5.12	0.000
Value of household output per acre (Kshs)	28,905.47	21,233.20	7,672.28***	3.83	0.000
Farmer specific variables					
Age (years)	46.68	41.4	5.28***	3.74	0.000
Main occupation (1 = farming , =0 otherwise)	0.93	0.87	0.06**	1.97	0.050
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)	6.1	5.52	0.59**	2.52	0.012
Household size (adult equivalent)	3.1	2.76	0.33***	3.46	0.001
Farm specific variables					
Distance to the nearest local market (Km)	2.56	2.21	0.35*	1.86	0.064
Market participation (1= yes, 0= No)	0.74	0.59	0.15***	3.16	0.002
Number of crop enterprises	3.31	2.67	0.64***	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	0.39	0.61***	18.98	0.001

Source: Author's computations based on eARN project survey data, 2010   Note: significance is at *10 percent, **5 percent and ***1 percent

Participants also had higher values of purchased seed per acre, purchased fertilizer per acre and total value of purchased non-labour inputs per acre compared to non-participants. These findings suggest that on average, participants in the ICT-based MIS project purchased more of the core non-labour improved inputs, i.e. seed and fertilizer, compared to non-participants. These findings were consistent with economic theory which posits that improved access to information reduces market information asymmetries and improve market linkage.

In the context of the study, these results may imply that participants had increased access to information about the right quality and quantity of inputs, hence promoting the use of improved inputs among the participating farmers.

The mean values of labour productivity – output per man-day and land productivity – output per acre also differed significantly between the two groups, with participants having higher values than non-participants. The higher land productivity among participants was attributed to the higher use of improved inputs, *ceteris paribus*. Similarly, the higher labour productivity among participants relative to non-participants was attributed to better access of information on inputs and outputs, and subsequent increased input use.

The results in Table 4.2 also show that the mean usage of hired and total labour per acre was significantly different between participants and non-participants, with participants using less labour per acre. This finding was consistent with the "Induced Innovation Hypothesis" developed by Hayami and Ruttan (1971) and later revised by Ruttan and Hayami (1998). The theory postulates that the scarcity of certain factors of production will induce a kind of agricultural development that will encourage the substitution of the relatively abundant resource for the relatively scarce resource. Therefore, the low usage of hired labour by participants suggests that the use of improved non-labour inputs substituted for the scarce labour resources; this might have been the case particularly in Kirinyaga district where family labour supply was inadequate to offset the total labour demand. Besides, participation in the ICT-based MIS project reduced transaction costs, especially search costs among participants, hence reducing the labour for searching for fertilizer, purchased seed, manure, pesticides and hired labour. This might have been the case due to the provision of such information by the ICT-based project and increased phone usage for agricultural transactions among the project participants.

4.2 Impact of ICT-based MIS projects on farm input use

This sub-section provides results of the non-parametric PSM technique. It begins with the results of the logit model which were used for generating propensity scores, followed by the matching results. It then concludes with diagnostic tests for robustness of the results.

The results of the logit model estimated to generate propensity scores for the observed factors that condition participation in an ICT-based MIS project are presented in Table 4.3. The estimation of the logit regression model was preceded by diagnostic tests for multicollinearity the Variance Inflation Factor (VIF) technique (see appendix 1). Gujarati (2007) notes that "although a study of partial correlations may be useful, there is no guarantee that they will produce an infallible guide to multicollinearity, some authors therefore, use VIF as an indicator of multicollinearity". Hence, the study used the two tests to check for the presence of high multicollinearity. The larger the value of the VIF, the more collinear a variable X_j. Furthermore, the author argues that "as a rule of thumb, if the VIF of a variable exceeds 10, which will happen if R^2_j exceeds 0.9, that variable is said to be highly collinear. The results of the VIF for the variables included in the model were less than 5 (implying that R^2_j was less than 0.8); therefore, there was no evidence of severe multicollinearity problem among the variables in the logit specification. A test of goodness of fit of the estimated logit model was also conducted. The likelihood ratio of the logit model reported in Table 4.3 indicates a low p-value = 0.000 which implies that the model fit the data well.

Table 4.3: Logit regression estimates of propensity scores for participation in ICT-based market information service projects (pooled sample).

Variable definition	Coefficient	p-value
Dependent variable = Participation in ICT-based MIS project		
Farmer specific variables		
Age	0.117^{**}	0.035
Age-squared	-0.001^{*}	0.096
Gender	- 0.005	0.984
Farming experience	0.001	0.957
Farm specific variables		
Household size	- 0.027	0.690
Distance to the local market	0.095	0.184
Number of Crops	0.224^{***}	0.007
Asset endowment variables		
Mobile phone user (ICT tool user)	1.015^{***}	0.008
Education	0.012	0.760
Group Membership prior to project	0.580^{**}	0.041
Land size owned prior to project	0.118^{**}	0.034
Regional variables		
Bungoma	1.268^{***}	0.000
Migori	- 0.143	0.696
Constant	-6.297^{***}	0.000
P-value : 0.000 No of observations 375 Pseudo R^2 : 0.15 Log Likelihood: -211.07 Hosmer-Lemeshow $\chi2$ (8) = 5.77 Prob > χ^2 = 0.6729		

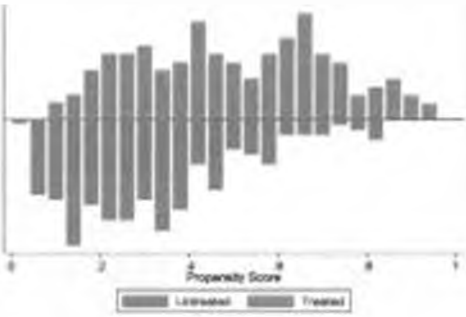
Source: Author's estimation based on eARN project survey data, 2010

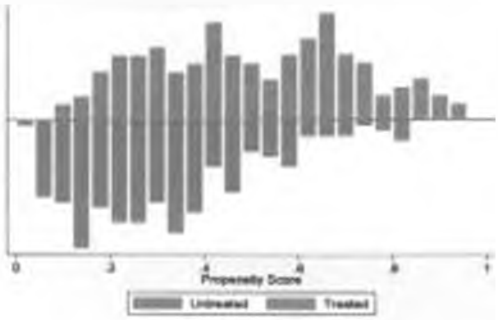
Note: significance level is at *10 percent, **5 percent and ***1 percent

Additionally, the Hosmer and Lemeshow's goodness of fit test was carried out. The Hosmer and Lemeshow's goodness of fit statistic is computed as the Pearson chi-square from the contingency table of observed frequencies and expected frequencies. Similar to a test of association of a two-way table, a good fit as measured by the Hosmer and Lemeshow's test will yield a large p-value. With a p-value of 0.67 as shown in Table 4.3, it was concluded that the model fit the data well.

The results in Table 4.3 indicate that age, number of crop enterprises (proxy for risk aversion), use of mobile phone, group membership, land size and being in Bungoma positively influenced the likelihood of participation in ICT-based MIS projects. However, age-squared negatively influenced the likelihood of participation in ICT-based MIS projects[1].

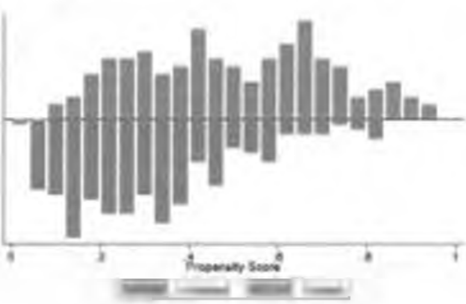
Figure 4.5:Distribution of the estimated propensity scores on the region of common support.





Nearest Neighbour Matching

Radius Matching



Kernel Based Matching

Source: Author's calculation based on eARN project survey data, 2010

Figure 4.5: 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

[1]Although the logit regression results are crucial for providing information regarding the key variables to target when introducing a new ICT-based MIS project, the study briefly discusses the results. This is because the study sought to use the model only for generation of propensity scores for matching. Besides, Okello *et al.* (2012a) has discussed in detail, the drivers of participation in ICT-based MIS projects in Kenya, using the same data.

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) was satisfied. Furthermore, the distribution of the propensities suggests that each participant had a corresponding non-participant with similar observed characteristics for comparison.

Table 4.4: 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**	2.35	285.41**	2.25	285.45**	2.17
Value of purchased fertilizer per acre	1,035.10***	2.61	1,009.86**	3.08	952.67***	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***	2.61	1,171.82***	2.62	1,129.33**	2.45
Hired labour man-days per acre	- 6.10*	-1.68	- 6.11**	- 2.16	-6.46**	-2.19
Family labour man-days per acre	-13.49***	-2.99	- 6.99**	- 2.00	-7.95**	-2.19
Total labour man-days per acre	-21.96***	- 4.62	-15.68***	- 4.43	-16.94***	-4.58
Value of output per man-day	406.95***	5.25	367.46***	5.22	374.85***	5.24
Value of output per acre	8,605.84***	3.30	7,007.14***	3.31	7,160.28***	3.28

Source: Author's computations from eARN project survey data, 2010

Note: significance level is at * 10 percent, ** 5 percent and *** 1 percent

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

Table 4.4 presents the average treatment effects estimated by Nearest Neighbour Matching (NNM), Radius Matching (RM) and Kernel Matching (KBM) methods. The results of the three matching methods indicate that participation in the ICT-based MIS project had a positive and significant impact on the value of purchased seed per acre, value of purchased fertilizer per acre and total value of purchased non-labour inputs per acre (an aggregation of the value of purchased seed, fertilizer, manure and herbicides or pesticides). Conversely, participation in the ICT-based MIS project had a negative and significant impact on the use of hired, family and total (family plus hired) labour man-days per acre.

Precisely, the results of NNM, RM and KBM suggest that non-labour inputs use was higher among project participants than non-participants. The average treatment effect on the treated (ATT) for the value of purchased seed per acre was Kshs 285.41 in RM, Kshs 285.45 in KBM and Kshs 359.21 in 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 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.

Additionally, the ATT of project participation on 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 project increased the use of fertilizer per acre by Kshs 1,009.86 in RM, Kshs 952.67 in KBM and Kshs 1,035.10 in NNM. Participation also 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, - 6.11in 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 project reduced the usage 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.

These findings led to the rejection of the hypothesis that participation in an ICT-based MIS project has no effect on the use of agricultural inputs by smallholder farm households in Kenya. Consequently, it is concluded that participation in an ICT-based MIS project enhances the use of non-labour improved inputs, but reduces the demand for labour. Improved access to right information on inputs reduces information asymmetries and transaction costs, and enhances input use through increased participation in inputs market. It was also argued that households with sufficient agricultural information provided by either ICT-based MIS projects or increased mobile phone usage for agricultural transactions were more likely to use less labour in negotiating contracts and searching for information on inputs e.g. good quality seeds, fertilizer, hired labour etc. Additionally, the negative, but significant impact of ICT-based MIS project on labour use was attributed to substitution effects as earlier argued.

4.3 Impact of ICT-based MIS projects on farm labour and land productivity

The results of the NNM, RM and KBM in Table 4.4 further show 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. As a result, the hypothesis that participation in an ICT-based MIS project has no effect on the productivity of labour in smallholder farms in Kenya was rejected. Labour productivity among ICT-based MIS project participants was particularly improved by the better access to information, which subsequently led to increased use of improved agricultural inputs.

Finally, participation in the ICT-based MIS project also increased the value of output per acre. As shown, the ATT for the value 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 significantly different from zero at 1 percent in all the matching methods. Participation in the ICT-based MIS project, therefore, increased land productivity by Kshs 7,007.14 and 8,605.84 per acre. This led to the rejection of the hypothesis that participation in ICT-based MIS projects has no effect on land productivity in smallholder farms in Kenya

These findings imply that the higher levels of labour and land productivity among participants are stimulated by the expanded use of improved agricultural inputs due better access to information. This is particularly important because increased use of non-labour inputs spurs productivity and subsequently leads to increased commercialization as farm households participate more in the market economy.

4.4 Test for robustness of results and unobserved heterogeneity

Propensity score estimation balances the distribution of the observed covariates in the groups of participants and non-participants in ICT-based MIS projects. The Results in Table 4.5 indicate that there was a substantial reduction in bias as a consequence of matching. The estimates showed that the standardized mean bias before matching was 29.60 per cent, while the standardized mean bias after matching was reduced to between 5.11 per cent and 12.93 per cent. The percentage reduction in the absolute bias was 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 was greater than 20 per cent, a value suggested by Rosenbaum and Rubin (1985) as sufficiently large enough reduction in standardized bias, it was deduced that matching substantially reduced selection bias.

The second diagnostic statistic employed was 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 was lower than before matching for all matching algorithms. This implies that after matching there were 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 had very 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 was 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.

Table 4.5: 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

The results of sensitivity analysis of hidden bias, which show the critical levels of gamma (γ) at which the causal inference of significant impact of participation in ICT-based MIS projects may be questioned, are also presented in the last column of Table 4.5. Since sensitivity analysis for insignificant effects is not meaningful, Rosenbaum bounds (rbounds) were calculated only for treatment effects that were significantly different from zero (Hujer *et al.*, 2004). The level of gamma (γ) reported in this study was up to the point where the 10 percent level of significance (tolerated limit for statistical significance) was exceeded, and was reported for two sided tests, i.e. positive effect (sig+) and negative effect (sig-), since the impact on the outcomes was both positive and negative. The level of gamma (γ) was defined as the odds ratio of differential treatment assignment due to an unobserved covariate.

The results show that robustness to hidden bias varied across different outcomes. Specifically, the values of gamma (γ) varied between 1.25 to 1.40, 1.15 to 1.20, 1.15 to 1.35, 1.70 to 2.90, 2.25 to 2.40, 3.65 to 4.25, 1.35 to 2.00 and 2.95 to 6.00 for values of fertilizer per acre, purchased seed per acre, total non-labour inputs per acre, hired labour, family labour, 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 was 1.95 to 2.00. This suggests that the unobserved variable would have to increase the odds ratio by 95 to 100 percent before it would bias the estimated impact, i.e. if individuals with the same characteristics were to differ in their odds of participating in ICT-based MIS projects by a factor of 95 to 100 percent, only then would the significance of the impact on value of output per acre, be questionable.

The lowest critical value of gamma (γ) was 1.15 to 1.20, whereas the largest critical value was 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: Beceeril and Abdulai (2010). Abdulai and Ali (2010) and Kiiza *et al.*, (2011). while, in the upper range. Kiiza *et al.*, (2011) and Clement (2011). This study therefore, concluded that the estimated average treatment effects of participation in ICT-based MIS projects on input use, labour and land productivity were robust even in the presence of substantial amounts of unobserved heterogeneity. Hence, the conclusion that participation in ICT-based MIS projects affects input use, labour and land productivity in Kenya.

CHAPTER 5: SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary and conclusions

Information asymmetry has traditionally constrained smallholder farmers' access to markets. Past studies indicate that it contributes to low adoption of modern agricultural technologies that have the capacity to enhance the productivity of smallholder farms. Low use of inputs in turn results to reduced farm productivity, which curtails the transformation from subsistence to commercial agriculture. As a result, smallholder farmers are still held in the low-equilibrium poverty trap. The desire to improve farmers' access to markets has seen the emergence of a number of projects that employ ICT tools in the provision of market information.

This study, therefore, evaluated the impact of participation in the ICT-based MIS project on farm inputs use, labour and land productivity among smallholder farmers in Kenya. The study employed propensity score-matching technique on cross-sectional data collected from 375 farmers. PSM was used to help reduce selection bias, and hence prevent overestimation of the projects effects. Data was collected through personal interviews using a semi-structured questionnaire in the three districts in April and May 2010. Additional data on trends in input use over the period 2005-2011 were also collected at the district level in April 2012 in the three study districts.

The study found that participation in the ICT-based market information service (MIS) project had a positive and significant effect on the level of use of farm inputs. Participants in the ICT-based MIS project spent Kshs 285.4 in Radius Matching (RM), Kshs 285.45 in Kernel Based Matching (KBM) and Kshs 359.21in Nearest Neighbour Matching (NNM) more than non-participants on purchased seed per acre. Similarly, project participants spent Kshs 1,009.86 in

RM, Kshs 952.67 in KBM and Kshs 1,035.10 in NNM more than non-participants on purchased fertilizer per acre.

However, participation in the ICT-based MIS project had a negative and significant impact on the usage of hired, family and total labour. Specifically, the hired labour man-days per acre used by participants was less by 6.10 in NNM, 6.11 in RM and 6.46 in KBM compared to non-participants. Moreover, participants used less family labour man-days per acre by 13.49 in NNM, 6.99 in RM and 7.95 in KBM than non-participants. The total labour man-days per acre used by participants was less by 6.10 in NNM, 6.11 in RM and 6.46 in KBM relative to the non-participants.

The hypothesis that participation in an ICT-based MIS project has no effect on input use was thus rejected. It was thus concluded that participation in ICT-based MIS projects increases the use of non-labour farm inputs such as seed and fertilizer. The logic being that reduced information asymmetries and transaction costs improves access to input markets. Furthermore, it was concluded that participation in ICT-based MIS projects reduces the use of labour. It was argued that the ICT-based MIS project provided agricultural information to its members and also promoted the use of mobile phones for agricultural transactions, hence reducing the labour man-days for negotiating contracts and searching for inputs such as purchased seed, fertilizer, herbicides, etc. It was further argued that the negative impact of the ICT-based MIS project on labour use was due to the substitution of non-labour inputs for the more expensive labour in accordance with the Induced Innovation Theory.

The study also found that participation in the ICT-based project increased labour productivity among the participants by Kshs 367.46 in RM, Kshs 374 in KBM and KShs 406.95 in NNM.

Moreover, land productivity among the project participants was increased by Kshs 7,007.14 in RM, Kshs 7,160.28 in KBM and KShs 8,605.84 in NNM. As a result, the hypotheses that participation in an ICT-based MIS project has no effect on labour and land productivity were both rejected. Thus, the study concluded that participation in an ICT-based MIS project increases labour and land productivity. Labour and land productivity were argued to be higher among ICT-based project participants, due to increased use or access to inputs.

To ensure that the effects of participation in the ICT-based MIS project as estimated by PSM were valid, it was crucial to test if the two underlying assumptions (common support assumption and conditional independence assumption (CIA)) of PSM were fulfilled. The satisfaction of the common support assumption (CSA) was proven by the distribution of the propensity score densities for both groups. The fulfillment of the CIA assumption was proven by running the Rosenbaum bounds (rbounds) test. The results of the rbounds test for hidden bias showed that even large amounts of unobserved covariates would not alter the conclusion about the estimated effects and that the treatment effects estimated were purely as a result of participation in the ICT-based MIS project.

5.2 Recommendations

The implication of these findings is that there is need to expand the coverage of ICT-based MIS projects in rural areas. This is due to the fact that they enhance smallholder farmers' participation in agricultural input markets, subsequently improving their labour and land productivity. Productivity gains are crucial for agricultural transformation i.e., smallholder farmers' exit from subsistence to commercial oriented agriculture. This has the capacity to increase their incomes and lift them from poverty.

Moreover, programs aiming to improve food security and farm incomes should consider the promotion of yield-augmenting agricultural technologies as well as improved access to ICT-based MIS. The study findings also suggest the need to create the necessary infrastructure to improve ICT usage in rural areas. Precisely, there is need for expansion of the rural electrification program to allow access to power for charging mobile phone batteries and other ICT devices. In addition, there is need for expansion of mobile phone network coverage in farming areas where mobile phone network is still poor.

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Appendix 1: Variance Inflation Factor (VIF) test for multicollinearity

Variables	VIF	1/VIF
Age	4.55	0.22
Age squared	4.34	0.23
Farming experience	2.62	0.38
Migori district	1.92	0.52
Bungoma district	1.87	0.53
Household size	1.52	0.66
Education	1.40	0.71
Land size owned prior to project	1.25	0.80
Mobile phone (ICT tool) user	1.21	0.83
Gender	1.18	0.85
Distance to the local market	1.15	0.87
Number of crop enterprises	1.12	0.89
Group membership	1.08	0.92
Mean VIF	1.94	

Source: Author's computations based on eARN project survey data 2010

Appendix 2: Covariate balancing tests for propensity score: NNM, RM and KBM methods

		Nearest Neighbor Matching (NNM)					Radius Matching (RM)				
		Mean			%reduct	t-test	Mean			%reduct	t-test
Variable	Sample	Treated	Control	%bias	bias	p>t	Treated	Control	%bias	bias	p>t
Bungoma	Unmatched	0.49	0.26	50.5		0.000	0.49	0.26	50.5		0.000
	Matched	0.49	0.45	9.2	81.7	0.462	0.49	0.36	28.7	43.2	0.121
Migori	Unmatched	0.20	0.39	-41.1		0.000	0.20	0.39	-41.1		0.000
	Matched	0.20	0.22	-4.7	88.7	0.667	0.20	0.27	-15.7	61.9	0.164
Age	Unmatched	46.68	41.40	39.2		0.000	46.68	41.40	39.2		0.000
	Matched	46.68	46.77	-0.6	98.4	0.954	46.68	44.78	14.1	63.9	0.218
Age squared	Unmatched	2338.20	1915.80	31.5		0.003	2338.20	1915.80	31.5		0.003
	Matched	2338.20	2357.50	-1.4	95.4	0.901	2338.20	2185.30	11.4	63.8	0.323
Gender	Unmatched	0.54	0.48	12.2		0.251	0.54	0.48	12.2		0.251
	Matched	0.54	0.58	-7.6	37.5	0.515	0.54	0.52	3.5	71.3	0.767
Education	Unmatched	8.75	8.20	15		0.156	8.75	8.20	15		0.156
	Matched	8.75	8.39	9.7	35.4	0.439	8.75	8.30	12.4	17.7	0.309
Distance to local market	Unmatched	2.56	2.21	19.8		0.062	2.56	2.21	19.8		0.062
	Matched	2.56	2.52	2.4	87.9	0.853	2.56	2.45	6.4	67.5	0.602
Household size	Unmatched	6.10	5.52	27		0.010	6.10	5.52	27		0.010
	Matched	6.10	6.07	1.5	94.4	0.904	6.10	5.82	12.9	52.3	0.289
Number of crop enterprises	Unmatched	3.31	2.67	42.1		0.000	3.31	2.67	42.1		0.000
	Matched	3.31	3.40	-6.3	85.1	0.638	3.31	3.04	17.3	58.9	0.168
Mobile phone user	Unmatched	0.88	0.81	18		0.097	0.88	0.81	18		0.097
	Matched	0.88	0.89	-2.9	84.1	0.786	0.88	0.86	5.4	69.7	0.624
Group Membership	Unmatched	0.32	0.16	36.7		0.000	0.32	0.16	36.7		0.000
	Matched	0.32	0.36	-9.5	74.2	0.476	0.32	0.26	14.2	61.4	0.266
Land size owned	Unmatched	2.72	2.12	25.6		0.016	2.72	2.12	25.6		0.016
	Matched	2.72	2.52	8.8	65.7	0.483	2.72	2.32	17.2	32.7	0.160
Farming experience	Unmatched	19.52	16.55	26		0.016	19.52	16.55	26		0.016
	Matched	19.52	19.32	1.8	93.1	0.880	19.52	18.52	8.8	66.2	0.463

Variable	Kernel Based Matching					
	Sample	Mean Treated	Mean Control	%bias	%reduct |bias|	Test p>|t|
Bungoma	Unmatched	0.49	0.26	50.5		0.000
	Matched	0.49	0.39	22.4	55.6	0.172
Migori	Unmatched	0.20	0.39	-41.1		0.000
	Matched	0.20	0.25	-10.8	73.7	0.329
Age	Unmatched	46.68	41.40	39.2		0.000
	Matched	46.68	45.27	10.5	73.3	0.356
Age squared	Unmatched	2338.20	1915.80	31.5		0.003
	Matched	2338.20	2221.90	8.7	72.5	0.448
Gender	Unmatched	0.54	0.48	12.2		0.251
	Matched	0.54	0.53	2.8	76.9	0.811
Education	Unmatched	8.75	8.20	15		0.156
	Matched	8.75	8.30	12.4	17.7	0.313
Distance to local market	Unmatched	2.56	2.21	19.8		0.062
	Matched	2.56	2.52	2.2	88.9	0.861
Household size	Unmatched	6.10	5.52	27		0.010
	Matched	6.10	5.88	10.4	61.4	0.395
Number of crop enterprises	Unmatched	3.31	2.67	42.1		0.000
	Matched	3.31	3.16	9.8	76.8	0.447
Mobile phone user	Unmatched	0.88	0.81	18		0.097
	Matched	0.88	0.86	2.9	84	0.793
Group Membership	Unmatched	0.32	0.16	36.7		0.000
	Matched	0.32	0.29	6.3	82.7	0.624
Land size owned	Unmatched	2.72	2.12	25.6		0.016
	Matched	2.72	2.36	15.4	39.8	0.210
Farming experience	Unmatched	19.52	16.55	26		0.016
	Matched	19.52	18.75	6.7	74.2	0.574

Appendix 3: Chi-square tests for variables in the pooled model

Age

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	43.8	12.5	1.1
Bungoma	130	43.7	13.1	1.2

T-Test of difference = 0 (vs not =): T-Value = 0.05 P-Value = 0.960 DF = 254

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	43.8	12.5	1.1
Migori	118	42.8	16.0	1.5

T-Test of difference = 0 (vs not =): T-Value = 0.56 P-Value = 0.577 DF = 220

Sample	N	Mean	StDev	SE Mean
Bungoma	130	43.7	13.1	1.2
Migori	118	42.8	16.0	1.5

T-Test of difference = 0 (vs not =): T-Value = 0.51 P-Value = 0.612 DF = 226

Education

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	8.96	3.44	0.31
Bungoma	130	8.85	3.49	0.31

T-Test of difference = 0 (vs not =): T-Value = 0.25 P-Value = 0.799 DF = 254

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	8.96	3.44	0.31
Migori	118	7.34	3.84	0.35

T-Test of difference = 0 (vs not =): T-Value = 3.47 P-Value = 0.001 DF = 235

Sample	N	Mean	StDev	SE Mean
Bungoma	130	8.85	3.49	0.31
Migori	118	7.34	3.84	0.35

T-Test of difference = 0 (vs not =): T-Value = 3.23 P-Value = 0.001 DF = 237

Household size

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	4.41	1.28	0.11
Bungoma	130	6.87	2.23	0.20

T-Test of difference = 0 (vs not =): T-Value = -10.88 P-Value = 0.000 DF = 206

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	4.41	1.28	0.11
Migori	118	5.93	2.11	0.19

T-Test of difference = 0 (vs not =): T-Value = -6.76 P-Value = 0.000 DF = 190

Sample	N	Mean	StDev	SE Mean
Bungoma	130	6.87	2.23	0.20
Migori	118	5.93	2.11	0.19

T-Test of difference = 0 (vs not =): T-Value = 3.41 P-Value = 0.001 DF = 245

Distance to the local market

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	3.07	1.93	0.17
Bungoma	130	3.11	1.43	0.13

T-Test of difference = 0 (vs not =): T-Value = -0.19 P-Value = 0.851 DF = 232

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	3.07	1.93	0.17
Migori	118	1.81	1.58	0.15

T-Test of difference = 0 (vs not =): T-Value = 5.61 P-Value = 0.000 DF = 239

Sample	N	Mean	StDev	SE Mean
Bungoma	130	2.12	1.45	0.13
Migori	118	1.81	1.58	0.15

T-Test of difference = 0 (vs not =): T-Value = 1.60 P-Value = 0.110 DF = 238

Number of crop enterprises

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	3.11	1.43	0.13
Bungoma	130	3.08	1.74	0.15

T-Test of difference = 0 (vs not =): T-Value = 0.15 P-Value = 0.880 DF = 247

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	3.11	1.43	0.13
Migori	118	3.08	1.74	0.16

T-Test of difference = 0 (vs not =): T-Value = 0.15 P-Value = 0.883 DF = 226

Sample	N	Mean	StDev	SE Mean
Bungoma	130	3.08	1.74	0.15
Migori	118	3.08	1.74	0.16

T-Test of difference = 0 (vs not =): T-Value = 0.00 P-Value = 1.000 DF = 243

Farming experience

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	18.1	10.5	0.93
Bungoma	130	16.2	11.0	0.97

T-Test of difference = 0 (vs not =): T-Value = 1.39 P-Value = 0.164 DF = 254

Sample	N	Mean	StDev	SE Mean
Kirinyaga	127	18.1	10.5	0.93
Migori	118	18.9	13.2	1.2

T-Test of difference = 0 (vs not =): T-Value = -0.51 P-Value = 0.611 DF = 223

Sample	N	Mean	StDev	SE Mean
Bungoma	130	16.2	11.0	0.97
Migori	118	18.9	13.2	1.2

T-Test of difference = 0 (vs not =): T-Value = -1.71 P-Value = 0.089 DF = 228

Mobile phone user

Sample	X	N	Sample p
Kirinyaga	114	127	0.897638
Bungoma	98	130	0.753846

Test for difference = 0 (vs not = 0): Z = 3.10 P-Value = 0.002

Sample	X	N	Sample p
Kirinyaga	114	127	0.897638
Migori	102	118	0.864407

Test for difference = 0 (vs not = 0): Z = 0.80 P-Value = 0.423

Sample	X	N	Sample p
Bungoma	98	130	0.753846
Migori	102	118	0.864407

Test for difference = 0 (vs not = 0): Z = -2.25 P-Value = 0.025

Group membership

Sample	X	N	Sample p
Kirinyaga	80	127	0.629921
Bungoma	94	130	0.723077

Test for difference = 0 (vs not = 0): Z = -1.60 P-Value = 0.109

Sample	X	N	Sample p
Kirinyaga	80	127	0.629921
Migori	30	118	0.254237

Test for difference = 0 (vs not = 0): Z = 6.40 P-Value = 0.000

Sample	X	N	Sample p
Bungoma	94	130	0.723077
Migori	30	118	0.254237

Test for difference = 0 (vs not = 0): Z = 8.36 P-Value = 0.000

Gender

Sample	X	N	Sample p
Kirinyaga	69	127	0.543307
Bungoma	64	130	0.492308

Test for difference = 0 (vs not = 0): Z = 0.82 P-Value = 0.413

Sample	X	N	Sample p
Kirinyaga	69	127	0.543307
Migori	57	118	0.483051

Test for difference = 0 (vs not = 0): Z = 0.94 P-Value = 0.345

Sample	X	N	Sample p
Bungoma	64	130	0.492308
Migori	57	118	0.483051

Test for difference = 0 (vs not = 0): Z = 0.15 P-Value = 0.884

Appendix 4: Survey questionnaire

Impact of ICT-based market information services on farm input use and productivity in Kenya

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Survey quality control

Date of interview. .... Start time.................. End time..........

Interviewed by: ....

Checked by: .... Date checked: ....

Date entered: .... Entered by: ....

1.0 Farmer and site identification

1. Respondent name (in full).. Phone number ....

2. District .... 3. Region.. ....

4. Village... 5.GPS Reading......................................

6. Distance to the nearest market centre (km)............. 7. Name of market..............................

8. Type of road to market centre[1] for selling produce and buying most of your agricultural inputs ....

9. Quality of road:[2] ....

10. Type of road to main market:[1] ....

11. Transport cost to the nearest market centre on public service vehicle (LOCAL CURRENCY/person)...............

12. Distance to agricultural field office (km) ....

13. Distance to nearest public phone service (km)..................................

14. Distance to nearest mobile phone service (repairs/charging/top-up etc) (km)....................................

15. Distant to nearest internet facility (km) ....

16. Distance to nearest electricity hook-up (km)......................................

17. Are you a member of any ICT-based agricultural project 1. Yes 0. No

18. If YES to Q17, what is/are the name(s) of the project(s)?...

19. When did you join the ICT-based project (s)? *[If more than 1, list in order of project]*.......................................

20. Are you a participant in any agricultural development project that is not ICT based 1. Yes 0. No

2. If YES to Q19, what is the main purpose of the project(s)?...

---

[1]. **Type of Road:** 1. Non paved dirt road, 2. Paved dirt road, 3. Paved gravel road, 4. Paved asphalt (tarmac)

2. Quality of road: 1. Bad, but passable all year round 3. Good (all weather)
2. Bad, and passable only parts of the year 4. Very Good (all weather)

3. Migration Status: 1. Native 2. Migrant

2.0 Household composition and characteristics *(YY) is year before joining the ICT - based project)*

HH member identification (start with respondent)	Gender **Codes A**	Marital status **Codes B**	Age (yrs)	Education (yrs) **Codes C**	Relation to HH **Codes D**	Main occupation **Codes E**	Experience (Years of farming)	Experience in other main entrepreneurial activity (Yrs)	Has mobile phone/ working Sim card **(Code F)**	Can read write? **(Codes F)**
1.										
2										
3.										
4										
5										
6										
7										
8										
9.										
10										

Codes A
1 Male
0 Female

Codes B
1. Married living with spouse
2. Married but spouse away
3. Divorced/separated
4. Widow/widower
5. Never married
6. Other, specify..........

Codes D
1. Household head
2. Spouse
3. Son/daughter
4. Parent
5. Son/daughter in law
6. Grand child
7. Other relative
8. Hired worker
9. Other, specify..........

3.0 Farm and household asset endowments

Asset name	Number currently owned	Year bought/built	Current value (LOCAL CURRENCY)
1. Ox-plough			
2. Ox-cart			
3. Chemical Sprayer pump			
4. Wheel barrow			
5. Bicycle			
6. Tractor			
7. Plough			
8. Harrow			
9. Planter			
10. Reaper			
11. Other tractor drawn equipment (specify………………)			
12. Store for farm produce			
13. Livestock kraal			
14. Other motorized vehicles (specify……………………………)			
15. Radio/radio cassette			
16. Mobile phone			
17. Television (TV)			
18. Computer/Internet			
19. Water pump			
20. Generator			
21. Refrigerator/freezer			
22. Landline phone			
23. Air Conditioner			
24. Sofa seats/coach			
25. Cooker			
26. Own House? 1 – yes, 0 – No			
27. Other………………			

4.1 Land holding (acres) during 2009 planting seasons

	Long rain season		Short rain season *[Do not answ... there is only one season]*	
	Cultivated	Fallow (e.g. grazing)	Cultivated	Fallow (e.g. graz...
1. Own used Sharecropped (A)				
2. Leased rented out (B)				
3. Borrowed out (C)				
4. Leased rented in (D)				
5. Borrowed in (E)				
4. Communal land (D)				
5. Total owned (A+B+C)				
6. Total irrigated (owned)				
7. Total rain-fed (owned)				

4.2 Social Capital Endowment: Membership to farmer organizations cooperative clubs

1. Are you a member of farmer club org association?	1. Yes 0. No
2. If Yes Q1 Specify type(s) of farmer club organization association	1. Community based org 2. Farmer cooperative 3. Farmer society 4. Farmers' club group 5. Women's club 6. Youth club 7. Faith-based organization 8. Saving and credit coop 9. Welfare funeral club 10. Other, specify.
3. Year first joined	
4. Functions of farmer organization association	1. Produce marketing 2. Input access marketing 3. Seed production 4. Farmer research group 5. Savings and credit 6. Welfare funeral club 7. Tree planting Nursery 8. Soil & Water conservation 9. Faith-based organization 10. Input credit 11. Other (specify)
5. Most important benefit derived from organization association	1. Access to lucrative markets for produce 2. Access to inputs at low cost 3. Access to financial service 4. Access to important agric information 5. Support for social functions (funerals, wedding, out-dooring etc) 6. Other (specify)..
6. Does this group use ICT in meeting any of its functions?	1. Yes 0. No
7. If YES to Q6, which ICT tools are used? *[Circle all that apply]*	1. Radio 2. TV 3. Mobile phone SMS 4. Mobile phone VOICE 5. CD Rom 6. Email

5. Non-labor input use in the 2009 Main or Long rain season *[Record separately by plots]*

Plot code (starting from plot nearest to house)	Plot size (Acres)	Crop grown (Code A)	Crop variety Code B	Purchased seed		Fertiliser type 1		Fertiliser type 2		Cost of oxen and tractor hire (LOCAL CURRENCY)	Farm manure		Pesticides/herbicides		Cost of irrigation (LOCAL CURRENCY)	Crop Output	
				Qty (units)	Price unit	Qty (units)	Price unit	Qty unit	Price Unit		Qty (units)	Price Unit	Qty (units)	Price unit		Qty	Units Codes C
Long Rains																	
Short Rains																	

Codes A
[Use the CROP CODE sheet]

Codes B
1. Improved
0. Local

Codes C
1 Kg. 2 Litre, 3 Bag. 4. Mini bag. 5 Basket
6. gorogoro 7. debe 8. Wheel barrow 9. ox cart 10. bucket
11. Other (specify) ________________

Codes D
1. Poor
2. Medium
3. Good

Codes F
1. Yes
0. No

6.0 How did you utilize the crops you harvested in 2009?

Crop type **(Codes A)**	Production (Specify unit) (From last column Table 5.0)	Sales (Specify unit)	Price obtained per unit	Consumption (Specify unit)	Saved as seed (Specify unit)	Gift, tithe, donations, paid as wages (Specify unit)
Long rains						
1.						
2.						
3.						
4.						
5.						
6.						
7.						
Short rains						
1.						
2.						
3.						
4.						
5.						
6.						
7.						

Codes A: *[Use CROP CODES sheet]*

7. Household Food security indicators (January to December 2009) *[Limit to staple crops only]*

	Maize	Rice	Beans	Bananas plantain	Yams	Cassava	Other
1. During which month did you harvest this staple crop **(Codes A)**							
2. Did your stocks of harvested crops from last season last household consumption need until the following season **(Codes B)**							
3. If **NO** to **Q2** above, for how many months was the harvest enough to meet the household needs?							
4. During which month(s) did you have to buy this staple? **(Codes A)**							
5. How much (kg) did you buy to meet the deficit?							
6. How much (kg) did you borrow or receive in gifts?							
7. What was **the main** source of money used to buy the food items **(Codes C)**							
8. How much food aid (specify unit) did you receive during the year (including food for work)?							

Codes A
1. January 2. February 3. March 4. April 5. May 6. June 7. July 8. August 9. September 10. October 11. November 12. December

Codes B
1. Yes
0. No

Codes C
1. Sale of other crops
2. Sale of livestock
3. Remittances
4. wage employment
5. Non-wage job
6. Other, specify……

8. Livestock production activities. *[Record for January to December 2009]*

Livestock type	Stock at start of the year	Value of stock at the beginning of year	Number sold during the year	Price head	Number bought during the year	Stock at end of year	Value of stock at the end of year
1. Bulls							
2. Cows							
3. Heifers							
4. Calves							
5. Trained oxen							
6. Goats							
7. Sheep							
8. Donkeys							
9. Pigs							
10. Chicken							
11. Ducks							
12 Turkey							
13. Guinea fowl							

9. Livestock maintenance costs in 2009*[Record for January to December 2009]*

Livestock type	Purchased feed	Veterinary services (Including AI, vaccinations and treatment)	Veterinary medicines	Housing repairs/maintenance
1. Bulls				
2. Cows				
3. Heifers				
4. Calves				
5. Trained oxen				
6. Goats				
11. Sheep				
12. Donkeys				
13. Pigs				
14. Chicken				
11. Ducks				
12 Turkey				
13. Guinea fowl				

10. Other sources of income (January – December 2009) ***[Convert payments into cash equivalent]***

Sources	Quantity (units)	Price/unit	Total income (LOCAL CURRENCY)
Milk			
Eggs			
Other livestock product (specify.............................)			
Rented out land			
Crop residues (e.g. stover)			
Rented out oxen for ploughing			
Off-farm labour income			
Non-farm agribusiness NET income (e.g., shop, tailoring, etc)			
Pension income			
Drought relief			
Remittances (sent from non-resident family living elsewhere)			
Marriage gifts (e.g., dowry)			
Sale of own trees/timber/firewood, etc			
Sale of communal resources (charcoal, bricks, stones, sand, etc)			
Other (specify)..			

Thank you!!!