AN ECONOMIC ANALYSIS OF IMPACT OF WEATHER INDEX-BASED CROP INSURANCE ON HOUSEHOLD INCOME IN HUYE DISTRICT OF RWANDA

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DECLARATION

This thesis is my original work and has not been presented for the award of a degree in any other academic institution.

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DEDICATION

This thesis is dedicated to my loving husband, my mother and my siblings for their unconditional support through my studies, their love, affection and all the sacrifice they have made in supporting me. May we live to enjoy the fruits of their effort.

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ABSTRACT

Agriculture remains a major source of livelihood in Rwanda. However, the sector is faced by many covariate risks. A major component of covariate risk in Rwandan agriculture is weather-related production risk. Weather index-based crop insurance is one tool used to improve risk management practices in many drought-prone countries including Rwanda. Despite the existence of crop insurance as a mechanism to mitigate weather-related losses, its impact on household income in Rwanda remains unknown. This study assessed the impact of farmer participation in a crop insurance scheme on household income in Huye District. A multi-stage random sampling strategy was used to collect primary data using a semi-structured questionnaire administered to a sample of 246 households. Descriptive statistics were used to characterize the patterns of farmer participation and uptake of crop insurance in the study area. Propensity score matching (PSM) was then used to assess the impact of farmer participation in crop insurance on household income. This involved an analysis of factors influencing farmer participation in the insurance scheme using a logit model. The results of the logit model showed that cooperative membership (p=0.001), use of irrigation (p=0.060), crop diversification (p=0.001), years of experience with crop insurance (p=0.000), distance to a paved road (p=0.01), and wealthy category (p=0.004) significantly influenced farmer participation in the crop insurance in Huye District. The Nearest Neighbor Matching, Radius Matching and Kernel-Based Matching algorithms showed that the matching process was justified among participants and non-participants in the insurance scheme. An average treatment effect of US$100 was found as the difference between participant and non-participant household income. This shows that the weather index-based insurance had a positive impact on participants' incomes in Huye District. Accordingly, the study recommends the promotion of the crop insurance among non-participants through educational and awareness campaigns by the

Ministry of Agriculture and insurance companies. The government of Rwanda in partnership with Rwanda Cooperative Agency should persuade more farmers to join cooperatives through regular and targeted campaigns.

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ABBREVIATIONS AND ACRONYMS

AGRA	Alliance for a Green Revolution in Africa
ARD	Agriculture and Rural Development
ATT	Average effect of Treatment on the Treated
CAADP	The Comprehensive Africa Agriculture Development Programme
CIP	Crop Intensification Programme
DD	Double Difference
DDP	District Development Plan
EDPRS	Economic Development and Poverty Reduction Strategy
EICV	*Enquête Intégrale sur les Conditions de Vie des ménages* (the French version of Integrated Household Living Conditions Survey(IHLCS))
FAO	Food and Agriculture Organization of the United Nations
GDP	Gross Domestic Product
GoR	Government of Rwanda
HIA	Health Impact Assessment
IBLI	Index Based Livestock Insurance
IFDC	International Fertilizer Development Center

IFPRI	International Food Policy Research Institute
IPAR	Institute for Policy Analysis and Research
IV	Instrumental Variables
MDGs	Millennium Development Goals
MINAGRI	Ministry of Agriculture and Animal Resources
MPCI	Multiple Peril Crop Insurance
NEPA	National Environmental Policy Act
PSM	Propensity Score Matching
RD	Regression Discontinuity
REMA	Rwanda Environment Management Authority
RWF	Rwandan Francs (Franc Rwandais)
SACCO	Savings and Credit Cooperative
SEA	Strategic Environmental Assessment
SIA	Social Impact Assessment
SID	Simpson Index Diversification
SSA	Sub-Saharan Africa
SONARWA	*Societé Nationale d'assurances du Rwanda*

VAT	Value Added Tax
WB	World Bank
WIBI	Weather Index Based Insurance
WII	Weather Index Insurance
WTP	Willingness to Pay

CHAPTER 1: INTRODUCTION

1.1 Background

Risk management in agriculture is increasingly receiving renewed attention by policy makers and researchers in the developing world because climate change is expected to increase the variability of weather conditions and the frequency of extreme events and, in turn, uncertainties in the agriculture sector (Anton *et al.,* 2013). In most sub-Saharan African (SSA) countries, agriculture contributes up to 29 percent of the Gross Domestic Product (GDP) (Nnadi *et al.*, 2013) and nearly 86 percent of its population depends on agriculture as their major livelihood source (World Bank, 2008). Agricultural insurance such as weather index-based crop insurance is one financial service mechanism aimed at mitigating risk in agriculture. The insurance provides farmers with improved income, economic security, peace of mind and future hope through lowering the level of risk (Nahvi *et al*., 2014).

Despite the importance of African agriculture in wealth and employment generation, the sector is faced by many covariate risks, particularly those associated with adverse weather changes. External shocks and weather variability result in negative financial outcomes for poor households that depend on agriculture as their major source of livelihood (Nnadi *et al.*, 2013). Weather variability is an impediment to human development and to progress towards the Millennium Development Goals (MGDs) (Patt *et al*., 2009). Further, it hinders the achievement of MDG number one of eradicating extreme poverty and hunger by 2015 (CAADP, 2003). Such negative consequences arise from the fact that SSA agriculture is highly weather-dependent such that changes in weather conditions result in high agricultural losses and compromised livelihoods (Barnett *et al*., 2006).

The impact of natural hazards such as weather variability and climate extremes on economic well-being and human suffering has increased alarmingly in the recent past mainly due to global warming (Barnett *et al*., 2007). In the East African region, studies indicate that periodic droughts and floods have resulted in significant economic losses with a long term drop in GDP of 1-3 percent per year (Smith and Glauber, 2012). It is predicted that these economies will face additional losses from climate change of at least 1-2 percent and possibly up to 5-10 percent of GDP by 2030 (Smith and Glauber, 2012).

Over the last 30 years, Rwanda has experienced climate fluctuations characterized by heavy rains, storms and droughts. The changing weather patterns have had a negative impact on agricultural production and on the country's GDP as well as the income of its citizens (Ngabitsinze *et al*., 2011). For instance, major floods occurred in 1997-1998, 2006, 2007, 2008 and 2009, which resulted in infrastructure damage, landslides, and losses and damage to crops. In some regions of the country, periodic droughts occurred in 1999/2000 and 2005/2006 with devastating effects on crop and livestock production (Byamukama *et al*., 2011).

In recent years, researchers have identified the potential of using weather index-based insurance to provide farmers with risk management opportunities in the context of climate change (Barnett and Mahul, 2007). For countries that depend heavily on agriculture, weather changes are a significant factor influencing the economic well-being of the citizens, particularly in areas where agriculture is predominantly rain-fed. Adverse weather conditions result in production losses, which keep farmers trapped in a vicious circle of poverty. Minimizing vulnerability to weather-related shocks in developing countries is important to guarantee food security and to abate the 20 percent loss in GDP that these African countries lose due to adverse weather (Barnett *et al*., 2006).

The Comprehensive Africa Agriculture Development Programme (CAADP) framework targets a growth rate for African agriculture of at least six percent per annum and encourages African governments to invest at least 10 percent of their budget in agriculture (CAADP, 2003). As a result, SSA economies are increasingly investing in agriculture in order to induce agriculture-led economic transformation. One of the strategies proposed in CAADP is mutual assistance during emergencies, including provision of food or cash grants and establishing other modalities such as crop insurance schemes.

Reliance on rainfall increases the propensity of agriculture-based SSA economies to suffer from yield and price risks because agriculture is affected more frequently and more severely by unfavorable weather conditions (Barnett and Mahul, 2007). Without a formal risk management mechanism, households self-insure against weather-related risks by employing informal risk management methods, such as crop rotation, which are unreliable when unpredictable weather conditions emerge (Cole *et al*., 2012). Risk in agriculture becomes more problematic because of the inability to control natural hazards or to effectively mitigate them. For instance, when unfavorable climatic conditions occur, they result in huge losses due to the nature of the farming systems in these countries. Uninsured weather-related risks not only have a direct income effect, but also impact the decisions made by poor households regarding their livelihoods. Nevertheless, farmers throughout the years have developed formal and informal mechanisms to cope with a changing climate. For instance, in Tanzania, households that were less able to access agricultural insurance were observed growing more potatoes because they found them to be much safer (Hill, 2010).

Weather index-based crop insurance has gained increased attention as a potentially sustainable market mechanism that transfers weather-related risk from farmers to insurance intermediaries in low-income countries (Barnett *et al*., 2007). It presents a promising alternative to traditional agricultural insurance for many low-income countries as traditional insurance is often unsustainable. Therefore, enabling resource-poor households to better deal with weather-related risk is vital for improving their short-term well-being as well as improving opportunities for income growth in the long run (Cole *et al*., 2012).

In Rwanda, agriculture is the second largest contributor to GDP after the services sector at 32 percent, and employs more than 80 percent of the population (EICV3, 2011). It provides 91 percent of the food consumed in the country and accounts for 70 percent of export revenues (World Bank, 2011). However, poor performance of the sector remains an obstacle to socio-economic development. For instance, the sector is prone to challenges due to weather changes associated with climate change (Ngabitsinze *et al*., 2011). Rwanda's goal is to transform its agricultural sector from a subsistence-oriented to a knowledge-based economy by 2020 (MINECOFIN, 2000). With increasing incidences of adverse weather, the country is unlikely to meet some of the targets in its Economic Development and Poverty Reduction Strategy (EDPRS), thereby failing to achieve MDG one (EICV, 2011).

In the last ten years, the Government of Rwanda (GoR) has instituted many agricultural reforms aimed at increasing agricultural productivity in order to make the country food self-sufficient and improve the well-being of its population. Among the strategies used is the introduction of the weather index-based crop insurance (WIBI) and livestock insurance schemes by the Ministry of Agriculture and Animal resources (MINAGRI). The GoR initiated the crop insurance scheme in Rwanda in 2011. Among the insurance intermediaries are Micro-Ensure, which arrived in Rwanda in 2010 and started piloting WIBI in 2011. The other intermediary is Syngenta Foundation for Sustainable Agriculture, also known as *Kilimo Salama* (Swahili for "Safe farming," KS) under their program of *Hinga urishingiwe* (protected farming). *Kilimo Salama* started piloting crop insurance in early 2011 in Huye and Karongi districts. The insurance scheme introduced in Rwanda covers losses resulting from unfavorable weather conditions. Weather parameters are recorded at the nearest weather station. The stations record the amount of rainfall received, wind speed, and moisture for use in the determination of insurance premiums. It is worth noting that the insurance companies do not cover losses due to pests, diseases or poor management. WIBI compensates for specific risks identified by farmers; the payout amount is calculated using independently measured weather data that is specified in the insurance contract. The payouts depend on historical records whereby more extreme weather conditions compared to the historical average result in larger payments (Kilimo Salama, 2014).

Livestock insurance is also available from SONARWA SA (*Societé Nationale d'assurances du Rwanda*) for cattle. However, the livestock insurance does not use a weather based-index. Karongi and Huye districts of Western and Southern provinces respectively were the first areas that piloted the WIBI model from 2011. In this model, the KS Company, in partnership with One Acre Fund (also known as *Tubura*) and the GoR's Crop Intensification Programme, collect farmers' premiums for the insured crops through a local insurance company called Soras.

Impact assessment studies on government or donor-funded projects/programs is increasingly becoming necessary in order to understand the value of funding to funders and beneficiaries by assessing accountability and measuring changes associated to a policy or program intervention (Khandker *et al.* (2010). Thus, program/project implementers are increasingly being required by their funders to demonstrate the effectiveness of their programs in terms of their contribution to livelihoods, employment and poverty reduction. Impact evaluation also provides stakeholders with evidence on what works or does not work, which is important to guide to further implementation of projects or programs among beneficiary communities.

1.2. Statement of the problem

Weather index-based insurance was introduced in Rwanda in 2011 to enable poor households to better deal with weather-related shocks, which had frequently challenged those who depended on farming for livelihoods under natural conditions. The initiative was expected to improve their welfare in the short run and improve their opportunities for income growth in the long run. So far, two payouts have been made in Huye District since the introduction of the insurance scheme. However, to date, no study has evaluated the impact of WIBI on farmer welfare and in particular, on participants' income, nor have the drivers of WIBI uptake been evaluated. Traditionally, crop insurance in Rwanda has been considered to be beyond the reach of smallholder farmers. However, since the introduction of the WIBI scheme in 2011, KS has been making payments for losses due to drought.

Previous studies have focused more on the demand for crop insurance, analyzing farm characteristics and farmers' willingness to pay for insurance scheme (e.g., Nicola, 2010; Cai, 2012). The impact of WIBI on household income has received no attention and hence it is the focus of this study. To the author's knowledge, there is no study to date that has examined the impact of WIBI on farmers' income in Rwanda.

1.3. Objectives of the study

The overall objective of this study was to assess the impact of weather index-based crop insurance on household income in Huye District of Rwanda. The specific objectives were to:

1. Evaluate the patterns of dissemination and uptake of weather index-based crop insurance among smallholder farmers in Huye District of Rwanda.
2. Assess the factors influencing uptake of weather index-based insurance crop in Huye District of Rwanda.
3. Evaluate the impact of weather index-based crop insurance on household income in Huye District of Rwanda.

1.4. Hypothesis

The following hypotheses were tested in this study:

1. Socio-economic drivers have no effect on uptake of weather index-based crop insurance in Huye District of Rwanda.
2. WIBI has no impact on the income of insured households in Huye District of Rwanda.

1.5. Justification of the study

The GoR has put in place different strategies to increase agricultural production. These strategies include environmental sustainability, resource allocation and production decisions that are market-oriented, and sensitizing farmers to adopt agricultural technologies. Accordingly, farmers have been sensitized to increase fertilizer use, adopt improved seeds and seek credit and as well as participation in WIBI (PSTA II, 2009; MINAGRI, 2009; IPAR, 2009). WIBI is key in Rwanda's strategy to achieve its Vision 2020 on transformation of the agricultural sector. Rwanda's EDPRS (2008-2012) identifies climate change and its adverse impacts on agriculture as a high priority intervention area. The EDPRS emphasizes the establishment of early warning systems to cope with drought in order to improve food security. This study provides policy makers with insights on the effect of WIBI on households' income thus guiding the implementation of the EDPRS. In addition, the study provides information on the uptake and patterns of dissemination of WIBI in Rwanda, which will inform the government and insurers on approaches that should be used to increase the number of farmers insured. The empirical results of the insurance scheme are desirable for further development of the initiative. Furthermore, relevant organizations such One Acre Fund, KS, SORAS and the GoR could draw from this study appropriate strategies and policies towards improving the insurance scheme. For instance, a policy document on crop insurance is needed by the GoR.

To the scientific community, this study provides invaluable literature on WIBI in the Rwandan context. Above all, this study provides planners, decision makers and implementers with information needed for effective implementation of WIBI in Rwanda.

1.6 Organization of the thesis

This thesis is organized into five chapters. The first chapter presents the introduction, which comprises the background information, problem statement, objectives and the hypothesis tested. Chapter two reviews the relevant theoretical and empirical literature, and chapter three presents the methodology. Chapter four reports and discusses the results of both the descriptive and econometric analyses. The final chapter summarizes the major findings, conclusions and policy recommendations.

CHAPTER 2: LITERATURE REVIEW

2.1 The concept of weather-based agricultural insurance

Weather shocks in agriculture present unfavorable conditions for billions of poor farmers in the developing world. Agricultural insurance is a tool that farmers use to manage weather-related risks. Nnadi *et al.* (2013) define agricultural insurance as the transfer of risk from one entity to another in exchange for a premium. The concept of agricultural insurance was initiated in Europe over 200 years ago mainly in the form of protection against livestock mortality and loss of crops due to hailstorms (Smith and Glauber, 2012).

Crop insurance is referred to as an indemnity that provides financial compensation for production losses (Mahul and Statley, 2010). Besides reducing the uncertainty faced by the insured, crop insurance also evens out the burden of potential production losses, especially those of a large-scale nature. Part of the risk is transferred to an insurance company that in turn pays the farmer compensation after the loss occurs. WIBI started from international weather derivative markets in Western Europe where major corporations were able to avoid or mitigate weather-related risks (Mirranda and Farrin, 2012; Smith and Glauber, 2012). WIBI has the advantage of resolving asymmetric information problems such as adverse selection and moral hazard as well as reducing transaction costs (Hazell *et al*., 1986).

According to Khandker *et al.* (2010), crop insurance is classified in two major groups: (i) indemnity-based insurance and (ii) index insurance. Indemnity-based insurance, also called peril crop insurance, is composed of two main indemnity products, i.e., damage-based indemnity insurance (peril crop insurance) and yield crop insurance. Damage-based indemnity insurance is a type of crop insurance in which the premium is calculated by measuring the extent to which a field has been damaged (in terms of percentage of crop damaged) soon after the damage has occurred (World Bank, 2011). It is best known for protecting against damage from hail, but can also be used for other perils such as frost and excessive rain. Damage-based indemnity insurance is the most common type of agricultural insurance provided in developed countries.

Yield-based crop insurance or multiple peril crop insurance (MPCI) commonly used in the USA is an insurance product in which an insured amount of yield is recognized as a percentage of farmer's historical average yield (Khandker *et al.* (2010). The insured yield is normally between 50 percent and 70 percent of the average yield on the farm (World Bank, 2011). If the actual yield is less than the insured, an equal indemnity is paid for the difference between the actual and the amount of the insured yield, multiplied by a pre-agreed value.

Index-based crop insurance consists of two types of index products: area-yield index insurance and weather-index insurance (Khandker *et al.* (2010). Area-yield index insurance provides an indemnity based on the realized average yield of an area, which can be a country or a district. The amount of the insured yield is computed as a percentage of the average yield for the area. An indemnity is paid if the realized yield for the area is less than the insured yield regardless of the actual yield on a policy holder's farm (Khandker *et al*., 2010). Area-yield index insurance requires historical area yield data and it is mostly used in developing countries.

With regard to weather-index insurance, the indemnity is based on the realizations of a specific weather parameter over a pre-specified period of time at a particular weather station (World Bank, 2011). Weather-index insurance measures a specific weather variable for a particular crop based on historical data. Furthermore, it specifies a threshold and a limit for making payouts. This type of insurance can be used to protect against either excessive rain or too little (Khandker *et al.,* 2010). An indemnity is paid when the realized value of the predetermined weather variable exceeds a pre-specified threshold. The indemnity is calculated based on a pre-agreed sum insured per unit of the index (World Bank, 2008). This type of insurance is commonly used in African countries and it is the type that is available in Rwanda.

For the weather-index based insurance (WIBI) that is offered to Rwandan farmers, the indemnity paid is based on the amount of rainfall, moisture content and temperature collected at a nearby weather station during the physiological phase of maize or bean crops (MINAGRI, 2013). The KS Statistics Department reported 87,000 insured farmers out of 1.4 million households in Rwanda in 2013.

2.2 Review of theoretical literature

2.2.1 Theories underpinning impact assessment

The theoretical foundations of impact evaluation are diverse and evolving (e.g., see Morgan (2012) for a detailed review). However, they mainly revolve around programme theory[1] or the theory of change advanced by Carl H. Weiss (Rogers, 2008). According to Msila and Setlhako (2013), Weiss defines the purpose of evaluation as a process "to measure the effects of a program against the goals it set out to accomplish as a means of contributing to subsequent decision making about the program and improving future programming" (p. 323). Therefore, programme theory describes

[1]According to Rogers (2008), programme theory is "… variously referred to as programme logic (Funnell, 1997), theory-based evaluation or theory of change (Weiss, 1995, 1998), theory-driven evaluation (Chen, 1990), theory-of-action (Schorr, 1997), intervention logic (Nagarajan and Vanheukelen, 1997), impact pathway analysis (Douthwaite et al., 2003b), and programme theory-driven evaluation science (Donaldson, 2005)" (p. 30).

"… a variety of ways of developing a causal modal linking programme inputs and activities to a chain of intended or observed outcomes, and then using this model to guide the evaluation" (Rogers, 2008; p. 30). In other words, programme theory describes the causal relationships along an impact pathway (Mayne and Johnson, 2015). As shown in Figure 2.1, an impact pathway relates inputs/activities (i.e., interventions [or treatment] such as a project, programme and policy) to expected outputs (such as increased or decreased production, consumption, etc) to outcomes (e.g., production, income, etc) and finally to impacts or long-term changes in wellbeing such as reduction of poverty and hunger, or improved health and nutrition. Impact evaluation focuses on the long-term effects of the project, programme or policy, i.e., impact. Underlying the impact pathway are various influences that affect the efficiency and effectiveness of the translation of interventions to impacts along the intervention-impact results chain. These influences constitute "external factors" or the "supra-environment context" ad are characterized by biophysical, economic, socio-cultural and idiosyncrasies that interact and anchor the intervention (ReSAKSS, 2014).

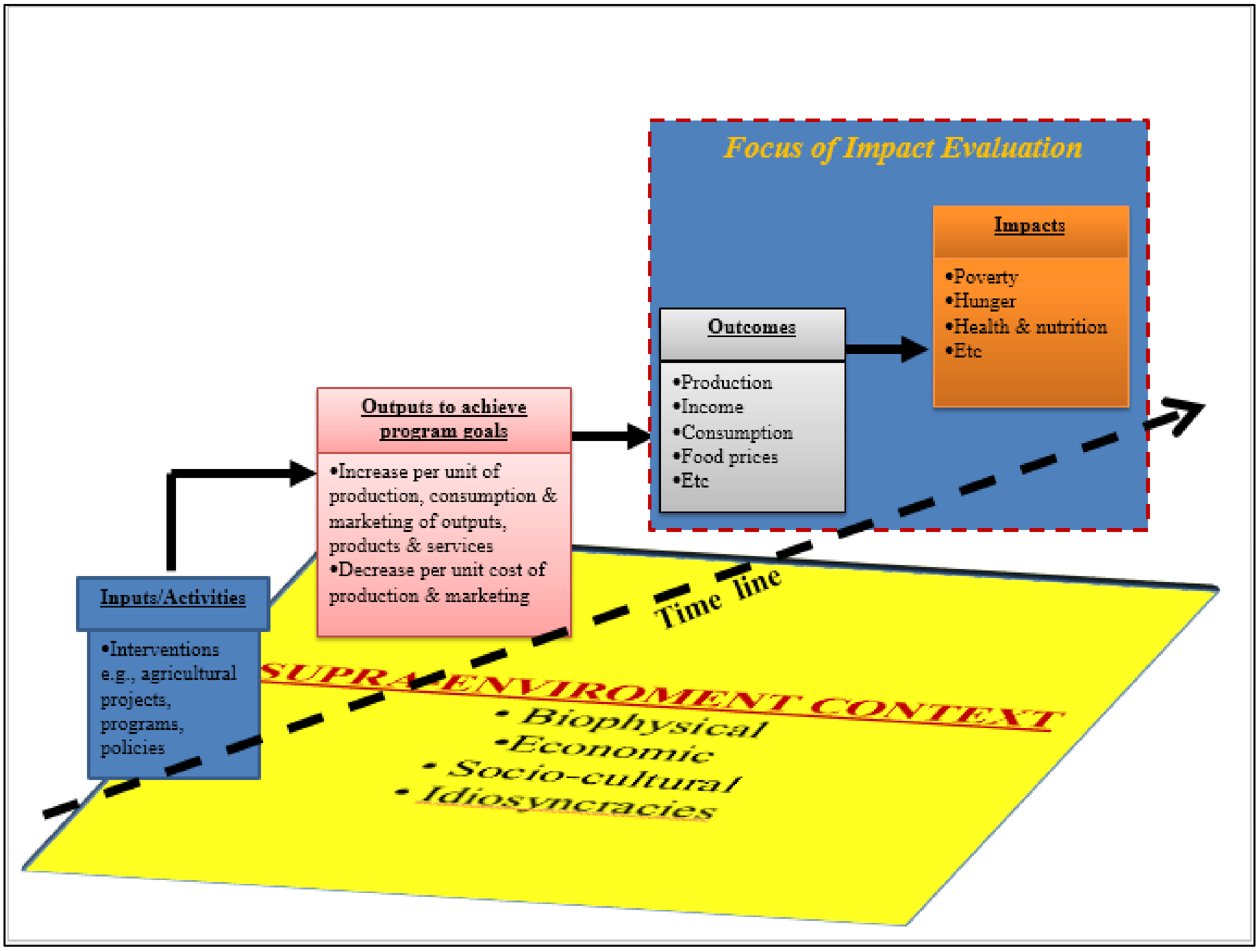

Figure 2. 1. A generic illustration of programme theory

Source: Adapted from ReSAKSS (2014)

The importance of impact evaluation is apply programme theory or the theory of change to both assess what works or does not work, as well as to gauge how long-term changes in wellbeing are attributable to a particular project, program or policy intervention (Khandker *et al*., 2010). This can help policy makers to develop informed decisions after determining whether programs, projects or policies are generating the intended benefits. In addition, impact evaluation promotes accountability in the allocation of scarce resources. Impact evaluation helps policy makers to clearly understand the effects of individual interventions and guides future evaluations of related interventions.

The theory and practice of impact assessment has continually developed since the introduction of the National Environmental Policy Act of 1969 (NEPA) in the USA (Pope *et al.*, 2013). This legislation was primarily adopted as a political response to the changing nature of industrial development post World War II and growing public concerns about the environmental consequences of economic development (Pope *et al.*, 2013). The first formal Environmental Impact Assessment (EIA) system was established on the 1st January 1970 by the NEPA (Cashmore, 2012). Over the last 15-20 years, EIA has gained popularity at the international level because of growing concerns about loss of biodiversity, threats to fresh water sources and water quality, damage to marine areas and other forms of global environmental change (Morgan, 2012).

Since the introduction of EIA in the USA, a number of specific forms have been developed as a result of some dissatisfaction with transferability of the EIA. These include health impact assessment (HIA), strategic environmental assessment (SEA), social impact assessment (SIA), policy assessment and sustainability impact assessment (Pope *et al.*, 2013). HIA came as a response from many public health professionals that EIA did not sufficiently address such areas as project impacts on community and individual health (Taylor *et al.*, 2004). Harris-Roxas (2012) noted that HIA originated from three distinct but related areas of public health, namely, environmental health, the wider determinants of health and health equity.

Environmental health focuses on potential health risks associated with major projects. Over the years, it has been recognized that non-health sector activities significantly determine human health outcomes (Harris-Roxas, 2012). SIA was developed in the late 1970s and 1980s because EIA was considered to have a strong biophysical emphasis, often neglecting social impacts (Morgan, 2012). Originally, SIA was used as a technique for predicting social impacts as part of EIA. Nowadays it is used as a process of analyzing, monitoring and managing the social consequences of planned interventions (Esteves, 2012).

Sustainability assessment is defined as any process that directs decision-making towards sustainability. This definition encompasses many potential forms of decision-making from choices of individuals in everyday life through to projects, plans, programmes or policies more familiarly addressed in the fields of impact assessment (Bond *et al.,* 2012; Morgan, 2012). Sustainability assessment uses analytical and participatory approaches aimed at incorporating environmental and associated social-economic considerations into policies, plans and programs (Bond *et al*., 2012).

SEA involves identifying and evaluating potential impacts of policies, plans and programmes (PPPs) and promoting more sustainable patterns of development (Fundingsland, Tetlow and Hanusch, 2012). Globally, SEA has been applied for identifying and evaluating potential impacts of PPPs in order to promote sustainable patterns of development (Pope *et al.,* 2013). SEA is useful in many levels of strategic activity (legislation, lending, policies, plans and programmes). It can be applied to a particular geographical area (national, regional, local), a particular sector (spatial planning, transport, agriculture, forestry, fisheries, energy, waste/water management, tourism) or to a specific issue (climate change, biodiversity) (Fundingsl Tetlow and Hanusch, 2012).

Policy assessment seeks to inform decision-makers by predicting and evaluating the potential impacts of policy options (Adelle and Weiland, 2012). It uses the same standard steps as EIA and SEA by identifying the problem, defining objectives, identifying policy options and analyzing impacts. Based on this literature, this study is a combination of SEA and policy assessment impact.

2.2.2 Impact assessment methods

Governments, researchers and the development community are often keen to determine the effectiveness of a policy, a program or project such as WIBI. This is because such interventions are expected to confer certain welfare-enhancing benefits on targeted recipients (Khandker *et al*., 2010).

Gertler *et al*. (2011) identify two types of quantitative impact evaluations with relevance to weather index-based crop insurance, i.e., "*ex post*" and "*ex ante*'' approaches. The "*ex post*" approach attempts to measure the intended impacts of future WIBI programs on beneficiaries, while the *ex post* approach measures the actual impacts accrued by the beneficiaries. While the program seeks to alter changes in the well-being of the intended beneficiaries, the main challenge is to determine what would have happened if the intervention was not made. The impact of the intervention is estimated as the difference between the outcome of interest in the treatment group (with the intervention) and that of the one without treatment (or the control group) (Gertler *et al*., 2011).

According to Smith and Todd (2005), the underlying conceptual basis of impact evaluation is the problem of missing data. That is, the beneficiaries cannot experience the effects of the intervention and without the intervention at the same time. Therefore, without information on the counterfactual, the next best alternative is to compare the outcome of the intervention between participants and non-participants (Rosenbaum and Rubin, 1983). Another problem that arises in impact studies is selection bias, which results from unknown underlying attributes that collectively influence respondents to either participate or not participate in the intervention.

Different methods are used in impact evaluation studies to address the counterfactual and selection bias problems. These include the randomized experiment methods, Heckman two-step technique, matching methods (most notably the propensity score matching (PSM)), double-difference (DD) methods, instrumental variable (IV) methods, regression discontinuity (RD) methods and pipeline methods (Rosenbaum and Rubin, 1983; Khandker *et al*., 2010). The choice of the method to use is largely driven by the assumptions made and the data available (Simtowe *et al*., 2012).

The randomized experimental method randomly allocates the treatment to individual experimental subjects or groups. Randomization usually eliminates selection bias by balancing both known and unknown factors in the assignment of experimental groups (Bai, 2011). The major advantage of this approach lies in the simplicity in interpreting the results; the program impact is measured by estimating the difference between the means of the samples of the treatment group and the control group (Baker, 2000). However, in many situations, it is difficult to ensure that the assignment was purely random and experimental designs can be expensive and time consuming (Bai, 2011). While the experimental method addresses both the counterfactual and selection bias problems, it is difficult to implement owing to concerns on ethical issues, external validity, partial or lack of compliance, as well as spillover effects (Gertler *et al*., 2010).

DD methods have an advantage of relaxing the assumption of self-selection on observed characteristics. The treatment effect is determined by taking the difference in outcomes across treatment and control units before and after the intervention (Khandker *et al*., 2010). The major drawback of the DD methods is that they attribute to the intervention any differences in trends between the treatment and control groups, which leads to biased results because differences occur even in the absence of the treatment (Gertler *et al*., 2010). Furthermore, DD methods are limited to studies with baseline data.

IV methods consist of finding a variable or instrument which is highly correlated with the outcome of interest but which is not correlated with unobservable characteristics that affect the outcome (Gertler *et al*., 2011). These methods yield unbiased and consistent estimates in the presence of hidden bias. The major drawback of this approach is that it is often difficult to find at least one variable in the selection model that can serve as a suitable instrument that influences the probability of the treatment (Wooldridge, 2002).

The pipeline and RD approaches are extensions of IV and they require factors such as eligibility to receive treatment in order to compare participants and non-participants (Gertler *et al.*, 2011). These methods allow both successful estimates of the impact of a program without excluding any eligible individual as well as observed and unobserved heterogeneity to be accounted for. However, fewer observations are used when compared to other methods that would include all units. Another concern with the RD method is the possibility of inadequate consistency in eligibility as well as changes that may arise over time (Gertler *et al.,* 2011).

The Heckman two-step method has an advantage of controlling for the differences in both observed and unobserved attributes in treated and control groups. However, the main drawback is that the selection bias estimators are dependent on a strong assumption that the hidden variables are normally distributed, resulting in doubts about the robustness of the estimates using both actual and simulated data (Ali and Abdulai, 2010; Khandker *et al*., 2010).

Unlike the RD as the extension of IV methods, the matching methods assume that conditioning observable variables eliminate the sample selection bias (Smith and Todd, 2005). Matching methods create the conditions of an experiment in which participants and non-participants are randomly assigned, allowing for the identification of a causal relationship between the intervention [treatment] and the outcome variable. The counterfactual problem is addressed through comparison of both participants and non-participants of the intervention (Ali and Abdulai, 2010).

One of the most commonly used matching method is the PSM, which is applicable to studies involving group comparisons in which a sufficient common support between groups can be found and in which a pure randomization cannot be reached (Bai, 2011). PSM computes the conditional probability that a farmer participates in a new intervention given the pre-participation characteristics (Rosenbaum and Rubin, 1983). Smith and Todd (2005) argued that systematic differences between outcomes of participants and non-participants may occur even after conditioning because selection bias is based on unmeasured characteristics. In the absence of panel data, the PSM method is used to address the sample selection bias problem (Dehejia and Wahba, 2002).

The PSM approach is desirable in studies where there are no panel data. The matching method has achieved popularity as a tool for impact assessment studies because it assumes that the selection bias can be explained purely in terms of observable characteristics (Todd and Smith, 2005). The main advantage of PSM over other non-experimental evaluation techniques is that the matching estimators highlight the problem of common support, since the treatment effect can only be estimated within the common support region (Austin, 2011). Matching does not require any functional form assumptions for the outcome equation whereas regression methods impose a form of relationships which may or may not be accurate and which PSM avoids. This becomes valuable because the functional form restrictions are usually justified neither by economic theory nor the data used (Todd and Smith, 2005).

PSM constructs a statistical comparison group by matching every individual observation of participants with similar characteristics from the group of non-participants (Rosenbaum and Rubin, 1983; Smith and Todd, 2005; Caliendo and Kopeinig, 2008). It is used to estimate the average treatment effect [ATE] of an intervention (Rosenbaum and Rubin, 1983). The method requires that a separate propensity score specification be estimated for each treatment group, comparison and group combination (Baker, 2000). The closer the propensity score, the better the match (Baker, 2000). Essentially, the PSM compares average outcomes of participants and non-participants, conditional upon the propensity score, with the parameter of interest being the ATE. Matching is in fact the best available method for selecting a matched comparison group which looks like the treatment group of interest (Heckman *et al*., 1998; Barbara, 2009). The major drawback of PSM is that it does not capture selection bias based on unobserved heterogeneity.

However, Rosenbaum bounds sensitivity analysis can check if the PSM results are sensitive to hidden bias (Rosenbaum and Rubin, 1983; Rubin, 1997).

Based on the attributes of PSM over other non-experimental methods, this study employed a PSM technique to control for both counterfactual and selection bias problems. PSM provides unbiased estimation of the treatment effects and can therefore be used to draw causal-effect inference. The technique does not depend on the functional form and distribution assumptions; it compares the observed outcomes of the participants and the non-participants of the intervention in two steps (Asfaw, 2010).

In the first step, a probability model for participation in an intervention is estimated to calculate the probability or propensity scores of participation for each observation. In this case, any standard probability model such as logit or probit can be used (Rajeev *et al*., 2007). Because it is difficult to determine that the random error term has a normal distribution *a priori*, a logit model was used in this study to generate propensity scores for farmer participation in the WIBI. The logit model was also preferred over others because of its consistency in parameter estimates owing to its logistic distribution (Baker, 2000; Revallion, 2001). In the second step, each participant is matched to a non-participant with similar propensity score value in order to estimate the ATE for the treated group (Caliendo and Kopeinig, 2008). Backer and Ichino (2002) and Caliendo and Kopeinig (2008) suggested different matching algorithms for the matching process. The most commonly used are (i) nearest neighbor matching (NNM), (ii) kernel-based matching (KBM), and (iii) radius matching (RM).

The NNM involves matching individual participants and non-participants that are closest in terms of propensity scores as matching partners. The main drawback of NN matching is that it faces bad matches if the closest neighbor is far way (Caliendo and Kopeinig, 2008). This problem can be avoided by using a tolerance level on the maximum propensity score distance. Applying caliper or tolerance criteria matching means that an individual from the comparison group is chosen as a matching partner for a treated individual that lies within the propensity range and the closest in terms of propensity score (Diaz and Handa, 2005). Smith and Todd (2005), however, note a possible drawback of caliper matching in that it is difficult to know *a priori* the reasonable tolerance level.

In kernel-based matching, each individual in the treatment group is matched to weighted averages of individuals who have similar propensity scores with greater weight being given to subjects with closer scores (Smith and Todd, 2005). Each of the matching algorithms presents different advantages on the quality and quantity of the matches and none of them is *a priori* superior to others. However, their joint consideration offers a way to achieve robust results.

Radius matching uses a tolerance level on the maximum propensity score distance between a subject in the treatment group and all individuals in the control group who are within that distance. If the radius is small, it is possible that some individuals in the treated group are not matched because the nearest neighbor does not contain the control group (Caliendo and Kopeinig, 2008; Becker and Ichino, 2002).

The main purpose of PSM is to balance the observed distribution of covariates across the groups of participants and non-participants (Rosenbaum and Rubin, 1985). In order to ensure credibility of results such as the absence of hidden bias, two key assumptions of PSM have to be met (Rosenbaum and Rubin, 1983; Becker and Caliendo, 2007; Ichino *et al*., 2008; Simtowe *et al*., 2012). The first one is the Conditional Independence Assumption (CIA) or the confoundedness assumption. This requires observing all variables influencing both participation and outcome variables simultaneously. The CIA implies that the selection into the treatment group is solely based on observable characteristics. For valid and reliable results, the CIA assumption must be met. The second assumption is known as the Common Support (or Overlap Condition). It requires the existence of a substantial overlap between the propensity scores of treated and untreated units (Caliendo and Kopeinig, 2008). If this assumption is not met, it is impossible to construct a counterfactual to estimate the impact of an intervention (Ali and Abdulai, 2009). No matches exist to estimate the ATT parameter when there is no overlap between the treatment and the control groups. The common support condition is ensured when any combination of characteristics observed in the treatment group can also be observed among the control group (Rosenbaum and Rubin, 1985).

2.4 Review of empirical literature

De Nicola (2010) estimated a dynamic stochastic optimization model to assess the impact of weather-based insurance on consumption, investment and welfare for farmers in Malawi. The study found that weather-based insurance had the potential to provide substantial welfare gains in terms of an almost 17% increase in consumption. In a model extension, the study showed that weather-based insurance allowed for the adoption of riskier but more productive improved seeds further improving farmers' welfare gains arising from increases in farmers' incomes. The study however did not show how much the income had increased due weather-based insurance. Employing a PSM approach, the present study assessed the change in income associated with WIBI in Huye District of Rwanda.

Cai (2012) used both difference-in-differences and triple difference estimation to assess the impact of an agricultural insurance program on household production, borrowing and saving behavior in China. Introducing insurance was found to increase the production area of insured crops by about 20%. It also decreased production diversification. Furthermore, the study found that providing insurance raised credit demand by 25% but decreased household savings by more than 30%. However, there was no direct effect on household income reported. Using a PSM approach, which is different from the difference-in-differences approach, the current study assessed the impact of WIBI on households' income in Huye District of Rwanda.

Varadan and Kumar (2012) employed Simpson Index of Diversification (SID) to study the extent of crop diversification practiced by farmers and assessed the impact of crop insurance on rice farming in Tamil Nadu in India. The study found that crop insurance had effectively absorbed production risk and had promoted crop specialization among farmers. The insurance was also found to influence the use of high-value inputs, which contributed towards enhancing returns from farming. Factors such as access to credit, education, off-farm income and the region in which the farmer was located significantly influenced the adoption of crop insurance. However, factors like group or cooperative membership and irrigation were not included in their analysis to assess their effect on uptake of insurance. Although Varadan and Kumar (2012) found a significant difference in revenue from rice cultivation for insured farmers, such a difference may not automatically be associated with adoption of insurance *per se*. The difference could arise from unobservable characteristics. Therefore, Varadan and Kumar's finding of a significant difference between the average revenue of insured and non-insured farmers could be biased. The current study overcomes this bias by employing the PSM approach, which captures the unobservable characteristics causing the change.

Ali (2013) evaluated farmers' willingness-to-pay (WTP) for agricultural insurance with 531 farmers in the Soon Valley and Talagang rain-fed areas of Pakistan. Social welfare and PSM approaches were used to assess the WTP for and the impact of the insurance scheme respectively. The results showed that farmers' economic status, household assets and membership in community organization were the important determinants of their WTP a higher insurance premium. The PSM results revealed that farmers were satisfied with index-based insurance and were also willing to increase the area under production for food as well as cash crops. The current study benefited from the PSM approach used in Ali (2013) to assess the impact of WIBI on farmers' incomes on Huye District of Rwanda. Furthermore, the current study determined the patterns of dissemination and uptake of WIBI.

Awel and Azomahou (2014) assessed the impact of WIBI on technology adoption, productivity and welfare at the household level of insured farmers in Ethiopia. The study employed different approaches to address the selection bias problem. First, a matching technique was used assuming the selectivity bias was due to observable characteristics. Second, the inverse probability weighted regression (IPWR) and IV approach were applied assuming that the selection bias was due to unobservable characteristics. The PSM and IV results suggested insignificant evidence on welfare improvements due to insurance. The study confirmed a positive benefit of insurance in terms of changing farmers' risk-taking behavior. The study also found consistent evidence that insurance had a positive and significant impact on technology adoption whereby insured farmers applied more inorganic fertilizers compared to uninsured. Furthermore, the study found a significant impact of insurance on farm productivity using IPWRA, but could not confirm the results using PSM and IV. There was no evidence supporting welfare gains due to insurance as expected. Based on the difficulty in finding an appropriate instrument *a priori* for the IV approach as indicated in the literature, the current study employed the PSM approach to assess the impact of WIBI on household incomes in Huye District.

2.5 Summary

From the reviewed literature, different approaches have been used to study WIBI in agriculture depending on the problem each researcher addressed. PSM has been widely used to assess the impact of policy, project or program intervention(s) on participants' welfare. This is because the approach addresses both the counterfactual and selection bias problems. Nevertheless, there has been little research on the impact of weather-based crop insurance schemes in developing countries. In Rwanda in particular, virtually no empirical research has been undertaken on crop insurance, probably because the agricultural insurance industry is still at its infancy. The present study intends to fill this gap in knowledge.

CHAPTER 3: METHODOLOGY

3.1 Conceptual framework

Figure 3.1 describes the conceptual framework of weather index-based insurance and the drivers of its uptake. The decision to participate in insurance programs is based on perceived utility by farmers, which is also influenced by socio-economic and individual characteristics, as well as market and institutional factors or changes due to enabling environment. The major farming objectives consists of increasing food availability in households and further improved household incomes. In order to participate to weather index based insurance, farmers have a perceived utility of the intervention/program associated with influencing factors. Farming objectives coupled with public policies, ie; taxes and subsidies, infrastructures contribute as basic conditions that influences a farmer to participate or not participate to interventions and programs such as the WIBI. The basic conditions, perceived utility and the factors influencing the participation decision all lead to impact: ie; increased income, food security and poverty reduction.

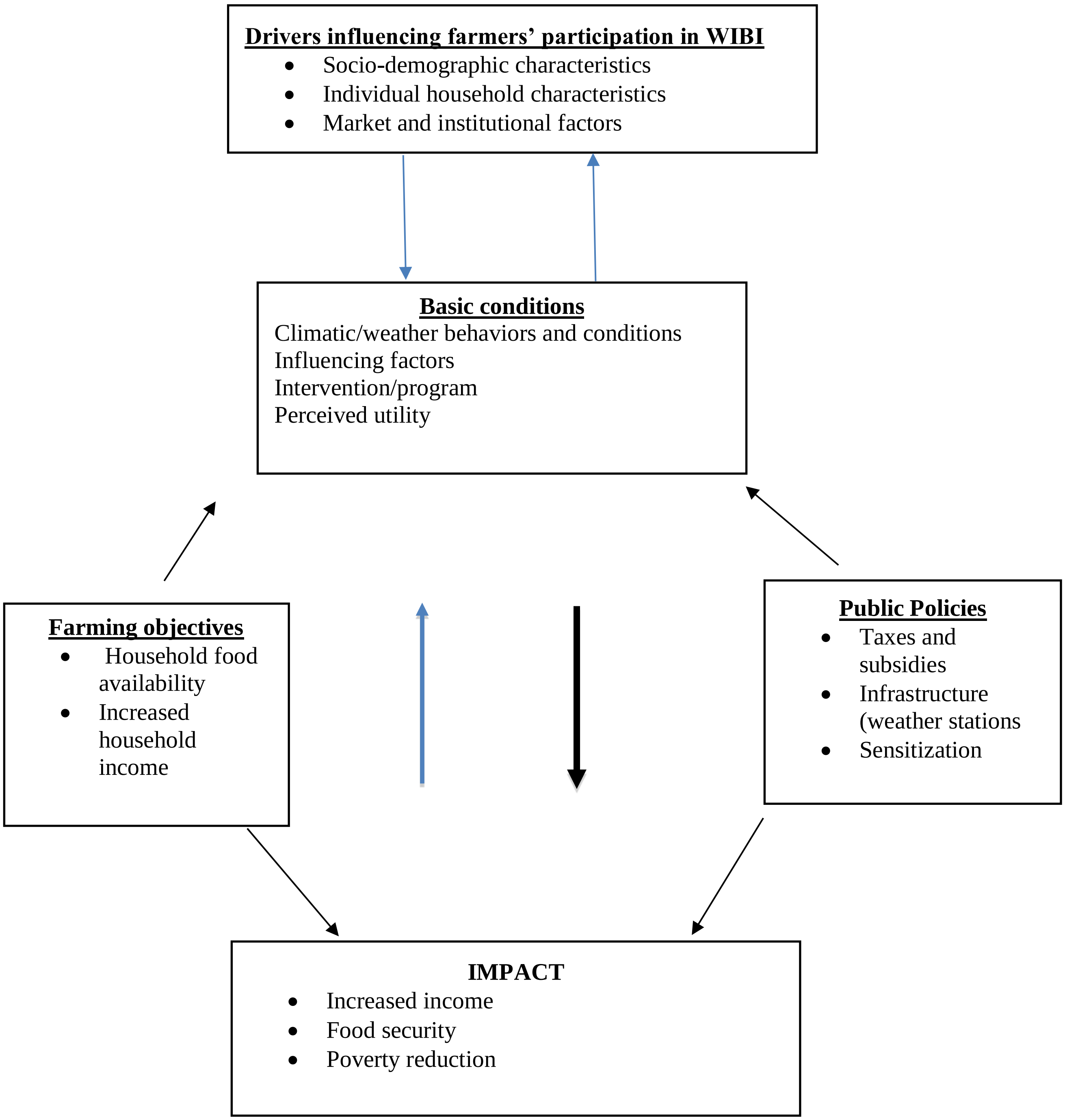

Figure 3.2 Conceptual framework of weather index-based insurance and the drivers of its uptake

Source: Adapted from Douthwaite *et al.* (2003)

3.2 Theoretical framework

This study is based on random utility theory. The theory posits that a farmer's decision to participate in a new intervention (either a project or a program) depends on the level of utility s/he expects to derive from that participation (U_p). Therefore, farmers will only participate in a WIBI scheme if the expected utility of participation (U_{ip}) is greater than the utility without (U_{in}) participation (Ali and Abdulai, 2010). Furthermore, the decision to participate in the insurance scheme is a dichotomous one in the sense that a farmer chooses whether or not to participate in the scheme based on his/her idiosyncratic preferences as well as on-farm characteristics. Participation also depends on each farmer's self-selection behavior rather than on a random assignment to the treatment or intervention. Denoting the difference between the net utility of participation and non-participation for each farmer *i* gives:

$$I_i^* = (U_{ip}) - (U_{iN}) > 0 \qquad (3.1)$$

Equation (3.1) means that farmer i will participate in a WIBI scheme if the perceived utility of participation exceeds that of non-participation, *ceteris paribus*.

Impact assessment studies suffer from three related problems that have important implications for empirical results. The first problem relates to the inference of the causal effect between the treatment [or having the intervention] and the outcome (Simtowe *et al*., 2012; Austin, 2011). With quasi-experimental designs, it is often difficult to randomly assign the treatment among the treatment group (e.g., participants in a WIBI scheme) and control group (e.g., non-participants). When participants and non-participants are left to assign themselves among the treatment and control groups, they may have attributes that collectively influence their decision to participate or not participate in the treatment (or intervention). Therefore, comparing the outcomes between the two groups would be misleading because they would differ even in the absence of treatment, leading to what is referred to as the selection bias problem (Austin, 2011). Because it is difficult to estimate the magnitude of selection bias in non-experimental data, the problem is addressed by undertaking a sensitivity analysis to assess the robustness of the results (Caliendo and Kopeinig, 2008).

The second problem pertains to omission of confounding variables, or what is referred to as the endogeneity problem (Diprete, 2004). This arises because the intervention may be caused by several factors that are not directly observable to the researcher. Even though the PSM technique does not address the problem itself, the Rosenbaum bounds in the sensitivity analysis provide evidence on whether important variables were omitted in the analysis and the sensitivity of estimated treatment effects with respect to unobserved heterogeneity (Caliendo and Kopeinig, 2008; Caliendo and Bonn, 2008).

The third is the counterfactual problem. That is, impact assessment studies often lack data about what the situation would be or would have been in the absence of the treatment (or intervention) (Rosenbaum and Rubin, 1983; Brundell and Costa, 2000; Wooldridge, 2001). Without information on the counterfactual, the next best alternative is to compare outcomes of treated individuals with those of a comparison group that has not been treated (Baker, 2000). It is, however, acknowledged that people will not participate in an event they do not know of or do not need; therefore comparing them with those who participate may often be faulty. The purpose of matching is to estimate the counterfactual outcome and thereafter correct for the selection bias by undertaking a sensitivity analysis. Rosenbaum and Rubin (1983) define the propensity score as the probability of receiving a treatment given pre-treatment characteristics. This is expressed as:

$$P(X) \equiv Pr\{Y = 1|X\} = E\{Y|X\} \quad (3.2)$$

where $Y = \{0,1\}$ is a binary variable indicating whether a household participates in a WIBI scheme (1=Yes; or 0=No), X is the multidimensional vector of pre-treatment characteristics of a household and $P(X)$ is the propensity score.

To estimate the impact of the WIBI, the average treatment effect on the treated (ATT) after matching was calculated. The ATT estimation assumes that the distribution of outcome variables for the control group is the same as the counterfactual in the treatment group. The expected value of ATT is defined as the difference between expected outcome values with and without treatment for individuals who actually participated in the treatment (Baker and Ichino, 2002). Thus, the ATT is estimated as follows:

$$E\{Y_{1i} - Y_{0i}|D_i = 1\}$$

$$= E\big\{E\{Y_{1i} - Y_{0i}|D_i = 1, p(X_i)\}\big\}$$

$$= E\{E\{Y_{1i}|D_i = 1,\ p(X_i)\} - E\{Y_{0i}|D_i = 0\}, p(X_i)|D_i = 1\} \quad (3.3)$$

where the expectation is over the distribution of $(X_i)|D_i = 1$; i denotes the household, with 1i and $0i$ as the potential outcomes in the two counterfactual situations of treatment and non-treatment respectively and D is the treatment group indicator.

The first step in the PSM approach consists of a binary estimation of factors hypothesized to influence the participation decision. In the current study, a logistic distribution was assumed. Following Pindyck and Rubin (1981), the logit model is given as follows:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 .....\beta_i X_i + \mu_i \quad (3.4)$$

The outcome variable, Y_i, is dichotomous and takes a value of 1 if the i^{th} farmer participated in the WIBI scheme and $Y_i = 0$ otherwise. The hypothetical population proportion of cases where $Y = 1$ was defined as $\pi = P(Y = 1)$ whereas for cases in which $Y = 0$ it was defined as $1 - \pi = P(Y = 0)$. The mathematical formulation is based on a linear model for the natural logarithm of the odds (Gujarati, 2004) (i.e., log odds) in favor of $Y = 1$. The expectation of equation (3.4) is given as:

$$\pi = E(Y_i = 1 | X_1 \dots X_i) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i \quad (3.5)$$

where π is a conditional probability of the form $P(Y_i = 1 | X_1 \cdots X_i)$. Taking the natural log on both sides of equation (3.5) gives:

$$\log e \left[\frac{P(Y=1|X_1 \dots X_i)}{1-P(Y=1|X_1 \dots X_i)}\right] = \log e \left[\frac{\pi}{1-\pi}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i \quad (3.6)$$

The study assumed that participating in the WIBI scheme depends on a combination of values of predictor variables. Using the substitution method and simplifying the fraction, equation (3.6) becomes:

$$P(Y = (Y_i = 1 | X_1 \dots X_i) = \pi = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 \beta_2 \cdots \beta_i X_i}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 \beta_2 \cdots \beta_i X_i}} \quad (3.7)$$

The simplified form of the above logistic function becomes:

$$P(Y = 1 | X_1 \dots X_i) = \pi = \frac{1}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 \beta_2 \cdots \beta_i X_i}} \quad (3.8)$$

Therefore, the probability of the i^{th} farmer participating in WIBI scheme was expressed as:

$$P(Y = 1 | X_1 \dots X_i) = 1 - \pi = \frac{1}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 \beta_2 \cdots \beta_i X_i}} \quad (3.9)$$

where β_0 is the constant term or the intercept; β_i are the regression coefficients to be estimated, X_i is a vector of explanatory or independent variables, and μ_i is the error term. Since the error term is not observed, there is not enough evidence to predict a farmer's participation decision, but it can be predicted based on households' observable characteristics.

A logit model was estimated to generate the propensity scores and the ATT for participation in WIBI. After obtaining the predicted probabilities conditional upon observable characteristics or propensity scores from the logit model, matching was done using NNM, RM, and KBM algorithms.

3.2 Empirical Framework

3.2.1 Propensity score matching

To assess the impact of the WIBI scheme on income among crop farmers in Huye District of Rwanda, a PSM approach was used. A participant's income in the absence of the intervention was drawn to be the counterfactual. In order to measure the ATT for the income variable, a logit model was estimated to obtain the propensity scores where the dependent variable was farmer participation in the WIBI scheme. The independent variables were factors hypothesized to influence the participation outcome.

3.2.2 Empirical model

In order to evaluate the probability of farmer participation in the WIBI scheme in Huye, Rwanda, the following empirical model was fitted into the data:

$$Yi = \beta_0 + \beta_1 Age + \beta_2 Agesquared + \beta_3 distancetoroad + \beta_4\ hheadgender + \beta_5 creditaccess + \beta_6\ group\ membership + \beta_7 Hheadeducation + \beta_8 farm\ size + \beta_9 irrigation + \beta_{10} diversification + \beta_{11} hhincome + \beta_{12}\ Wealth\ category \quad (3.10)$$

where Y_i represents farmer's participation decision, $Y_i = 1$ when the farmer participates, and $Y_i = 0$ otherwise. Table 3.1 presents a description of independent variables in Equation (3.10) and their hypothesized signs.

Table 3.1 Description of independent variables hypothesized to influence farmer participation in WIBI scheme in Huye District, Rwanda

Variable	Description	Measurement	Hypothesized sign
Hheadage	Age of the household head	Years	+/-
Hheadagesqaured	Age-squared	Years	-
Hheadgender	Gender of the household head	Dummy 1=Male 0=Female	+
Distancetoroad	Distance to a main road	Km	+
ExpwithWIBI	Years of experience with WIBI	Years	+
Hheadeducation	Education level of the household head	Formal education where 0=No 1=Primary school 2=Secondary school 3=Tertiary education	+
Farmsize	Farm size	Acres	+
Creditaccess	Access to credit	Dummy where: 1=Credit access 0=Otherwise	+
GPmembership	Membership in farmer group/association/cooperative	Dummy where: 1=Membership 0=Otherwise	+
Income	Household income	Amount earned from the household activities	+
Diversification	Crop diversification	Dummy where 1=Yes 0=No	-
Irrigation	Use of irrigation on maize and beans	Dummy where: 1=Yes 0=No	-
Wealthcat	Wealth category	1=Second category 2=Third category 3=Fourth category	+

Source: Author

3.2.3 Justification for inclusion of various regressors

AGE (Hheadage): Age was measured in years as a continuous variable. Previous studies reported mixed results on the relationship between age and insurance participation. Older farmers are expected to participate more in the insurance scheme than young ones because they are likely to have more resources compared to younger farmers. However, a decrease in participation is expected at an old age. Onyimbo *et al*. (2013) found that age was significant and positively influenced the probability of farmers' participation in agricultural insurance schemes in Nigeria. Sargazi *et al*. (2013) found that the age of the household head increased participation in agricultural insurance schemes where older farmers were also more willing to purchase crop insurance in Iran. In this study, age was hypothesized to be positively associated with the decision to participate in insurance schemes among farmers in Huye District.

AGESQUARED (Hheadagesqaured): This was estimated as a continuous variable and measured in number of years squared. Advancement in age was expected to decrease farmer participation in WIBI scheme. The lower participation is largely attributed to less receptivity of older farmers to new interventions unlike the young people who are less risk averse as well as more receptive to new interventions. For instance, Dhanireddy and Frisvold (2012) in the USA found that as the age of a farmer increased, the farmer would be more experienced and buy crop insurance as a risk management tool. However, participation was found to be low for farmers with more than 65 years of age. Furthermore, Gine *et al*. (2008) found age irrelevant with respect to farmers' decision to participate in crop insurance in India. In the current study, the square of household head's age was hypothesized to have a negative influence on farmer's participation in the WIBI scheme.

GENDER (Hheadgender): This was coded as a dummy variable. Previous studies show that male farmers are more likely to participate in the insurance schemes compared to their female counterparts. This is because male farmers are expected to bear the responsibility of providing food to their families. Therefore, to be food secure in dry seasons; male farmers could opt to insure their crops. Kwanzo *et al*. (2013) found that insurance was a male-dominated venture in the Kintampo North Municipality in Ghana. Hill *et al.* (2012) found that female farmers were 12% less likely to pay for insurance in Ethiopia. In this study, being male was expected to be positively associated with farmer participation in the WIBI scheme in Huye District.

DISTANCE TO A MAIN ROAD (Distancetoroad): This was continuous and measured in kilometers travelled by farmers in order to contact insurance agents. Ali (2013) found a positive relationship between participation in an insurance scheme and road access in Pakistan because access to roads facilitated farmers in making more income and in accessing agricultural inputs more easily. Therefore, in this study, shorter distance to a paved road was expected to have a positive influence on farmers' WIBI participation decision.

YEARS OF EXPERIENCE WITH WIBI (ExpwithWIBI): This was a continuous variable measuring the number of years the farmer had known about the existence of the insurance scheme and its benefits. Knigh and Coble (2006) found that years of experience with insurance played an important role in enabling farmers to understand the associated benefits in Nigeria. Fallah *et al*. (2012) also found that farmers with more knowledge on insurance had wider insurance coverage than those who did not in Iran. Jarvie and Nieuwoudt (2010) found that the older, more experienced farmers in South Africa were more risk-averse and therefore attempted to reduce risk through insurance. Therefore, as risks increased, more insurance was purchased by risk-averse producers. In this study, years of experience with the WIBI scheme was expected to positively influence farmers' participation decision in Huye District.

YEARS OF FORMAL EDUCATION (Hheadeducation): This was measured as a categorical variable representing the number of formal education years undergone by the household head at the time of the survey. Formal education positively influences participation in new interventions because educated farmers know the benefits associated with a new intervention such as WIBI and aim to have stable farm incomes or compensation in case of losses. In the USA, subscribers of crop insurance programs were generally found to be more experienced and better educated, which explained their greater uptake of insurance (Sherrick *et al*., 2004). Furthermore, Frisvold and Dhanireddy (2012) found that education had a positive influence on the probability of purchasing crop insurance in the USA. Farmers with higher education were found to be very responsive to risk management initiatives. Their study also found that highly educated farmers were more risk averse than non-educated ones and considered crop insurance to be more valuable to them. Fallah *et al*. (2012) found that farmers with higher levels of education were more likely to participate in an insurance scheme in Iran because they were aware of and understood the premiums for insuring their products. In this study, more years of formal education were expected to positively influence farmers' participation decision in the WIBI scheme in Huye District.

FARM SIZE (Farmsize): This was measured in acres as a continuous variable indicating the total land size allocated to maize and beans in 2013. Larger pieces of land give farmers the confidence to invest in and develop their land. Onyimbo *et al.* (2013) and Knigh and Coble (1997) found that the size of the farm increased the likelihood of farmer participation in crop insurance in Nigeria. Fallah *et al*. (2012) found that farmers with larger areas for farming dry land wheat were more likely to participate in agricultural insurance compared with their counterparts with smaller farms in Iran because they were more likely to acquire services provided by insurance in order to hedge against the possibility of crop failure. Nahvi *et al.* (2014) also found a positive relationship between farm size and farmers' tendency to participate in a rice insurance scheme in Iran. In Rwanda where land is a major constraint to crop production, farmers with larger farm sizes were expected to have a higher tendency to participate in the WIBI scheme than those with small farms. This is because farmers with larger parcels of land are more likely to be able to afford to insure their crops compared with their counterparts with smaller farms.

ACCESS TO CREDIT (Creditaccess): This was coded as a dummy variable taking a value of one if the household had access to credit and zero otherwise. Having access to credit not only provides farmers with working capital to invest, but also helps them access trainings and knowledge of market channels thus opening the opportunity to participate in new interventions. Ali (2013) showed that farmers who were more willing to participate in index-based insurance had higher household incomes and also had a credit facility compared to the non-participants in Pakistan. Onyinbo *et al*. (2013) also found that farmers who had more access to credit participated more in a crop insurance scheme in Nigeria than those without. Hill *et al*. (2013) found that adopters of weather-index insurance were more wealthy, educated and had more access to credit and formal financial markets in Ethiopia. Additionally, Abdulmalik *et al*. (2013) found that access to credit had a positive and significant influence on farmer participation in agricultural insurance in Nigeria. This is because farmers that accessed bank loans were able to more easily access insurance products. Therefore, most farmers subscribed to insurance schemes in order to increase their access to loans. In the current study, access to credit was hypothesized to positively influence farmers' decision to participate in the WIBI scheme in Huye District.

MEMBERSHIP IN A COOPERATIVE OR FARMER ASSOCIATION (GPmembership): Cooperative membership was coded as a dummy variable taking a value of one if the farmer was a member of a cooperative and zero otherwise. Being a member of a cooperative provides farmers with information on new interventions and technologies. For instance, Gine *et al*. (2008) found that membership in a farmer association had a positive effect on the decision to participate in crop insurance in India because these farmers were better informed than their counterparts who were not group members. Getachew (2010) showed that farmers form cooperatives for collective action and this positively affects the dissemination of information. In this study, cooperative membership was hypothesized to positively influence farmers' decisions to participate in WIBI scheme in Huye District.

INCOME (Income): This was a continuous variable and measured in terms of the amount a farmer earned seasonally from the farm. Well-off farmers have more resources to invest in new technologies as well as participate in new agricultural interventions. For example, Fallah *et al*. (2012) found that income increased farmer participation in agricultural insurance in Iran. This is because farmers with high incomes had more resources to invest in new interventions compared to their counterparts with less income. Sargazi *et al.* (2013) also found that farmers with higher incomes had a tendency to participate in agricultural insurance in Iran in order to secure their farm products. Therefore, household income was expected to have a positive influence on farmer participation decision in WIBI scheme in Huye District of Rwanda.

CROP DIVERSIFICATION (diversification): This was coded as a dummy variable, taking the value of one if the farmer grew more than one crop and zero otherwise. Farmers diversify crops mainly to reduce the risks associated with farming. Ginder and Spaulding (2006) found that diversification increased participation in crop insurance in Northern Illinois, USA, because crop insurance was considered as a coping mechanism for food security, production and market risks. However, Sherrick *et al*. (2004) found that undertaking both livestock and crop production and the reliance on off-farm income by farmers represented a form of diversification, which contributed to the stability of overall income thus reducing the demand for crop insurance in the USA. Furthermore, Knigh and Coble (2006) found that farmers who practiced crop diversification were less likely to participate in crop insurance. In this study, crop diversification was expected to negatively influence farmers' decision to participate in the WIBI scheme in Huye District. This is because farmers diversify their enterprises as an alternative way to informally cope with weather-related risk.

USE OF IRRIGATION (Irrigation): This was coded as a dummy variable taking the value of one if the farmer irrigated maize and beans and zero otherwise. Use of irrigation is believed to increase production and reduce the risk associated with weather changes. Farmers who practice irrigation were expected to participate less in the WIBI scheme. Studies have demonstrated that investment in irrigation negatively influences farmer participation in insurance programs. For example, Sherrick *et al*. (2004) showed that use of irrigation negatively influenced farmers' insurance participation decisions in the USA. De Nicola (2010) also found that use of irrigation significantly reduced farmer participation in insurance schemes in Malawi where farmers with stable farm production were less willing to purchase insurance. In this study, therefore, use of irrigation for crop production was hypothesized to negatively influence farmers' participation in the WIBI scheme in Huye District.

WEALTHY CATEGORY (Wealthcat): Wealth was measured as a categorical variable with three levels. These three categories were derived from the four captured by the National Institute of Statistics of Rwanda and the Ministry of Local Government Statistics Department in 2014. The wealth categories are known as *Ubudehe* in the local Kinyarwanda language. The first category describes poorer households that do not have a home, and have limited ability to rent one. Such households struggle to get food and meet other basic needs, such as being able to purchase toiletries, salt and clothes. The second category describes more "middle class" households that either own a house or have the capacity to rent. Such households are more food secure, and at least one person in the household earns wage income from casual labor. The third category describes richer households in which either at least one person is employed as a civil servant or in private employment (e.g., running a small retail business). Such households have enough food from either own production or market purchase. The fourth category consists of wealthier households with a wholesaling business, with at least one person working in the service industry, civil service or manufacturing industry. Such households have a residential house and a commercial building or other businesses like a gas station. In Huye District, the study targeted farmers from the second, third and fourth categories because they were considered to be able to purchase crop insurance.

Studies have shown that wealthier farmers are more likely to be early adopters of new interventions and technologies because they have more resources. For example, Hill *et al*. (2013) found that wealthier farmers in Ethiopia were more likely to buy insurance than poorer individuals even though poorer households had more to gain from an insurance product. Wealthier farmers with large farms were found to purchase insurance to secure their assets in South Africa (Mohammed and Ortmann, 2005). However, Sherrick *et al.* (2004) found that less wealthy farmers who operated on larger acreages acquired insurance extensively because they placed higher values on risk management and considered insurance as one among several risk management practices. In this study, therefore, being in the second, third and fourth category was hypothesized to positively influence participation in crop insurance in the study area.

3.3. Research design

This study used a quantitative research design to estimate the relationship between variables in the data collected in Huye District, Rwanda. This involved the computation of descriptive statistics such as means and frequencies. These statistics were used to characterize the WIBI scheme as well as farmers' socio-demographic attributes. The PSM was thereafter used in hypothesis testing.

3.3.1 Study area

Huye District is one of the eight districts in Southern Province of Rwanda. It comprises 14 sectors, namely, Mbazi, Kinazi, Simbi, Rwaniro, Rusatira, Huye, Gishamvu, Mukura, Ruhashya, Tumba, Kigoma, Ngoma and Karama. It has 77 cells and 509 villages. According to the District Development Plan statistics (DDP, 2013), Huye had a population of 319,000 inhabitants with a density of 548 people per square kilometer. The district headquarters are located in Huye town in

Southern Province. The district experiences 1,200mm average rainfall and 19°C average temperature annually (EICV3, 2011). The climate of Huye District is marked by four distinct seasons, namely, long rains (from mid-February to May), long dry season (June to mid-September), short rains (mid-September to December), and a short dry season (January to mid-February).

Huye District is among the districts in Rwanda with a high proportion of poor people - approximately 47 percent. About 53 percent of the population in Huye was identified as non-poor, 21.4 percent as poor and 25.2 percent as extremely poor (EICV3, 2011). Overall, Huye District ranks sixteenth among all 30 districts, with a high percentage of extreme poverty.

Being a rural district, agriculture is the main economic activity involving 76% of the population aged 16 years and above, followed by trade (7%) and other services (5%) (EICV3, 2011). Furthermore, Huye District is sixth in the ranking of all districts by employment rate with an overall employment rate of 80% of the resident population aged 16 years. The district is seventeenth in terms of literacy, with a literacy rate of 68%, compared with the national average of 69.7% (EICV3, 2011).

The choice to study Huye District was based on the fact that it was one of the pilot districts where crop insurance was first introduced in Rwanda in 2011. The insurance company, KS, had targeted Huye District due to its climatic conditions being characterized by frequent droughts. Therefore, KS introduced the insurance scheme in Huye after seeing the negative impacts of drought and heavy rains on farming there. For instance, according to KS and Tubura records, since the introduction of the insurance scheme in 2011, the district lost more than half of the expected harvests in 2011 and 2012 due to drought. Automated weather stations were installed at the Sector level in order to monitor the effects of variability in rainfall, temperature and leaf moisture content on maize and beans throughout their physiological life cycle. The WIBI targeted maize and bean farmers as these crops are the main focus of the Crop Intensification Program introduced by the Rwanda's Ministry of Agriculture (MINAGRI) in Huye District. The survey was carried out in two Sectors of Rusatira and Kinazi within five Cells, namely, Gahana, Gatovu, Kabona, Gasange and Buhimba (Figure 3.2).

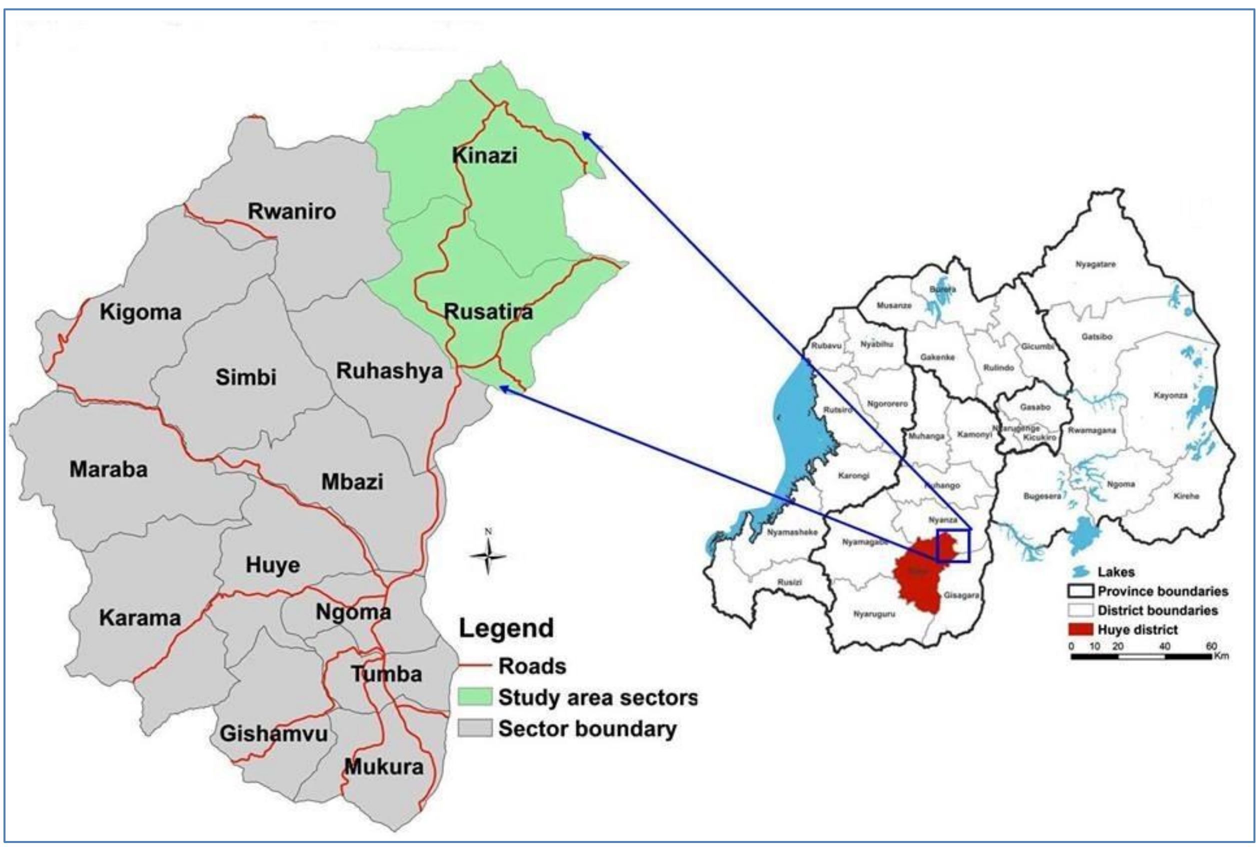

Figure 3. 2 Administrative map of Rwanda showing Huye District

Source: EICV3 (2011)

3.3.2 Sampling procedure

A multi-stage random sampling procedure was used to select potential respondents. The district was purposefully selected, and then Sectors and villages where WIBI had been introduced were selected. These strata were identified with the help of the GoR Sector Agronomist, and Tubura field officers. During the time of the survey, six Sectors were registered with the insurance scheme; i.e., Kinazi, Rusatira, Rwaniro, Ruhashya, Mbazi and Maraba. Of these, two Sectors, Kinazi and Rusatira, were intentionally selected based on their similar climate conditions. The two Sectors had 438 and 343 registered farmers respectively. From the two Sectors, 19 villages were selected based on their shared climatic conditions and the location of weather stations for the WIBI. In each village, a list of insured farmers was drawn with the help of Tubura field officers. Then, systematic sampling was done where every 5th household was selected. This gave a total of 146 and 100 households in Kinazi and Rusatira Sectors, respectively, given that Kinazi had more insured farmers. Non-insured farmers were also systematically selected from a list of farmers obtained from the Local Administration at the Cell level. This exercise resulted in a total sample size of 246 farmers comprising 123 participants and 123 non-participants in WIBI in Huye District.

3.3.3 Data collection techniques

Both primary and secondary data were collected in this study. Primary data were collected using a semi-structured questionnaire (see Appendix I) from a sample of farmers. The questionnaire gathered information on the head of the household's socio-economic characteristics, farming practices, institutional characteristics and details of the insurance scheme. Six enumerators from the Agricultural Economics and Statistics departments at the University of Rwanda, Huye Campus, were recruited and trained by the author. A pre-test survey was done by the author, and thereafter information was collected using the local dialect language (Kinyarwanda) in June 2014. The survey targeted farmers who were registered with Tubura in the study areas as well as their neighbors who had not participated in the insurance scheme. The questionnaire took 90 minutes to complete, on average. Key informant interviews (KIIs) were undertaken using a checklist of questions (Appendix II). The target interviewees were staff in the MINAGRI, KS and Tubura. The purpose of these KIIs was to validate the responses recorded collected from the beneficiaries. The KIIs concentrated on the activities of the insurance scheme in Huye District.

3.4 Data analysis

The data collected were captured in Statistical Package for the Social Sciences software (SPSS) version 20 and analyzed using STATA version 11. The analysis included both descriptive statistics and econometric modeling. Descriptive statistics such as means, standard deviations, and frequencies were computed in STATA to show the patterns and uptake of the crop insurance scheme in Huye District. The means between participants and non-participants were generated and compared using a T-test, and frequencies were compared using a chi-square test. A PSM model was thereafter applied to estimate the impact of WIBI on household income. The results were presented in tabular and graphical formats.

3.5 Diagnostic tests

Prior to the PSM modeling, some diagnostic tests were carried out on the explanatory variables to assess their suitability for inclusion in the empirical model. Accordingly, the following tests were undertaken:

3.5.1 Testing for multicollinearity

The existence of multicollinearity means that there is a perfect linear relationship among some or all the explanatory variables of the regression model (Wooldridge, 2000). In the presence of multicollinearity, the regression coefficients are indeterminate and their standard errors are infinite or, if definite, they are large, resulting in a greater chance of committing type I error (rejecting the null hypothesis when it is in fact true) (Greene, 2003). This means that the coefficients cannot be estimated with accuracy because they might have incorrect signs and smaller *t*-values, which may lead to drawing incorrect inferences (Gujarati and Sangeetha, 2007). This study assessed multicollinearity in the explanatory variables using Variance Inflation Factor (VIF). A common rule of thumb is that if VIF is greater than 5, then the correlation among explanatory variables is high (Greene, 2002). The mean VIF was 1.17 and for each explanatory variable, the VIF ranged between 1.05 and 1.17 (see Appendix III). Because the VIF was less than 5 for all the explanatory variables, there was negligible linear relationship among the variables therefore justifying their inclusion in the logit model, the first step of PSM. The results from the Pearson correlation matrix (see Appendix V) showed no strong linear relationship between variables because none of the variables were very close to 1(strong positive linear correlation) or -1(negative linear correlation).

3.5.2 Testing for heteroskedasticity

Homoskedasticity is an important assumption in the classical linear regression model. This assumption means that the disturbance term has a constant variance (Gujarati and Sangheeta, 2007). If this is not the case, there is a problem of heteroskedasticity, which is most common in cross-sectional data such as those collected in this study. In the presence of heteroskedasticity, Ordinary Least Squares (OLS) estimates are asymptotically inefficient. The Breusch–Pagan test was used to test for heteroskedasticity. The chi-square was 0.32 with one degree of freedom and not statistically significant (p=0.5723). Therefore, the null hypothesis of homoskedasticity could not be rejected, indicating the absence of heteroskedasticity (see Appendix VI).

3.5.3 Specification error test

The 13 explanatory variables (see equation 3.10) were assessed to determine whether the model had all relevant predictors and if the linear combination was sufficient. The specification test was done in STATA using the LINKTEST command. The rationale behind LINKTEST is that if the model is properly specified, there should not be any additional statistically significant predictors (Gujarati and Sangeetha, 2007). The LINKTEST command uses the linear predicted value (_HAT) and its square (_HATSQ) as the predictors to rebuild the model. If the model is correctly specified, the variable (_HAT) should be statistically significant because it is the predicted value from the model whereas (_HATSQ) should not be. The results given in Appendix VI indicate that the model was correctly specified as (_HAT) was statistically significant (p=0.000) while (_HATSQ) was not (p=0.240).

3.5.4 Assessing the goodness-of-fit

The goodness-of-fit of a model shows how well the probabilities produced by the model accurately reflect the true behavior captured in the data or how well the regression model fits the data (Hosmer *et al.,* 2013; Gujarati and Sangheeta, 2007). A good fit for a logit model is indicated by a statistically non-significant Hosmer-Lemeshow chi-square value.

3.5.5 Testing for robustness of results and unmeasured bias

A balancing test is normally required after matching to find out whether the differences in covariates in the two groups of the matched sample have been eliminated (Caliendo and Kopeinig, 2008). The results of the test indicate the validity of using the matched comparison group as a plausible counterfactual. The basic idea behind checking the quality of matching is to compare before and after matching and verify whether any differences remain (Lee, 2008). The results were therefore tested using different balancing tests. According to Rosenbaum and Rubin (1985) and Sianesi (2004), the pseudo-R^2 should be compared before and after matching. The pseudo-R^2 indicates how well regressors explain the probability of participation. In this study, the pseudo-R^2 was high before matching and low after matching (below 5 percent) as shown in Table 4.6. After matching, the p-values of the likelihood ratio test were all insignificant, indicating that no differences remained in the distribution of covariates between participants and non-participants of WIBI (Table 4.5). The mean and median biases were all below 20 percent as required (Table 4.6); in fact, they were all below 10 percent, indicating a very good match. As suggested by Rosenbaum and Rubin (1985), a standardized difference greater than 20 percent should be considered as large. The joint significant effect of the covariates on participation, as explained by the significant chi-square, could not be rejected before matching, but was rejected after matching in each of the three matching algorithms (NNM, RM and KBM).

Rosenbaum (2002) noted that hidden bias and lack of robust estimators may still be present if there are unobservable variables that simultaneously affect assignment into the treatment group and the outcome variable. Hidden bias occurs when two individuals with the same observed characteristics have different probabilities of receiving the treatment. Rosenbaum (2002) suggested the use of a sensitivity analysis called ‘bounding’ to address this problem. Therefore, a bounding approach to address the problem of hidden bias was used in this case; the results were largely insensitive to unobserved characteristics (Appendix VII).

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Socio-economic and demographic profiles of WIBI participants and non-participants in Huye District

Table 4.1 presents the means of various socio-economic characteristics of household heads in Huye District of Rwanda. The average distance to the nearest paved road was higher for participants than non-participants and statistically significant (p=0.01). Years of experience with WIBI are statistically different between participants and non-participants (p=0.000), with participants having more experience.

Distance to the nearest paved road was statistically significant between the two groups. On contrary, non-participant farmers were located near a paved road compared to weather index-based insurance (WIBI) participant farmers. This implies that having nearby facilities does not necessarily influence farmers' decision to participate in new interventions such as WIBI in Huye District. This finding is consistent with Magrini and Vigani (2014) who found that distance to the nearest major road reduced transaction costs, constraining economic development, but did not influence farmer participation in new technologies in Tanzania. Birinci and Tumar (2006) found that the distance from a village to a larger town had a negative effect on the knowledge of farmers about agricultural insurance because as the distance between village and town increases, the number of farmers having knowledge about the insurance scheme decreased in Turkey.

Years of experience with WIBI were statistically significant between participant and non-participant farmers. Participants had more years of experience with the insurance scheme, which implies that this group of farmers had better knowledge of insurance benefits and dynamics. For instance, Spörri *et al*. (2012) found that the likelihood of farmers participating in crop insurance was reduced by lack of experience and lack of trust in insurance systems in Hungary. Premium subsidies alone could not increase insurance use among farmers; better communication, education and information flows were also needed to increase farmers' use of crop insurance.

Table 4.1 Means of socio-economic and institutional characteristics of respondents in Huye District, Rwanda

Characteristic	Non-Participants n=123	Participants n=123	Mean difference	t-value
Age	43.08	42.97	.11	0.94
Age squared (years)	2004.89	2047.65	-42.76	-0.27
Years of formal education	.90	.93	-.032	0.64
Distance to road (Km)	.60	.85	-.25	-2.56***
Years of experience with WIBI	1.31	2.58	-1.26	-7.82***
Farm size (acres)	.64	.83	-.18	-1.30

Source: Survey data (2014)
***and ** indicate 1% and 5% significance levels respectively.

Table 4.2 presents the comparison of frequencies of socio-demographic attributes of the survey respondents in Huye District, Rwanda.

Table 4.2 Frequencies of socio-economic and demographic characteristics of respondents in Huye District, Rwanda

Characteristics		Non-participants		Participants		Pooled		Chi-square
		n	**%**	**N**	**%**	**n**	**%**	
Gender	Female	50	40.65	62	50.41	111	45.12	1.98
	Male	73	59.35	61	49.59	135	54.88	
Group membership	No	32	26.02	12	9.76	44	17.89	11.07***
	Yes	91	73.98	111	90.24	202	82.11	
Credit access	No	20	16.26	11	8.94	31	12.60	2.98*
	Yes	103	83.74	123	91.06	215	87.40	
Land tenure	No	18	14.63	12	9.76	30	12.20	1.36
	Yes	105	85.37	111	90.24	216	87.80	
Irrigation	No	97	78.86	84	68.29	181	73.58	3.53*
	Yes	26	21.14	39	31.71	65	26.42	
Diversification	No	62	50.41	37	30.08	99	40.24	10.56***
	Yes	61	49.59	86	69.92	147	59.76	
Wealth category	First	8	2.44	3	6.50	11	4.47	
	Second	64	72.36	89	52.03	153	62.20	11.23**
	Third	51	25.20	31	41.46	82	33.33	

Source: Survey data (2014)
***, **and * indicate 1%, 5% and 10% significance levels respectively.

Non-participant farmers had better access to credit compared to participants ($\chi^2 = 2.98$; p= 0.084). Farmers who worked with lending organizations such as savings and credit cooperatives (SACCOs) participated less in WIBI possibly because of less knowledge and experience with the crop insurance in Huye District. This result is consistent with Fallah *et al*. (2012) who found that this was due to low trust levels and less experience with agricultural insurance in Iran. In Huye District, farmers had less experience with insurance services and therefore may have been skeptical of WIBI.

Significantly more WIBI non-participants were found to practice irrigation compared to their counterparts (χ^2=3.53; p= 0.060). Use of irrigation stabilizes farmers' production thus leading to less use of insurance as protection against weather challenges. This finding is consistent with Sherrick *et al*. (2004) who reported that farmers who had better use of irrigation facilities participated less in crop insurance in the USA.

Crop diversification was also significantly different between the two groups where participant farmers diversified less than their counterparts (χ^2=10.5648; p= 0.001). Sherrick *et al*. (2004) found that diversification contributed to overall farm income in the USA, thus impeding participation in crop insurance because farmers had stable incomes.

The wealth categories were significantly different among non-participants and participants in WIBI (χ^2 =11.23; p=0.004). The non-participant group had many more very poor farmers than the participant group. Generally, farmers in Huye District fall into any of the three categories; however, insured farmers get a package of inputs along with the insurance, which makes their incomes more stable compared to their counterparts. The result is consistent with Hill *et al*. (2013) in Ethiopia where wealthier farmers were the major buyers of crop insurance compared to poorer ones, although poor households gained more from an insurance scheme than the rich farmers.

4.2 Patterns of dissemination and uptake of weather index-based insurance in Huye District of Rwanda

Kilimo Salama statistics reported a total number of 87,000 farmers who had subscribed to crop insurance in Rwanda in 2014. These farmers were distributed as 2,000, 13,000 and 50,000 in 2011, 2012, and 2013 respectively. In Kinazi and Rusatira Sectors where this study was carried out, 438 and 343 farmers were registered with the insurance scheme respectively during the time of the survey. The adoption rate was 100% because the product was distributed in conjunction with agricultural loans from One Acre Fund/Tubura (Tubura Statistics Department, 2014). Furthermore, insurance providers worked with existing farmer cooperatives in the area. The maize and bean cooperatives are organized in such a way that the insurance providers as well as other government interventions reach out to farmers through their leadership.

Table 4.3 presents the frequency of farmers' years of knowledge on WIBI. As expected, more participants than non-participants had known the existence of the insurance scheme and for more years than their counterparts. Indeed, 26 percent of participants had known WIBI for four years compared to only 11.4 percent of non-participants. Furthermore, only 2.4 percent of participants compared to 39.8 percent of non-participants had at least one year of knowledge on WIBI. These results show that the level of knowledge about WIBI scheme is still low among non-participant farmers. This probably accounts for the overall uptake of WIBI in Huye District. This implies that the GoR together with the relevant stakeholders should do well to sensitize farmers on WIBI to ensure more uptake.

Table 4.3 Knowledge of WIBI scheme in years among survey respondents in Huye District

	Participants		**Non-participants**	
Years of knowledge	**Frequency (n=123)**	**%**	**Frequency (n=123)**	**%**
Less than one year			12	9.8
One year	24	19.5	14	11.4
Two years	37	30.1	22	17.9
Three years	26	21.1	26	21.1
Four years	33	26.8	49	39.8

Source: Survey data (2014)

Previous studies have shown that more years of experience with crop insurance significantly affect its uptake. For example, Fallah *et al*. (2012) showed that farmers with better knowledge of crop insurance in Iran had wider insurance coverage than those with less. Patt *et al.* (2009) found that personal experience with crop insurance was a major determinant of whether or not a farmer enrolled in the insurance scheme in India. In this study, knowledge of WIBI among the participants could have increased their participation rates.

4.3. Factors influencing farmer participation in WIBI in Huye District

Table 4.5 presents the maximum likelihood estimates of the factors hypothesized to influence participation in WIBI in Huye District of Rwanda. The Hosmer and Lemeshow's chi-square testing the goodness-of-fit was 9.65 (p=0.524) at 12 degrees of freedom. The p-value of the test was not significant indicating that the model fitted the data well. Out of 12 variables, 7 were statistically significant two of which had unexpected signs.

4.5. Maximum likelihood estimates of factors influencing farmer participation in WIBI in Huye District

Variable	Coef.	Stderror	Z-value	Marginal effects
Household head age	-.105	.077	-1.35	-0.003
Household head age squared	.001	.0008	1.41	0.023
Household head gender	.548	.329	1.67*	.547
Distance to road	.468	.209	2.24**	.584
Years of experience with WIBI(years)	.752	.128	5.87***	.371
Household head' years of education	-.004	.282	-0.02	.500
Farm size	.046	.184	.25	.017
Credit access	.333	.478	0.70	.506
Cooperative membership	.972	.453	2.14**	.525
Diversification	.766	.328	2.33**	.552
Irrigation	.820	.372	2.20**	.458
Wealth category	.674	.296	2.28**	.566
Constant	-2.695	1.846	-1.46	0.12
Number of observation:246				
Log Likelihood: -124.98				
Pseudo R^2:0.26				
Prob >Chi^2 = 0.0000				
LR Chi^2(12) = 91.06				

Source: Author's computation based on survey data (2014)
***, **, * indicate 1%, 5% and 10% significance levels respectively.

Being malepositively and significantly influenced the decision to participate in WIBI in Huye District. This finding is consistent with Hill *et al*. (2013) who found that women were less likely to pay for crop insurance because male farmers were the primary controllers of farms in Ethiopia. Kwanzo *et al*. (2013) found that insurance was a male-dominated venture in Ghana. Charged with the responsibility of providing for their families, it seems male heads of householdsopted to insure their maize and beans as a means of dealing with uncontrolled weather changes relative to their female counterparts. This could have also been because of being more resource endowed than women.

Distance to the nearest road was positively and significantly associated with farmer's decision to participate in WIBI in Huye District. This means that households located far from the road had a higher likelihood of participating in WIBI than those located next to the road. Farmers located near paved roads had better access to diverse agricultural interventions and opportunities, which gives them access to various options to income diversification and cope with weather related consequences. This finding contradicts Birinci and Tumer (2006) who found that farmers located more than 10 kilometers from the paved road had a lower tendency to participate in agricultural insurance in Turkey. The authors explained that this was because as the distance between the village and the paved road/town increased the number of farmers who had knowledge of agricultural insurance decreased. However, Ali (2013) found a positive and significant relationship between participation in crop insurance and road access in Pakistan. Distance to road facilitated these farmers to better access agricultural inputs as well crop insurance. In this study, the relationship between distance to road and crop insurance can be explained by the high penetration of Tubura/One Acre Fund in remote areas in the District in order to reach farmers with limited options to cope with weather related shocks.

The number of years of farmer's experience with WIBI was found to be positive and significantly associated with farmers' participation decisions, as expected *apriori*. More experience on a technology or innovation is expected to enable farmers to evaluate and better comprehend the technology or innovation prior to uptake (Hill *et al.*, 2013). In this study, farmers with more years of experience with WIBI seemed to have better knowledge of the mechanics of the scheme and therefore had a higher likelihood of participating than those with less experience. This finding tallies with Mohammed and Ortmanna (2005) who found that the greater the extent of information and awareness on livestock insurance, the greater the probability of participation in Eritrea. Hassanpour *et al.* (2013) also found a positive and significant effect of farmers' experience with an insurance scheme on the participation decision in Iran.

Membership in a cooperative society or a farmer group was found to be positively and significantly associated with farmers' decisions to participate in WIBI. This could be attributed to the fact that farmers who participate in cooperatives share information easily as compared to those who are not members of cooperatives. In addition, cooperatives required that their members purchase insurance in order to hedge against weather-based shocks. Olila (2014) demonstrated that membership of a farmer in a social and/or community-based organization increased the level of awareness of crop insurance in Kenya thus influencing farmers' purchase decisions. The significant relationship could also be attributed to the GoR's policy of sensitizing farmers to join cooperatives, associations or farmer groups in order to easily access markets and inputs, and for easier transmission of new interventions and technologies. Farmer cooperatives in Rwanda are used by local agronomists and extension workers as means of information dissemination to sensitize farmers about new technologies, interventions and programs.

Contrary to expectation, crop diversification was found to positively and significantly influence farmer participation in WIBI. The unexpected behavior was attributed to the low dissemination level of the insurance scheme to farmers in Huye District as well as relatively shorter experience with the insurance. Additionally, it could be showing a high level of risk aversion where farmers would not leave anything to chance; they dealt with risk in all ways available to them. This finding is consistent with Ginder and Spaulding (2006) who found that crop diversification influenced purchase of crop insurance in Northern Illinois, USA; farmers considered insurance as a coping mechanism for food security, production and market risks.

Use of irrigation was positively and significantly associated with farmers' likelihood to participate in the WIBI scheme in Huye District as expected. This was attributed to the fact that farmers who invested in irrigation facilities to protect their crops against weather shocks also insured their crops, which in a way is a kind of "over-insurance." It had been expected that use of irrigation would reduce the likelihood of a farmer participating in WIBI as irrigation reduces weather-based risks. However, the over-insurance behavior was attributed to the Tubura model in which farmers get a full package comprised of inputs along with crop insurance in addition to the limited access to sufficient irrigation facilities. This finding is inconsistent with De Nicola (2010) who found that use of irrigation reduced farmer participation in insurance in Malawi. Farmers with stable farm production were less willing to purchase insurance.

Being in the second wealth category was positively associated with farmers' participation decisions in Huye District as expected. This finding was attributed to the fact that the majority of farmers fall in the range of households that are food secure and earn a wage from working for others. This category of farmers has a relatively higher income compared to the first category, enabling them to invest in crop insurance as well. Hill *et al.* (2013) found that wealthier farmers bought crop insurance more than poorer households in Ethiopia, even though poor households had more to gain from insurance because this group of farmers focused more on meeting basic needs and were left with too few resources to invest in crop insurance. Sherrick *et al*. (2004) found that farmers in the USA's Midwest who were located in higher risk zones, were less wealthy and operated larger farms, were widely found to be insurance subscribers because they considered insurance to be one among several risk management approaches. In this study, the second category of farmers was more involved in crop insurance than the other categories. Furthermore, the largest number of farmers in Rwanda fall into the second category compared with the other wealth categories.

4.4 Validation of PSM results

4.4.1 Testing for common support assumption

Figure 4.1 presents the distribution of the estimated propensity scores and the region of common support for the WIBI participants and non-participants.

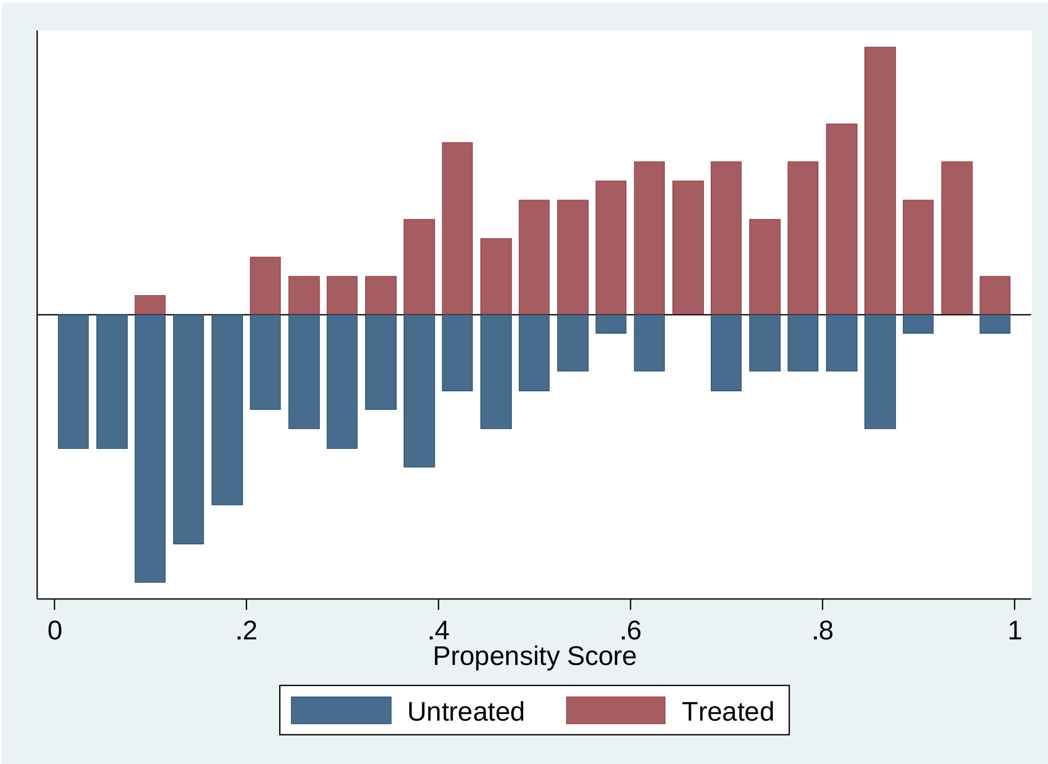

Figure 4.1. Distribution of propensity scores on the region of common support using NNM, RM and KBM algorithms

Source: Survey data (2014)

The upper and bottom half of the graph show the distribution of propensity scores for participants and non-participants respectively. The y-axis represents the propensity scores for the two groups. Visual assessment of the density distributions for the two groups shows that all the treated and the untreated group scores were within the region of common support (see Caliendo and Kopeinig, 2008). This means that each individual had a positive probability of being either a participant or a non-participant of WIBI, thus justifying the Common Support Assumption (CSA) that requires each treated household to have a corresponding untreated household as a match (Austin, 2011).

4.4.2 Covariate balancing tests

The major purpose of propensity score estimation is to balance the distribution of covariates among the groups of participants and non-participants (Rosenbaum and Rubin, 1983). The balancing test is necessary after matching to check whether the differences in the covariates in the two groups have been removed, in which case the matched comparison group can be considered as a plausible counterfactual (Caliendo and Kopeinig, 2008). Balancing tests were performed after matching to check whether the differences in the covariates between the two groups had been eliminated using different methods such as NNM, RM and KBM. These were used to verify the quality of the matches and the robustness of the results.

Table 4.4 presents the covariates resulting from the balancing tests. As shown in column (6, 11 and 16), there was a considerable reduction in bias as a result of the matching process by comparing the percentage bias column and the percentage reduced bias. After matching, there were no significant differences between the matched participants and non-participants at any acceptable significance level for all the variables under each of the three matching algorithms. None of the p-values shown in columns 7, 12 and 17 for the matched results of the likelihood ratio test after matching were significant, implying that there were no systematic differences in the distribution of covariates among participants and non-participants. Rosenbaum and Rubin (1985) observe that the robustness of the results should be indicated by insignificant p-values of the likelihood ratio and a reduction in bias after matching. Before matching, differences are expected; however, after matching the covariates should be balanced in both groups implying that no significant difference is found (Caliendo and Kopeinig, 2008).

Other statistical measures were performed before and after matching to test the quality of matches. These included the standardized mean and median bias as well as the pseudo-R^2.

Table 4. 4. Results of covariate balancing tests for propensity score using NNM, RM, and KBM algorithms

		Nearest Neighbor Matching (NNM)					Radius Matching (RM)					Kernel Based Matching (KBM)				
		Mean		%	%reduced	Test	Mean		%	%reduced	Test	Mean		%	%reduced	Test
Variable	Sample	Treated	Control	Bias	|bias|	p>|t|	Trtd	Ctrl	Bias	|bias|	p>t	Ttd	Ctl	bias	|bias|	p>t
Age	Unmatched	42.976	43.089	18.0		0.160	42.976	43.08	-0.9		0.94	42.97	43.08	-0.9		0.946
	Matched	42.976	42.014	17.2	4.5	0.180	42.976	43.64	-5.1	-488.5	0.70	42.97	43.17	-1.5	-73.9	0.911
Gender	Unmatched	.49593	.40	18.0		0.160	.49	.40	18.0		0.160	.49	.40	18.0		0.160
	Matched	.49593	.32	35.1	-95.5	0.101	.49	.39	20.9	-16.2	0.102	.49	.39	20.3	13.2	0.111
Age squared	Unmatched	2047.7	2004.9	3.5		0.784	2047.7	2004.9	3.5		0.784	2047.7	2004.9	3.5		0.784
	Matched	2047.7	2131.2	-6.8	-95.3	0.601	2047.7	2088.3	-3.3	5.0	0.798	2047.7	2094.4	-3.8	-9.3	0.768
Dstnctroad	Unmatched	.85366	.60163	32.7		0.011	.85	. 60	7.9		0.011	.85	.60	32.7		0.011
	Matched	.85366	.76777	11.1	65.9	0.386	.85	.78	32.7	72.9	0.492	.85	.79	7.4	77.2	0.564
Education	Unmatched	.93496	.90244	5.8		0.649	2.76	2.61	21.3		0.096	2.76	2.61	21.3		0.096
	Matched	.93496	.95291	-3.2	44.8	0.799	2.76	2.73	4.5	78.9	0.696	2.76	2.74	2.8	86.8	0.805
Coopmember	Unmatched	.90244	.73	43.2		0.001	.90	.73	43.2		0.001	.90	.73	43.2		0.001
	Matched	.90244	.85	12.1	71.9	0.273	.90	.85	11.7	72.9	0.289	.90	.85	12.4	71.3	0.263
Creditaccess	Unmatched	.91	.83	22.1		0.084	.91	.83	22.1		0.084	.91	.83	22.1		0.084
	Matched	.91	.87847	9.7	56.1	0.415	.91	.86	14.9	32.7	0.226	.91	.86	12.9	41.6	0.287
Experience withWIBI	Unmatched	2.58	1.31	99.7		0.000	2.58	1.31	99.7		0.000	2.58	1.31	99.7		0.000
	Matched	2.58	2.53	3.9	96.1	0.754	2.58	2.53	3.9	96.1	0.754	2.58	2.59	-0.7	99.3	0.953
Farm size	Unmatched	.83	.64	16.7		0.192	.83	.64	16.7		0.192	.83	.64	16.7		0.192
	Matched	.83	.71878	10.0	40.4	0.437	.83	.69	11.8	29.5	0.355	.83	.68	12.9	23.0	0.311
Irrigation	Unmatched	.31707	.21138	24.0		0.061	7443.1	3363.8	34.7		0.007	7443.1	3363.8	34.7		0.007
	Matched	.31707	.31367	0.8	96.8	0.954	7443.1	6827.6	5.2	84.9	0.719	7443.1	7009	3.7	89.4	0.801
Diversification	Unmatched	.69	.49	42.2		0.001	.69	.49	42.2		0.001	.69	.49	42.2		0.001
	Matched	.69	.69	1.1	97.4	0.930	.69	.68	3.3	92.2	0.788	.69	.69	1.3	96.9	0.914
Wealth category	Unmatched	1.54	1.30	43.0		0.001	1.54	1.30	43.0		0.001	1.54	1.30	43		0.001
	Matched	1.54	1.54	0.0	100.0	1.000	1.54	1.41	23.3	45.8	0.862	1.54	1.43	18.6	56.8	0.170

Table 4.5 presents other statistical tests used to evaluate the quality of matching algorithms in PSM. As shown, there was a substantial reduction in the standardized mean (see columns 6 and 7) and median bias (columns 8 and 9). The mean bias reduced from 29.8 before matching for all the three matching algorithms to 9.9, 7.2 and 7.0 for NNM, RM and KBM respectively. The median bias fell from 23.1 before matching to 6.9, and 6.8 after matching for NNM, RM and KBM respectively. After matching, both mean and median bias fell below 10 percent implying a good match (column 7 and 9), which means that after matching there were no observable differences in the characteristics of non-participants and participants. Therefore, the non-participant group was a good counterfactual.

Table 4. 5. Summary of other statistical tests used to evaluate the quality of matching among different algorithms in PSM

Matching algorithm	Pseudo-R^2 before matching	Pseudo R^2 after Matching	p>Chi^2 before	p>Chi^2 after	Mean bias before	Mean bias after	Median bias before	Median bias after
NNM	0.25	0.037	0.000	0.410	29.8	9.9	23.1	6.9
RM	0.25	0.020	0.000	0.859	29.8	7.2	23.1	6.8
KBM	0.25	0.019	0.000	0.899	29.8	7.0	23.1	6.8

Source: Author's computation based on survey data (2014)

In order to balance the distribution of covariates both in the treatment and the comparison groups, Rosenbaum and Rubin (1985) suggest that a difference in the standardized mean and median bias between the treatment and the control of greater than 20% should be considered large. In this study, the mean and median biases were all below 10%, indicating a very good match. The pseudo-R^2 indicates how well the covariates explain the probability of participation in WIBI. Sianesi (2004) suggests comparing the pseudo-R^2 before and after matching to test how well the covariates explain the probability of participation. It was high before matching at 0.25 (see Table 4.6) and very small after matching at 0.037, 0.020 and 0.019 for NNM, RM and KBM respectively. After matching, the pseudo-R^2 should be fairly low to reflect the absence of differences in the distribution of covariates between the two groups (Sianesi, 2004).

The low pseudo-R^2, low standardized mean bias and high total bias reduction (see Table 4.6), as well as the insignificant p-values after matching (Table 4.5), all imply that the matching process was able to successfully balance the distribution of the covariates between the treatment and control groups, and therefore provided a credible counterfactual. These results indicate that there was no systematic difference in covariate distribution of participants and non-participants of WIBI with regard to the outcome of interest, namely, household income. This implies that any difference in the household income between the two groups that might arise would be due to the treatment, or farmer participation in WIBI.

4.4.3 Testing for hidden bias and sensitivity analysis

The conditional independence or the unconfoundness assumption requires inclusion of all variables that simultaneously influence the treatment (in this case, farmer participation in WIBI) and the outcome (in this case, household income) (Becker and Caliendo, 2007). Rosenbaum (2002) noted that hidden bias and lack of robustness of the estimators may still arise if there are unobserved variables that simultaneously affect assignment into treatment and the outcome variable. A sensitivity analysis using Rosenbaum bounds was therefore performed. The Rosenbaum bounds tested whether the treatment effect was not affected by unobserved covariates. The test computes rbounds or the gamma level, which is defined as the odds ratio of differential treatment assignment due to an unobserved covariate (Rosenbaum, 2002). The results of the sensitivity analysis are given in Appendix (VII). These results show insensitivity to hidden bias. This is because the odds of differential assignment due to unobserved factors were found to increase by a factor of 0.3 and 0.4 for the inference on the effect of participation in WIBI on household income. This means that the unobserved variable would have to increase the odds ratio by 30-40% before it would bias the estimated impact. The Rosenbaum bounds (rbounds) under the treatment effect were overestimated (sig+) because the treatment effect was found to be positive (Appendix VII).

4.5 Impact of farmer participation in WIBI on household income in Huye District

The ATT captured the impact of the insurance scheme on household income. Based on Table 4.7, the impact of WIBI on farmers' household income in Huye District was positive and significant under all three matching algorithms. This implies that average household incomes for WIBI participants were higher than those of non-participants. Based on this finding, the null hypothesis that WIBI has no effect on farmers' income was rejected at the one percent significance level, meaning that WIBI had a significant effect on the incomes of participant farmers.

Table 4.7. Impact of weather index-based insurance on household income in Huye District, Rwanda

Outcome variable: Income (RWF)			
Matching Algorithm	**ATT**	**Standard error**	**T-value**
NNM	77327.15***	(16972.01)	4.56
RM	67876.17***	(16547.28)	4.10
KM	69874.27***	(16660.27)	4.19

***Significant at 1%.

Source: Author's computation based on survey data (2014)

The positive ATT is consistent with Varadan and Kumar (2012) who found that crop insurance had absorbed production risk and influenced high use of inputs in India. Consequently, insured farmers realized higher returns from farming than their non-insured counterparts. Ali (2013) also found that the rain-fed areas in Pakistan considered index-based insurance to be an important risk management approach. Accordingly, farmers were satisfied with index-based insurance and were willing to increase the area under food production. Nahvi *et al*. (2014) found a significant and positive relationship between income and crop insurance in Iran. In this study, WIBI seems to be important to farmers in Huye District as it led to significantly higher household incomes among participants. An amount of about US$100 in all the matching algorithms was found to be the difference in incomes between participants and non-participant farmers, which is a relatively big difference given that the study only focused on two crops: maize and beans.

CHAPTER 5: SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

Rwanda is prone to many weather-related risks and shocks that directly affect the performance of the agricultural sector. Weather index-based insurance (WIBI) was initiated in 2011 to cope with losses due to weather changes in Rwanda. Since the introduction of the insurance scheme, virtually no research has been undertaken to understand the associated impact on household income, in Rwanda overall and particularly in Huye District. However, better understanding this impact would lead to more informed decisions, as a result of clearly understanding the paths of dissemination and uptake of the scheme, the main drivers influencing maize and bean farmers to take up the insurance and the actual impact it has on farmer incomes.

Huye District in Rwanda's Southern Province was purposefully selected because it was one of the two pilot districts where the crop insurance scheme was introduced by Kilimo Salama in 2011. A systematic sampling technique was employed to select potential respondents resulting in a sample size of 246 households. Descriptive statistics were used to evaluate the socio-economic and demographic profiles of respondents and the patterns of dissemination and uptake of the scheme. A propensity score matching method (PSM) was later used to assess the impact of WIBI on household income.

The results showed that significant differences existed between WIBI participants and non-participants. For instance, there was a significant difference in terms of distance to paved roads between participants and non-participants. Additionally, membership in farmer cooperatives was significantly different between the two groups, as were years of experience with WIBI ($p=0.000$), credit access (p=0.084), diversification (p=0.001), use of irrigation (p=0.060) and wealth category (p=0. 004). This implied that there indeed existed differences among participants and non-participants of WIBI, thereby justifying the use of PSM. After matching, there were no significant differences between participants' and non-participants' attributes, implying that the non-participant group was a good counterfactual.

The logit model showed that cooperative membership (p=0.001), use of irrigation (p=0.060), crop diversification (p=0.001), years of experience with crop insurance (p=0.000), distance to a paved road (p=0.01) and wealthy category (p=0.004) were the significant drivers that influenced farmer participation in the crop insurance program in Huye District.

The PSM results showed a significant and positive impact of WIBI on participants' household income, of an amount of approximately US$100. Therefore, the null hypothesis that WIBI had no effect on income could not be sustained. The study therefore concludes that WIBI has a positive impact on participants' household income in Huye of Rwanda.

5.2 Conclusion

Weather Index-Based Insurance is a risk management tool with the potential to be used in the Rwandan agriculture sector to cope with weather related shocks. Within four years of its existence in Huye District, the scheme has made significant changes to farmers' household incomes. The results revealed that participation in insurance schemes increased the incomes of participating households by between US$ 90-105.

The main determinants of the insurance uptake are wealth category, participation in cooperative communities, years of experience with the insurance scheme, the insurance was found to be dominant in the study area, and farmers used irrigation facilities to protect their crops against weather shocks also participated in crop insurance which is a kind of over insurance.

The study showed that participation in crop insurance increased the incomes of participants compared to their counterparts who did not.

5.3 Recommendations

Based on the findings of this study, the following recommendations were made:

1. Given that participation in WIBI led to an increase in household income, more efforts are needed to promote the uptake of crop insurance by farmers. This product can be offered by GoR, crop insurers and/or civil society organizations. Public seminars, training and media advertising on crop insurance will raise farmer awareness and knowledge about the insurance scheme. The dissemination of knowledge on WIBI could also be increased through more contact with extension agents, insurance agents and agronomists.

2. Cooperative membership was found to significantly influence farmers' participation decisions in WIBI in Huye District. The GoR through the Ministry of Agriculture and the Rwanda Cooperative Agency (RCA) should intensify recruitment of farmers into cooperatives and farmer organizations. Farmers should be educated on the importance of crop insurance for their farming operations either through rigorous marketing of the insurance program by the insurer or through the activities of cooperatives. In this regard, the cooperative societies in Rwanda need to be strengthened in order to adequately play their advocacy and information dissemination roles for their members.

3. Contrary to expectation, crop diversification and use of irrigation were found to be positively associated with farmers' decisions to participate in the WIBI scheme. Farmers in Huye District were found to over-insure their crops. Therefore, measures to improve better use of irrigation and/or campaigns to encourage more participation in the insurance scheme should be put in place in order to reduce this tendency through choice of optimal insurance plans.

5.4 Areas for further research

1. Considering the significant impact that WIBI had on household income in Huye District, a similar study should be undertaken in other districts of Rwanda to generate location-specific information on the drivers and impacts of crop insurance. This information can be used by policy makers, civil society organizations and insurance companies in designing evidence-based policies, strategies and programs aimed at promoting nationwide uptake of crop insurance in Rwanda.

2. Given the tendency of farmers to practice over-insurance in Huye District, a study to understand the drivers and effects of "over insurance" in Rwanda should be carried out. The results will inform policy makers and insurance companies on better strategies to promote crop insurance.

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APPENDICES

Appendix I: Survey questionnaire

Enumerator's name……………………………………………….
Questionnaire number……………………………………………..
Date…………………………………..Start time………..End time………….
Approved OK/Not ok
Entered date………………………Entered by………………………………..

A) General information about the household and site identification

1. Respondent name…………………………………..Phone number……………………
2. District…………………………………………
3. Sector……………………………………………Cell…………………………………..
4. Village……………………………………………….
5. Are you insured? Yes
   No
6. Household characteristics

Household head	Gender	Age	Education level	Main occupation
		0-10		
		11-20		
		21-65		
		65+		

7. Experience years in farming……………………
8. How many kilometers from you farm/home to the nearest market? ....
9. How many kilometers from you home to the paved road?
10. Membership to farmer organization
    a) Are you a member of a cooperative? Yes/ No
    b) When did you join the cooperative (Year)……….
    c) Functions of the cooperative:

1. production and marketing of agricultural inputs(seeds, pesticides, etc)
2. Input supply(fertilizer, seeds, etc)
3. Gives loans
4. Is for savings
5. Other(specify)
   d) Does your cooperative get involved in weather index-based agricultural insurance? Yes /No

11. Do you have to access to credit? Yes/ No
    If yes specify

Family and friends	
Informal saving and credit groups	
Microfinance institutions	
Banks	
Sacco	
Other(specify)	

B) General information on Weather index-based insurance

12. When did you first hear about the insurance scheme (Year)?
13. Where did you first learn about WIBI?
14. a) Which crops are insured in your farm?

Crop	Acreage

b) What kind of crop risks do you usually experience in this area?

Types of loss	Approximate monetary value	Frequency of occurrence

15. Other types of problems encountered in farming

Type of problem	Frequency of occurrence

16. What are the benefits of crop insurance?
    1) Payouts
    2) Access to credit
    3) Increase area under cultivation
    4) Access to extension services
    5) Increase income
    6) Other(specify)
17. Any disadvantages? Specify………………………………………………….....
18. When is it paid? ....
19. How is the insurance paid? ……………………………………………………….
20. Who pays the insurance? ………………………………………………………
21. To whom do you pay? ……………………………………………………….
22. Have they experienced any problems with WIBI program? Yes/ No
23. What kind of problems? ....
24. Have they been able to resolve those problems? Yes/No
25. Through which channels or how? ………………………………………………….
26. Have they been successful in resolving those problems? ………………………….
27. How many years have you been insured? ....
28. Generally how do you rate weather index insurance services?
    a) Very bad
    b) fairly bad
    c) bad
    d) Good
    e) Very good
29. How much VAT tax do you pay?

30. How many times were you visited by an extension agent in the last 12 months?
31. Have you ever received any kind of training on the index insurance? Yes/No
32. Land ownership
a) How much land do you own in acres?
b) Do you have any cash crops?
b) Do you have a title deed for this land?
24. What are your other sources of income?

Source of income	**Quantity**	**Unit(s)**	**Price(frw)**	**Total income**
Sell of crops				
Animal(s)				
Rented out land				
Milk				
Eggs				
Other livestock products				
Crop residues				
Off-farm labour income				
Non-farm agribusiness income(shop, tailoring, others)				
Pension income				
Sale of own trees, timber, firewood				
Remittances from a family member				
Other (specify)				

33. Financial assets and sources of credit

a) Do you borrow to buy agricultural inputs? 1=yes, No=0

Purpose of borrowing	**Needed credit**	**If yes, did u get it**	**How much**	**Source of credit**
Buying seeds				
Fertilizer				
Other agricultural inputs				
Farm equipment				
Buying an animal				
Non-farm business				
Buying food				
Children's education				

Family health care				
Buy land				
Improve on the house				
Social obligation				
Other(specify)				

34. Crop production inputs and outputs

Season A

Crop	Tot Output	Qty consumed	Qty sold	Sales price(frw)	Market/Buyer

Season B

Crop	Tot Output	Qty consumed	Qty sold	Sales price(frw)	Market/Buyer

35. How much do you spend on the following?

Item	Season A	Season B
Storage		
Irrigation		
Harvesting		

36. Household asset other than land does your household own any of the following:

Asset name	Number	Current value	When did you buy it(year)
Bicycle			
Motorbike			
Plough			
Tractor			
Mobile phone			
Hoes			
Store for farm produce			
Radio			
TV			
Other(specify)			

Thank you for your time!

Appendix II. Key informant interview guide

A) GENERAL INFORMATION ABOUT THE KEY INFORMANT

Institution ………………………………………………..
Name …………………………………………………..
Position of respondent …………………………………...
Contact (e-mail/phone) ………………………………….
Date of interview ………………………………………….

B) QUESTIONS FOR KEY INFORMANT

1. How is WIBI organized? ……………………………………………………...
   …………………………………………………………………………………..
2. How is it funded? ……………………………………………………………
   …………………………………………………………………………………..
3. How is it performing? ……………………………………………………….
   …………………………………………………………………………………..
4. How many times have had payouts since the insurance scheme started? ……………...
   …………………………………………………………………………………..
5. How much do you pay per acre? ……………………………………………
6. Do you train farmers about WIBI? ………………………………………….
   …………………………………………………………………………………..
7. Are farmers aware of the VAT they pay? ……………………………………...
8. Are farmers compliant? …………………………………………………………...
9. What are the major challenges that you face dealing with the insurance scheme?
   ………………………………………………………………………………
   ………………………………………………………………………………
10. What are other support measures (e.g: policy, regulatory, institutional facilitation) are necessary in order to improve the overall performance of the scheme? ……………….
    ………………………………………………………………………………
11. What are the future plans for the scheme? ……………………………………....
    ....

Thank you for your time!

Appendix III: Variance Inflation factor (VIF)

Variable	VIF	1/VIF
Production variability	1.17	0.855868
Diversification	1.16	0.863891
Irrigation	1.12	0.892451
Knowledge of insurance	1.12	0.896462
Household income	1.10	0.912747
Distance to road	1.08	0.922062
Farm size	1.08	0.927183
Group membership	1.08	0.929865
Education	1.07	0.937279
Land tenure	1.07	0.937588
Gender	1.06	0.941702
Agesquared	1.06	0.946721
Creditaccess	1.05	0.949052
Mean VIF	1.09	

Appendix IV. Results of LINKTEST

Households	Coefficient	Std. Error	T-stat	p-value
_HAT	1.332	. 239	5.57	0.000***
_HATSQ	-.331	. 221	-1.49	0.137
_cons	-.054	.062	-0.88	0.382

*** indicating significant at 1% percent

Appendix V: Correlation matrix for explanatory variables hypothesized to influence participation in WIBI in Huye District of Rwanda.

	Age squared	Distance to road	Knowledge of WIBI	Farm size	Hh income
Age squared	1.0000				
Distance road	0.0180	1.0000			
	0.7791				
Knowledge WIBI	-0.0191	-0.0268	1.0000		
	0.7653	0.6754			
Farm size	0.1054	0.1493	0.1331	1.0000	
	0.0991	0.0192	0.0369		
Hh income	-0.0268	0.0926	0.1176	0.0689	1.0000
	0.6760	0.1478	0.0656	0.2816	

	Gender	Education	Grp membership	Credit access	Land tenure	Irrigation	Diversification	Prdctnvrblty
Gender	1.0000							
Educatn	-0.0729	1.0000						
	0.2544							
Grp mmbrp	0.1461	-0.0681	1.0000					
	0.0219	0.2874						
Credit access	-0.0249	0.0545	0.1424	1.0000				
	0.6974	0.3946	0.0255					
Land tenure	0.0384	0.0125	-0.0767	-0.0666	1.0000			
	0.5493	0.8453	0.2307	0.2978				
Irrigation	-0.1173	-0.1111	0.0391	0.0609	-0.0021	1.0000		
	0.0663	0.0820	0.5414	0.3418	0.9743			
Diversification	-0.0721	0.1332	0.0063	0.0880	0.1501	0.1722	1.0000	
	0.2598	0.0369	0.9213	0.1687	0.0185	0.0068		
Productn vrblity	-0.0693	0.1135	-0.0600	-0.0087	0.0264	0.0130	0.2110	1.0000
	0.2788	0.0756	0.3487	0.8925	0.6809	0.8388	0.0009	

Appendix VI: Breusch-Pagan/Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: fitted values of household insured

Chi2 (1) = 0.32

Prob> Chi2 = 0.5723

Appendix VII: Results of sensitivity analysis with Rosenbaum bounds

Gamma	Sig+	Sig-
1	.000963	.000019
1.05	.000297	.002797
1.1	.000087	.007009
1.15	.000025	.015459
1.2	6.6e-06	.030523
1.25	1.7e-06	.054729
1.3	4.4e-07	.090216
1.35	1.1e-07	.138173
1.4	2.6e-08	.198444
1.45	6.1e-09	.269423
1.5	1.4e-09	.348271
1.55	3.2e-10	.431365
1.6	7.2e-11	.514860
1.65	1.6e-11	.595204
1.7	3.4e-12	.669533
1.75	7.3e-13	.735867
1.8	1.5e-13	.793151
1.85	3.2e-14	.841149
1.9	6.8e-15	.880265
1.95	1.3e-15	.911336
2	3.3e-16	.935441
2.05	1.1e-16	.953738
2.1	0	.967346
2.15	0	.977279
2.2	0	.984402
2.25	0	.989428
2.3	0	.992921
2.35	0	.995314
2.4	0	.996931
2.45	0	.998011
2.5	0	.998723
2.55	0	.999188
2.6	0	.999488
2.65	0	.999680
2.7	0	.999801
2.75	0	.999878
2.8	0	.999925
2.85	0	.999955
2.9	0	.999973
2.95	0	.999984
3	0	.999990

Gamma is the log odds of differential assignment due to unobserved factors

Sig+ is the upper bound of significance level or overestimation of treatment effect

Sig- is the lower bound of significance level or underestimation of treatment effect

Source: Author’s computation based on survey data (2014)