IMPACT OF ADOPTION OF PUSH-PULL TECHNOLOGIES ON SMALLHOLDER MAIZE FARMER'S PRODUCTIVITY IN EASTERN RWANDA

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Declaration

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

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Dedication

This thesis is dedicated to my lovely parents, Mr. and Mrs. Misango, as well as my siblings Ceciliah, Elvine, Gloriah and Maxson for their prayers, encouragement and support that has continually motivated me in my academic life. Special dedication goes to my late aunt Norah, for being my guardian and supporting my academic life right from primary school to the university level.

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List of Acronyms and Abbreviations

AD:	Adoption-Diffusion
AERC:	African Economic Research Consortium
AGRA:	Alliance for a Green Revolution in Africa
AIC:	Akaike's Information Criterion
AIEI:	African Impact Evaluation Initiative
ATT:	Average Treatment Effect of Treated
ATU:	Average Treatment Effect of Untreated
BIC:	Bayesian Information Criterion
CIP:	Crop Intensification Program
DAAD:	Deutscher Akademischer Austauschdienst
DiD:	Difference in Difference
DM	Durbin and McFadden
EDPRS:	Economic Development and Poverty Reduction Strategy
ESR:	Endogenous Switching Regression
FAO:	Food Agricultural Organization of the United Nations
FAW:	Fall Armyworm
FLM:	Fractional Logit Model
FRM:	Fractional Response Model
GLM:	General Linear Models
GLS:	Generalized Least squares
GOR	Government of Rwanda
HA:	Hectare
ICIPE:	International Center of Insect Physiology and Ecology
IIA:	Independence of Irrelevant Alternatives

IITA: International Institute of Tropical Agriculture

IUCN: International Union for Conservation of Nature

IV: Instrumental Variable

MESR: Multinomial Endogenous Switching Regression

METE: Multinomial Endogenous Treatment Effect

MINAGRI: Ministry of Agriculture and Animal Resources

MLE: Maximum Likelihood Estimate

MLND: Maize Lethal Necrotic Diseases

MNL: Multinomial Logit

MVTE: Multi-Valued Treatment Effect

OLS: Ordinary Least Squares

PMT: Pest Management Technologies

PP: Push-Pull

PPT: Push-Pull Technology

PSM: Propensity Score Matching

PSTA: Strategic Plan for Agricultural Transformation

QMLE: Quasi-Maximum Likelihood Estimate

RAB: Rwanda Agricultural Board

RUT: Random Utility Theory

SAPs: Sustainable Agricultural Practices

SCEPs: Soil Carbon Enhancing Practices

SD: Standard Deviation

SDG: Sustainable Development Goals

SIPs: Sustainable Intensification Practices

SLS: Two-Stage Least Squares

SSA:	Sub-Saharan Africa
MT:	Metric Tonnes
TLU:	Tropical Livestock Unit
UD:	Use-Diffusion
UN:	United Nation
USD:	United State Dollars
VIF:	Variance Inflation Factor
WISP:	World Initiative for Sustainable Pastoralism

ABSTRACT

The push-pull technology (PPT) as an alternative to conventional pesticide use in the control of fall armyworm (FAW) and stemborer pests in maize production has received considerable attention in the recent past. However, the impact of adoption of PPT on the productivity of smallholder maize farmers in Eastern Rwanda where the technology was introduced in 2017 remains largely unknown. This study assessed the intensity of adoption of PPT in Nyagatare and Gatsibo districts of Rwanda using a fractional logit model (FLM) and evaluated the impact of adoption of PPT on maize productivity using a multinomial endogenous switching regression (MESR). The study applied a 2019 survey data from a sample of 398 households operating 967 maize plots selected using a stratified random sampling technique.

The results of the fractional logit model revealed that while only 5 percent of the maize farmers had adopted the technology, on average, farmers practiced PPT on 26 percent of their maize plots. The results of the Fractional Logit Model (FLM) showed that the perceived PPT benefits, perceived PPT effectiveness in control of pests, livestock ownership, gender and group membership had positive significant influence on the intensity of adoption of PPT in Rwanda. Overall, 25, 20, and 14 percent of the households adopted traditional, PPT and pesticides respectively in the control of stemborer and fall army worms. In addition, 8 and 7 percent of the households adopted a combination of pesticides and traditional, and a mix of PPT and traditional practices respectively. The results of the MESR model revealed that perceived cost of technology, perceived technology effectiveness, wealth status, perceived pest severity, perceived soil fertility and group membership significantly influenced the adoption of pest control practices in the Eastern Rwanda. Furthermore, the MESR results revealed that adopting PPT and its combinations had a significant positive impact on maize yields while using pesticides or traditional and its combinations had a negative impacts on maize yield. The study recommends investment in awareness creation to improve farmers understanding on the perceived PPT benefits while using group methods (such as farmer-farmer, farmer field schools, demonstrations etc) that are gender disaggregated to enhance adoption of push-pull technologies. The study also recommended promotion of push-pull technology as a low cost pest control management practices in controlling FAW and stemborer pests in maize to improve agricultural productivity.

Key words: *Fall armyworm, Stemborer, Push Pull Technology, Adoption, Impact, Fractional Logit Model, Endogenous Switching Regression Model, Rwanda*

CHAPTER ONE: INTRODUCTION

1.1 Background

The push-pull technology (PPT) refers to a stimuli-deterrent technology developed by the International Centre of Insect Physiology and Ecology (*icipe*) and its partners as an integrated pest management technology to control cereal pest. Khan *et al.* (2010) and Khan *et al.* (2014) distinguished two types of PPT namely conventional and climate-smart PPT. The conventional PPT involves intercropping of maize with silver leaf Desmodium (push component) acting as a repellent to the pest moths and suppressing Striga weed and Napier grass (pull component) acting as a predisposed pulling crop which is planted around the plot crop (Khan *et al.,* 2008a).

Conversely, Climate-smart PPT involves intercropping of maize with drought-tolerant green leaf Desmodium acting as a push component to the pest moths and Brachiaria planted surrounding the farm plot acting as a pull component (Khan *et al.,* 2014; Chepchirchir *et al*., 2017). However, the use of conventional PPT is found to demonstrate high profit with a benefit-cost ratio of about 2.2:1 relative to 0.8:1 for farmer's individual practice of maize mono-cropping and 1.8:1 for pesticide use (Khan *et al*., 2001; 2008a).Khan *et al*. (2008b) also found the technology to have a sustainable increase in maize yield and higher labour returns.

For instance, maize farmers in Uganda and Kenya using PPT reported yield increment by 1.54 and 2.2 times higher compared to those farmers planting maize without PPT (Khan *et al*., 2008a; Chepchirchir *et al*., 2018). Furthermore, PPT has been found to be effective in control of stemborer and Striga weed in maize fields simultaneously and even recently documented to control fall armyworm (FAW) although pathway through which this technology minimize the pest still under investigation (Khan *et al*., 2008a; Murage *et al.,* 2015a; Midega *et al*., 2015; 2018; Hailu *et al.,* 2018; Kumela *et al*., 2018; *icipe*, 2019a).

The secondary importance of PPT comprise of reducing soil erosion and pesticides usage, provision of fodder for increasing milk productivity as well as improving soil fertility through soil shading and nitrogen fixation (Pickett *et al*., 2014; Chepchirchir *et al*., 2017; Kassie *et al*., 2018a; Maina *et al*., 2020). PPT has also reduced the usage of herbicides and costly synthetic insecticides that are unaffordable and costly to resource poor farmers thus enhancing human health and increasing biodiversity (Pickett *et al.,* 2014). Although primary establishment of the PPT is labour intensive, the labour demands reduce significantly once the crop system is established (Muriithi *et al.,* 2018). Moreover, evidence from sub-Saharan Africa (SSA) indicates that PPT can double or even, in other cases, triple cereal yields and livestock fodder (Cook *et al.,* 2006; Khan *et al.,* 2001; 2008a and b; Murage *et al.,*2015a,b).

However, low agricultural productivity emanating from both abiotic and biotic constraints remains a key challenge for smallholder farmers in SSA despite the numerous benefits of PPT (Murage *et al*., 2015a; Midega *et al*., 2015; Hailu *et al.,* 2018; Kumela *et al*., 2018; *icipe*, 2019b). Biotic factors specifically FAW and stemborer pest are ranked to be most important constraints with economic impacts caused by these pests in the field being of particular concern to policy makers and researchers in East African countries (*icipe, et al.,* 2019b).

For instance, FAW pest is estimated to cause annual maize yield losses in African countries ranging from 21-53 percent under no control technologies (Day *et al.,* 2017). These losses are estimated at 8.3-20.3 million metric tonnes of produce, valued at US dollars 4334 million lost annually (Day *et al*., 2017). Although studies have found losses to vary from country to country, in Kenya and Ethiopia is estimated at 32 and 47 percent respectively (Kumela *et al.,* 2018) .In Zimbabwe the yield losses was estimated at 9.4 percent (Baudron *et al.,* 2019) while 40 and 45 percent of maize produce is lost in Ghana and Zambia respectively (Day *et al.,* 2017).

Conversely, maize stemborer pest is estimated to cause a loss of about 44-50 percent of potential maize output in Kenya (Nyukuri *et al.,* 2014; IITA, 2019). However, with the recent outbreak of fall armyworm (FAW) in African countries, Rwanda is even expected to have huge economic impacts on maize productivity. Specifically, Rwanda‘s maize sub-sector loses up to 44 percent of potential maize output to pest infestation (Rukundo *et al*., 2020). These losses raised a major concern especially with maize being one of the prioritized crops under crop intensification program (CIP) and engine to the Rwandan economy (Uwizeyimana *et al.* 2018). Thus, without appropriate interventions in Rwanda, FAW and stemborer pests can derail effort towards the attainment of the Sustainable Development Goals number 1 and 2 of poverty reduction and ending hunger by the year 2030.

Smallholder farmers in Rwanda have used various approaches to control FAW and stemborer pests (Rukundo *et al*., 2020). These approaches comprise of handpicking and elimination of larvae and caterpillars of the pests, soil/ash, plant extracts, sawdust or pepper mixture, use of cattle urine, mixed cropping, and use of pesticide (Midega *et al.*, 2018; Kumela *et al*., 2018; 2019; Kassie *et al.*, 2020; Rukundo *et al*., 2020). Although some of these approaches are deemed efficient on small maize plots, the efficacy is questionable in Rwanda where most maize plots are scattered (Rukundo *et al.*, 2020). Pesticides on the other hand, continue to be the most preferred pest control method for FAW and stemborer accounting for 87 percent among smallholder maize farmers in Rwanda (Tambo *et al*., 2020). However, the over-reliance on pesticide application has elicited pest resistance and harmful influence on animals, human and raises environment health concerns (Nicolopoulou-Stamati *et al*., 2016; Kim *et al.,* 2017; Sharma and Singhvi, 2017). Furthermore, the accessibility of pesticides and highly specialized safety equipment for their application remains a challenge to smallholder farming households in SSA (Day *et al*., 2017; Kumela *et al.*, 2018).

This has been evident in situation where majority of farmers in Rwanda failed to use personal protective gears such as goggles, gloves, masks and overalls during application of highly hazardous pesticides resulting to incidences of acute pesticide poisoning among them (Day *et al*., 2017; Rukundo *et al*., 2020). In an attempt to reduce the high maize yield-related production losses associated with FAW and stemborer pests, *icipe* in collaboration with the Government of Rwanda implemented PPT pilot project in 2017 (*icipe*, 2019a). The technology involved a system where maize is intercropped with drought tolerant green leaf Desmodium acting as a push component through production of chemical compounds some of which repel the fall armyworm and stemborer while the Brachiaria acting as a pull component through production of other chemical substances such as dusts that attracts the FAW and stemborer moths to lay eggs there (Chamberlain *et al*., 2006). The pest's larvae are then trapped by gummy substance produced by Brachiaria and only less number survives reducing their population (Khan *et al*., 2001; 2008a).

The project aimed at controlling FAW and stemborer and eventual reducing maize yield losses as well as improving agricultural productivity (*icipe*, 2019a, and b). The project was conducted in two districts of Eastern province of Rwanda: Nyagatare and Gatsibo districts. The government of Rwanda, through the Rwanda Agricultural Board (RAB) recommended local partners (Food for the Hungry/ Rwanda organization) who undertook farmer identification, training and establishment of demonstration plots (*icipe*, 2019a; Niassy *et al*., 2020). Other farmers would later learn from demonstration plots before adopting and receiving necessary support through extension visits from both *icipe* field monitors and government extension officers. The program was supposed to stem low productivity, which is key in moving with pace of high population growth.

1.2 Statement of the research Problem

With the outbreak of FAW and stemborer pests, the availability of effective control pest management technology become a serious concern, especially for resource poor smallholder maize farmers. Pesticide use, one of the most commonly preferred pest control methods among smallholder farmers in Rwanda is limited due to pest resistance and negative human, animal and environmental health effects (Nicolopoulou-Stamati *et al*., 2016; Sharma and Singhvi, 2017). However, the adoption rate of PPT in Rwanda still remains low since its introduction in 2017 despite the combined efforts from both government of Rwanda and the *icipe*, PPT developers to promote its adoption (*icipe*, 2019a). Moreover, the impact of adoption of PPT on maize productivity in Rwanda remains largely unexplored.

Previous empirical studies have evaluated the impact of adoption of PPT on household welfare, farm level economic benefits and aggregate welfare. The impact of adoption of PPT on maize productivity has received minimal attention while these studies did not incorporate the key drivers of technology adoption such as perceived PPT benefits, its perceived effectiveness, perceived cost and wealth category of the household yet they are pre-requisite for PPT adoption. Subsequently, previous studies on impact of agricultural technology focused on single technology in isolation without incorporating its combinations which might results to underestimation or overestimation of the results of the same technologies. Khonje *et al*., (2018) and Kassie *et al*., (2018b) argued that smallholder farmers rarely adopts single technology but rather sequentially adopts a combination of technologies jointly as complements.

1.3 Objectives of the Study

The overall objective of this study was to examine the impact of adoption of push-pull technology (PPT) on farm productivity among smallholder maize farmers in Nyagatare and Gatsibo districts of Eastern Rwanda. The specific objectives of this study were:

1. To assess the factors influencing the intensity of adoption of PPT amongst maize farmers in Nyagatare and Gatsibo districts.
2. To evaluate the impact of adoption of PPT on maize productivity amongst maize farmers in Nyagatare and Gatsibo districts.

1.4 Hypotheses

The hypotheses tested were:

H_o: The perceived benefits of PPT effectiveness in pest control have no influence on the intensity of PPT adoption among smallholder maize farmers in Nyagatare and Gatsibo districts.

H_o: Push-pull technology has no influence on maize productivity among smallholder maize farmers in Nyagatare and Gatsibo districts.

1.5. Justification for the study

Evaluating the impact of adoption of PPT is important as an alternative and affordable pest control method to synthetic pesticides option in control of FAW and stemborer pests. Rwanda, specifically, Nyagatare and Gatsibo districts are classified as potential maize producing areas and were pilot areas for PPT that are facing high infestation of FAW and stemborer pests (*icipe*, 2019a). Information collected from this study will play vital role in decision-making for farmers, international organization such as *icipe* and the Government of Rwanda (GOR) (both at national and districts levels). Information on the impact of adoption of PPT will play a vital role to farmers in making informed investment decisions and acting as a motivation to choosing the low cost pest control method in controlling FAW and stemborer on maize production.

Scientist in *icipe*, other stakeholders and extension agents in Rwanda will also benefit from the results of this study in identifying key indicators needed in designing and formulating training extension platforms that can be used in widespread promotion and dissemination of PPT. The GOR can also utilize all the information to design and formulate policy briefs that would enhance investment on the factors influencing intensity of adoption and impact of adoption of PPT as an effective pest control technologies which in turn enhances reduced yield losses and improves productivity. The results on increasing maize productivity will contribute towards attainment of global sustainable development goals (SDG) , namely goal 1 on poverty eradication, goal 2 on ending hunger and goal 12.3 on reducing food waste and food losses (United Nations, 2017). Achievement of food security is also in line with strategies under the Economic Development and Poverty Reduction Strategy (EDPRS) and Crop Intensification Program (CIP) identified as an engine to the Rwandan economy. The results are also in line with the GOR's fourth Strategic Plan for Agriculture Transformation (PSTA IV, 2018-2024) that purposes to improve agricultural productivity and commercialization (MINAGRI, 2018).

1.6 Organization of the thesis

This thesis is structured into six chapters. The first chapter one introduces the study, states the research problem and justification of the study along with the overall objective, the objectives and hypotheses. Chapter two explains the reviews of relevant literature and the review on methodology respectively. Chapter three describes the methodology comprising of the theoretical framework, empirical methods, data sources and sampling procedure and measurement of key variables. Furthermore, chapter four and five explains empirical analysis, results, discussions and key conclusions presented in paper format, which focused on each specific research objective. Lastly, chapter six presents summary of key results, conclusions and policy implications.

CHAPTER TWO: LITERATURE REVIEW

2.1 Approaches for analyzing impact of agricultural technologies on productivity

Impact evaluation aims at establishing if or not an intervention yields its intended effects (African Impact Evaluation Initiative (AIEI), 2021). Wainaina *et al*., (2012) distinguished two ways of evaluating the impact of a particular project, namely "with and without" and "before and after" methodologies. "With and without" approach matches the behavior of the main variables in a sample of a program group of the treatment (intervention) to that of controlled (non-program group) of the intervention. The approach is applicable when baseline data is missing and contrast group is used as a proxy to measure whatever could have taken place before the program.

The "before and after" approach matches the performance of main variables during and after the intervention with variable earlier to the program (Wainaina *et al*., 2012). The approach entails conducting a baseline survey for the program and non-program group before the intervention and follow up after the intervention and uses statistical methods in measuring if there is substantial variation in a number of important variables over time (Gittinger, 1984). However, the method fails to explain the outcome of the confounding variables on the variation resulting in biased estimate.

Impact evaluation assess the impact of the project has on beneficiaries through comparison of outcome between the members and non-members group (AIEI, 2021). The approach relies on both econometrics and statistical models. Baker, (2000) grouped impact evaluation designs into three, namely experimental, non-experimental and quasi-experimental, which are related with comparison, non-participants and control group. An experimental or randomized design involves random selection of a set of sample into treatment (intervention) and control group.

On the other hand, non-experimental or quasi-experimental designs are applicable when it is not easy to construct treated and controlled group through experimental designs. In such situation, econometric method is applied to create comparison group that is related to the treatment group basing on observable characteristics. Econometric technique has been put in place to overcome problem of counterfactual and self-selection bias. These econometric approaches include matching method, difference in difference (DD), reflexive comparison and instrumental variable (Baker, 2000; Wainaina *et al*., 2012).

The DD method is applicable when using longitudinal or panel data. The method involves making comparison between the treated and untreated groups before and after program (Baker, 2000; Wainaina *et al*., 2012). The total impact of program involves computation of the differences in outcomes for the treated and untreated group after project implementation less prior change in outcome of treated and untreated group before the project (AIEI, 2021). Although the method removes biases coming from comparisons overtime in the treated group, it requires baseline information for the two groups, which is not easy to get as intervention may have started without doing baseline study. The DD approach does not account for time-invariant selection bias (Kibira *et al*., 2015).

Propensity score matching (PSM) is a non-parametric technique that is applied to relax selectivity bias. The method involves association of the beneficiaries (adopters) and non-beneficiaries (non-adopters) of the intervention using similar recognizable features assumed to influence participation in the program (Kassie *et al*., 2011; Maina *et al*., 2020). However, it fails to account for the difference of unobservable characteristics that could have influenced the program intervention (Kassie *et al*., 2018a).

Reflexive comparison method is applicable in quasi-experimental design where there is prior baseline survey and follow-up survey after the intervention. It entails construction of counterfactual on basis of characteristics of participants before the intervention, which are compared among them before and after intervention. The method is useful in evaluating policies that cover entire population since no control group is used. However, it fails to account for scenarios of members, which may vary owing to the various factors irrespective of the intervention (Baker, 2000). It is not easy to differentiate between external effects and intervention resulting in unpredictable outcomes (Morton, 2009).

Instrumental variable (IV) method entails using one or more variables that affects the treatment but not the outcome of intervention (Shiferaw *et al*., 2014; Khonje *et al*., 2015). The method identifies exogenous variant in outcome attributed to intervention, knowing that its occurrence is purposive but not by chance. The approach helps to account for selectivity bias on unobserved features through use of a variable (for instance instrument) that is associated with participation but uncorrelated with unobservable characteristics influencing the outcome (Shiferaw *et al.*, 2014).

The IV entails two-stage regression model where the additional variable (instrument) in the second step of the model introduces element of randomness into the equation yielding consistent and unbiased estimation in the existence of hidden biases. This accounts for endogeneity problem through estimation of selectivity and outcome equations concurrently (Lokshin and Sajala, 2004). The limitation of the approach is difficult to select the instrument. The method is extensively employed since it relaxes the selectivity and endogeneity problem. The approach is sub-divided into endogenous switching regression (ESR) and two stage least square (2SLS) regression.

2.2 Review of Empirical Approaches for modelling agricultural technologies

2.2.1 Review of Empirical approaches for modelling intensity of adoption of agricultural technologies

Several empirical studies assessing the intensity of adoption of PPT have used the Tobit regressions, truncated regressions and censored models (Murage *et al.,* 2015b; Gwada *et al.,* 2019) and fractional response model (Papke and Wooldridge, 1996, 2008;). In such analysis, the dependent variable that are continuous are normally proportions (restricted) in nature. The censored models, truncated regressions, or Tobit regressions are usually restricted when the dispersion of the dependent variable is both below and above and a large share of the sample observation falls at one of the borders (Papke and Wooldridge, 1996). Therefore, the application of truncated regression, censored models, and Tobit regressions are considered restrictive by some empirical studies (Papke and Wooldridge, 1996; 2008; Gallani *et al.,* 2015).

To overcome this restriction of the Tobit models, Papke and Wooldridge (1996) proposed a fractional response model (FRM), which are flexible and allows modelling of continuous bounded dependent variable that are linked with non-linear methods. The FRM captures the non-linearity of the data while predicting unbiased and consistent estimates when the dependent variable are bounded from both below and above and yielding response values that fall inside the interval bounds of the dependent variable. The current study was specifically interested in assessing the intensity of adoption of PPT defined as the number of acres of maize under PPT per household divided by the total maize acreage per household, which is a fraction. The FRM overcomes the restrictive assumption of bounded dependent variable and provides a material number of corner observation (Wooldridge, 2012). Therefore, FRM is considered suitable for this current study and has been used by preceding empirical studies to assess the intensity of adoption of agricultural technologies (Papke and Wooldridge, 1996, 2008; Ramalho *et al*., 2011; Pokhrel *et al*., 2018; Ogoudedji *et al*., 2019; Nyabaro *et al*., 2019).

2.2.2 Review of Empirical Approaches for Modelling Impact of Adoption of agricultural technologies

Most empirical studies analyzing impact of adoption of agricultural technologies use the difference in difference methods (DiD) (Wainaina *et al*., 2012; Nakano *et al*., 2018; Zhou *et al*., 2020), propensity score matching (PSM) (Kassie *et al*., 2011; Maina *et al*., 2020), endogenous switching regression (ESR) (Wainaina *et al*., 2012; Kassie *et al*., 2018a,; 2018b; Khonje *et al*., 2018; Marwa *et al*., 2020; Kanyenji *et al*., 2022) and Average treatment effect (ATE) method. In such analysis, the dependent variables relies on *"with and without"* and "*before and after"* approaches (Wainaina *et al.,* 2012). The *"before and after"* approach which usually utilizes the DiD model to control fixed time invariant are usually restricted when the baseline data is missing (Kassie *et al*., 2018b; AIEI, 2021). Therefore, the application of DiD models are considered restrictive by some empirical studies especially where the program was implemented without the prior baseline data (Kassie *et al.*, 2018b).

To overcome this limitation of DiD model, Wainaina *et al*. (2012) proposed a "with and without" approach, which utilizes a counterfactual as a proxy to measure what could have happened without the intervention (when there is missing baseline data). The approach extensively uses the PSM and ESR models, which removes the restriction arising from selectivity bias when using cross-sectional data (Wainaina *et al*., 2012; Teklewold *et al*., 2013; Kassie *et al.,* 2018a). The PSM method relaxes selectivity bias, but fails to account for difference of unobservable characteristics (endogeneity) (Asfaw *et al*., 2012; Shiferaw *et al*., 2014; Khonje *et al*., 2015; Kassie *et al.*, 2018a; Maina *et al*., 2020). To remove this restriction of PSM model, Shiferaw *et al*. (2014) proposed an ESR model, which are flexible and allows modelling of cross-sectional data that are linked to restrictions of endogeneity and self-selection bias. The ESR involves a two-stage estimation process consisting of adoption equation and outcome equation (Shiferaw *et al*., 2015; Khonje *et al.,* 2015; 2018).

The current study was specifically interested in evaluating the impact of adoption of PPT on maize productivity. The dependent variable of the adoption equation in the first stage was measured as a categorical variable influencing the choice of the pest control practices, which is a set of eight choice set. On the other hand, the dependent variable of the outcome equation of the second stage was measured as yield for instance the kilograms of maize harvest per acres. However, an extension of ESR, the multinomial endogenous switching regression (MESR) was preferred since the dependent variable had more than two categories (Teklewold *et al*. 2013; Kassie *et al*., 2015a, b; Khonje *et al*., 2018).

The MESR overcome the restriction of self-selection bias arising from the choice of potentially interdependent and combined technology packages such as pest control practices and their interactions (Khonje *et al*., 2018). Therefore, a MESR which comprises a two-stage estimation procedure is considered suitable for this current study and has been used by previous empirical studies to evaluate the impact of adoption of agricultural technologies on maize productivity (Teklewold *et al*. 2013; Kassie *et al.*, 2015a, b and 2018b; Khonje *et al*., 2018).

The first-stage is modelled using a multinomial logit model thus allowing farmers to make choices of either individual or combined pest control practices while considering interactions between them (Kassie *et al.*, 2015a; Khonje *et al*., 2018). In the second-stage, the outcome equation which utilizes the ordinary least squares (OLS) with selection control is used to evaluate the impacts of single and joint technology practices combinations on maize yield (Khonje *et al*., 2018).

2.3 Review of Empirical Studies

2.3.1 Review of Empirical Studies on intensity of PPT adoption

Most empirical evidence on PPT in Eastern Africa has focused either on gender and adoption (Murage *et al.,* 2015a and b, Muriithi *et al*., 2018), the effectiveness of its dissemination pathways (Murage *et al*., 2012), willingness to pay (Niassy *et al.*, 2020) and its welfare benefits (Kassie *et al.,* 2018a). Murage *et al.* (2012) assessed the effectiveness of different dissemination pathways the in adoption of PPT among smallholder maize farmers in Western Kenya using a two-limit Tobit model based on the proportion of land under PPT as a proxy for effectiveness. While the use of the proportion of land under PPT is an appropriate measure of the intensity of adoption, it obscures the intensity of PPT adoption on maize since it is an aggregate measure for the entire farm that in practice is committed to multiple crop enterprises. The current study overcome this limitation by defining the intensity of adoption of PPT as the number of acres of maize under PPT per household divided by the total maize acreage per household, which is a fraction.

Murage *et al.* (2015a) applied a multinomial logit model (MNL) to evaluate the determinants of adoption of PPT in Eastern Africa. The MNL model estimates the probability of adoption but is inappropriate in analyzing the intensity of adoption. Murage *et al.* (2015b) assessed the gender specific perceptions and the extent of adopting climate-smart PPT in controlling stemborer in Eastern Africa using a Tobit model. The Tobit model is only suitable for analyzing the intensity of adoption when the dependent variable is bounded on one extreme (e.g., land area) but is inappropriate when the dependent variable is bounded on both extremes (e.g., between 0 and 1).

Moreover, Chepchirchir *et al*. (2017) evaluated the impact of PPT adoption on smallholder maize household's welfare in Eastern Uganda using a generalized propensity score method constructed on the absolute area allocated to the technology. The current study employed a fractional logit model based on the proportion of the maize area under PPT to overcome the econometric limitations with such estimations when the dependent variable is a fraction that is bounded between 0 and 1.

Muriithi *et al*. (2018) examined gender differences in PPT adoption and other sustainable agricultural practices (SAPs) on smallholder maize farmers' fields in Western Kenya using an ordered probit model. This study though insightful, generalizes the estimation to that of the intensity of adoption of SAPs and is not specific to PPT. Kassie *et al.* (2018a) employed a pooled probit model and an economic surplus model to evaluate the probability and welfare impacts adoption of PPT in smallholder maize farms in Kenya. The binary probit model is suitable for assessing the probability of adoption, but does not capture the difference in households regarding allocating land to PPT.

Gwada *et al*. (2019) assessed the factors influencing the extent of PPT expansion among smallholder resource-poor maize farmers in Homabay County, Kenya, using a censored Tobit model. The farm-wide measure of the intensity of adoption of PPT used in the Gwada *et al.* (2019) suffers from the same aggregation problems cited under Murage *et al.* (2012). Niassy *et al.* (2020) used a binary logit model to evaluate the probability of adoption and willingness to pay for PPT amongst smallholder maize farmers' in Rwanda. However, while the binary logit model is suitable for analyzing the probability of adoption, it is inappropriate for evaluating the intensity of adoption.

2.3.2 Review of empirical studies on impact of adoption of PPT on agricultural productivity

Several empirical studies on impact of agricultural technologies on maize productivity in SSA have focused on either impact of PPT (Chepchirchir *et al*., 2017; Kassie *et al*., 2018a), maize production technologies (Kassie *et al*., 2018b; Khonje *et al*., 2018), Brachiaria a component of PPT (Maina *et al*., 2020), FAW and its management strategies (Kassie *et al*., 2020) and soil carbon enhancing practices (SCEPs) (Kanyenji *et al*., 2022).

For instance, Chepchirchir *et al*. (2017) evaluated the impact of adoption of PPT on smallholder maize household's welfare in Eastern Uganda constructed on the absolute area allocated to push-pull technology using a combination of econometric methods (generalized propensity score (GPS) and dose-response function (DRF). The use of an absolute area as the dependent variable in evaluating the impact of PPT and its combinations is inappropriate since such a measure is a categorical variable and is best measured as the number of pest control practices chosen by a farmer's s in controlling FAW and stemborer pests.

Kassie *et al*. (2018a) estimated the probability and welfare impacts of adoption of PPT amongst smallholder maize farmers in Kenya using a combination of econometric methods (pooled probit and pooled OLS model) and an economic surplus model. This study though insightful, the use of binary probit and OLS models ignores important aspects of adoption such as perceived benefits, its perceived effectiveness in pest control, wealth status and perceived cost of the technology and its impacts of combinations of using other inter-related pest control technologies used by smallholder farmers which might lead to either underestimation or overestimation.

Maina *et al*. (2020) assessed drivers of adoption and the impact of climate-smart Brachiaria grass adoption on milk productivity and feed sufficiency among dairy farmers in Western and Eastern regions of Kenya using propensity score matching (PSM). Although Brachiaria is a component of PPT, the evaluation of impact of Brachiaria is not specific to maize productivity. However, while the PSM is suitable for analyzing the impact of a single technology, it is inappropriate for evaluating the impact of multiple pest control technology. More so, the binary probit model in assessing propensity scores of the likelihood of adoption used in the Maina *et al*. (2020) suffers from the same problems cited under Kassie *et al.* (2018a). The use of PSM although solves selectivity bias, but fails to account for unobserved characteristics (endogeneity) making it inappropriate under the current criterion.

Kanyenji *et al*. (2022) evaluated the impact of soil carbon enhancing practices (SCEPs) adoption on maize yields in Western Kenya using a combination of a multinomial endogenous treatment effect (METE) and a multi-valued treatment effect (MVTE) model. Although, METE and MVTE are suitable for measuring impact of multiple agricultural technologies, Kanyenji *et al*. (2022) study is not specific to PPT and its heterogeneity in terms of FAW and stemborer pest control technologies.

Khonje *et al*. (2018) used a multinomial endogenous switching regression (MESR) to evaluate the impact of multiple agricultural practices (conservation agriculture and improved maize varieties) on maize yield, income and poverty in eastern Zambia. Although this study is insightful, it is not specific to PPT. More so, this current study builds on the same methodology of using MESR approach in evaluating the impact of PPT and its combinations on maize yield in Eastern Rwanda. The dependent variable under the current scenario had eight option which is a categorical variable thus using the MESR model.

Kassie *et al*. (2018b) assessed both farm-level and market level economic impacts of maize production practices (improved maize seeds, chemical fertilizer and legume diversification of maize-legume intercropping or rotation) on maize yield and maize production costs using a combination of economic surplus and the MESR model. However, while the use of MESR is suitable for evaluating the impact of multiple agricultural technologies, it's not specific to PPT and its combinations in terms of pest control technologies. The current study builds on Kassie *et al*. (2018b) on evaluating the impact of PPT and its combinations on maize productivity in Eastern Rwanda since the dependent variable is a categorical variable with eight choice sets.

2.4 Summary

While the foregoing review of past evaluations on the adoptions of PPT in Eastern Africa provide useful insights on the drivers of adoption, only a few (e.g., Murage *et al*. (2012) and Gwada *et al*. (2019)) attempted to analyze the intensity of adoption using the censored Tobit models that are appropriate when the dependent variable is proportional. However, these two studies used an aggregate measure of the intensity of adoption that obscures the actual intensity of adoption of PPT among maize farmers. The current study employed a fractional logit model based on the proportion of the maize area under PPT to overcome the econometric limitations with such estimations when the dependent variable is a fraction.

Furthermore, studies on impact of PPT on the agricultural productivity have focused either on single technology framework for instance PPT and Brachiaria a component of PPT while others have focused on multiple technology framework such as maize production technologies and SCEPs. However, Kassie *et al*. (2018a) provide insightful information on the impact of PPT on maize productivity, although in their analysis ignores combinations of other inter-related pest control management technologies that might results in underestimation or overestimation.

The current study employed a MESR model based on the decisions of the multiple choices of technologies faced by the smallholder farmers in controlling FAW and stemborer pests to overcome the econometric limitations associated with such estimations when the dependent variable is a categorical in estimating the impact of single and joint pest control practices on maize yield in Eastern Rwanda.

This study contributes to the body of knowledge on the intensity of PPT adoption and its impact on maize productivity in Rwandan household. The study improves on previous studies on PPT adoption through inclusion of technology specific attributes such as perceived PPT benefits, its perceived effectiveness of technology, wealth status and perceived cost of technology. This study further builds on previous studies through analysis of the impact of PPT and its combinations rather than PPT in isolation which might results to either underestimation or overestimation but jointly to solve this problem in estimation. This information would help in identification of the weak linkages in the formulation of strategies that can be promoted to ensure wider dissemination and adoption of PPT among smallholder maize farmers in Rwanda.

Furthermore, the study underscored the positive impact of PPT, combination of PPT and traditional practices and lastly combination of pesticide and traditional practices on maize yield. Such information will be vital to smallholder farmers in making decisions on effectiveness of different pest control management technologies in controlling FAW and stemborer unlike previously similar technology that was promoted in western Kenya in curbing Striga weed. This would lead to increased agricultural productivity and reduce fall armyworm and stemborer pests that are major biotic constraints to maize production in Rwanda among smallholder maize farmers.

CHAPTER THREE: METHODOLOGY

3.1. Theoretical Framework

The random utility theory (RUT) of McFadden (1974) provides the theoretical framework of this study. Greene (2012) pointed that a farmer who is a consumer of any agricultural technology always select the alternative that maximizes his or her utility when faced with a set of mutually exclusive choices. A rational farmers when faced with a set of different alternatives then pursues the alternative that gives maximum expected utility (Baltas and Doyle, 2001; Mercer, 2004). Following Greene (2002), we specify the utility function for the adoption of pest control practices as follows:

$$U^a = x'_{ipt}\alpha + \mathrm{u}_{ipt}$$

$$U^b = x'_{ipt}\alpha + \mathrm{u}_{ipt} \quad \text{……} \quad (3.1)$$

where U^a is the utility derived from adopting the k^{th} pest control management practice: where k represents choice of push-pull method (PPT); U^b is the utility derived by the farmers using another pest control management practices such as pesticide method or traditional methods. On the other hand, x'_{ipt} are the observed independent variables (farm, farmer, pest and technology-specific attributes), α are the parameter to be estimated and u are the error term. The farmer decides to adopt the k^{th} pest control management practice on plot p if $Y^*_{ipkt} = U^a_k - U^b > 0$. The observed measure of adoption is equivalent to one if $U^a > U^b$ and equivalent to zero when $U^a = U^b$. Therefore, following RUT, farmers chooses to adopt the k^{th} pest control management practice when the net benefit (Y^*_{ipkt}) (latent variable) is higher compared from adopting the alternative technologies such as synthetic pesticides or traditional method in controlling FAW and stemborer pests.

3.2. Empirical Methods

3.2.1 Objective 1: Assessing the factors influencing the intensity of adoption of PPT

To assess the factors influencing the intensity of adoption of PPT, a Fractional Logit Model (FLM) was applied using the number of acres of maize under PPT per household divided by the total maize acreage per household as the dependent variable (proportion) which is bounded between 0 and 1. The dependent variable in this case is a fraction. The independent variable included in the FLM regression are as follows; perceived PPT benefits, perceived PPT effectiveness, age, gender, education, family size, off-farm income, group membership and livestock ownership.

Following Papke and Wooldridge (1996), the functional form of FLM was specified as follows;

$E(Y_i|X_i) = Z(\beta X_i)$ …………………………………..……………..….…………..……....….. (3.2)

where Y_i refers to the intensity of adoption of PPT, X_i is a vector of farmers, farm and technology-specific characteristics (Table 3.1) and β a vector of unknown parameters to be approximated. *Z (·)* is a cumulative distribution function that follows a logistic distribution function representing a nonlinear link function satisfying $0 \leq \mathrm{Z}(\cdot) \leq 1$, ensuring that the approximated values ranges from 0 and 1 and E is the expectations operator.

Equation 3.1 is approximated using a quasi-maximum likelihood estimation method where the likelihood for an observation is specified as the Bernoulli likelihood as follows;

$Li = [F(\beta X_i)]^{Yi} [1 - F(\beta X_i)]^{1-Yi}$…………………………...……..…………………......…….. (3.3)

Equation 3.3 was applied to evaluate intensity of adoption of PPT and the exogenous variables incorporated in the model follows the use-diffusion theory and previous studies hypothesized by (Kassie *et al.*, 2011; Murage *et al.*, 2012; 2015b; Ghimire *et al.*, 2015; Obuobisa-darko, 2015; Chepchirchir *et al.*, 2017; Maina *et al.*, 2020; Kolady *et al.*, 2020)

3.2.2 Objective 2: Evaluating the impact of adoption of PPT on maize productivity

To evaluate the impact of adoption of PPT on maize productivity, a multinomial endogenous switching regression (MERS) model was used. Maize productivity was measured in terms of yield i.e., kilograms of maize harvested per acre (kgs/acre). Following Teklewold *et al.* (2013), the MESR model employed a two-stage approximation technique to evaluate the impact of PPT on maize productivity. In the first stage of MESR, a multinomial logit (MNL) model was applied to evaluate the factors influencing the choice of pest control practices in Eastern Rwanda. The dependent variable in the MNL model was a categorical variable of 8 choice sets and specified following Teklewold *et al.* (2013) as follows:

$$P_{ij} = \mathrm{p}\left(\eta_{ij} < 0 | X_{ij}\right) = \frac{\exp\left(X_{ij}\beta_j\right)}{\sum_{m=1}^{j} \exp\left(X_{ij}\beta_m\right)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

where P_{ij} denotes a categorical dependent variable for the pest control practices (comprising of 1.traditional method, 2. pesticides, 3. push-pull, 4, combination of PPT and traditional, 5. combination of pesticides and traditional methods, 6. Combination of pesticides and PPT, 7. combination of traditional, pesticides and PPT and lastly 8 is non-adopter(control) which is neither adoption of traditional, or pesticides or PPT used in controlling FAW and stemborer pests, X_i is a vector of farm (farm size), farmers (age, gender, education of household head, wealthy category and group membership), pest attributes (perceived FAW severity, perceived stemborer severity) and technology-specific attributes (perceived cost of technology, perceived effectiveness) (Table 3.1) and β a vector of unknown parameters to be approximated.

In second stage of MESR model, an OLS was used to evaluate the average treatment effect arising from the adoption of PPT in the control of FAW and stemborer pests' infestation on maize productivity and specified as follows:

Following Teklewold *et al*. (2013), the possible category for each yield functions are specified as in equation $S=1$ for a non-adopter and $S=j$ for an adopter as follows:

$$\begin{cases} Category\ \ 1\ (Non-adopters){:}\ Y_{i1} = \alpha_1 X_i + u_{i1}\ if\ S = 1 \\ \qquad\qquad \vdots \quad \vdots \qquad \vdots \\ Category\ \ j\ (adopters){:} \qquad Y_{i1} = \alpha_j X_i + u_{ij}\ \ if\ S = j \end{cases} \quad \text{j=2, 3, 4, 5, 6……..….. (3.5)}$$

where Y_{ij}'s are the outcome equations of the i^{th} farmer in category, j, and the disturbance terms (u's) that are normally distributed with zero mean $(E(u_{ij}|X,Z = 0)$ and constant variance $[var(u_{ij}|X,Z)= \sigma_j^2$. Y_{ij} is observed if, and only if, control technology j is chosen and happens when $U_{ij}^* > max_{m\neq j}(U_{im}^*)$. The OLS will be biased if the *ε's* and *u's* are not exogenous in equation (3.5) and therefore incorporation of the selection correction terms of the different choices are ideal for a consistent estimation of the α_j.

The MESR model follows Durbin and McFadden (1984) (henceforth denoted to as DM model) and Bourguignon *et al*. (2007) to correct for selectivity bias. The advantage of the approach evaluates the individual technologies as well as alternative combinations of technologies while capturing the selectivity bias and the interactions between sets of different practices (Mansur *et al*., 2008; Wu and Babcock, 1998). The linearity assumption is assumed in the DM model as follows:

$$E(\varepsilon_{ij}\ |u_{i1}\ \dots\dots u_{ij}\ ) = \sigma_j \sum_{m\neq j}^{j} r_j(u_{im}\ - E(u_{im}\ ))$$

where the correlation between *ε's* and *u's* totals to zero by construction, that is $\sum_{m=1}^{j} r_j = 0$.

$$\begin{cases} Category\ \ 1{:}\ Y_{i1} = \alpha_1 X_i + \sigma_1\lambda_1 + \omega_{i1}\ if\ S = 1 \quad (3.6a) \\ \qquad\qquad \vdots \quad \vdots \qquad \vdots \\ Category\ \ j{:}\ Y_{ij} = \alpha_j X_i + \sigma_j\lambda_j + \omega_{ij}\ \ if\ S = j \quad\ (3.6b) \end{cases} \quad \text{j=2, 3, 4, 5, 6 ……..…..…. (3.6)}$$

where σ_j denotes covariance between ε's and u's while inverse mills ratio (IMR) denoted by λ_j is calculated from the estimated odds in equation (3.4) as follows:

$$\lambda_j = \sum_{m \neq j}^{j} \rho_j [\frac{\hat{S}_{im} In(\hat{S}_{im})}{1-\hat{S}_{im}} + In(\hat{S}_{ij})] \ldots\ldots (3.7)$$

where ρ is the correlation coefficient of *ε's* , *u's* and $\omega's$ are disturbance terms with an expected value of zero. In the multinomial choice setting, there are *j-1* selection correction terms, one for single different pest control technology. Bootstrapping of standard errors in equation (3.6) is used to control for the heteroscedasticity arising from the generated regressor (λ_j). Equation (3.6) is improved by addition of plot characteristics (perceived soil fertility) and plot varying covariates such as seed rate, average fertilizer use, pesticide and labour use. According to Wooldridge (2002), plot-varying covariates are incorporated to control for unobserved heterogeneity.

The average treatment effect (ATT) of treatment was computed by making comparison in expected outcomes of adopters and non-adopters of pest control technologies. However, Teklewold *et al*. (2013) argued that the problem of estimating the counterfactual with the use of observational data in impact evaluation (outcome adopters could have received had they not adopted the pest control technologies) is problematic.

Following Teklewold *et al*. (2013), the average treatment effect (ATT) on the treated was computed as the difference between the actual scenarios for adopters and counterfactual scenarios for non-adopters in equation 3.8 and 3.9 as follows:

Actual adoption observed in the sample (Adopters with adoption)

$$\begin{cases} E(Y_{i2}|S=2) = \alpha_2 X_i + \sigma_2 \lambda_2 & (3.8a) \\ \vdots \quad \vdots \quad \vdots & \\ E(Y_{ij}|S=j) = \alpha_j X_i + \sigma_j \lambda_j & (3.8b) \end{cases} \quad j=2, 3, 4, 5, 6 \ldots\ldots (3.8)$$

The counterfactual unobserved in the sample (Adopters, had they decided not to adopt)

$$\begin{cases} E(Y_{i1}|S=2) = \alpha_1 X_i + \sigma_1 \lambda_2 & (3.9a) \\ \quad \vdots \quad \vdots \quad \vdots & \\ E(Y_{i1}|S=j) = \alpha_1 X_i + \sigma_1 \lambda_j & (3.9b) \end{cases} \quad \text{j=2, 3, 4, 5, 6} \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.9)}$$

The unbiased estimates of the ATT was then derived from the expected values in equation 3.8 and 3.9. The ATT is expressed as the difference between equation (3.9a) and (3.8a) or equation (3.8b) and 3.9b) as follows:

$$ATT =$$

$$\begin{cases} E(Y_{i2}|S=2) - E(Y_{i1}|S=2) = (\alpha_2 X_i + \sigma_2 \lambda_2) - (\alpha_1 X_i + \sigma_1 \lambda_2) & (3.10a) \\ \qquad or & \\ E\left(Y_{ij}|S=j\right) - E(Y_{i1}|S=j) = \left(\alpha_j X_i + \sigma_j \lambda_j\right) - (\alpha_1 X_i + \sigma_1 \lambda_j) & (3.10b) \end{cases} \ldots\ldots\ldots(3.10)$$

$$ATT = \begin{cases} E(Y_{i2}|S=2) - E(Y_{i1}|S=2) = \mathrm{X_i}(\alpha_2 - \alpha_1) + \lambda_2(\sigma_2 - \sigma_1) & (3.11a) \\ \qquad or & \\ E(Y_{ij}|S=j) - E(Y_{i1}|S=j) = \mathrm{X_i}\left(\alpha_j - \alpha_1\right) + \lambda_j(\sigma_j - \sigma_1) & (3.11b) \end{cases} \ldots (3.11)$$

When adopters have similar attributes as non-adopters, the estimated variation in adopters' mean outcome are represented by first term on the right-hand side of equation 3.11. The remaining term (λ_j) denotes selection term capturing all possible effects of variance in unobserved variables.

3.3. Data Sources and Sampling Procedures

The study employed a survey data obtained from the Eastern Province of Rwanda conducted in 2019 by *icipe* as part of the attempt to assess the adoption and impacts of adoption of PPT on farmers' yield outcomes. The survey data was obtained from a sample of 398 households (194 PPT adopter and 204 PPT non-adopter) in the Gatsibo and Nyagatare districts of Rwanda. A stratified sampling procedure was used to draw respondents. In the first stage, two districts out of seven (Gatsibo and Nyagatare) were purposively selected since they formed the pilot places where PPT project was implemented (*icipe*, 2019a).

Within each district, the project intervention had been conducted in one sector from the Gatsibo and Nyagatare districts respectively were purposively selected. A simple random sampling technique was then used in the second stage to select a total of 398 maize farmers comprising of 194 PPT adopters and 204 non-adopters from two sampling frames provided by the RAB. The selected households were then interviewed using pre-tested semi-structured questionnaires programmed into CSpro. The data was analyzed in STATA version 14.

3.4. Measurement of Key Variables

Table 3.1 presents the description and measurement of the variables used in the FLM and MESR model analysis. The dependent variable of the FLM used in this study is the intensity of adoption of PPT among smallholder maize farmers in Rwanda (proportion of land allocated to PPT). On the other hand, the dependent variable of the MESR, in the first stage of the MNL used in this study is the pest control practices (comprising of 1. Traditional method, 2. Pesticides, 3. PPT, 4. Traditional and PPT, 5. Pesticides + traditional, 6. Pesticides + PPT, 7. Traditional + pesticides + PPT and 8. Control which is neither adoption of traditional or pesticides or PPT) in the control of FAW and stemborer among smallholder maize farmers in Eastern Rwanda. The MNL was tested to ensure it does violate the independence of irrelevant alternatives (IIA) although assumes categorical variable have same order. The second stage of the outcome equation of the yield function of the OLS used in this study is the maize productivity measured in kilograms per cares (kgs/acre) among smallholder maize farmers in Eastern Rwanda.

Table 3.1: Description of variable used in the FLM and MESR analysis

Variable	Description	Unit of measurement	Sign
Dependent variable			
Intensity of adoption of PPT	Acres of maize under PPT divided by the total acreage under maize per farm	Proportion	
Pest control practices	Technology used by the farmers to control FAW and stemborer pest	Categorical with 8 options	
Maize productivity	Maize yields in kilograms per acre	Kgs/acre	
Exogenous Variables			
Perceived PPT Benefits	Farmers perceptions on PPT's ability to increase maize yields	Dummy (1 = Yes, 0 otherwise)	+
Perceived PPT Effectiveness	Farmers perceptions on the effectiveness of PPT to control FAW and stemborer	Dummy (1 = Effective, 0 otherwise)	+
Age	Age of the farmer in years	Years	+/-
Gender	Gender of the farmer	Dummy (1 =Male, 0 Female	+/-
Education	Number of years spent in school	Continuous	+
Family size	Number of persons in the household	Continuous	+
Off-farm income	Participation in off-farm income activity	Dummy (1 = Yes, 0 otherwise)	+
Group membership	Membership to farmer groups	Dummy (1 = Member, 0 otherwise)	+
Livestock ownership (TLU)	Livestock ownership	Continuous	+
Farm size	Area under maize cultivation in acres	Continuous (acres)	+/-
Perceived cost of technology	Farmers perceptions of the cost of pest control practice	Dummy (1=costly, 0 otherwise)	+/-
Wealth category	Household asset index	Continuous (-1 to +1)	+
Perceived pest severity	Percent of maize plot that farmers perceived to be severely infested by FAW and stemborer pest	Dummy (1=Severe, 0 otherwise)	-
Perceived effectiveness	Perceived technology effectiveness in the control of FAW and stemborer	Dummy (1=effective, 0 otherwise)	
Perceived soil fertility	Farmers perceptions on plot soil fertility	Dummy (1=fertile, 0 otherwise)	+
Perceived soil depth	Farmers perceptions on plot soil depth	Dummy (1=shallow, 0 otherwise)	+
Perceived plot slope	Farmers perceptions on plot soil slope	Dummy (1=gentle, 0 otherwise)	+
Cost of seed	Costs of seed per acre	RWF/acre	+/-
Cost of pesticides	Costs of herbicides and insecticides	RWF/acre	+/-
Fertilizer	Fertilizer used in kilograms per acre	Kgs/acre	+/-
Labour	Labour usage for both family and hired in person days per acre	Person day per acre	+/-

3.5. Model diagnostic tests

3.5.1. Model Goodness of Fit test

To test for the goodness of fit of Fractional Logit model (FLM), a deviance tests for unequal dispersion was used to confirm if the model fitted the data well (Appendix1). On the other hand, to test for the goodness of fit of Logit model, Hosmer Lemeshow was used and rejected probit in favour of Multinomial Logit model (MNL) (Appendix 2).

3.5.2. Multicollinearity

Multicollinearity exist when there is linear association between explanatory variables. To test for multicollinearity in the data, variance inflation factor (VIF) and Pearson partial correlation tests of all variables included in FLM and multinomial endogenous switching regression (MESR) models were calculated. The mean Variance Inflation Factor (VIF) score for both FLM and MESR was 1.12 (critical value 10) while the Pearson partial correlation coefficients for all the explanatory variables were less than 0.5 indicating that multi-collinearity of the explanatory variable was not a problem in both models included in the analysis (O'brien, 2007; Gujarati, 2009). (See appendixes 1 FLM (Appendix 3 and 5) and MESR (Appendix 4 and 6)

3.5.3. Heteroscedasticity

Following Wooldridge (2010), the Breusch-Pagan test was used to test existence of heteroscedasticity if constant variance existed across error terms in the FLM and MESR models. The results failed to reject the null hypothesis of homoscedasticity (Chi^2 (1) = 0.01; Prob > chi^2 = 0.907) ruling out the presence of heteroscedasticity in the FLM (Appendix 7). On the other hand, the results rejected the null hypothesis of homoscedasticity (Chi^2 (1) = 15.67; Prob > chi^2 = 0.0001) in the MNL model indicating the presence of heteroscedasticity that was corrected using robust standard errors (Appendix 8).

3.5.4. Test for Independence of Irrelevant Alternatives (IIA) Property

Following Mwololo *et al*. (2019), the IIA assumption was confirmed using the Hausman and Suest-Based Hausman tests to validate the assumption that error terms were independently and identically distributed. The results of Hausman test and Suest-based Hausman tests failed to reject the null hypothesis concluding that the IIA assumption was not violated and the estimated results from MNL were unbiased, consistent and reliable (Appendix 9a, b and c).

CHAPTER FOUR: PAPER I

Intensity of Adoption of Integrated Push-Pull Pest Management Practices in Rwanda: A Fractional Logit Approach[1]

Abstract

The push-pull technology (PPT) is considered as an alternative integrated pest management strategy for the control of fall armyworm and stemborer, among smallholder maize farmers in sub-Saharan Africa to conventional pesticides. However, the extent of PPT use in Rwanda where the technology was introduced in 2017 remains largely unexplored. This study employed a fractional logit regression model to assess the factors influencing the intensity of adoption of PPT among smallholder maize farmers in Gatsibo and Nyagatare districts of Rwanda using survey data obtained from 194 PPT adopter households selected using a cluster sampling technique. While only 5 percent of smallholder farmers in Rwanda have adopted PPT as an integrated pest management strategy, on the average, these farmers cultivated 26 percent of their maize plots to the technology. The results show that the perceived benefits of PPT, its perceived effectiveness in pest control, group membership, livestock ownership, and gender of the household head had significant influences on the intensity of adoption of the PPT in Rwanda. These findings give compelling evidence to recommend that development initiatives should focus on creating awareness on the perceived benefits of PPT adoption using group approaches that are gender disaggregated.

Key words: *Fall armyworm, Fractional Logit model, Intensity of Adoption, Push-pull technology, Stemborer.*

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[1]

4.1. Introduction

Low agricultural productivity emanating from both biotic and abiotic constraints remains a key challenge for smallholder rural farmers in sub-Saharan Africa (SSA) (Murage *et al*., 2015a; Midega *et al*., 2015). Abiotic constraints such as droughts, unpredictable weather patterns, climate change and limited access to quality inputs (seeds, fertilizer and chemicals) have continuously limited agricultural productivity in the region (AGRA, 2014). Biotic constraints (living organisms that shape the ecosystem and comprise of soil organisms) include on the one hand pest (both storage and field) and disease incidents such as the maize lethal necrotic disease (MLND) and predators such as mites, moles, locust, birds etc. and on the other hand field pest specifically the fall armyworm and stemborer pests (AGRA, 2014; Midega *et al*., 2015). The low productivity among smallholder maize farmers in SSA is exacerbated by high post-harvest losses that are estimated at 24 percent of output minus any intervention (Affognon *et al.*, 2015).

Fall armyworm (FAW) and stemborer pests remain the most important field pests in Eastern Africa owing to their negative economic impacts on maize production, the main food staple in the Eastern African region (Midega *et al*., 2015; Kumela *et al*., 2018; IITA, 2019). The FAW moth (*Spodoptera frugiperda,*) originated from the tropics and sub-tropics of America in early 2016 and spread to West and Central Africa in late 2016 and even later to other parts of Eastern, Northern, and Southern Africa (Goergen *et al*., 2016; Midega *et al*., 2018). The moth lays eggs hatching into larvae that feeds on leaves at night and hide in the maize funnel during the day (Day *et al*., 2017). Stemborer (*Chilo partellus*) is a native of Asia that spread into Eastern, Southern, and Central Africa in the early 1930s and is now endemic in SSA (Harris, 1990; Midega *et al*., 2015). The larvae of the stemborer moth burrows in the maize stem as they grow, competing with the plant for the food that is necessary to produce quality grain (Kumela *et al*., 2019).

According to Khan *et al*. (2014), FAW and stemborer losses are on average estimated at 37 and 80 percent respectively of annual maize production in Africa under no control technologies. These losses are valued at US$ 4.3 billion annually (Day *et al.,* 2017). Recent studies in Kenya and Ethiopia have estimated losses of 32 and 47 percent respectively of maize production due to FAW (Kumela *et al.,* 2018). The pest is also estimated to cause losses of 40 and 45 percent of maize production in Zambia and Ghana, respectively (Day *et al.*, 2017). Conversely, maize stemborer pest is estimated to cause a loss of about 44-50 percent of potential maize output in Kenya (Nyukuri *et al.,* 2014; IITA, 2019).

Smallholder farmers in Rwanda and other parts of SSA have applied various approaches to control FAW and stemborer pest. These methods consist of handpicking, plant extracts, sawdust/pepper and soil/ash mixture, mixed cropping, and use of pesticide (Midega *et al.,* 2018; Kumela *et al*., 2018; Kumela *et al.,* 2019; Kassie *et al.*, 2020). Pesticides continue to be the most widely applied method in controlling FAW and stemborer. However, the continued use of pesticides has elicited pest resistance and has harmful human, animal, and environmental effects (Nicolopoulou-Stamati *et al*., 2016; Sharma and Singhvi, 2017). Furthermore, the accessibility of pesticides and highly specialized safety equipment for their application remains a challenge to resource-poor farmers in SSA (Day *et al*., 2017; Kumela *et al.*, 2018).

In cognizance of the negative effects of pesticides and in an attempt to reduce the high maize production losses associated with pests in SSA, the International Center of Insect Physiology and Ecology (*icipe*) and its allies established a habitant management technology well-known as the push-pull technology (PPT) (Khan *et al.,* 2001). PPT is an integrated pest management method encompassing the intercropping of cereal crops such as maize with *Desmodium* that “pushes” the pest away from the cereal while *Brachiaria* is planted as a border crop to “pull” the pest (Khan *et al.*, 2008a; 2014; Chepchirchir *et al*., 2017). The secondary benefits of PPT include improvement of soil fertility through nitrogen fixation, reduced soil erosion and lower use of pesticides, and provision of high-quality fodder for livestock production (Pickett *et al*., 2014; Kassie *et al*., 2018a; Maina *et al*., 2020). This biological pest control technology concurrently reduces the impact of four major production constraints in Africa's cereal-livestock farming system: weeds, pests, poor soil health, and fodder shortage (Chepchirchir *et al.*, 2017).

Introduced in 2017 in Rwanda, the PPT has been widely used in East and Southern Africa to control stemborer pests, Striga weed, and currently FAW pests (Murage *et al.,* 2015a; Midega *et al*., 2018; Kumela *et al*., 2018; *icipe*, 2019a). Previous studies from SSA reveals that cereal yields and livestock fodder can be twofold or even, in other cases, threefold with use of PPT (Khan *et al.,* 2001; 2008a, b; Cook *et al.,* 2006; Murage *et al.*, 2015a, b). Although the use of PPT technology is labour demanding during initial establishment, the labour requirements decrease substantially after the cropping system is well established (Muriithi *et al.,* 2018). PPT was found to have a benefit-cost ratio of about 2.2:1 relative to 0.8:1 for mono-cropping of maize (Khan *et al*., 2008a). Yields for maize farmers using the PPT in Uganda and Kenya have been reported to be 1.54 and 2.2 times higher than planting maize without PPT (Khan *et al.,* 2008a; Chepchirchir *et al*., 2018).

In Rwanda, *icipe*, in collaboration with the Government of Rwanda, introduced a PPT pilot project in 2017 to control FAW and stemborer pests (*icipe*, 2019a). The government of Rwanda, through the Rwanda Agricultural Board (RAB) recommended local partners (Food for the Hungry/Rwanda organization) who undertook farmer identification, training and establishment of demonstration plots (*icipe*, 2019a; Niassy *et al*., 2020).

Other farmers would later learn from demonstration plots before adopting and receiving necessary support through extension visits from both *icipe* field monitors and government extension officers. However, despite the promotion efforts by *icipe* and the government of Rwanda, the adoption of PPT remains low at only 5 percent (*icipe,* 2019a; Niassy *et al*., 2020). Moreover, the intensity of adoption of the technology in Rwanda remains largely unexplored.

While several recent empirical studies (e.g., Murage *et al.,* 2012; 2015a and b, Muriithi *et al*., 2018; Chepchirchir *et al*., 2017; Kassie *et al*., 2018a; Gwada *et al.,* 2019; Naissy *et al*., 2020) have evaluated the adoption of PPT among maize farmers in SSA, we only find one study (Naissy *et al.*, 2020) from Rwanda. However, a majority of these studies are limited to the analysis of adoption using linear econometric models. This study contributes to the existing knowledge by evaluating the intensity of adoption of PPT using a fractional response model that is specific to the maize area under PPT in the Nyagatare and Gatsibo districts of Rwanda. The study's answers a fundamental but often ignored research question, "*do the perceived benefits of a technology influence the intensity of its adoption?"* and answers this question in the affirmative for the case of PPT in Rwanda.

The study find that the perceived PPT benefits, perceived PPT effectiveness, livestock ownership, group membership, and gender of the farmer had a significant influence on the intensity of adoption of the PPT in Rwanda and recommends awareness creation as a reliable pathway to increasing usage of new agricultural technologies. The rest of this study is arranged as follows; Section 4.2 presents study's methodology, which explain data sources, the conceptual and empirical framework. Finally, the study's findings are discussed in section 4.3 while the conclusions and policy recommendations in section 4.4 respectively.

4.2. Study Methods

4.2.1. Conceptual Framework

The use-diffusion (UD) theory proposed by Shih and Venkatesh (2004) has been widely used to explore farmers' decision-making process on whether to adopt new technology and how much of that technology to adopt (Hu, 2007; Turner *et al.*, 2010). It is an extension of the adoption-diffusion (AD) theory of Rodgers (1995), which examines the process by which an innovation reaches a high number of adopters, the diffusion is expedited, and the innovation is considered successful (Mahajan, *et al.*, 1990: Rodgers, 1995). The UD theory addresses the limitation of AD theory that fails to account for the diffusion process with discontinued behavior (Golder and Tellis, 1998; Turner *et al.*, 2010). It provides an understanding of both the rate of use (high/low) and the variety (intensity) of using a technology. It can be applied to model the drivers of technology adoption and the outcomes of technology adoption.

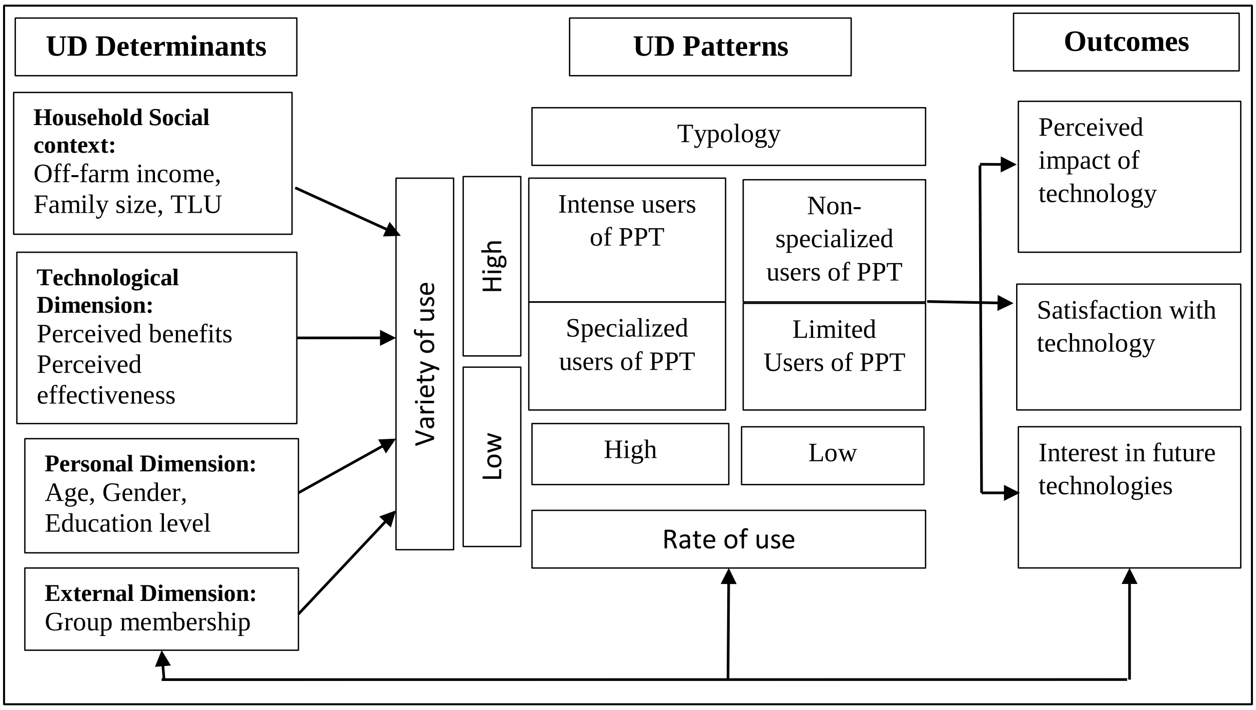

Figure 4.1: Use-diffusion model adapted from Shih and Venkatesh (2004)

The theoretical basis of the AD model comprises of an S-shaped diffusion curve that integrates the speed of penetration and a critical number of users in a two-stage model of diffusion (Theotokis and Doukidis, 2009). The corresponding theoretical components of the UD model are the progressing nature of use (variety and rate), sustained uninterrupted use (disadoption), and technology outcomes (perceived usefulness and integration) (Shih and Venkatesh, 2004). While the variable of interest in the AD model is the rate or time of adoption, the return variable in the UD model is the rate of use and variety of use. Shih and Venkatesh (2004) proposed the use of two distinct measures (variety of use and rate of use) to estimate the degree (intensity) of use of new technology. The rate of use indicates the time a person spends using the product during a designated period. Variety of use signifies the different ways the product is used (Shih and Venkatesh, 2004). Figure 4.1 presents the conceptual framework of the UD theory on which this study is based.

The UD model comprises of threefold important elements: (1) factors of UD model, (2) patterns of UD, and (3) outcomes of UD model. Factors that affect variety and rate of usage constitute UD factors (household social-context, personal aspect, technological aspect, and external aspect). Combining rate and variety of usage (high/low) produces a four-way typology of usage (specialized usage, intense usage, non-specialized usage, and limited usage), henceforth UD patterns (Figure 4.1). Intense usage deal with the individuals who apply product of innovation to an important degree in relation to both rate of usage and variety of usage. Non-specialized usage deal with the individuals who apply numerous roles of the product, however, take little time in using the product. Finally, limited usage deal with the individuals who apply the product of innovation to a minor degree in relation to both rate of usage and variety of usage; specifically, user's discover small, if any, worthy potential application and hence commit the product to a quite negligible function, even to the level of "disadoption" (Lindolf, 1992).

Different types of users have different experiences of the UD outcomes of the technology (perceived impact, degree of satisfaction, interest in future features of the technology, etc.). In practice, the drivers of technology adoption are modeled using discrete choice (e.g., logit, probit) models and their extensions such as Tobit, censored and truncated regressions, and discriminant analysis methods (Maddala, 1991; Noreen, 1998; Wooldridge, 2002; Wooldridge, 2012). The binary choice models (probit and logit models) estimate the likelihood of event's occurrence and are appropriate for binary response-dependent variables (Greene, 2003).

A number of empirical models have been applied to evaluate the intensity of adoption of new technologies including Poisson (Awuni *et al.,* 2018; Mahama *et al*., 2020; Kolady *et al.*, 2020), Tobit (Murage *et al.,* 2015b; Gwada *et al.*, 2019) and fractional response (Papke and Wooldridge, 1996, 2008; Ramalho *et al*., 2011; Pokhrel *et al*., 2018; Ogoudedji *et al*., 2019; Nyabaro *et al*., 2019). The choice of model to use depends on the nature of the dependent variable. Continuous variables that are restricted (proportions) in nature are normally assessed using truncated or censored models, Tobit regression, and fractional models (Papke and Wooldridge, 1996; 2008; Gallani *et al.,* 2015). These methods, though, suffer from some constraints, specifically wherever the dispersion of the variable is restricted both below and above and a quantifiable share of the sample observations falls at one of the borders. The Fractional Response Models (FRM) offer a feasible option to addressing several of the econometric restrictions associated with nonlinear methods presently used in modelling continuous bounded dependent variables (Papke and Wooldridge, 1996). The FRM yield estimates of higher fit compared to other linear approximation models through control of dependent variable that is bounded from both below and above, predicting response values that fall inside the interval bounds of the dependent variable while capturing the nonlinearity of the data. Additionally, the FRM allow a direct approximation of the conditional expectation of the dependent variable given the predictors and thus do not need special data transformations at the corners. The FRM control for limitations of the existing methodologies for the statistical analysis of bounded dependent variables and provide a material number of corner observations. Given their simplicity in computation, FRM provide high levels of flexibility in its application to longitudinal, panel, and cross sectional data. Furthermore, the FRM control for nonlinearity, and solve the various restricting assumptions that are crucial in traditional econometric results. The FRM extend the general linear models (GLM) to a class of functional forms that overcome the restrictions of the outdated econometric models for variables that are bounded in nature (Wooldridge, 2012).

The approximation of the parameters in the model is grounded on a quasi-maximum likelihood method (QMLE), generating estimates that are proportionately efficient and entirely robust under the GLM circumstances (Papke and Wooldridge, 1996). According to Gillani and Krishnana (2016), the FRM offers a better fit whereas controlling for the non-constant returns of the dependent variable along the range of the predictors and the nonlinearity in the data. Moreover, the estimation of average partial effects at different levels of the independent variables indicate that the FRM affirms more precise inferences, specifically in circumstances where observations at the end of the distribution are of specific interest for the researcher. Given the incremental explanatory power and the simplicity in computation, the use of the FRM should be contemplated at least as an option to other traditional econometric approaches applied in survey-based research.

4.2.2 Empirical Framework

This study employed a fractional logit model (FLM) to evaluate the intensity of adoption of PPT among smallholder maize farmers in Rwanda. The intensity of adoption of PPT is defined as the number of acres of maize under PPT per household divided by the total maize acreage per household, which is bounded between 0 and 1. Following Papke and Wooldridge (1996), the specification follows the functional form for the expectation of the intensity of adoption of PPT Y_i of the i^{th} household conditional on X_i, (a vector of explanatory variables):

$E(Y_i|X_i) = Z(\beta X_i)$ …………………………..……………..…………..……...….. (4.1)

where Y_i refers to the intensity of adoption of PPT, X_i is a vector of farm, farmers and technology-specific characteristics (Table 4.1) and β a vector of unknown parameters to be approximated. $Z\ (\cdot)$ is a cumulative distribution function that follows a logistic distribution function representing a nonlinear link function satisfying $0 \leq Z(\cdot) \leq 1$, ensuring that the approximated values lie in the interval of 0 and 1 and *E* is the expectations operator.

Equation 4.1 is approximated using a quasi-maximum likelihood estimation method where the likelihood for an observation is specified as the Bernoulli likelihood as follows;

$Li = [F(\beta X_i)]^{Yi}\ [1 - F(\beta X_i)]^{1-Yi}$……………………...……..………………....…….. (4.2)

The QMLEs of β are consistent provided that the conditional expectation in equation 4.1 is properly stated even if the Bernoulli specification is incorrect (Papke and Woolridge, 2008). A FLM constructed on the logistic conditional mean function and quasi-likelihood method is advantageous (Murteira and Ramalho, 2016). Following Hausman and Leonard (1997), the asymptotic variance-covariance of the matrix of the QMLE estimates is approximated, with maintenance of only first momentum assumptions without any additional second momentum assumptions.

4.2.3. Data sources and sampling procedures

The study applied survey data collected in 2019 from a sample of 194 PPT adopter households in the Nyagatare and Gatsibo districts in Rwanda. A cluster sampling technique was used to select the respondents. In the first step, the two districts (Gatsibo and Nyagatare) were purposively selected since they were the pilot areas for the PPT project. Within each district, the pilot had been conducted in one sector, and thus, Gatunda and Nyagihanga sectors, from the Nyagatare and Gatsibo districts were selected, respectively. A simple random sampling procedure was used in the second step to select 240 adopter households from a sampling frame of households who had participated in the pilot provided by the Rwanda Agricultural Board in the two districts. However, 46 of the selected households had stopped using the technology in the preceding 12 months and were therefore dropped from the sample resorting to a sample size of 194 adopters farming households who were interviewed using a pre-tested semi-structured questionnaire. The 194 adopter households selected comprised of 133 and 61 farmers from the Gatsibo and Nyagatare districts respectively, were then interviewed with a pre-tested semi-structured questionnaire. The data was then analyzed using Stata version 14.

4.2.4 Measurement of Variables

Table 4.1 presents the description and measurement of the variables used in the analysis. The dependent variable of the FLM used in this study is the intensity of adoption of PPT among smallholder maize farmers in Rwanda. It is derived by dividing the number of acres of maize under PPT per household by the total maize acreage owned by a household. It is a fractional variable bounded between 0 and 1. To derive the proportion of land area under PPT, farmers were asked two successive questions: i) *how many acres of land have you set aside for maize production?* The second question asked was: ii) *of the total acreage you have set aside for maize production, how many acres have you allocated to push-pull technology (acres)?*

The use-diffusion theory and preceding studies (e.g., Kassie *et al.*, 2011; Murage *et al.*, 2012; 2015b; Ghimire *et al*., 2015; Obuobisa-darko, 2015; Chepchirchir *et al*., 2017; Maina *et al.,* 2020; Kolady *et al*., 2020) inform the choice of the independent variables (Table 4.1) used in the analysis. They included the perceived benefits of PPT use, the perceived effectiveness of PPT use as compared to other pest control methods, group membership, off-farm income sources, education level, gender, tropical livestock units (TLU), age and family size.

Table 4.1: Description of variables used in the Fractional Logit Model

Variable	Description	Unit of measurement
Dependent variable		
Intensity of adoption of PPT (Proportion)	Acres of maize under PPT divided by the total acreage under maize per farm	Proportion
Independent variables		
Perceived PPT Benefits	Farmers perceptions on PPT's ability to increase maize yields	Dummy (1 = Yes, 0 otherwise)
Perceived PPT Effectiveness	Farmers perceptions on the effectiveness of PPT to control FAW and stemborer	Dummy (1 = Effective, 0 otherwise)
Age	Age of the farmer in years	Years
Gender	Gender of the farmer	Dummy (1 =Male, 0 Female
Education	Number of years spent in school	Continuous
Family size	Number of persons in the household	Continuous
Off-farm income	Involvement in off-farm income activity	Dummy (1 = Yes, 0 otherwise)
Group membership	Member to a farmer groups	Dummy (1 = Member, 0 otherwise)
Livestock ownership (TLU)	Livestock ownership	Continuous

Note: TLU is tropical livestock unit. TLU equivalents for different livestock were computed as cattle=1, camels=1, donkeys=0.8, goats and sheep=0.2 and poultry=0.04 (WISP, 2010)

Farmer's assessment of maize yields with PPT adoption as compared to the yields before PPT adoption was used to proxy for the perceived PPT benefits. Farmers were asked to compare their maize yields before and after the adoption of PPT. Their responses were grouped into a dummy outcome variable equivalent to 1 if households perceive PPT increased yields and zero otherwise. Positive relationships have been reported between the perceived benefits of new technologies and their adoption (Ghimire *et al*., 2015; Kolady *et al*., 2020).

Similarly, PPT's perceived effectiveness control stemborer and FAW relative to other methods was also measured as a binary response variable, equal to one 1 if PPT was effective and zero otherwise. Group membership was another important variable used as a representation for sources of information sharing on PPT, procuring inputs, and marketing output. It was measured as a dummy variable equivalent to one if a farmer was a member of an agricultural group and zero otherwise. Social networks such as groups or farmer associations facilitated the exchange and gathering of information related to PPT and provided platforms through which farmers accessed inputs and marketed output. Previous studies have revealed positive associations between group membership and PPT adoption (Kassie *et al*., 2011; Ghimire *et al*., 2015; Obuobisa-darko, 2015; Chepchirchir *et al*., 2017). Off-farm income played a key role in providing financial resources necessary for investment in PPT and was measured as a dummy variable equivalent to one if a farmer had an off-farm income source and zero otherwise.

Gender, education, age, livestock ownership, and family size were also used as control variables following preceding studies (see Murage *et al.*, 2012; 2015b; Maina *et al.*, 2020). Gender was measured as a dummy variable equivalent to 1 if the household head was male and zero otherwise. The available literature on the influence of gender on the PPT adoption is mixed. Age was used as a proxy of farmers' experience.

Education was measured by the number of schooling years spent by the respondent, while age was measured in years. Several previous studies have shown positive relationships between age and education on one side and the adoption of PPT on the other (Obuobisa-darko, 2015; Mahama *et al*., 2020). The number of livestock owned was used as a proxy for wealth status and measured in TLU. Family size was also incorporated as a proxy for available family labour and measured as the entire number of persons per household.

4.3 Results and Discussion

4.3.1 Descriptive results

Table 4.2 presents the demographic characteristics of PPT adopter maize farmers in Rwanda. Average farm sizes for PPT adopters were 3 acres, which was slightly higher than the national average at 2.6 acres (MINAGRI, 2018). The adopter household's allocated approximately 1.035 acres (35 percent) of their farms to maize production, out of which 0.269 acres was under PPT to yield an intensity of adoption of 0.26. On average, the PPT adopter farmers were middle aged (50 years) with about 6.42 years of schooling corresponding to the attainment of a primary school level of education.

Table 4.2: Demographic characteristics of PPT adopter maize farmers in Rwanda

Variables	Mean (n=194)	SD	Minimum	Maximum
Farm size (Acres)	3.115	3.252	0.250	24.700
Land area under maize (Acres)	1.035	1.059	0.100	5.100
Maize area under PPT (Acres)	0.269	0.279	0.050	1.250
Age (Years)	50.02	10.76	24	85
Education (Years)	6.42	2.97	0	18
TLU (Number)	1.91	4.09	0	39
Family size (Number)	5.24	2.04	2	13
Frequencies	**Count**	**Percent**		
Gender of household head (% Male)	146	74.74		
Off-farm income source (% accessing)	91	46.91		
Group membership (% belonging)	118	60.82		
Perceived PPT benefits (% positive)	112	57.73		
PPT effectiveness in stemborer control (%)	117	60.31		
PPT effectiveness in FAW control (%)	115	59.28		

Note: TLU is tropical livestock unit were computed as cattle=1, camels=1, donkeys=0.8, goats and sheep=0.2 and poultry=0.04 (WISP, 2010)

The average family size in the study area was 5.24 persons, which compares favourably with the national average at 4. Three quarters of the respondents were male, which was expected given the patriarchal nature of the society. Moreover, 61 percent of the households belonged to farmers' groups through which they share information on PPT, procured inputs and marketed output. Almost all households in the study area owned livestock with an average TLU of 1.91, which is understandable given the small land holding sizes. As expected with adopters of any technology, maize farmers in Rwanda had a positive perception of PPT use. Fifty-eight percent of the respondent's perceived PPT use to increases maize yields, while 60 percent of the farmers perceived the technology to be effective in the control of FAW and stemborer relative to other methods. Moreover, 47 percent of the respondents undertook other off-farm income earning undertakings, which was used to complement farm incomes required to cover the initial labour costs for setting up the PPT plots that can be a hindrance to adoption.

4.3.2 Econometric results

Table 4.3 presents the quasi-maximum likelihood estimates (QMLE) of the intensity of adoption of PPT from the fractional logit model. The mean Variance Inflation Factor (VIF) score was 1.12 (critical value 10) while the partial correlation coefficients for all the independent variables were less than 0.5 suggesting that multi-collinearity of the explanatory variables was not problematic (Kennedy, 1985; O'brien, 2007).

Table 2.3: Fractional Logit QMLE of the intensity of adoption of PPT in Rwanda

Variable	Coefficient	Robust Std deviation	Marginal effects	Robust Std error
Perceived PPT benefits	0.292***	0.113	0.0632***	0.024
Perceived effectiveness of PPT	0.301***	0.112	0.0648***	0.024
Age	-0.004	0.005	-0.001	0.001
Gender	0.274**	0.132	0.058**	0.027
Education	0.018	0.018	0.004	0.004
Family size	-0.024	0.023	-0.005	0.005
Off-farm income	0.037	0.105	0.008	0.023
Group membership	0.246**	0.113	0.053**	0.024
Livestock ownership (TLU)	0.074**	0.033	0.016**	0.007
Constant	-1.364***	0.341		
Number of observations	194			
Wald Chi^2 (9)	58.630	0.000		
Pseudo R^2	0.021			
Log pseudo likelihood	-120.012			
Breusch-pagan/Cook-Weisberg	Chi^2 (1)=0.011	Prob > Chi^2=0.907		

Mean Variance inflation factor	1.120
Deviance	4.468
Pearson	4.468

Note: ***, ** and * denotes 1%, 5% and 10% level of significance respectively.

The Breusch-pagan test fails to rejects the null hypothesis of homoscedasticity (Chi^2 (1) = 0.01; Prob > chi^2 = 0.907) ruling out the presence of heteroscedasticity. The Wald statistic was significantly at the one percent level signifying a high prediction power of the model (Mwololo *et al.*, 2019). Finally, the Pearson and deviance tests for unequal dispersion were not significant ($p > 0.05$) suggesting that the FLM fitted the data well. The results show that the perceived PPT benefits and effectiveness, group membership, livestock ownership, and gender had a significant positive effect on the intensity of adoption of PPT in Rwanda. Gender, education, age, livestock ownership, and family size were also used as control variables but were insignificant in explaining the intensity of adoption of PPT in Eastern Rwanda. The quasi-maximum likelihood estimates of the FLM are consistent as long as the conditional expectation of the intensity of adoption of PPT is correctly specified even if the Bernoulli specification is inappropriate. Thus they are more reliable than recent estimates of the intensity of adoption of agricultural innovations using both linear and non-linear models of estimation.

Farmer's perceptions of the ability of PPT use to increase maize yields had significant positive influence on the intensity of adoption and was significant at the 1 percent level signifying that the intensity of adoption increased with a respondents' positive perception of the benefits of the technology. Farmers who perceived PPT use to increase yields had higher intensities of adoption of the technology of 6.32 percent than their counterparts who thought otherwise. This finding is in agreement with the result of previous studies (Meijer *et al*., 2014; Ghimire *et al.,* 2015; Murage *et al.,* 2015a, b and Kolady *et al*., 2020). Meijer *et al*., (2014), which reported that farmer's initial information of the benefits of the technology increased the probability of adoption. Ghimire *et al. (*2015) reported that positive perception of technology's superiority in yield increased intensity of adoption of improved maize technologies.

In conformity with the expectations, the perceived effectiveness of PPT in control of FAW had a significant positive influence on the intensity of adoption of PPT at the 1 percent level. Positive perceptions on the effectiveness of PPT increased the intensity of adoption by 6.48 percent. Maize farmers would readily adopt a technology that effectively controls pests compared to the alternative pesticides that have been linked with the negative environmental effects. This finding supports the results of Gwada *et al*. (2019), who reported a positive association between farmers' perceptions on the severity of stemborer infestation and the intensity of adoption of PPT in Kenya. Similar result were reported by Kolady *et al*. (2020) in South Dakota, who observed that positive perceptions of profitability increased producers' intensity of adoption of precision agriculture technologies.

Group membership had a positive and significant influence on the intensity of adoption of PPT at the 5 percent level. Belonging to a farmers group increased the intensity of adoption of PPT by 5.8 percent. Groups play an important role in transferring information and knowledge and availing inputs (Okello *et al*., 2021). Often, smallholder farmers procure inputs, market outputs and acquire information through farmers' groups that are used to leverage the benefits of economies of scale. Obuobisa-Darko (2015) find a positive association between group membership and intensity of adoption of cocoa research innovations in Ghana. A similar result was reported by Ghimire *et al*. (2015) who find maize farmers belonging to groups and local cooperatives in Nepal were exposed to numerous information sources, enabling the farmers to evaluate the risks, benefits and take advantage of new agricultural innovations. Group membership acts as a proxy for social capital and farmer-based extension support methods such as field days, farmer-teacher, and farmer-farmer are modelled on group learning methods where social capital forms the basis for interactions and information exchange among members and other extension agencies (Wossen *et al.,* 2017). Thus, social capital not only provided social networks but also facilitated in information flow and provided opportunities for peer learning where farmers shared experiences and information about PPT adoption. This means dissemination of PPT reached more farmers when conducted through farmer groups and was more likely to increase intensity of adoption (Kassie *et al.,* 2011; Chepchirchir *et al.,* 2017).

Livestock ownership had a positive significant influence on the intensity of adoption of PPT at the 5 percent level. A positive relationship between livestock ownership and the intensity of adoption is expected given that Napier grass and *Desmodium spp* are used as animal feeds, and thus the technology compliments livestock production. Livestock ownership is indicative of a farmer's wealth status, an important component of technology adoption. A one percent increase in the TLU increased the intensity of adoption of PPT in Rwanda by 1.6 percent. A similar result was reported in Maina *et al.* (2020) who observed that farmers with a higher number of livestock assets were more willing to adopt and increase land acreage under Brachiaria grass and Desmodium that are components of PPT. Other studies noted a direct association between livestock ownership and adoption of agricultural technologies due to the utilization of fodder and crop residues as animal feeds (Khan *et al*., 2014; Murage *et al*., 2015a; Kassie *et al*., 2018).

Male farmers in Rwanda committed larger maize acreage to PPT relative to their female counterparts. The significant positive association between gender and the intensity of adoption of PPT is expected given the limited access of female-headed households to productive resources such as land, credit and extension. Male headed households had 5.8 percent more likelihood of allocating their maize plots to PPT relative to their female counterparts. This can be due to number of socio-cultural factors (Mbugua *et al*., 2020). This finding is in agreement with the result by Murage *et al.* (2015b), who observed a positive correlation between gender and intensity of adoption of climate-smart PPT in Kenya.

4.4 Conclusions and policy implications

This study evaluates the factors influencing the intensity of adoption of PPT among smallholder maize farmers in Gatsibo and Nyagatare districts of Rwanda. Cross-sectional survey data from 194 PPT adopter maize farmers was analyzed using a fractional logit model. Overall, fifty-eight percent of the respondent's perceived PPT use to increase yields, while 60 percent of them perceived PPT to be effective in the control of both FAW and stemborer relative to other methods. The results revealed that the perceived PPT benefits, the perceived effectiveness of PPT in control of FAW, group membership, livestock ownership and gender had a significant positive effect on the intensity of adoption of PPT among smallholder maize farmers in Rwanda. The study concludes that farmer's perception of technology attributes and sources of information play crucial roles in technology adoption decisions.

Therefore, given these findings, development initiatives in Rwanda should focus on strategies that create and disseminate information that enhances farmer awareness on the perceived benefits of the technology and its effectiveness in pest control relative to other existing methods such as pesticides. Such strategies could include the use of extension methods (e.g. farmer field schools, demonstrations etc.) that disseminate information on PPT and focus on farmer groups especially those whose members own livestock. Furthermore, efforts to disseminate PPT information should target male farmers differently from female farmers given their different access to productive resources that are important drivers of technology adoption.

Lastly, while the biological and societal background has been eloquently discussed, a direct comparison against other (or similar) models has not been elaborated. Moreover, despite the rigorous econometric methods validating the results on intensity of adoption of PPT, the study recognize the limitations in approximation. First, the study used cross-section data that does not capture the dynamics changes in integrated pest management used by smallholder maize farmers. Secondly, the study's limitation pertains to small sample size conducted when the technology was being disseminated among smallholder farmers. Thirdly, although the estimates demonstrate the factors influencing intensity of adoption of PPT, the study did not take into account plot-varying characteristics and institution factors such as credit and extension accessibility. Fourth, the non-adopters of PPT were not part of the analysis as the technology attributes questions were biased to only PPT adopters reducing the sample size. In view of overcoming this weakness, the study recommends future studies to include additional variables and years of sampling to validate the study's findings and get results that are more robust.

CHAPTER FIVE: PAPER II

Impact of Adoption of Fall Armyworm and Stemborer Pest Control Practices on Maize Productivity in Rwanda: An Endogenous Switching Regression

Abstract

The use of push-pull technologies (PPT) as an alternative to pesticides in the control of fall armyworm and stemborer pests among smallholder maize farmers has recently received considerable global attention. However, the impact of adoption of PPT on the maize productivity remains largely unexplored. This study employed a multinomial endogenous switching regression (MESR) to evaluate the impact of adoption of PPT on smallholder maize farmer's productivity in Gatsibo and Nyagatare districts of Rwanda. The MESR model was estimated on sample of 398 households operating 967 maize plots selected using a stratified random sampling technique. Overall, 25, 20, and 14 percent of the households used traditional methods, PPT and pesticides respectively in isolation to control stemborer and fall armyworm pests in Eastern Rwanda. Another 8 and 7 percent of the households used a combination of pesticides and traditional methods and a mix of PPT and traditional methods respectively to control the pests while none of the farmer used a combination of pesticides and PPT and a mixture of pesticides, PPT and traditional practices. The econometric results revealed that traditional practices was the commonly used technology. Furthermore, adopting PPT in isolation, and its combination had a positive significant impact on maize yields while using traditional methods and pesticides in isolation and a combination of pesticides and traditional method had negative impacts on maize yield. Thus, the study recommends promotion of PPT as an alternative low cost pest control method and optimal technology combination in controlling fall armyworm and stemborer pests in maize.

Key words: *Multinomial Endogenous Switching Regression, Impact Evaluation, Pests, Rwanda, Push-Pull Technologies, Productivity*

5.1 Introduction

Improving agricultural productivity in Sub-Saharan Africa (SSA) remains a critical developmental goal with efforts being directed towards meeting the food demand of the present as well as the future generation (*icipe*, 2019b). Thus, agricultural productivity must grow above the current population growth rate to match with the ever rising food demands (FAO, 2017). However, agricultural productivity in SSA is continuously constrained by both abiotic and biotic factors that cause substantial yield losses (Midega *et al*., 2018; Hailu *et al*., 2018; Kumela *et al.*, 2019; *icipe*, 2019b). Abiotic factors such as climate change, drought, land fragmentation, low soil fertility, limited access to quality farm inputs and inefficient production methods are common among smallholder farmers in SSA (Getu *et al*., 2013; Kumela *et al*., 2019; Kanyenji *et al*., 2020). On the other hand, biotic factors such as diseases (maize lethal necrotic), parasitic Striga weed, insect pests (both storage and field), predators such as locusts, birds, termites etc. are the most prevalent (Getu *et al*., 2013; Kumela *et al*., 2019).

Among the biotic constraints to crop productivity , fall armyworm (FAW) and stemborer pests are of high economic importance and cause huge maize yield losses (Kumela *et al*., 2018; 2019; *icipe*, 2019b; Omwoyo *et al.*, 2022). The FAW and stemborer yield-related losses in SSA and Kenya are estimated on average at 37 and 47 percent respectively of the total annual maize production under no control technologies (Khan *et al*., 2014; Day *et al.*, 2017; IITA, 2019). In Rwanda, FAW induced yield losses are estimated to range from 15 to 73 percent of total maize production (Rukundo *et al*., 2020). Thus, without appropriate interventions, FAW and stemborer pests could derail efforts towards attainment of the Sustainable Development Goals number 1 and 2 of poverty reduction and ending hunger respectively by the year 2030 in Rwanda (United Nations, 2017).

This use of improved agricultural technologies has been proposed as a viable alternative in reversing the yield losses caused by abiotic and biotic constraints and increasing agricultural productivity (Kassie *et al.,* 2018a and b; *icipe*, 2019b; Maina *et al.,* 2020). Over the past half-decade, smallholder maize farmers in Rwanda have relied on use of synthetic pesticides in controlling FAW and stemborer pests (Tambo *et al*., 2020). However, smallholder farmers have to content with the costly pesticides and specialized safety gears for pesticide application (Day *et al*., 2017; Kumela *et al*., 2018; Tambo *et al*., 2020; 2021).

The heavy reliance on pesticide application causes pesticide resistance while excessive use of pesticides has negative effects to human, animal and environment health (Nicolopoulou-Stamati *et al*., 2016; Sharma and Singhvi, 2017; Tambo *et al*., 2020; 2021). Conventionally, maize farmers use other traditional pest control management technologies such as hand picking, application of soil/ash and sawdust/pepper mixture, use of plant extracts and intercropping which are cost-effective and environmentally friendly but are less effective (Hailu *et al*., 2018; Midega *et al*., 2018; Kumela *et al*., 2018; 2019; Kassie *et al*., 2020; Rukundo *et al*., 2020; Tambo *et al.*, 2021; Omwoyo *et al*., 2022).

As an alternative, the "push-pull" technology (henceforth PPT), an integrated pest management (IPM) practice designed by the International Center of Insect Physiology and Ecology (*icipe*) and its partners has been promoted in the control of FAW and stemborer infestation in maize (Khan *et al*., 2001; *icipe*, 2019a; Niassy *et al*., 2022). PPT comprises intercropping of cereal crops such as maize with *Desmodium* repelling ("pushes") the pest away from the cereal while *Brachiaria* or Napier grass planted as a border crop attracting ("pull") the pest (Khan *et al*., 2008a; 2008b; 2014; Pickett *et al*., 2014; Chepchirchir *et al.*, 2017). Additionally, PPT improves soil fertility through increasing nitrogen use efficiency, decreases soil erosion, lowers pesticide use, controls the spread of Striga weed and provides quality fodder for livestock (Pickett *et al*., 2014; Kassie *et al*., 2018a; Maina *et al*., 2020; Niassy *et al*., 2022). Despite being labour intensive at establishment, the labour demands of PPT decline significantly once the crop is well established (Muriithi *et al.,* 2018). Recent studies have revealed an increase in average maize yields from 1 to 3 metric tonnes/hectare (MT/Ha) with the use of PPT (Midega *et al.,* 2015; *icipe*, 2019b). Other studies have reported a reduction in the use of herbicides and synthetic insecticides in maize production with use of PPT thus enhancing human health and increasing biodiversity (Pickett *et al.,* 2014). However, despite the apparent benefits and promotion efforts made by *icipe* and the government of Rwanda since 2017, the adoption of PPT remains low at 5 percent while its impact on maize productivity in Rwanda is largely unexplored (*icipe*, 2019a; Niassy *et al.,* 2020; Misango *et al*., 2022).

While numerous recent empirical studies (e.g., Chepchirchir *et al*., 2017; Kassie *et al*., 2018a; Maina *et al*., 2020 ; Kassie *et al*., 2020) have evaluated the impact of PPT among maize farmers in SSA, we only found one study (Kassie *et al*., 2018a) from Kenya and none from Rwanda. However, the bulk of these studies are restricted to the analysis of impact assessment using linear econometric models. This study evaluates the impact of adoption of PPT practices on maize productivity in Rwanda using a MESR model. It contributes to the literature by evaluating the impact of adoption of single and joint pest control practices on maize yields. The study pursues a fundamental but often ignored research question, *"does PPT adoption increase maize productivity?"* and answers it to the affirmative in the case of smallholder maize farmers in Eastern Rwanda. The remainder of this study is structured as follows; Section 5.2 presents study's methodology, which explain data sources, theoretical and empirical framework. The study's findings are discussed in section 5.3 while the conclusions and policy recommendations are presented in section 5.4 respectively.

5.2 Methodology

5.2.1 Analytical Framework

The Theory of Change (ToC) of Weiss (1995) provides the analytical basis of this study. The ToC describes how an intervention or set of interventions bring forth developmental changes from a casual analysis based on the evidence. Gertler *et al*. (2016) pointed that ToC provides a blueprint of how intended activities result to a chain of outcomes with a logical explanation of the necessary conditions. The ToC has been widely used in impact evaluation studies due to its ability to accounts for underlying assumptions and risks in program implementation process

According to theory of change, the inputs or activities include treatment/intervention such as PPT project while the expected outputs include either a decrease or increase in productivity or consumption of maize. The outcome variables of interest include intermediate variables such as productivity or incomes and long-term welfare or impacts i.e. food security, poverty health and nutrition (Funnell and Rogers, 2011; Mayne and Johnson, 2015; Thornton *et al.*, 2017).

Following Khonje *et al*. (2015), given the treatment group Y_{1i} and a control group Y_{0i} then the Average Treatment effect (ATT) is specified as:

$$ATT = E(Y_{1i} - Y_{0i}|P_i = 1) \quad (5.1)$$

where Y_{1i} represents the yield when i^{th} farmer adopts PPT (actual productivity), Y_{0i} is the yield of i^{th} farmer when he/she does not adopt PPT (productivity had they not adopted PPT) and P_i represents the PPT adoption, 1=adopted; 0=otherwise. ATT presents the conditional mean impact or Average Treatment effect on Treated (ATT) as based on PPT participation. The mean difference between treatment and control after expanding equation (5.1) following Khonje *et al*. (2015) is specified as:

$$D = E(Y_1|P_i = 1) - E(Y_0|P_i = 1) = ATT \quad (5.2)$$

According to Weiss (1995), the expected impact of a project is evaluated on the basis of a *"with and without project"* or *"before and after project"* analysis. The ToC is analyzed using treatment effect models such as propensity score matching, difference in difference, and instrumental variable models (Khonje *et al.,* 2015; Kirchweger and Kantelhardt, 2015; Aker and Ksoll, 2016; Marwa *et al.,* 2020; Ogutu *et al.*, 2020; Adeyanju *et al.*, 2021). A number of empirical models have been used to evaluate the impact of agricultural projects within the framework of the ToC. These include difference-in-difference (DiD) (Nakano *et al*., 2018; Zhou *et al*., 2020), propensity score matching (PSM) (Kassie *et al*., 2011; Chepchirchir *et al*., 2017; Maina *et al.,* 2020), and endogenous switching regression (ESR) models (Teklewold *et al.*, 2013; Shiferaw *et al.,* 2014; Khonje *et al*., 2015; 2018; Kassie *et al*., 2015a and b; 2018a and b; Kanyenji *et al*., 2022). The choice of which model to use in impact evaluation depends on whether a *"with and without"* or a *"before and after"* approach is adopted (Wainaina *et al.,* 2012). The *"before and after"* approach requires both pre and post-intervention data for both treatment and control groups to enable utilization of statistical methods such as DiD to eliminate fixed variations in key variables over time (AIEI, 2021).

The *"with and without"* approach to impact analysis on the other hand is appropriate where baseline data are missing and a counterfactual is used as a proxy to measure what could have happened without the intervention (Wainaina *et al*., 2012; AIEI, 2021). The methodology has extensively employed PSM and ESR to overcome the econometric limitations that arise when the baseline data are missing while solving for the selectivity bias that arises from the use of cross-sectional data (Wainaina *et al*., 2012; Teklewold *et al*., 2013; Kassie *et al.,* 2018a).

The PSM method relaxes the self-selection bias by comparing beneficiaries and non-beneficiaries but fails to account for unobservable variables (endogeneity) that affect the choice of the technology and outcome variable that are not accounted for directly (Asfaw *et al*., 2012; Shiferaw *et al*., 2014; Khonje *et al.*, 2015; Kassie *et al.,* 2018a). On the other hand, the ESR offers a viable solution for addressing the restrictions of self-selection bias and endogeneity between adopters and non-adopters (Teklewold *et al*., 2013; Shiferaw *et al*., 2014; Kassie *et al.,* 2018a). The model uses conditional means in estimating actual and counterfactual outcomes while accounting for limitations of the existing methodologies for statistical analysis for both observed and unobserved heterogeneities. ESR involves a two-stage estimation process comprising a first-stage (adoption equation) and second-stage (outcome equation) (Shiferaw *et al*., 2015; Khonje *et al.*, 2015; 2018).

However, in situations where more than two categories exist (for instance more than two categories of adopters and non-adopters of pest control technologies), an extension of ESR, multinomial endogenous switching regression (MESR) model is mostly preferred to be used (Teklewold *et al*. 2013; Kassie *et al*., 2015a, b; Khonje *et al*., 2018). According to Teklewold *et al*. (2013), MESR model accounts for the self-selection arising from the choice of potentially interdependent and combined technology packages such as pest control practices and their interactions. The modelling comprises of a two-stage estimation procedure. The first-stage is modelled using a multinomial logit model thus allowing farmers to make choices of either individual or combined pest control practices while considering interactions between them (Kassie *et al.,* 2015a; Khonje *et al*., 2018). In the second-stage the ordinary least squares (OLS) with selection control is used to evaluate the impacts of single and joint technology practices (Khonje *et al*., 2018).

5.2.2 Empirical Model

This study employed a multinomial endogenous switching regression (MESR) model to evaluate the impact of adoption of PPT on maize productivity among smallholder farmers in Rwanda. Productivity was measured in terms of yield i.e. the kilograms of maize harvested per acres (kgs/acre). The MESR model was applied to control for selection bias and interdependence between the outcomes variables (Teklewold *et al*., 2013; Kassie *et al*., 2015a). Following Teklewold *et al*. (2013), the MESR was estimated in two-stages.

In the first stage, a multinomial logit model (MNL) was used to evaluate the factors influencing the choice of pest control practices in Eastern Rwanda using *mlogit* command in STATA version 14. The pest control practices considered included; traditional methods, pesticides, PPT and their combinations. Given the three major pest control technologies used in control of FAW and stemborer pests in Rwanda, namely, traditional methods, pesticides and push-pull technologies, there are eight possible combinations. These comprise of (1) maize plots that did not adopt any of the three technologies, which is the base category (non-adopters) and other maize plots controlled FAW and stemborer using either: (2) traditional methods only, (3) pesticides only, (4) push-pull only, (5) traditional methods + pesticides, (6) traditional methods + push-pull, (7) pesticides + push-pull, and (8) traditional methods + pesticides + push-pull. However, the combination 7 and 8 respectively were not observed from the maize plots using the data under the current study resorting to 6 possible combinations used for the analysis. The multinomial logit model with identically and independently Gumbel distributed error terms, ε_{ij}, is specified following Teklewold *et al*. (2013) as:

$$P_{ij} = \mathrm{p}\left(\eta_{ij} < 0 | X_{ij}\right) = \frac{\exp\left(X_{ij}\beta_j\right)}{\sum_{m=1}^{j} \exp\left(X_{ij}\beta_m\right)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(5.3)}$$

where P_{ij} denotes dependent variable for the pest control management technologies (comprises of traditional methods, pesticides, push-pull, combination of PPT and traditional jointly and a combination of pesticide and traditional jointly) used in controlling FAW and stemborer, X_i is a vector of farm (farm size) , farmers (age, gender, education of household head, family size, wealthy category; livestock ownership and group membership), pest-specific attributes (perceived FAW severity, perceived stemborer severity) and technology-specific attributes (perceived cost of the pest control practice, perceived effectiveness, etc) (Table 5.1) and β a vector of unknown parameters to be estimated. The estimation of the MESR utilizes the maximum likelihood method.

Following Kassie *et al*. (2018b) adoption of the three pest control technologies (Traditional methods, pesticides and push-pull) gives eight possible combinations (no technology, single or a combination of the technologies) that are then analyzed using MNL model giving eight OLS equations. In the base category, non-adoption of pest control technology, was represented as *j=1*. In the second stage, eight pest control technologies (j=1, 2, 3, 4, 5, 6, 7, 8) which represents traditional methods only, pesticides only, push-pull only, combination of pesticide and traditional methods and lastly combination of push-pull and traditional methods on condition that at least one of the pest control technologies was used per every maize plot in the household were analyzed.

The OLS model in the second stage of each outcome equation for both adopters and non-adopters of pest control practices are specified following Teklewold *et al*. (2013) as:

$$\begin{cases} Category\ \ 1\ (Non-adopters)\colon Y_{i1} = \alpha_1 X_i + u_{i1}\ if\ S = 1 \\ \qquad\qquad\qquad \vdots \quad \vdots \qquad \vdots \\ Category\ \ j\ (adopters)\colon \qquad Y_{i1} = \alpha_j X_i + u_{ij}\ \ if\ S = j \end{cases} \quad \text{j=2, 3, 4, 5, 6, 7, 8……... (5.4)}$$

where Y_{ij}'s are the outcome equations of the i^{th} farmer in category, j, and the error terms (u's) that are distributed with zero mean $(E(u_{ij}|X, Z = 0)$ and constant variance $[var(u_{ij}|X, Z)= \sigma_j^2$. Y_{ij} is observed if, and only if, control technology j is chosen and happens when $U_{ij}^* > max_{m\neq j}(U_{im}^*)$. The OLS will be biased if the *ε's* and *u's* are not independent in equation (5.4) and therefore addition of the selection correction terms of the different choices are ideal for a consistent estimation of the α_j. The MESR model follows Durbin and McFadden (1984) (henceforth referred to as DM model) and Bourguignon *et al*. (2007) to correct for selectivity bias. The advantage of the approach is that it evaluates the individual practices as well as alternative combinations of practices while capturing the selectivity bias and the interactions between choices of different practices (Mansur *et al*., 2008; Wu and Babcock, 1998). The linearity assumption is assumed in the DM model as follows; $E(\varepsilon_{ij}\,|\mathrm{u}_{i1} \ldots \ldots \mathrm{u}_{ij}) =$

$$\sigma_j \sum_{m\neq j}^{j} r_j(\mathrm{u}_{im} - E(\mathrm{u}_{im}))$$

where the correlation between *ε's* and *u's* sums to zero by construction, that is $\sum_{m=1}^{j} r_j = 0$.

Therefore, equation (5.4) was re-specified for adopters and non-adopters following Teklewold *et al*. (2013) as:

$$\begin{cases} Category\ \ 1\!: Y_{i1} = \alpha_1 X_i + \sigma_1\lambda_1 + \omega_{i1}\ if\ S = 1 \quad (6a) \\ \qquad\qquad\quad \vdots \qquad \vdots \qquad\quad \vdots \\ Category\ \ j\!: Y_{ij} = \alpha_j X_i + \sigma_j\lambda_j + \omega_{ij}\ \ if\ S = j \quad\ (6b) \end{cases} \qquad \text{j=2, 3, 4, 5, 6, 7, 8} \ldots\ldots\ldots (5.5)$$

where σ_j denotes covariance between ε's and u's while inverse mills ratio (IMR) denoted by λ_j is computed from the estimated probabilities in equation (5.3) as follows:

$$\lambda_j = \sum_{m\neq j}^{j} \rho_j \left[\frac{\hat{S}_{im} In(\hat{S}_{im})}{1-\hat{S}_{im}} + In(\hat{S}_{ij})\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5.6)$$

where ρ is the correlation coefficient of *ε's* , *u's* and $\omega's$ are error terms with an expected value of zero. In the multinomial choice setting, there are *j-1* selection correction terms, one for each alternative pest control technology. Bootstrapping of standard errors in equation (5.5) is used to control for the heteroscedasticity arising from the generated regressor (λ_j). Equation (5.5) is augmented by addition of plot characteristics (perceived soil fertility) and plot varying covariates such as seed rate, average fertilizer use, pesticide and labour use. The plot-varying covariates such as plot soil fertility are included to control for unobserved heterogeneity (Wooldridge, 2002).

The average treatment effect (ATT) of treatment was then computed by making comparison in expected outcomes of adopters and non-adopters of pest control technologies. However, Teklewold *et al*. (2013) argued that the problem of estimating the counterfactual with the use of observational data in impact evaluation (outcome adopters could have received had they not adopted the pest control technologies) is problematic. Following Teklewold *et al*. (2013), the average treatment effect (ATT) on the treated was computed as the difference between the actual scenarios for adopters and counterfactual scenarios for non-adopters in equation 5.7 and 5.8 as follows:

Actual adoption observed in the sample (Adopters with adoption)

$$\begin{cases} E(Y_{i2}|S=2) = \alpha_2 X_i + \sigma_2 \lambda_2 & (5.7a) \\ \quad \vdots \quad\quad \vdots \quad\quad\quad \vdots & \\ E(Y_{ij}|S=j) = \alpha_j X_i + \sigma_j \lambda_j & (5.7b) \end{cases} \quad \text{j=2, 3, 4, 5, 6, 7, 8} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \;(5.7)$$

The counterfactual unobserved in the sample (Adopters, had they decided not to adopt)

$$\begin{cases} E(Y_{i1}|S=2) = \alpha_1 X_i + \sigma_1 \lambda_2 & (5.8a) \\ \quad \vdots \quad\quad \vdots \quad\quad\quad \vdots & \\ E(Y_{i1}|S=j) = \alpha_1 X_i + \sigma_1 \lambda_j & (5.8b) \end{cases} \quad \text{j=2, 3, 4, 5, 6, 7, 8} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \;(5.8)$$

The unbiased estimates of the ATT was then derived from the expected values in equation 5.7 and 5.8. The ATT is expressed as the difference between equation (5.8a) and (5.7a) or equation (5.7b) and 5.8b) as follows:

$$ATT = \begin{cases} E(Y_{i2}|S=2) - E(Y_{i1}|S=2) = (\alpha_2 X_i + \sigma_2\lambda_2) - (\alpha_1 X_i + \sigma_1\lambda_2) & (5.9a) \\ or & \\ E(Y_{ij}|S=j) - E(Y_{i1}|S=j) = (\alpha_j X_i + \sigma_j\lambda_j) - (\alpha_1 X_i + \sigma_1\lambda_j) & (5.9b) \end{cases} \quad .. (5.9)$$

$$ATT = \begin{cases} E(Y_{i2}|S=2) - E(Y_{i1}|S=2) = X_i(\alpha_2 - \alpha_1) + \lambda_2(\sigma_2 - \sigma_1) & (5.10a) \\ or & \\ E(Y_{ij}|S=j) - E(Y_{i1}|S=j) = X_i(\alpha_j - \alpha_1) + \lambda_j(\sigma_j - \sigma_1) & (5.10b) \end{cases} \quad .... (5.10)$$

When adopters have similar attributes as non-adopters, the expected change in adopters' mean outcome are represented by first term on the right-hand side of equation 5.10. The remaining term (λ_j) denotes selection term capturing all potential effects of difference in unobserved variables.

5.2.3 Data Sources and Sampling technique

The study used survey data collected in 2019 from a sample of 398 households operating 967 maize plots in the Nyagatare and Gatsibo districts of Rwanda (Figure 5.1). A stratified sampling method was used to select the respondents. In the first step, Nyagatare and Gatsibo districts were purposively selected since they were the pilot sites for the PPT project. Within each district, the pilot had been conducted in one sector and thus, Gatunda and Nyagihanga sectors from the Nyagatare and Gatsibo districts respectively were purposively selected. A stratified sampling procedure was used to draw the sampling frames for adopters and non-adopters of PPT at the sectoral level. In the second step, a simple random sampling procedure was used to select 194 PPT adopter and 204 non-adopters from the sampling frames provided by the Rwanda Agricultural Board (RAB).

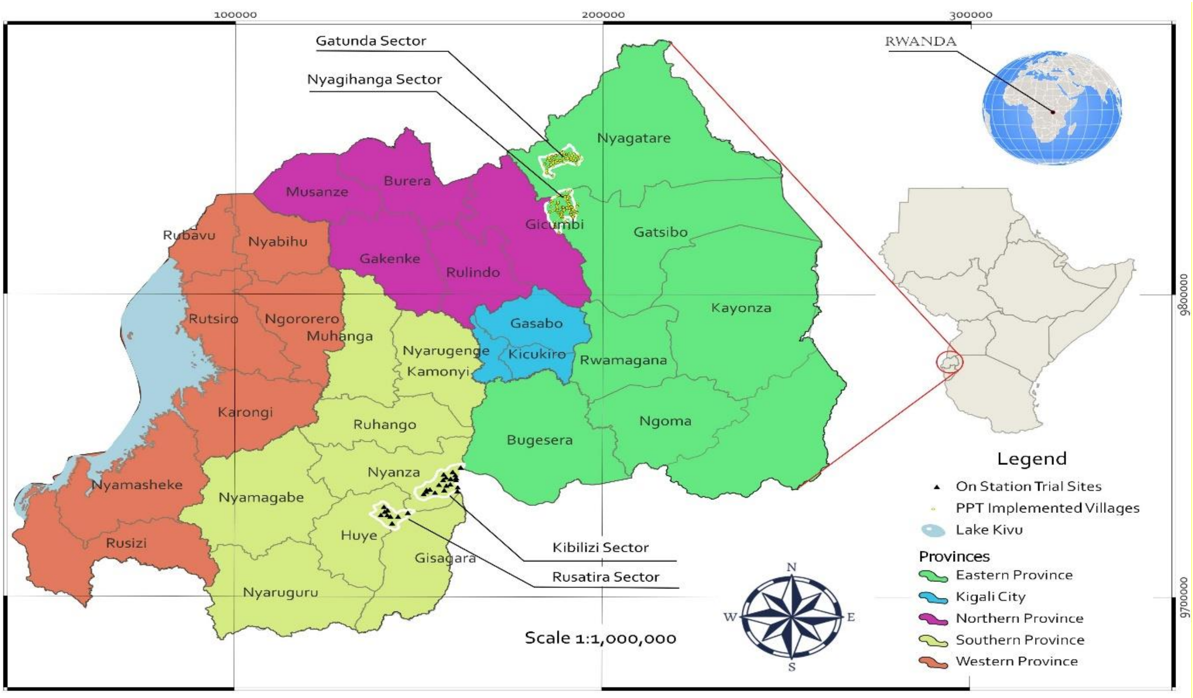

Figure 5.1: Map of the study area

Source: *Icipe* GIS Section

The selected households were then interview using pre-tested semi-structured questionnaires programmed into CSpro. Adopters in this study referred to maize farmers who had used PPT continuously for more than a year at the time of data collection. The data collected comprised of both household, plot and technology characteristics as well as pest constraints, pest management technologies and maize productivity. The data was analyzed in Stata version 14.

5.2.4 Measurement of Variables

Table 5.1 presents the description and measurement of the variables used in the analysis. The outcome variables of interest in this study are the choice of pest control practices and maize yields. The pest control practices used to control FAW and stemborer pests in maize are represented as a categorical variables with eight (8) options. The dependent variable for the MNL model had eight (8) categories which comprised of 1= pesticides, 2= Traditional methods, 3= PPT, 4= a combination of pesticides + traditional methods, 5= a combination of pesticides+ PPT, 6= a combination of PPT + traditional, 7= a mixture of pesticides + traditional + PPT and lastly 8= None of pesticide, PPT or traditional practices is adopted in the maize plot.. On the other hand, maize yields a proxy for productivity measured in Kgs/acre was used as a dependent variable in the OLS model. The choice of the independent variables for both models were informed by previous empirical studies (Teklewold *et al*., 2013; Kassie *et al*., 2015a and b; 2018a; 2020; Khonje *et al*., 2015; 2018; Diiro *et al*., 2018; Maina *et al*., 2020; Gebre *et al*., 2021; Manda *et al*., 2021; Kanyenji *et al*., 2020; 2022; Niassy *et al*., 2020; 2022).

Table 5.1: Description of variables used in the Multinomial Endogenous Switching Model

Variable	Description of the variable	Unit of Measurement
Dependent Variables		
Choice of pest control practice	Technology used by the farmers to control FAW and Stem borer pest	Categorical with 8 options
Maize productivity	Maize yields	Kgs/acre
Exogenous Variables		
Perceived cost of technology	Farmers perceptions on the cost of pest control practice	Binary (1=costly, 0=Otherwise)
Wealth category	Household asset index computed from PCA	Index (-1 to +1)
Perceived effectiveness	Perceived technology effectiveness in the control of FAW and stemborer pests	Binary (1=effective, 0= otherwise)
Perceived pest severity	Percent of maize plot that the farmer perceived to be severely infested by FAW and stemborer pest	Binary (1=Severe, 0 otherwise)
Group membership	Membership to a farmer group	Binary (1=Yes, 0 otherwise)
Family size	Number of persons in the household	Number
Farm size	Area under maize cultivation	Acres
Perceived soil fertility	Farmers perceptions on plot soil fertility	Binary (1=fertile, 0 otherwise)
Age	Age of the household head	Years
Gender	Gender of the household head	Binary (1=Male, 0 Female)
Education	Number of years spent in school	Years
Livestock ownership (TLU)	Livestock ownership	Number
Cost of seed	Costs of seeds per acre	RWF/acre
Cost of pesticides	Costs of pesticides	RWF/acre
Fertilizer use	Fertilizer used in kilograms per acre	Kgs/acre
Labour cost	Labour usage in maize production	Man days per acre

Note: TLU is tropical livestock unit. TLU corresponding for different livestock were computed as camels=1, cattle=1, donkeys=0.8, goats and sheep=0.2 and poultry=0.04 (WISP, 2010); Rwandese Franc (RWF), Kilograms (Kgs).

Farmer's perception on the cost of pest control practices measured as a dummy variable equivalent to 1 if households perceived pest control practice to be costly and zero otherwise Farmers were asked about their perceptions of the cost of pest control practice whether it was a constraint to its adoption. . The available literature on the influence of perceived cost of technology on the technology adoption is mixed (Mwangi and Kariuki, 2015; Muzira *et al*., 2021; Otieno *et al*., 2023).

Farmers were asked to compare the effectiveness of the pest control practice with other methods in terms of controlling FAW and stemborer. Their responses were measured as a dummy variable, equivalent to one if the pest control practice was rated effective and zero otherwise. Positive associations have been reported between the perceived effectiveness of new practices and their technology adoption (Gwada *et al*., 2019).

Household asset index was used as a proxy for wealth category in measuring resource constraint. Following Davila *et al*. (2022) farmers were asked six questions categorized into 4 levels comprising of the asset ownership of beds and mobile phones, house construction material such as the roofing and wall materials, access to water/sanitation and source of lighting (Table 5.2). A principal component analysis (PCA) was then used to compute a wealth index based on the household assets ownership which was weighted to generate an index that measured the wealth index status of the household. The household wealth index computed was measured as a continuous variable. Available literature on the influence of wealth category on the technology adoption is positive (Cavanagh *et al*., 2017; Nyangau *et al*., 2020; Kanyenji *et al*., 2022).

Farmers were asked of the percentage of maize plot perceived to be severely infested by FAW and stemborer pests. Their responses were measured as a dummy variable equivalent to one if the farmer perceived the plot to be severely infested by the pest and zero otherwise. Available literature on the effect of FAW and stemborer pest perception and adoption of agricultural technologies is positive (Murage *et al*., 2015a; Kassie *et al*., 2015b; Gwada *et al*., 2019).

Table 5.2: Household asset ownership

Asset Category	Question	Unit of measurement
Asset Ownership	Does a household own more than three beds?	Dummy (1=Yes, 0 otherwise)
	Does a household own more than two mobile phones?	Dummy (1=Yes, 0 otherwise)
Housing construction material	What is the main material used for roofing the house?	Dummy (1=improved if made of metal sheets/corrugated iron or concrete), 0 otherwise)
	What is the main construction material of the external walls	Dummy (1=Improved if made of mud bricks with cement, oven-fired bricks, logs with mud and cement, stones, cement blocks or wooden planks), 0 otherwise)
Access to water and sanitation	A proxy for access was distance to the drinking water source	Continuous (Walking minutes)
Source of Lighting	What is the main source of lighting in the residence of the household?	Dummy (1=Yes if using electricity, generator or solar, 0 otherwise)

Farmer's perceptions of their maize plot fertility was used as a proxy for soil fertility. Farmers perceiving plots to be of low fertility and susceptible to soil erosion increases investments in agricultural technologies to restore fertility. Their responses were later grouped into dummy variable, which took value of one if a farmer perceived soil to be fertile and zero otherwise. The available literature shows positive relationship between soil fertility perception and the adoption and impact of agricultural technologies on the other side (Muriithi *et al.*, 2018; Kassie *et al*., 2018a; 2020; Kanyenji *et al*., 2020; Gebre *et al*., 2021). Gender, age, education, family size, group membership and farm size were also included as control covariates following previous studies (see Kassie *et al*., 2015a and b; 2018a, and b; 2020; Khonje *et al*., 2015; 2018; Diiro *et al*., 2018; Maina *et al*., 2020; Gebre *et al*., 2021; Manda *et al*., 2021; Kanyenji *et al*., 2020; 2022). Gender was measured as a binary variable taking a value of one if the household head was male and zero female. Several previous studies have shown indeterminate relationship between gender and adoption of agricultural technologies (Murage *et al*., 2015a; Kassie *et al*., 2015b; 2020). On the other hand, family size was also included as a proxy for family labour and measured as the total number of persons per household. Several previous studies have shown positive associations between family size on one side and the PPT adoption and its impact on the other (Kassie *et al*., 2015b; 2018a; Maina *et al*., 2020).

Age was measured in years. Education on the other hand, was measured as the number of years of formal schooling spent by the household head. A number of previous studies have shown positive association between the age and education on one side and the adoption of agricultural technologies on the other (Asfaw *et al.,* 2012; Teklewold *et al*., 2013; Kassie *et al*., 2011; 2018; Niassy *et al*., 2020; Maina *et al*., 2020).

Group membership was measured as a binary variable with a value of one if a farmer was a member of an agricultural group and zero otherwise. Previous studies have shown a positive association between group membership and adoption of agricultural technologies (Kassie *et al.,* 2011; Teklewold *et al*., 2013; Maina *et al.,* 2020; Niassy *et al*., 2020; Gebre *et al*., 2021). Farm size was also incorporated as a source of land availability for enhancing adoption of agricultural technologies and measured as a continuous variable (number or acres farmer owner household). Available literature have shown positive relationship between farm size and adoption of agricultural technologies (Teklewold *et al.,* 2013; Kassie *et al*., 2015b). On basis of the outcome equation in the yield functions, cost of seeds, cost of pesticides, fertilizer and labour were incorporated. Cost of seeds was measured as a continuous variable by taking actual costs in Rwandese Franc spent in purchasing the seeds per acre. Cost of pesticides was used as a proxy for the control of pests and weeds in crop production. It was measured by summing up the total costs incurred for insecticides and herbicides used per acre by maize farmers in control of pests and weeds infestation. Later the costs of pesticides and seed cost were summed together and included in the yield function analysis as one variable.

Fertilizer use was measured as the number of kilograms of DAP and Urea used per acre. Labour on the other hand, was measured in man-days per acre. Labour plays an important factor of production in doing farming activities from ploughing, planting, weeding, harvesting to threshing and is one of the major constraints in the adaptation of new agricultural technologies. Available literature have shown a positive relationship between input variables that is seeds, fertilizer, labour and pesticides on one side and maize productivity on the other side (Teklewold *et al*., 2013; Kassie *et al*., 2015a; 2018a and b; 2020; Kanyenji *et al*., 2020; Gebre *et al*., 2021; Diiro *et al*., 2018; Niassy *et al*., 2022).

5.3. Results and Discussions

5.3.1 Descriptive Results

Table 5.3 presents the distribution of pest management technologies used in the control of FAW and stemborer infestation by smallholder maize farmers in Rwanda. Above a quarter of the maize farmers in Rwanda did not control for FAW and stemborer in their maize plots. The most widely used pest control practices in declining order of importance included traditional methods, PPT and pesticides as reported by 25, 20 and 14 percent of the respondents respectively Another 8 percent of the households in Eastern Rwanda used a combination of pesticides and traditional methods while 7 percent of the respondents used a combination of PPT and traditional methods. However, none of the households reported to use the combination of pesticides + PPT, and a mixture of pesticides+ traditional + PPT practices since PPT was used under trials to affirm its effectiveness in control of FAW pest.

Table 5.3: FAW and Stemborer pest control practices in Nyagatare and Gatsibo districts of Rwanda

Strategy set	T_1	T_0	Pe_1	Pe_0	PP_1	PP_0	Frequency	Percent (%)
No technology method		√		√		√	249	25.75
Traditional methods	√						238	24.61
Pesticides only			√				140	14.48
PPT only					√		196	20.27
Pesticides+ Traditional method	√		√				74	7.65
PPT + Traditional method	√				√		70	7.24
Pesticides+ PPT method			√		√		0	0.00
Pesticides+ PPT+ Traditional method	√		√		√		0	0.00
Total							967	100.00

Note: T, Pe and PP denotes Traditional, Pesticide and Push-pull technologies respectively. Subscript 0 denotes non-adoption and 1 adoption of that pest management technology in controlling FAW and stemborer pests.

The results (Table 5.4) show that eighty percent of the respondent were male-headed with significant differences observed between the non-adopters and PPT adopter. The average age of the household heads was statistically different across the adopters and non-adopters on PPT. On average, the maize farmers were middle aged (48 years) with PPT adopters being slightly older compared to the non-adopters. The PPT adopters (6.42) were relatively more educated compared to the non-adopters (4.84) with an average of 5 person per household. Further, the PPT adopter maize farmers were coming from wealthy households with an average wealth index of 1.86 compared to the non-adopters who had an average wealth index of 1.13.

Table 5.4: Demographic characteristics of maize farmers in Rwanda differentiated by adopters and non-adopters of PPT

Variables	PPT adopter (n=500)	PPT non adopter (n=467)	Pooled (n=967)	Statistic
Continuous variables	**Means (Standard errors)**			**T test**
Age (Years)	50.54 (11.43)	45.12 (11.72)	47.92 (11.88)	7.28***
Education (Years)	6.42 (2.89)	4.84 (3.00)	5.65 (3.05)	8.36***
Family size (Number)	5.35 (2.50)	4.94 (1.92)	5.15,(2.25)	2.89***
Farm size	1.04(0.87)	0.89(1.50)	0.97(1.22)	1.92*
Wealth Index	1.86 (2.94)	1.13(3.35)	1.51(3.17)	3.62***
Maize yield	1688.82 (1660.82)	617.50 (719.60)	1171.34 (1400.51)	12.86***
Seed cost	2602.39 (3343.68)	7897.08 (13127.52)	5159.39 (9793.67)	8.72***
Fertilizer rate	20.20(40.99)	22.28(45.95)	21.21 (43.45)	0.74
Cost of labour (man days per acre)	49.45(59.70)	61.95(78.79)	55.19 (69.82)	2.79***
Pesticide cost	3507.82 (9471.03)	4179.32 (30959.27)	3832.11 (22557.02)	0.46
Categorical variables		**Percentages**		**Chi^2 test**
Perceived technology cost	46.80	70.24	58.12	54.48***
Perceived technology effectiveness	60.20	24.84	43.12	123.10***
Group membership	60.80	53.96	57.50	4.62***
Gender of the household head (% Male)	74.80	86.30	80.35	20.21***
Perceived FAW pest severity (% severe)	88.80	79.44	84.28	15.96***
Perceived stemborer pest severity (% severe)	65.60	50.75	58.43	21.92***
Perceived soil fertility (percentage fertile)	94.60	80.09	87.59	46.80***

Note: ***, ** and * denotes level of significance at 1%, 5% and 10% respectively.

About 58 percent of the respondent in the study area were belonging to a farmer group through which they procured inputs, marketed output and acquired market information on both markets and PPT. A majority of the non-adopters perceived the cost of technology (70 percent) to be a constraint towards adoption of pest control practices compared to the adopters of the technology (47 percent).

About 43 percent of the farming households perceive the pest control practices to be effective in the control of FAW and stemborer pests with significant differences observed between the adopter and non-adopter of agricultural technologies. Furthermore, eight-four and fifty-eight percent of the maize plots were reported to have been infested with FAW and stemborer pest respectively, with significant differences observed between the maize plots for adopters and non-adopters of PPT. Moreover, eighty-eight percent of the maize plots were rated to be fertile with significant difference observed between the adopter and the non-adopter.

The average yield for PPT adopter's plots (1689 kgs/acre) was significantly higher compared for the non-adopters plots (618 kgs/acre). The PPT adopter maize farmers were also owning larger acreages of maize farm sizes (1.04 acres) compared to the non-adopters (0.89 acres). Moreover, the non-adopters spends significantly higher costs of seeds per acre (7897 Rwandese Franc) and more labour days per acre (62 days) compared to the adopters of PPT using 2602 Rwandese Franc and forty-nine days respectively.

The labour use in person days per acre on maize plots farming activities was significantly higher for non-adopters compared to the adopters of PPT. The possible reason being that PPT had already established in most farm maize plots at the time of survey unlike labour intensive at the time of initial establishment which reduces substantially one the cropping system is established (Muriithi *et al.*, 2018).

4.3.2 Econometric Results

Table 5.5 presents the MNL maximum likelihood estimates (MLE) of the factors influencing adoption of FAW and stemborer pest control practices among smallholder maize farmers in Eastern Rwanda. The control group (no technology) was used as the base scenario for comparison with all other scenarios. The Breusch-pagan test rejected the null hypothesis of homoscedasticity (Chi^2 (1) =15.67 Prob > Chi^2=0.0001) indicating the presence of heteroscedasticity that was corrected using robust standard errors.

The generalized Hosmer-Lemeshow statistic (Chi^2 (8) = 12.47 Prob > Chi^2=0.131) was insignificant indicating that the model fitted the data well while Wald statistic was significant at one percent to affirm the results. Furthermore, the results of the Hausman test (Chi^2 {44} = 4.862; p-value=1, for all alternatives), Suest-based Hausman tests (Chi^2 {44} = 31.554; p-value=1) and small-Haiao test (Chi^2 {44} = 56.203; p-value=1, for all alternatives) indicated that the IIA was not violated and the estimated results were consistent, efficient and reliable (Mwololo *et al*., 2019). Therefore, the results of the marginal effects of the MNL model indicated that perceived cost of technology, perceived effectiveness, wealth index, perceived pest severity, perceived soil fertility and group membership significantly influenced adoption of pest control practices.

The perceived cost of technology, a proxy for technology adoption constraint, positively and significantly influenced the adoption of traditional methods, but negatively influenced adoption of PPT in isolation and a mix of PPT and traditional methods at the one and 5 percent level respectively. A farmer perceiving the cost of pest control practice to be higher were more likely to adopt traditional methods by 5.5 percent.

Table 5.5: Multinomial Logit (MNL) MLE of the adoption of FAW and Stemborer pest control practices in Eastern Rwanda

Variables	Traditional	Pesticides	Push-Pull (PPT)	Pesticides and Traditional	PPT and Traditional
Perceived technology cost	0.0600 (0.0256)**	-0.0554 (0.0211)***	-0.0857 (0.0235)***	-0.0355 (0.0184)**	-0.0377 (0.0165)**
Perceived technology effectiveness	-0.3020 (0.0283)***	0.1058 (0.0185)***	0.1453 (0.0216)***	0.0327 (0.0148)**	0.0391 (0.0148)***
Wealth Index	0.1050 (0.0755)	0.0249 (0.0642)	0.1841 (0.0810)**	0.0198 (0.0555)	0.0249 (0.0547)
Perceived FAW severity	-0.0650 (0.0316)**	0.0707 (0.0349)**	0.0241 (0.0366)	-0.0139 (0.0223)	0.0525 (0.0310)*
Group membership	-0.0876 (0.0245)***	-0.0684 (0.0203)***	0.1137 (0.0255)***	-0.0379 (0.0169)**	0.0497 (0.0189)***
Farm size	-0.0375 (0.0159)**	0.0412 (0.0071)***	0.0153 (0.0104)	-0.0146 (0.0108)	-0.0073 (0.0090)
Age	-0.0017 (0.0010)*	-0.0059 (0.0010)***	0.0048 (0.0011)***	0.0001 (0.0007)	0.0015 (0.0007)**
Gender	-0.0863 (0.0317)***	0.1289 (0.0379)***	-0.0269 (0.0302)	0.0359 (0.0252)	0.0022 (0.0211)
Education	-0.0119 (0.0043)***	-0.0111 (0.0036)***	0.0149 (0.0041)***	-0.0002 (0.0030)	0.0000 (0.0028)
Perceived soil fertility	-0.0629 (0.0405)	0.0458 (0.0296)	0.1374 (0.0358)***	0.0303 (0.0229)***	-0.0891 (0.0471)*
Constant	1.0928 (0.5695)**	-1.1815 (0.8240)	-4.6502 (0.7446)***	-2.4909 (0.9043)*	-4.7897 (1.0318)***
Number of observations	967				
Wald chi^2 (65)	478.430				
Prob > chi^2	0.0000				
Pseudo R^2	0.1469				
Log pseudo-likelihood	-1392.6531				
Breusch-pagan/Cook-Weisberg	Chi^2 (1)=15.67 Prob > Chi^2=0.0001				
Mean VIF	1.12				

Note: Marginal effects of coefficients and robust standard error in parenthesis. ***, ** and * denotes level of significance at 1%, 5% and 10% respectively

On the other hand, farmers perceiving the cost of technology to be expensive, were less likely to adopt pesticides and PPT in isolation, and their combinations with traditional methods by 6.0, 8.6, 3.6 and 3.8 percent on their maize plots respectively. Muzira *et al*. (2021) noted that cost of hired labour was a major constraint to farmers investing in adoption of soil fertility management and conservation technologies in potato production systems in Uganda. Contrary, Otieno *et al*. (2023) also reported that mango farmers in Kenya were more likely to adopt IPM technology when the benefits of the technology outweighed the cost of adoption.

Perceived technology effectiveness positively and significantly influenced the adoption of pesticides, PPT, a mix of PPT and traditional methods, and a combination of pesticides and traditional methods at the one and 5 percent level respectively, but negatively and significantly influenced the adoption of traditional practices at the one percent level. Farmer perceiving the technology to be effective were likely to use pesticides, PPT, a mix of PPT and traditional methods, and a combination of pesticides and traditional methods by 10.6, 14.5, 3.9 and 3.3 percent respectively, but less likely to use traditional practices by 30.2 percent. Intuitively, farmers will use a pest control practice that effectively controls FAW and stemborer. Gwada *et al*. (2019) find a positive relationship between perceived technology effectiveness and adoption of PPT.

The wealth status (wealth index) positively influenced the adoption of PPT in isolation at the 5 percent level but was insignificant for all other technology combinations. Wealthier farmers were more likely to adopt PPT in the control of FAW and stemborer than their poor counterparts by at least 18 percent. Source of wealth provides avenues of resource endowments that plays key role in adoption of agricultural practices (Kanyenji *et al*., 2022). The possible reason is that PPT requires huge capital investments during its initial establishment but reduces sequentially in the subsequent seasons. Cavanagh *et al*. (2017) reported that wealth farmers were in position of adopting more climate smart agricultural practices in Kenya that needed huge capital investments for implementation compared to their counterparts. Kanyenji *et al*. (2022) also reported that wealthy farmers in Kenya were less likely to adopt farmyard manure due to availability of capital that enabled them to purchase farm inputs such as inorganic fertilizer.

Farmer's perception about the severity of FAW positively and significantly influenced the adoption of pesticides and a mix of PPT and traditional methods at the 5 and 10 percent level, but negatively and significantly influenced the adoption of traditional methods at the 5 percent level. Farmers perceiving FAW to be more severely infested on their maize plots were more likely to use pesticides and a mix of PPT and traditional methods by 7.1 and 5.3 percent, but less likely to use traditional methods by 6.5 percent respectively. Intuitively, farmers always will always choose the pest control practices that will effectively control for the FAW and stemborer constraints. The results corroborates the findings of Murage *et al.* (2015a) in East Africa, who reported that farmers perceiving Striga infestation as severe problem on their farm plots were more likely to adopt agricultural practices compared to their counterparts. Kassie *et al*. (2018a) and Gwada *et al*. (2019) in Kenya, also observed a positive relationship between stemborer pest severity and adoption of agricultural technologies.

Social capital through being a member to a group dealing with agricultural activities positively influenced the adoption of PPT and a mix of PPT and traditional methods, but negatively influenced the adoption of traditional methods, pesticides method and a combination of pesticides and traditional methods at the one and 5 percent level respectively. The groups provides platform for availing farm inputs, transfer of new information and knowledge to farmers (Okello *et al*., 2021; Kanyenji *et al*., 2022).

Farmers belonging to a group dealing with an agricultural activity were more likely to adopt PPT method and a mix of PPT and traditional methods by 11.4 and 5.0 percent, but less likely to adopt traditional methods, pesticides usage and a combination of pesticide and traditional methods by 8.8, 6.8 and 3.8 percent respectively. The results are in agreement with the findings of preceding studies (Chepchirchir *et al*., 2017; Kanyenji *et al*., 2011). The results finds support with Chepchirchir *et al*., (2017) who observed that farmers belonging to social groups were in position of gathering more information through their contacts and accessed market for both inputs and outputs that increased chances of adopting new agricultural technologies. A similar results was reported in Kanyenji *et al*. (2022) in Kenya, who observed that group membership provided platform for farmers on information sharing on the advantages and disadvantages and required inputs for the adoption of two technologies and other innovations.

The age of the farmer positively and significantly influenced the adoption of PPT method and a mix of PPT and traditional methods, but negatively influenced the adoption of pesticides and traditional methods in isolation at the one, 5 and 10 percent respectively. Age plays a key role in technology adoption as older farmers are more knowledgeable, wealthy and experienced therefore having higher chances of adopting new agricultural technologies (Kassie *et al*., 2013). A year increase in age increased the probability of a farmer adopting PPT method and a mix of PPT and traditional methods on their maize plots by 0.5 and 0.2 percent, but reduced the adoption of pesticides and traditional method in isolation by 0.6 and 0.2 percent respectively. Maina *et al*., (2020) reported in Kenya a positive association between age and adoption of brachiaria that is a component of PPT. Teklewold *et al*. (2013) also reported in Ethiopia that older farmers who had experience were more likely to adopt combination of sustainable agricultural practices (SAPs) compared to their counterparts.

The gender of the farmer positively and significantly influenced the adoption of pesticides method, but negatively and significantly influenced the adoption of traditional methods at the one percent level. Being a male increased the likelihood of adopting pesticides method by 12.9 percent, but reduced the adoption of traditional methods by 8.6 percent respectively. This result although mixed but are in agreement with the results of the previous studies (Murage *et al*., 2015a; Kassie *et al*., 2015b; 2020; Mahoussi *et al*., 2021). Mahoussi *et al*. (2021) in Benin in West Africa, who observed a positive relationship between gender and adoption of improved maize seeds. A similar results was reported by Murage *et al*. (2015a) observed a negative relationship between gender and adoption of PPT stating that the agricultural technologies favored women preferences compared to their male counterparts.

Education of the farmer positively and significantly influenced the adoption of PPT method, but negatively influenced the adoption of traditional method and pesticide usage in isolation at the one percent level respectively. Education plays key role in decoding information related to agricultural technologies and even interacting effectively with other information sources that facilitate in adoption and dissemination of similar technologies (Maina *et al*., 2020; Niassy *et al*., 2020). A year increase in the level of education of the farmer increased the likelihood of adopting PPT method by 1.5 percent, but reduced the likelihood of using traditional method and pesticides usage by 1.2 and 1.1 percent respectively. These results tally with those of Maina *et al*. (2020) who reported that more educated farmers had higher chances of adopting Brachiaria that is a component of PPT through integrating new information and assessing the advantages of using the Brachiaria in Kenya.

Plot covariates such as perceived soil fertility play key role in the adoption of pest control practices (Kassie *et al*., 2018a; Maina *et al*., 2020). The perceived soil fertility positively influenced the adoption of PPT method and a combination of pesticides and traditional methods, but negatively influenced the adoption of using a mix of PPT and traditional methods at one percent level respectively. This is possible as farmers adopts agricultural technologies that increases soil fertility (Kanyenji *et al*., 2020). Farmers perceiving the plot to be fertile increased the adoption of PPT method and a combination of pesticides and traditional methods by 3.0 and 13.7 percent, but reduced adoption of using a mix of PPT and traditional methods s by 8.9 percent respectively. These results supports the findings of Kanyenji *et al*. (2020), who reported that farmers increased the adoption of soil carbon enhancing practices in Kenya stating that mulching increased soil organic matter which later improved the soil structure and soil fertility. Kassie *et al*. (2018a) also observed that farmers perceiving positive plot soil fertility increased the probability of adopting PPT in Kenya relative to their counterparts.

Farm size positively and significantly influenced the adoption of pesticides method, but negatively and significantly influenced the adoption of traditional method at the one and 5 percent level respectively. An increase in the size of the farm size by one acre increased the likelihood of using pesticides method in control of FAW and stemborer by 4.1 percent, but reduced the likelihood of using traditional method by3.8 percent respectively. The results are in support with the findings of the previous studies (Teklewold *et al.,* 2013; Kassie *et al*., 2015b). Teklewold *et al*. (2013) in Ethiopia, who reported that farmers who were having larger farm sizes had higher chances of adopting sustainable agricultural practices due to increased demand for labor-saving technologies. A similar result was reported in Kassie *et al.* (2015b) in Eastern and Southern Africa, who observed a positive relationship between farm size and adoption of sustainable intensification practices.

Table 5.6 presents the MESR estimates of the impact of adoption of alternative pest control practices on maize yields in Eastern Rwanda. The results indicate that the adoption of PPT and a mix of PPT and traditional methods significantly increased maize yield while adoption of pesticide, traditional methods in isolation and a combination of pesticides and traditional methods significantly decreased maize yield for both adopters and non-adopters. The adoption of PPT increased maize yield by 59 percent (607 kilograms per acre per season (kgs/acre/season)) while a mix of PPT and traditional methods increased by 70 percent (571 kgs/acre/season). On the other hand, adoption of pesticides methods decreased maize yield by 46 percent (646 kgs/acre/season), traditional methods by 7 percent (36 kgs/acre/season) while a combination of pesticides and traditional methods reduced by 24 percent (182 kgs/acre/season).

After comparison with their counterfactuals, there was significant differences in the maize yield of the adopters of the pest control practices compared to their non-adopters counterparts. Furthermore, the maize yield difference between the average treatment effect on the treated (ATT) and average treatment effect on the untreated (ATU) translating to total heterogeneity effect (HT) revealed that an average increment in maize yield per acre by 137 and 112 kilograms (kgs) with adoption of PPT in isolation and a mixture of PPT and traditional methods respectively. However, on the other hand, adoption of traditional methods, pesticides in isolation and a combination of pesticides and traditional methods reduced the maize yield per acre per season by 6, 443 and 201 kgs respectively. An increment in maize yield by 59 and 70 percent through adoption of PPT in isolation and a mix of PPT and traditional methods respectively are consistent with recent study in Malawi and Kenya, which reported a 47 and 61 percent increment with adoption of PPT respectively (Niassy *et al*., 2022; Kassie *et al*., 2018a).

Table 5.6: MESR estimates of the impact of alternative FAW and Stemborer pest control practices on maize yields in Eastern Rwanda

Sample	To adopt (Actual outcome)	Not to adopt (counterfactual outcome)	Average Treatment effect	Changes (%)
Adopters	**Average Treatment Effect for the Treated (ATT) (Kgs/acre)**			
Traditional only	507.86	544.26	-36.40	-6.69%
Pesticides only	763.59	1409.09	-645.50***	-45.81%
Push-pull (PPT) only	1635.44	1028.67	606.77***	58.99%
Pesticides & Traditional combined	585.61	767.72	-182.11*	-23.72%
Push-pull & Traditional combined	1382.01	811.15	570.86***	70.38%
Non-adopters	**Average Treatment Effect for the Untreated (ATU) (Kgs/acre)**			
Traditional only	584.06	626.41	- 42.35***	- 6.76%
Pesticides only	424.11	626.41	-202.30***	-32.30%
Push-pull (PPT) only	1096.63	626.41	470.22***	75.07%
Pesticides & Traditional combined	645.48	626.41	19.07	3.04%
Push-pull & Traditional combined	1085.72	626.41	459.31***	73.32%
Total Heterogeneity Effect (HT)			**HT=ATT –ATU (Kgs/acre)**	
Traditional only	-36.40	-42.35***	.5.95***	
Pesticides only	-645.50***	-202.30***	-443.20***	
Push-pull (PPT) only	606.77***	470.22***	136.55***	
Pesticides & Traditional combined	-182.11*	19.07	-201.18***	
Push-pull & Traditional combined	570.86***	459.31***	111.55***	

Note: the ATET and ATEU estimates are computed based on the selectivity corrected yield equations (MESR), details equations under each pest control technologies conditions are presented in appendices. ***, ** and * denotes level of significance at 1%, 5% and 10% respectively

This findings also supports the results of Kassie *et al*. (2018a) in Kenya, who observed that farmers adopting PPT increased their maize yield by 61.9 percent translating to 619 kilograms per acre. Kanyenji *et al*. (2022) in Kenya, also reported an increment in maize yield by 162 kgs per acre (18 percent), 288 kgs per acre (35 percent) and 260 kgs per acre per season (33 percent) with adoption of farmyard manure, intercropping and a combination of both farmyard manure and intercropping. Similarly, a study by De Groote *et al*. (2010) using long-term researcher managed trial data and partial budget and marginal analysis in Kenya, observed PPT to be more profitable compared to other pest control technologies used in controlling stemborer and Striga weed. Furthermore, a study by Teklewold *et al*. (2013) and Muriithi *et al*. (2018) in Ethiopia and Kenya, observed that adoption of multiple sustainable agricultural practices (SAPs) increased maize yield and net income among the adopting farmers in their respective countries.

However, the low impact of pesticides on maize productivity could be justified by farmers having limited information on pesticide application at the time data was collected. Furthermore, previous studies have revealed farmers perceiving pesticides not to be effective in control of FAW in Kenya and Ethiopia, and even others not following technical guidance during pesticides application (Kumela *et al*., 2019). This recommends application of pesticides using technical guidance at the recommended time and rate could lead in a higher maize yield impact.

5.4. Conclusions and Policy Recommendations

This study evaluates the impact of adoption of PPT on maize productivity among smallholder maize farmers in Gatsibo and Nyagatare district of Rwanda. The study used a multinomial endogenous switching regression (MESR) model on a survey data obtained from 398 households operating 967 maize plots. The study considered the adoption decision of eight pest control practices choice sets and the outcome variables of maize yields as a result of the adoption of the pest control practices in control of FAW and stemborer pests' infestation.

The MESR was used for accounting of selectivity bias as well as capturing differential impacts of adopting pest control technologies on adopters and non-adopters of the eight technologies.

The results of MNL model revealed that the perceived cost of technology, perceived technology effectiveness, wealth status, perceived pest severity, perceived soil fertility and group membership significantly influenced the adoption of pest control practices in Eastern Rwanda. The study concludes that technology attributes and wealth status of the household play key role in the adoption decisions of pest control practices. The results of MESR further revealed that the adoption of PPT in isolation and a mixture of PPT and traditional methods resulted to an increment in maize productivity.

On the other hand, the adoption of pesticides and traditional practices in isolation and a mixture of pesticides and traditional practices resulted to a decrease in maize productivity. Therefore, the adoption of PPT and its combination with traditional practices had the highest impact on maize yield (70 percent), followed closely by adoption of PPT in isolation (59 percent), while traditional methods, pesticides in isolation and a combination of pesticides and traditional methods had the lowest impact on maize yield of –7, -46 and -24 percent respectively. Nevertheless, pesticide would lead to higher maize yield when correctly followed by the technical guidance.

The study recommends the promotion of PPT among maize farmers as an alternative low cost pest control practices to pesticides in controlling FAW and stemborer pests. Developing countries should also enhance investment and training farmers on the direct advantages of the PPT effectiveness in control of FAW and stemborer and indirect advantages on the increment in maize yield (positive impact of PPT on maize yield). Furthermore, capacity building should be enhanced by making the PPT available and affordable to improve the net incomes and reduce the amount of pre and postharvest losses due to FAW and stemborer infestation. Information dissemination using maize farmers belonging to groups is also important while introducing cost efficient PPT and subsidy program to reduce the use of pesticides in control of FAW and stemborer pests. Therefore, policies that are directed towards information-seeking through use of extension platforms such as group membership, *icipe* field monitors and government of Rwanda extension officers are highly encouraged.

CHAPTER SIX

General Summary, Conclusions and Recommendations

6.1 General Summary

The FAW and stemborer are ranked most important biotic field pests due to the huge economic losses caused in the production of maize. To control these pests, maize farmers have used various approaches that are deemed unsustainable management technologies such as widely used synthetic pesticides and traditional practices. In recognizing the negative effects of pesticides and with the view of reducing the maize yield losses, *icipe* developed and promoted PPT to enhance the effectiveness of the technology in control of FAW and stemborer.

This study evaluated the impact of adoption of PPT on smallholder maize farmer's productivity in the Eastern Rwanda. The specific objectives were two: to assess factors influencing intensity of PPT adoption and to evaluate the impact of adoption of PPT on farm level maize productivity. The study used survey data obtained in 2019 from the 394 households operating 967 maize farming plots in Eastern Rwanda. The intensity of PPT adoption was assessed based on proportion of land allocated to PPT which was bounded between 0 and 1 and analyzed using a fractional logit model. The descriptive results showed that 5 percent of the smallholder maize farmers in Eastern Rwanda had adopted PPT as an integrated pest management technology while on average, these farmers had allocated 26 percent of their maize plots to the technology. The empirical results indicated that perceived benefits of PPT, its perceived effectiveness in pest control, group membership, livestock ownership and gender had a positive influence on the intensity of adoption behavior of smallholder maize farmers in Eastern Rwanda.

The results on objective two evaluating the impact of adoption of PPT on maize productivity showed that the maize farmers who had adopted PPT and its combination reported highest increase in maize yield. Compared to the control group, the adoption of PPT and a mix of PPT and traditional method had a positive impact on maize yield while using traditional methods and pesticides in isolation and a combination of pesticides and traditional method had negative impacts on maize yield. Further, adoption decision of the pest control practices was determined by perceived cost of technology, perceived technology effectiveness, wealth status, perceived pest severity, perceived soil fertility and group membership.

6.2 Conclusions

In general, the study concludes low intensity of adoption of PPT amongst maize farmers in Eastern Rwanda as revealed by average land allocated to the technology. The results further showed the key role of farmer perceptions of technology attributes and source of information in facilitating households' technology adoption decisions. For instance, awareness of perceived benefits of the technology is likely to enhance wider adoption and up-scaling of the technology. Furthermore, results also demonstrated the potential of PPT as an alternative low cost pest control practice in controlling FAW and stemborer pests as revealed by the positive impact of adoption of PPT on maize yield. The findings validates the contribution of PPT adoption in terms of reduction of yield losses as well as controlling FAW and stemborer pests' infestation. Therefore, there is potential of upscaling to other parts through training farmers on the direct and indirect advantages of the pest control practices. Additionally, the findings illustrated that perceived cost of technology and wealth status play key role in technology adoption behavior of smallholder farmers. Even though the perceived cost of technology was a determinant for the adoption of pest control practice among the maize farmers, it has a negative impacts on the upscaling and wider adoption of the technology.

6.3 Recommendations

6.3.1 Policy Recommendations

The PPT should be made affordable and easily available to promote its adoption as a low cost pest control practices. Capacity building of maize farmers through training on the perceived benefits on the effectiveness of PPT in control of FAW and stemborer pests is highly recommended to enhance wider adoption and dissemination of the technology. This calls for a need of technology developers (*icipe* field monitors) in collaboration of the government of Rwanda (extension field officers) investing in training maize farmers on the direct and indirect advantages of PPT especially its contribution to maize yield while controlling FAW and stemborer pests using the extension platforms and farmer groups on the key role of the technology. This can also be done through use of group approaches such as field days, farmer-teacher, farmer demonstration and farmer-farmer which forms group learning extension support methods and social capital for farmer interactions and information sharing platform about PPT adoption

Building the capacity of maize farmers through availability and promotion of affordable PPT packages to enhance net household maize incomes and reduce the huge share of pre and post-harvest losses due to FAW and stemborer infestation. This can be done through factoring of farmers' perceptions of technology attributes especially on perceived cost of technology and promotion of subsidy program in development of the PPT package to ensure promotion of adoption of low-cost efficient pest control management technology through simultaneously reduction of the infestation of FAW and stemborer pests among the smallholder maize farmers.

Base on the findings from this study, there is also a need for more investment in policy formulation that seek to enhance capacity building and knowledge on the benefits of PPT adoption. This calls for an information dissemination channels using maize farmer group that are important in reducing on the use of pesticides. Therefore, policies geared towards information-seeking using both Rwanda extension field officers and *icipe* field monitors, as well as farmer groups through creation of awareness and platform for helping farmers understand the perceived benefits and perceived technology effectiveness in pest control is highly recommended. The fact that group membership influences PPT adoption implies that the Government of Rwanda should formulate policies that seek to strengthen existing farmer groups in order to ensure smooth dissemination of PPT information on the advantages and disadvantages of adopting the PPT and other pest control practices. Strengthening farmer groups provides avenues for farmer interactions and sharing experiences on the benefits of the technology and relaying feedback for extension support services thus scaling up its adoption.

6.3.2 Recommendations for Further Research

Although these results provides worthwhile intuitions into the adoption of single as well as combinations of different pest control practices, the study lacked sufficient data for empirical panel analysis due to limitation on the use of cross-sectional data that doesn't permit rigorous use of panel models such as difference in difference (DiD) models. Therefore, further research should focus on the empirical impact assessment of the different combinations of pest control practices using panel data and inclusion of time-varying variables for rigorous empirical analysis and getting more robust coefficient estimates. Secondly, the study's limitation concerns the low impact of pesticide method used in control of FAW and stemborer pests conducted when the pests had infested Rwanda and most farmers lacked technical guidance on the right and efficient pesticides to apply which calls for validation of the findings.

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APPENDICES

Appendix 1: Model Goodness of Fit Test; Results of the Calculation of deviance

Pearson and Deviance test for unequal dispersion for Fractional Logit model	
Deviance	4.468
(1/df) Deviance	0.0243
Pearson	4.468
(1/DF) Pearson	0.0243
Observations	194

Source: Survey data, 2019

Appendix 2: Results of Hosmer-Lemeshow of Probit Model using estat gof command

Hosmer-Lemeshow for the Logit model in favour of MESR model	
Hosmer-Lemeshow $Chi^2(8)$	12.47
$Prob>Chi^2$	0.1313
Number of groups	10
Observations	967

Source: Survey data, 2019

Note: The study failed to reject the null hypothesis and concluded that Fractional Logit and MESR fitted the data well respectively.

Appendix 3: Test for Multicollinearity; VIF of Fractional Logit Model

Results of Variance Inflation Factor (VIF) of Fractional Logit Model

Variable	VIF	1/VIF
Perceived PPT benefits	1.07	0.931
Perceived PPT effectiveness in control of FAW	1.31	0.762
Perceived PPT effectiveness in control of Stemborer	1.34	0.744
Age of the household head	1.08	0.926
Gender of the household head	1.06	0.947
Education of the household head	1.09	0.916
Family size	1.03	0.969
Off-farm income of the household head	1.09	0.920
Ground membership of the household head	1.06	0.941
Livestock ownership (TLU)	1.05	0.956
Mean VIF	1.12	

Source: Survey data, 2019

Appendix 4: Results of VIF of Multinomial Endogenous Switching Regression (MESR)

Variable	VIF	1/VIF

Perceived cost of technology	1.03	0.969
Perceived technology effectiveness	1.07	0.938
Wealth index	1.15	0.867
Perceived FAW severity	1.15	0.870
Perceived Stemborer severity	1.16	0.863
Perceived soil fertility	1.08	0.925
Age of the household head	1.09	0.919
Gender of the household head	1.15	0.872
Education of the household head	1.14	0.877
Family size	1.18	0.845
Group membership	1.10	0.907
Farm size	1.10	0.906
Mean VIF	1.12	

Source: Survey data, 2019

Appendix 5: Pearson partial Correlation Matrix of independent variables in FLM

	1	2	3	4	5	6	7	8	9	10	11
1	1.000										
2	0.240	1.000									
3	0.254	0.159	1.000								
4	0.198	0.225	0.464	1.000							
5	0.235	0.083	0.148	0.109	1.000						
6	0.091	-0.032	0.108	0.127	0.035	1.000					
7	0.123	0.022	0.058	0.039	-0.008	0.182	1.000				
8	0.205	0.029	0.080	0.081	0.140	0.068	0.096	1.000			
9	0.205	0.079	0.062	0.074	0.117	0.142	0.126	0.055	1.000		
10	-0.043	-0.018	0.116	0.112	-0.034	-0.100	-0.147	0.075	-0.014	1.000	
11	-0.050	0.004	0.039	0.071	-0.028	-0.014	0.101	-0.002	0.067	0.095	1.000

Note: Names of explanatory variables from number 1 to11

1. Intensity of adoption of PPT (proportion)
2. Perceived PPT benefits
3. Perceived PPT effectiveness in control of FAW
4. Perceived PPT effectiveness in control of Stemborer
5. Group membership
6. Off-farm income
7. Education
8. TLU
9. Gender
10. Age
11. Family size

NOTE: The mean VIF score were 1.12 and 1.09 (critical value 10) while the partial correlation coefficients for all independent variables were less than 5 ruling out the presence of multicollinearity.

Appendix 6: Pearson partial correlation matrix of independent variables in MESR model

	1	2	3	4	5	6	7	8	9	10	11	12
1	1.000											
2	-0.018	1.000										
3	-0.002	0.111	1.000									
4	0.003	0.077	0.055	1.000								
5	-0.027	0.031	0.119	0.321	1.000							
6	-0.055	0.018	0.150	0.036	0.107	1.000						
7	0.004	0.133	0.205	0.116	0.059	0.047	1.000					
8	0.089	0.063	-0.067	0.035	0.008	0.064	0.006	1.000				
9	0.013	-0.069	0.117	0.062	0.005	0.066	0.018	-0.190	1.000			
10	-0.062	0.140	0.245	0.099	0.052	0.126	0.204	-0.071	0.112	1.000		
11	-0.122	0.131	0.121	0.068	0.154	0.090	0.113	0.028	-0.028	0.121	1.000	
12	0.035	0.074	0.158	0.100	0.009	0.232	0.122	0.101	0.246	0.067	0.035	1.000

Note: Names of explanatory variables from number 1 to12

1. Perceived cost of the technology
2. Perceived technology effectiveness
3. Wealth index
4. Perceived FAW severity
5. Perceived stemborer severity
6. Group membership
7. Farm size
8. Age
9. Gender
10. Education
11. Perceived soil fertility
12. Family size

Note: Explanatory variables were less than 0.5 implying that multicollinearity of the independent variables was not a problem. However, perceived PPT effectiveness in control of stemborer dropped from the FLM analysis due to high correlation with perceived PPT effectiveness in control of FAW. Moreover, in MESR, perceived stemborer severity was dropped from analysis due to high correlation with perceived FAW severity.

Appendix 7: Test for Heteroscedasticity; Results heteroscedasticity of Fractional Logit Model

Breusch-Pagan / Cook-Weisberg test for heteroscedasticity	
	H_0: Constant Variance Variables: fitted values of X1 Chi^2 (1) = 0.01 Prob> chi^2 = 0.907

Source: Survey Data (2019)

Note: Breusch –pagan test failed to reject the null hypothesis of homoscedasticity and concluded the absence of heteroscedasticity.

Appendix 8: Results of heteroscedasticity of MESR model

Breusch-Pagan / Cook-Weisberg test for heteroscedasticity	
	H_0: Constant Variance Variables: fitted values of X1 Chi2 (1) = 15.67 Prob> chi^2 = 0.0001

Source: Survey data, 2019

Note: Breusch –pagan test rejected the null hypothesis of homoscedasticity and concluded the presence of heteroscedasticity that was corrected using robust standard error in analysis.

Appendix 9a: Test of Independence of Irrelevant Alternatives (IIA) Property for MNL

Results of Hausman tests of IIA assumption (N=967)

H_0: Odds (Outcome-J vs Outcome-K) are independent of other alternatives

Dependent variables	Chi^2	df	P> Chi^2
No Technology (Null set)	4.862	44	1.000
Traditional Technologies	15.480	44	1.000
Pesticides Technologies	0.204	44	1.000
Push-Pull Technologies	3.900	44	1.000
Combination of Pesticides and Traditional Technologies	11.266	44	1.000
Combination of Push-Pull and Traditional Technologies	0.054	44	1.000

Source: Survey data, 2019

Note: A significant test is evidence against H_0

Appendix 9b: Results of Suest-Based Tests of IIA assumption (N=967)

H_0: Odds (Outcome-J vs Outcome-K) are independent of other alternatives

Dependent variables	Chi^2	df	P> Chi^2
No Technology (Null set)	31.554	44	0.920
Traditional Technologies	26.765	44	0.981

Pesticides Technologies	33.925	44	0.864
Push-Pull Technologies	37.256	44	0.754
Combination of Pesticides and Traditional Technologies	38.349	44	0.712
Combination of Push-Pull and Traditional Technologies	27.060	44	0.979

Source: Survey data, 2019

Note: A significant test is evidence against H_0

Appendix 9c: Results of Small-Hsiao Tests of IIA assumption (N=967)

H_0: Odds (Outcome-J vs Outcome-K) are independent of other alternatives

Dependent variables	InL(full)	InL(omit)	Chi^2	df	P> Chi^2
No Technology (Null set)	-454.102	-426.001	56.203	44	0.103
Traditional Technologies	-493.523	-466.951	53.145	44	0.162
Pesticides Technologies	-545.873	-522.118	47.510	44	0.332
Push-Pull Technologies	-501.474	-472.945	57.058	44	0.190
Combination of Pesticides and Traditional Technologies	-568.470	-545.845	45.251	44	0.420
Combination of Push-Pull and Traditional Technologies	-597.335	-574.906	44.859	44	0.436

Source: Survey data, 2019

Note: A significant test is evidence against H_0

Appendix 10: Random Effects Generalized Least Squares (GLS)

Factors influencing maize productivity in Eastern Rwanda (Dependent variable =Log maize yield of non-adopters) (base category)

Variables	Yield with Traditional technologies	Yield with Pesticide technologies	Yield with PPT technology	Yield with Pesticides & traditional combined	Yield with PPT & traditional combined
Log of Seeds and pesticides costs	-0.1930 (0.1365)	-0.0479 (0.0672)	-0.2179 (0.0647)***	-0.2861 (0.1405)**	-0.2038 (0.0633)***

Fertilizers in kilograms per acre	0.0253 (0.0309)	0.0195 (0.0467)	0.0386 (0.0388)	0.0598 (0.0678)	0.0330(0.0814)
Perceived FAW severity	-0.2027 (0.2572)	0.2851 (0.2676)	0.5131 (0.3825)	0.1066 (0.5265)	0.05443(0.8232)
Perceived stemborer severity	-0.5604(0.2354)**	0.0943 (0.2333)	-0.4258(0.3073)	-0.2984(0.4579)	0.9940(0.5524)*
Age of the farmers	0.02318 (0.0091)***	-0.0016 (0.0076)	0.0051 (0.0105)	-0.0104 (0.0141)	0.0047(0.0183)
Gender of the household head	-0.1429 (0.2081)	0.6165 (0.4219)*	0.4774 (0.2237)**	0.7750 (0.4419)*	0.1996(0.3794)
Inverse Mills Ratio 1	0.0406 (0.04812)	0.0743 (0.0589)	0.0905 (0.0707)	-0.0930 (0.1192)	0.0586 (0.1060)
Inverse Mills Ratio 2	-0.0212 (0.0377)	0.0046 (0.0338)	-0.0246 (0.0341)	0.0667 (0.0627)	0.0040 (0.0413)
Inverse Mills Ratio 3	-0.0873 (0.0246)***	0.0570 (0.0242)**	0.0104 (0.0254)	0.0131 (0.0493)	-0.0050 (0.0376)
Inverse Mills Ratio 4	0.1150 (0.0432)***	0.0855 (0.0465)*	0.1278 (0.0479)***	0.1031 (0.0971)	0.0856 (0.0984)
Inverse Mills Ratio 5	-0.0865 (0.0264)***	-0.0934 (0.0220)***	-0.0369 (0.0307)	-0.0521 (0.0444)	-0.0338 (0.0602)
Inverse Mills Ratio 6	-0.1275 (0.0531)**	-0.0699 (0.0358)**	-0.1426 (0.0522)***	-0.0212 (0.0850)	-0.1105 (0.0992)
Constant	6.3268 (1.6893)***	5.5142 (1.3592)***	6.8133 (1.4002)***	8.9345 (2.1475)***	7.0335 (2.3120)***
Sigma_u	0.5549	0.6536	0.5047	0.8224	0
Sigma_e	0.5103	0.3315	0.7766	0.2834	0.9173
Rho	0.5417	0.7953	0.2969	0.8938	0
Model:	234	140	196	74	70
Observation	127.20	119.87	41.67	45.94	22.05
Wald chi2 (12)	0.0000	0.0000	0.0000	0.0000	0.0369
Prob > chi2					
R Squared:	0.2385	0.1616	0.0030	0.0014	0.0198
Within	0.3783	0.4543	0.2226	0.3144	0.2867
Between	0.3663	0.4506	0.2013	0.3164	0.2541
Overall					
Corr (u_i, X)	0	0	0	0	0
Observation per group Minimum	1	1	1	1	1
Average	1.2	1.2	1.2	1.0	1.1
Maximum	3	3	3	2	3

Coefficients and robust standard error in parenthesis. ***, ** and * denotes level of significance at 1%, 5% and 10% respectively